DYNAMIC MANAGEMENT OF INTEGRATED RESIDENTIAL ENERGY SYSTEMS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of the Ohio State University

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ABSTRACT

This study combines principles of energy systems engineering and statistics to develop integrated models of residential energy use in the United States, to include residential recharging of electric vehicles. These models can be used by government, policymakers, and the utility industry to provide answers and guidance regarding the future of the U.S. energy system.

Currently, electric power generation must match the total demand at each instant, following seasonal patterns and instantaneous fluctuations. Thus, one of the biggest drivers of costs and capacity requirement is the electricity demand that occurs during peak periods. These peak periods require utility companies to maintain operational capacity that often is underutilized, outdated, expensive, and inefficient. In light of this, flattening the demand curve has long been recognized as an effective way of cutting the cost of producing electricity and increasing overall efficiency. The problem is exacerbated by expected widespread adoption of non-dispatchable renewable power generation. The intermittent nature of renewable resources and their non-dispatchability substantially limit the ability of electric power generation of adapting to the fluctuating demand.

Smart grid technologies and demand response programs are proposed as a technical solution to make the electric power demand more flexible and able to adapt to power generation. Residential demand response programs offer different incentives
and benefits to consumers in response to their flexibility in the timing of their electricity consumption. Understanding interactions between new and existing energy technologies, and policy impacts therein, is key to driving sustainable energy use and economic growth. Comprehensive and accurate models of the next-generation power system allow for understanding the effects of new energy technologies on the power system infrastructure, and can be used to guide policy, technology, and economic decisions.

This dissertation presents a bottom-up highly resolved model of a generic residential energy eco-system in the United States. The model is able to capture the entire energy footprint of an individual household, to include all appliances, space conditioning systems, in-home charging of plug-in electric vehicles, and any other energy needs, viewing residential and transportation energy needs as an integrated continuum. The residential energy eco-system model is based on a novel bottom-up approach that quantifies consumer energy use behavior. The incorporation of stochastic consumer behaviors allows capturing the electricity consumption of each residential specific end-use, providing an accurate estimation of the actual amount of available controllable resources, and for a better understanding of the potential of residential demand response programs.

A dynamic energy management framework is then proposed to manage electricity consumption inside each residential energy eco-system. Objective of the dynamic energy management framework is to optimize the scheduling of all the controllable appliances and in-home charging of plug-in electric vehicles to minimize cost. Such an automated energy management framework is used to simulate residential demand response programs, and evaluate their impact on the electric power infrastructure. For instance, time-varying electricity pricing might lead to synchronization of the individual residential demands, creating pronounced rebound peaks in the aggregate
demand that are higher and steeper than the original demand peaks that the time-varying electricity pricing structure intended to eliminate.

The modeling tools developed in this study can serve as a virtual laboratory for investigating fundamental economic and policy-related questions regarding the interplay of individual consumers with energy use. The models developed allow for evaluating the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand.

In particular, two case studies are reported in this dissertation to illustrate application of the tools developed. The first considers the impact of market penetration of plug-in electric vehicles on the electric power infrastructure. The second provides a quantitative comparison of the impact of different electricity price structures on residential demand response. Simulation results and an electricity price structure, called Multi-TOU, aimed at solving the rebound peak issue, are presented.
To those who follow their dreams.
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Things are as beautiful as the people you share them with. I had the pleasure of sharing this experience with wonderful people, and for this I am grateful.

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Chapter 1

INTRODUCTION

Energy and related technologies have shaped the evolution of human societies since the dawn of history. In 2003 the National Academy of Engineering chose electrification as the preeminent engineering achievement of the twentieth century. Starting from the mid 1880’s, electrification radically transformed society as a whole, substantially improving the life-style of people, and allowing for commodities such as mass-communication, electric lighting, cooling technologies, indoor comfort, computer processing, and many others.

Nowadays, fossil fuel dependency, the need for greater energy security, macroeconomic considerations, and concern about climate changes call for a paradigm shift in the energy industry. In the next decades, the world electric power system may see the largest change since the beginning of the industrial revolution, as a centralized system based on fossil fuels is replaced by a diversified system including renewables, energy storage, and distributed generation – also referred to as the third industrial revolution. Efficiency at all levels (supply, demand, and transportation) and effective integration and coordination will play a pivotal role in this revolution. Integration and coordination of the overall electric power system is made possible by smart grids, that through advanced connection and communication allow for increasing the flexibility of the integrated system.

According to the U.S. Department of Energy, smart grid generally refers to a class
of technologies used to bring utility electricity delivery systems into the 21st century, using computer-based remote control, and communication [22]. These systems are made possible by two-way communication technologies and computer processing that has been used for decades in other industries. They are beginning to be used on electricity networks, from power plants and wind farms all the way to the consumers of electricity in homes and businesses. They offer many benefits to utilities and consumers – mostly seen in big improvements in energy efficiency on the electricity grid and in homes and offices [22].

The smart grid will mark a total transformation of the industry’s operating model – the first major architectural change since alternating current became the dominant system after the Chicago World’s Fair in 1893 [23]. To make this revolution possible, a system of over one million megawatts (solely in the United States [24]) will require a trillion-dollar retooling in the span of the next several decades [25].

Traditionally, electric power generation follows demand extremely closely, making adjustments to keep the grid balanced. One of the biggest drivers of costs and capacity requirement is the electricity demand that occurs during peak periods. For example, it is estimated that a 5% lowering of demand would have resulted in a 50% price reduction during the peak hours of the California electricity crisis in 2000/2001 [26].

To meet the high demand during these peak periods utility companies are required to maintain a significant amount of operational capacity, which is often outdated, expensive, and underutilized.

Electric utilities are extremely interested in finding a stable and sustainable solution to such a problem, especially with expected widespread adoption of non-dispatchable renewable power generation. Widespread adoption of non-dispatchable

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1A term for an energy system that cannot be expected to provide a continuous output to furnish power on demand, because production cannot be correlated to load. From The Energy Library [27].
renewable energy sources limits the flexibility of the power generation and its ability to follow the fluctuations of the demand.

Instead of adapting electricity generation to match changes in demand, the demand itself could be made more flexible to reduce requirements on the electric power generation infrastructure and allow for an easier integration of non-dispatchable renewable resources. The smart grid allows for the implementation of demand response,\(^2\) which is a way of making electricity demand more flexible allowing private customers to modify their demand profiles to fit the needs of energy supply. This enables energy consumers to participate actively in energy markets. In such a scenario, the entire energy grid becomes more efficient, costs less to operate, and presents a smaller environmental impact [29].

Demand response is the key aspect that allows efficient interaction between electricity demand and supply. The ability to reduce electricity demand and shift peak loads through better demand-side management is currently one of the most promising approaches to solve problems related to peak demand.

The present study focuses on the role of the residential sector in this transformation. To understand and realize this transformation a comprehensive and accurate model of the next-generation power system is needed.

Recently, Plug-in Electric Vehicles (PEVs) have introduced a connection between the energy consumptions of residential and transportation sectors, creating a Residential Energy Eco-System (REES) that comprises energy consumption inside the household and residential charging of PEVs’ batteries.

A detailed model of a residential energy eco-system is developed in this study,

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\(^2\)Demand response is defined by the U.S. Federal Energy Regulatory Commission as: “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [28].
that is able to capture the entire energy footprint of an individual household, including energy consumed inside the house and energy consumption related to personal transportation.

Further, a dynamic energy management framework is developed with the objective of intelligently managing energy consumption of a REES. Dynamic energy management is used in this study to simulate decentralized automated demand response.

The set of tools developed in this study allows for evaluating challenges and advantages in the integrated residential and personal transportation sector for electric utilities, as well as costs/benefits for consumers, and positive/negative externalities for the society as a whole. This tool serves as a virtual laboratory for investigating fundamental economic and policy-related questions regarding the interplay of individual consumers with energy use.

Large-scale simulations of groups of REESs are performed to simulate aggregate-level results and allow to evaluate the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand. The modeling developed in this study can serve as a tool to guide electric utilities and energy policy makers on topics regarding residential electric power systems, and the integration of plug-in electric vehicles. The development of integrated energy consumption models allows for the simulation of different “what-if?” scenarios and the evaluation of different technology adoption, so as to provide answers and guidance towards a sustainable future for integrated residential energy systems.

In the demand response paradigm, electric utilities provide some sort of incentive to their customers to change their consumption pattern. Utilities also provide a signal to their customers that is intended to guide the power consumption so as to obtain an aggregate demand that better matches the needs of the power generation.
The overall objective is to improve the operation of the electric power system in one or more of the following ways:

- reduce electricity generation and grid operation costs for electric utilities;
- manage demand peaks (better interaction between demand and generation);
- reduce overall pollutant and carbon dioxide emissions from electricity generation;
- improve overall grid efficiency and minimize primary energy consumption (national energy policy).

In this study, a state-of-the-art dynamic energy management framework is developed to evaluate the potential of residential demand response. The dynamic energy management framework is based on highly-resolved personal energy consumption models developed using a novel bottom-up approach that quantifies consumer energy use behavior. The incorporation of stochastic consumer behaviors provides more accurate estimation of the actual amount of available controllable resources, allowing for a better understanding of the potential of residential demand response programs.

This chapter is structured as follows: Section 1.1 provides a brief overview of the current energy situation in the United States, with focus on residential electricity consumption. Section 1.2 analyzes the motivation for this research and defines the problem being studied. Section 1.3 describes the concept of demand response, with focus on residential programs in the United States. Section 1.4 reports a general review of the relevant literature. A summary of the present study is reported in Section 1.5, together with the objectives of this research.
1.1 Current Energy Situation in the United States

The United States are responsible for 19% of the global primary energy consumption, namely 97.3 quadrillion BTU in 2011 (corresponding to $1.03 \cdot 10^{20} J$) [30]. This is equivalent to almost 7 gallons (over 25 liters) of gasoline consumed daily by each American. Looking at the primary energy sources, 36% of the total primary energy consumed in the United States comes from petroleum; 26% from natural gas; 20% from coal, 8% from nuclear, and 9% from renewable sources. Figure 1.1 shows the use of energy in the United States by sector, with particular focus on buildings.

This study focuses on the energy consumption of integrated residential and personal transportation systems. The residential sector accounts for about 22% of the total primary energy consumption. Personal transportation accounts for over 65% of the transportation sector [20], and thus for 18% of total primary energy consumption. Combined residential and personal transportation are responsible for about 40% of the total primary energy consumption in the United States.

In September 2011 the U.S. Department Of Energy (DOE) published its first quadrennial technology review, with the objective of defining a simple framework for understanding and discussing the challenges that the energy system presents and discuss the roles that DOE, the broader government, the private sector, the national laboratories, academia, and innovation itself play in energy transformation [13].

DOE identified six strategies, summarized in Figure 1.2, for achieving three broad national energy goals: reducing U.S. dependence on oil, reducing environmental impact, and investing in research and development for clean-energy technologies in the United States.

The present study centers on the demand side and its interaction with electricity
Figure 1.1: Energy use in residential and commercial buildings in the United States. From the U.S. Department of Energy report on the first quadriennial technology review [13].

supply, including both stationary and transport applications. In particular the residential energy eco-system model and the dynamic energy management framework developed allow for:

- exploring opportunities to increase building efficiency;
- investigating opportunities related to electrifying the vehicle fleet and its impact on the electric power system;
- studying residential demand response programs, and their role in modernizing
Figure 1.2: Six strategies identified by the U.S. Department of Energy in its 2011 quadrennial technology review to address national energy challenges. From the U.S. Department of Energy report on the first quadriennial technology review [13].

1.2 Motivation and Problem Definition

Electricity is a commodity that is expensive to store. Therefore, currently electric power generation must match the total demand at each instant, following seasonal and diurnal patterns and instantaneous fluctuations. Thus, one of the biggest drivers of costs and capacity requirement is the electricity demand that occurs during peak periods, for example during the hours between 5 p.m. to 7 p.m. – when residents
return home and prepare meals – and during excessively hot and cold days. These peak periods require utility companies to maintain operational capacity to meet such a high demand. This peak capacity is often outdated, expensive, and underutilized.

Electric utilities are extremely interested in finding a stable and sustainable solution to such a problem, especially with expected widespread adoption of non-dispatchable renewable power generation. The intermittent nature of renewable resources and their non-dispatchability substantially limit the ability of electric power generation of adapting to the fluctuating demand.

Recently, smart grid technologies and demand response programs have been proposed as a technical solution to make the demand more flexible and able to adapt to power generation. Aghaei and Alizadeh present a review of challenges and opportunities for demand response programs in smart electricity grids equipped with renewable energy sources [31].

The current electric power system is mostly mechanical, with little use of electronic sensors and control technologies. A smart grid, so-called because of the widespread use of sensors, communication technologies, computational abilities, and control systems, promises more efficient electricity generation, distribution, and consumption [32]. The smart grid requires the integration of various control and communication technologies that allow for continuous monitoring and real-time responses to demand variations and other conditions (e.g., weather changes, transmission or generation issues, etc.) [33]. For residential consumers, smart grid technologies might consist of the adoption of smart appliances and real-time demand monitoring and control [34]. Currently, the roll-out of smart grid technologies in the residential sector has focused on the replacement of old meters with smart meters. This allows for time-varying electricity pricing, and the use of smart appliances. A smart meter is an energy meter that is equipped with advanced electronics that can communicate with the energy
provider and provide information about the consumer’s energy use [35]. A smart appliance is one that is able to respond to external signals without direct action by the consumer [36]. In other words, the smart appliance responds to the signal sent to the smart meter, typically electricity price, automatically and independently. Smart appliances can be integrated into a network that automatically manages, monitors, and adjusts consumption in response to needs of the consumer, the availability of electricity supply, and signals from the electric utilities [37].

Optimal management of the whole system requires two-way communication between the demand side and a centralized controller on the electricity supply side in order to coordinate the needs of individual consumers and the needs of electric utilities. Still, such a technology is not expected to be available in the United States in the near future. Alternatively, smart appliances can simply respond to external pricing signals, without communicating back their operating response to those signals nor communicate with each other. This simpler system, analyzed in this study, requires only one-way communication, namely a signal sent from the utilities regarding the price of electricity.

Foundational to the implementation of the smart grid are demand response programs, which offer different incentives and benefits to consumers in response to their flexibility in the timing of their electricity consumption. These programs are needed in order to entice consumers to relinquish some control over their energy consumption.

Figure 1.3 reports typical summer and winter electricity demand curves for the PJM region showing base, intermediate, and peak load. Such curves might vary depending on geographical location and country, but the daily and seasonal variation

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3PJM is a regional transmission organization that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia.
in the demand remains a common issue for electric power generation throughout the globe.

Figure 1.3: Typical daily electric power profile.

In order to satisfy such a fluctuating demand, electric utilities are forced to maintain different generation assets [38]. Moreover, to insure a stable operation of the electric system, and to ensure the security of supply in the face of uncertainty of available generation and variations in demand, the total capacity of installed generation in the system must often be significantly larger than the maximum demand, exacerbating the problem. A safety factor of 20% of excess capacity is reported in the literature [39], but in several regions of the United States this figure reached 40% in summer 2013, as reported by the U.S. Energy Information Administration [40].

Electric power generation assets are typically classified between base-load, intermediate, and peak power plants. Base-load electricity is provided by extremely reliable, inexpensive, and efficient power plants, which run continuously during the year (over 70% of the time), except in the case of repairs or scheduled maintenance.
Such plants including nuclear, hydroelectric, geothermal, and coal power plants often take a long time to start up and are designed to work at their nominal capacity with a small degree of flexibility. Intermediate power plants are operated between 20% and 70% of the time, with the objective of following the fluctuations of the load, curtailing their output in periods of low demand, such as during the night. These plants are typically coal- or gas-fired, including high-efficiency combined cycle gas turbine plants. Wind and solar power plants are typically considered intermediate power plants [38], since their operations are limited by the availability of the renewable sources exploited. Even though they are run as much as possible they do not achieve base-load availability, and they are hardly used to match peak demand, as they cannot be dispatched. Intermediate power plants fill the gap between base load and peak plants, from cost, size, and flexibility standpoints. Peak power plants run only when there is a high demand for electricity, typically for less than 20% of the hours in a calendar year. Peak plants are generally smaller, can be started up quickly, and are flexible enough to follow rapid fluctuations in the demand. The U.S. Energy Information Administration reports that in 2012 a capacity of 121 GW of natural gas combustion turbines – accounting for over 11% of the total electricity generating capacity [30] – was maintained to contribute about 3% of the overall electricity generation [41]. The average capacity factors of these plants varied significantly by time of day and region, ranging from 0 to 30%. Peak plants are very expensive to operate and less efficient compared to intermediate and base-load power plants. The main reasons for this high cost is underutilization, as peak power plants are operated just a few hours a year, resulting in significant maintenance and capital recovery costs. Nevertheless, due to their smaller size, they are less expensive and easier to build. They are most often single cycle gas turbines that run on natural gas or, in some cases, oil derivatives. Figure 1.4 reports the load duration curve for the three
categories of power plants. A load duration curve is used in electric power generation to illustrate the relationship between generating capacity and capacity utilization. It is similar to a load curve but the demand data is ordered in descending order of magnitude, rather than chronologically. The load duration curve shows the capacity utilization for each increment of load.

The exponential increase in electricity price for peak generation is clearly shown in Figure 1.5, which reports the average aggregate wholesale electricity supply curve in the PJM market during 2011 and 2012 summer operations. Data shown in Figure 1.5 confirms that peak demand drives the high cost of electricity.

In the United States the electricity market price is regulated, resulting in a fixed retail electricity price, which is the price that consumers see. This is set by the
Figure 1.5: Average PJM aggregate supply curves: Summer 2011-2012. From 2013 state of the market report for PJM [15].

regulator to maintain a profit margin for the electric utilities and at the same time protect consumers. As a result, utilities are constrained by the price that they are allowed to charge a customer, and consequently the revenue that can be made on any given kWh of electricity sold. The profit that the utilities make is dependent on the generation cost.

Figure 1.6 reports the frequency distribution of hourly wholesale electricity generation cost and the average retail price of the PJM real-time energy market in 2012. The disconnection between supplier cost and retail price has been observed in previous studies [42]. In Figure 1.6 profit and loss areas are shown in green and red, respectively.
As shown in Figure 1.6, for approximately 75% of the time, the cost of generating electricity is below the retail price, and therefore, the utilities operate at a profit. For the remaining 25% of the time, utilities actually operate at a loss. For the case reported in Figure 1.6, in the PJM market the cumulative loss in 2012 resulted to be 57% of the cumulative profit (ratio of red and green areas). Overall, the high generation cost drives the average electricity retail price to increase. Reducing the demand during high-cost periods, would reduce the average retail price, and potentially save consumers money.

One of the challenges in the operation of electric power systems is that generally consumers are protected from the volatility of the wholesale market even in so-called deregulated markets. In the United States, deregulation refers to the wholesale market not to the retail market. In a competitive unregulated market, the marginal cost should equal the marginal price, but in the electricity market this is not the case. Higher generation costs during peak periods are not reflected in retail electricity prices seen by the final consumers. In essence there is an economic “iron curtain
between the wholesale and retail markets” [43] meant to protect the final customers. However, this protection also creates the situation in which consumers are unaware of the cost differential of generating electricity during peak periods. Therefore, with a flat electricity price, consumers have no economic incentive to respond to changing generation costs.

In light of this, it is in the interest of the electric utilities to find a way to smooth out demand to avoid the high costs of meeting peak demand resulting from the peculiarities of the electricity market where supply is forced to match demand at each instant. There are five possible mechanisms for addressing this problem:

1. Storage of excess electricity during non-peak periods for use to match peak demand;
2. Complete deregulation of the retail electricity market;
3. Direct load control by the utilities;
4. Energy conservation, efficiency, and education;
5. Techno-economic solutions, including incentive-based and time-based demand response programs.

Large-scale electricity storage is currently expensive. There are several methods of storing electricity. The most commonly used method is to use the electricity to pump water to an elevated height, hold it in a reservoir, and then use the potential energy stored in the water to produce electricity when it is needed. However, this form of storage requires significant tracts of land and water, which are not always readily available. Alternatively, energy can be stored in electrochemical storage devices, typically batteries. However, batteries of the kind needed to support large electricity demand are still prohibitively expensive. Deregulation of the retail electricity market is impractical for political and socio-economic reasons. Likewise, complete direct load control by electric utilities would be unacceptable by American consumers and
to utilities, who are concerned about privacy and legal issues. Local efforts at energy conservation, efficiency, and education are currently being made; however, these have generally proven to be insufficient at resolving the peak demand problem.

One of the most prominent techno-economic solutions proposed to cope with the high cost associated with peak generation is the use of smart grids and demand response programs. Demand response provides a way to convey electricity generation costs to final consumers, making wholesale electricity market fluctuations visible in the retail market. Électricité De France (EDF), the world’s largest producer of electricity, identifies three main motivations for demand response development [44]:

1. **Past issues still existing**: reduce investment and operation cost in generation, transmission, and distribution of electricity due to peak demand; cut down energy bill of consumers.

2. **New market issues**: reduce price volatility and peak prices on wholesale market; improve the link between wholesale and retail market (right signal for consumption); develop competition in retail market.

3. **New environment issues**: develop renewable energy by correlating the consumer’s consumption profile with production of green electricity; reduce CO$_2$ emissions from fossil fuel power plants.

Also, EDF underlines the need to especially clip peak consumption of residential customers, who create a disproportionate percentage of the peak demand [44].

In the present study, highly-resolved models are used to perform large-scale simulations. These models allow to simulate residential electric power demand and to evaluate the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand.
1.3 Demand Response in the United States: a Brief Review

Flattening the load curve has long been recognized by electric utilities as an effective way of cutting the cost of producing electricity [45]. Demand response has proved effective at shifting consumption away from peak hours, thus increasing system efficiency and stability, reducing the need for investment in peaking generation, and bringing several environmental and financial benefits [44]. A power system equipped with demand response capabilities can lead to a reduction in systems costs, CO$_2$ emissions, and price volatility by shifting power consumption to periods characterized by low prices and high renewable power production [46].

In modern electricity markets, trading of electricity is organized in pools or exchanges. Short-term electricity transactions are traded in the day-ahead market, which is organized as a two-sided auction. In the day-ahead market producers submit offers and bids for electricity delivery to the grid throughout the following day. Accordingly, retailers and large consumers submit bids for electricity withdrawals for the same period of time. The process of selling wholesale energy begins with a bidding process whereby generators offer an amount of energy for sale during specific periods of the day at a specific price for the following day. These offers are arranged by the market operator in ascending order, and the generators are dispatched (told to generate) in this order until generation matches the expected load [47]. When the market is cleared, the intersection between the aggregate supply and demand curves sets the wholesale market price, which then applies to all market participants (all the dispatched generators receive the same compensation, called the “clearing price”, which corresponds to the offer of the last generator dispatched). The goal of the system operator is to determine the dispatch that minimizes total cost, as measured by generators bids, subject to security constraints.

Later adjustments of day-ahead contracts are possible in intra-day markets, also
known under the more generic name of adjustment markets [46]. A balancing market is then performed in real-time to ensure system balance (supply must match demand at any given time). Day-ahead, intra-day, and balancing markets are energy markets, in that the payment to or from the market operator is proportional to the amount of energy (kWh) actually delivered to or withdrawn from the grid. In addition to energy markets, reserve capacity markets are in place in some countries to guarantee the availability of sufficient balancing power during the real-time operation of the power system. Producers participating in reserve capacity markets are compensated proportionally to the power capacity offered (MW), rather than the energy actually delivered. Additionally, they are compensated for the actual amount of electrical energy (kWh) sold in the balancing market.

Reducing the load during peak periods, when power plants with high marginal costs are required to operate, will reduce spot market prices [46]. Depending on the specific electric power generation mix and the load level such reductions can be significant, as there are significant step changes in electricity generation cost depending on the generation technology and utilization factor. Moreover, flattening the load curve has additional advantages as certain types of conventional power plants are not designed for quick load changes.

Figure 1.7 shows an example of the balancing of supply and demand in the day-ahead wholesale electricity markets used to determine the electricity price. The blue line represents the aggregated power supply curve of the system. This curve is built by the market operator by sorting all the offers made by the electricity producers, one day in advance of the physical power delivery. The black line represents the aggregate demand curve. If the demand is completely inelastic such a line is vertical. Normally, a portion of the demand is indeed inelastic (essential services), but demand response acts on part of the demand either reducing it or shifting it to off-peak periods, reducing
the total peak demand. As shown in Figure 1.7 demand response has the effect of decreasing the overall electricity price cleared by the wholesale market.

![Figure 1.7: Day-ahead market clearing price considering inelastic demand and demand response.](image)

Demand response lowers the point at which the demand curve intersects the supply curve. Also, it can decrease the need for local network investments, as it can shift consumption away from peak hours in regions with tight network capacity. Demand response delivers these benefits through providing consumers (residential, commercial, or industrial) with guiding signals and/or financial incentives to lower or adjust their consumption at strategic times. In so doing, demand response offers end consumers the opportunity to benefit directly from the smart grid [44]. It can also encourage them to raise their consumption during periods where renewable energy is readily available. Demand thereby acts as an intelligent partner with generation [44].
The overall goal of demand response programs is to influence consumers to change their electricity consumption patterns, or demand, in response to the needs of the supplier [48]. Demand response is the key aspect that allows efficient interaction between electricity demand and supply. The ability to reduce electricity demand and shift peak loads through better demand-side management is currently one of the most promising approaches to solving problems related to peak demand, thus allowing for a better operation of the overall electricity system.

Demand response models are based on the assumption that consumer demand is elastic and, thus, that consumers will respond to higher prices by reducing and/or shifting demand. Studies have shown that generally this is the case. Beginning in the mid-1970s, several U.S. utilities have successfully applied time-varying (often called dynamic) electricity price structures to their largest commercial and industrial customers, exploiting demand elasticity [49]. Espey and Espey [50] summarize several studies of residential electricity demand elasticities, confirming the elasticity of residential demand for electricity in the United States.

Caves and Christensen [51] use data from five experimental implementations of residential TOU rates in the United States, and concluded that customers responded to higher prices during the peak period by reducing peak period usage and/or shifting it to less expensive off-peak periods. The results were consistent around the country. The elasticity of substitution for the average customer was 0.14. Over the entire set of customers, it ranged between 0.07 and 0.21. Furthermore, Faruqui and Sergici report that several studies have consistently demonstrated that direct feedback alone (namely informing the residential consumer of high generation cost during peak periods) motivates behavior change, resulting in energy savings ranging up to 20 percent [52].

Demand response programs can be classified into incentive-based and time-based
programs [19, 48, 53]. Both are established by electric utilities to change consumption patterns by effectively changing the cost of electricity for consumers. Table 1.1 summarizes the classification of demand response programs included in the 2012 FERC Survey [19].

<table>
<thead>
<tr>
<th>Incentive-Based Programs</th>
<th>Time-Based Programs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand Bidding and Buyback</td>
<td>Critical Peak Pricing with Control</td>
</tr>
<tr>
<td>Direct Load Control</td>
<td>Critical Peak Pricing (CPP)</td>
</tr>
<tr>
<td>Emergency Demand Response</td>
<td>Peak Time Rebate (PTR)</td>
</tr>
<tr>
<td>Interruptible Load</td>
<td>Real-Time Pricing (RTP)</td>
</tr>
<tr>
<td>Load as Capacity Resource</td>
<td>Time-of-Use (TOU) Pricing</td>
</tr>
<tr>
<td>Non-Spinning Reserves</td>
<td>System Peak Response Transmission Tariff</td>
</tr>
<tr>
<td>Regulation Service</td>
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<tr>
<td>Spinning Reserves</td>
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Table 1.1: Summary of demand response types in the 2012 FERC Survey [19].

Both incentive-based and time-based mechanisms can be used at the same time. Albadi and Saadany provide a detailed overview of these mechanisms [54]. Incentive-based demand response programs provide financial compensation to consumers to shift their consumption.

Time-based pricing programs provide customers with economic incentives to shift consumption away from periods of increased demand, giving an opportunity to reduce energy expenditures. In addition, shifts in consumption may reduce the need to construct new power plants to meet increasing peak demand [19]. This is done by providing a time-varying electricity price that is intended to be a signal to guide consumer consumption to better match generation. The Energy Information Administration (EIA) reports that in the U.S. twenty-nine states have adopted time-based pricing requirements, have requirements pending, or are studying these rate structures [55].
When proposed with time-based demand response programs consumers voluntarily adjust their electricity consumption based on time-based electricity prices, typically Time of Use pricing (TOU), Critical Peak Pricing (CPP), Peak Time Rebates (PTR), or Real Time Pricing (RTP) [33, 56, 57, 58]

TOU rates are defined as different electricity prices for different periods of the day or of the year. For instance, consumers might see a higher price during the day than during the period between midnight and 6 in the morning. Consumers know prices paid for energy consumed during different periods in advance, allowing them to vary their usage in response to such prices and manage their energy costs by shifting usage to a lower cost period or reducing their overall consumption. TOU programs can be characterized by two or more price tiers.

CPP is essentially a TOU program, with a significantly higher price tier during peak periods. Two variants of this type of price structure exist: one where the time and duration of the peak periods are predetermined and another where the time and duration of the peak periods may vary based on the needs of the electric power infrastructure. Outside these peak periods TOU prices are typically in effect.

In the PTR paradigm customers receive electricity bill rebates for reducing their electricity consumption during peak periods (established \textit{a priori} by the electric utility) relative to a previously established baseline, which is determined for each individual customer. The baseline is usually identified using historical household electricity consumption. PTR are similar to CPP in some instances, but do not provide a time-varying price, in general. Faruqui and Sergici [59, 60] suggest that the equivalence between CPP and PTR may be explained both empirically and theoretically. Newsham and Bowker [56] state that: PTR is similar to CPP, except that it provides a “carrot” – a bill rebate for electricity not used on peak, rather than a “stick” – a high price for electricity used on peak. Newsham and Bowker [56] find that PTR has
been generally less effective than CPP, suggesting that people respond less well to carrots than sticks, in this context. Also, PTR is likely more costly for utilities to implement, because of the need to develop very accurate, household-specific, baselines. Imprecise baselines can compromise the fairness and economic viability of the program [56]. Further, Wolak notes that PTR provides an incentive for house-holders to elevate their electricity use during the period in which baselines are established, and found evidence for such behavior [61]. A study conducted at MIT finds that demand response programs that pay customers for reducing consumption from a baseline generally provide excessive compensation and give customers incentives for strategic behavior [47].

RTP is a dynamic electricity price structure that adjusts electricity prices on an ongoing basis throughout the day, following the wholesale electricity generation cost, on an hourly or sub-hourly basis (generally 10-15 minutes). RTP is intended to convey actual generation cost to the final consumer allowing for optimal use of generation resources. In this scenario, when the electricity price drops and consumers start increasing their demand, the generation infrastructure will be confronted with a cost increase and convey this to the consumers, who adjust their demand consequently.

Overall, time-varying price structures are designed with the objective of changing the timing of electricity consumption so as to reduce peak demand, and are not aimed at reducing overall energy use. Clearly, the ability to shift demand depends on the specific activity related to the energy consumption. Smart controllable appliances greatly enhance the opportunities for load control and postponement in residential applications. According to a study performed by the EU Parliament, residential demand response relies mainly on time-based programs, while incentive-based are targeted primarily towards commercial and industrial applications [44].
Cappers and his colleagues [62] found that demand response programs have significant potential in terms of peak load reduction in the United States. The potential demand response resource in 2010 ranges from 3 to 9% of a region’s summer peak demand in most regions, with the notable exception of the Midwest Reliability Organization region where demand response resources represent 20% of summer peak demand.

In 2011 the demand response market in the United States generated approximately 6 billion dollars in direct revenues for local businesses, industry, and households as well as enabling avoided investment costs. In the PJM interconnection, demand response allowed for cutting 7% of their seasonal peak [44].

According to the U.S. Federal Energy Regulatory Commission, potential peak reduction in the U.S. increased from 2010 to 2012 by more than 10,000 MW, from 53,062 to 66,351 MW in 2012 [19]. The 2012 FERC Survey respondents identified a total of 20,256 MW of actual peak reductions from demand response resources, representing use of 31 percent of the total reported potential peak reduction [19]. Moreover, over the past 20 years the ratio of annual peak-hour electric demand to average hourly demand has risen across the United States [24]. In particular, in the PJM interconnection the peak-to-average ratio increased from 1.59 in 1993 to 1.74 in 2012. Thus, the importance of demand response is expected to increase in the years ahead.

The buildings sector represents a significant portion of the overall U.S. energy consumption, nearly equally divided between residential (22%) and commercial (18%) [13]. Building electrical end-uses are highly heterogeneous and present great time variations, driving the “peakiness” of the overall electricity demand [63].

The residential sector alone makes up 37% of the total electricity consumption in the United States [24]. Also, despite efficiency improvements leading to a decrease
in electricity consumption per household, EIA expects total delivered electricity use in the residential sector to increase with number of households at an average rate of 0.7% per year from 2012 to 2035 [30]. The residential end-use sector has the largest seasonal variance, with significant spikes in demand every summer and winter [64]. Moreover, households are major contributors to peak demand [56], as the residential sector accounts for a disproportional amount of peak electricity use, that can reach up to 60% for some areas of the U.S. [65]. Faruqui and Sergici [59] assess that in the United States residential customers are responsible for a third of overall (electrical) energy consumption, and for a larger share of peak demand.

Currently, demand response programs focus mainly on industrial and large commercial consumers, with fixed compensations attributed to small numbers of large end-users, using direct load control and interruptible loads. Market-based demand response programs are successful in attracting participation in energy management during emergencies, which require relatively modest commitments from end users [66]. Walawalkar et al. [66] predict that in order for demand response to scale up, and enable greater level of renewable integration, technologies that are suitable for participating every day to demand response are needed. The vast potential of building energy management strategies is still untapped, not to mention future possibilities as home automation and smart appliances become standardized along with deployment of smart grid infrastructure [66]. Thus, in the future, large numbers of end-users, including small commercial customers and households could be involved in demand response programs with compensations consisting of price and deliberate shifts in electricity demand in correspondence with peak loads [67].

Navigant Research estimates less than 3% of U.S. residential customers have access to time-varying pricing today and well below 1% have actually adopted it. In a best-case scenario, as predicted by Navigant, time-varying pricing will be available to 60%
of residential customers in the U.S. by 2020, with about 20% participating to demand response [68].

In Europe over the last few years, load growth, increases in intermittent generation, declining technology costs and increasing recognition of the importance of customer behavior in energy markets have brought about a change in the focus of demand response. The long standing programs involving large industries, through interruptible tariffs and time of day pricing, have been increasingly complemented by programs aimed at commercial and residential customer groups [67].

Given the amount of electricity consumed by the U.S. residential sector, and given that residential demand is the main driver of peak demand, electric utilities and regulators are extremely interested in complementing industrial and commercial demand response with programs targeted towards a large number of small end-use consumers.

Many studies and pilot projects have shown that U.S. residential customers are willing to participate in properly designed demand response programs [51, 56, 60, 62, 69, 70, 71]. A 2013 consumer survey conducted by Navigant Consulting found that nearly 75% of Americans “have concerns about the impact electricity costs have on their monthly budgets, and 63% are interested in managing energy used in their homes” [72]. Nevertheless, residential consumers are not likely to be the drivers for the adoption of these technologies, as the monetary savings are not dramatic. On the other hand, the aggregate impact can be significant, and noteworthy opportunities arise for electric utilities, especially to alleviate capacity constraints and deal with peak demand management. Also, availability of individual service quality measurements (e.g. number and duration of network outages, voltage deviations from nominal value, etc.) allows regulators to design new incentives/penalties aimed at
improving the performance of distribution network operators and automatically compensating customers suffering from particularly poor technical quality of service [73]. Electric utilities and regulators have interest in the development of demand response programs, and can provide further economic incentives and benefits to customers participating in such programs. In addition to overall reduction of electricity-related expenditures, residential customers would also benefit from a series of advantages deriving from a better operation of the system, including reduced power sags and interruptions, better service continuity and reliability, and improved power quality (reduced voltage and frequency variations and transients phenomena).

**REVIEW OF RESIDENTIAL DEMAND RESPONSE PROGRAMS**

One of the primary methods pursued to reduce on-peak use of electricity in households is through behavioral modification, that is, encouraging people to eliminate on-peak electricity-using activities, or shift them to other periods [56]. This has been achieved using various time-varying electricity pricing, like TOU and CPP. Another variation is to provide a payment to a customer for every kWh not used during system peak periods (PTR), compared to administratively set baseline level of consumption. Bushnell *et al.* argue that this is a weak form of demand response, that could crowd out more reliable and effective time-varying pricing approaches [74].

Studies of time-varying electricity pricing go back several decades [51, 75, 76]. Residential demand response programs have been proposed in various countries, with increasing focus on programs requiring deliberate and informed demand decisions by small customers. An example of successful CPP program is EDF’s Tempo tariff, launched in 1995, which is offered to private and small business customers with a minimum capacity of 9 kW [67]. Around 350,000 residential customers and more
than 100,000 small business customers use the Tempo tariff, which makes use of different prices for different days, according to the weather. Customers can adjust their consumption manually and/or using a programmable thermostat. It has been estimated that for the average French house, the Tempo tariff brought about a reduction in consumption of 15% on “non-critical” days and 45% on “critical” days [73]. For 15 years the Tempo tariff has shown that load shifting through deliberate action by the consumer are feasible [77].

TOU pricing has been shown to effectively shift electricity demand by varying amounts. Henley and Peirson [78] found that most consumers in their UK study shifted demand to lower-cost pricing periods. Hartway et al. describe the results of a residential program based on TOU rates which demonstrates that offering a TOU option can be profitable to a utility [79].

Cappers et al. [62] provide empirical evidence on the evolution of demand response resources in U.S. electric power markets. This evidence shows that demand response is a growing industry in the United States, as evidenced by the increasing number of entities that offer demand response programs and dynamic pricing tariffs and the emergence of wholesale market programs.

Herter [69] found that consumers in California were very responsive to critical peak pricing during a 15-month experiment, with participants with programmable communicating thermostats using 25% less electricity during five-hour critical events and 41% less during two-hour critical events. Even those participants without programmable communicating thermostats reduced their consumption during these periods by an average of 13%, showing that even an awareness of critical conditions can help reduce demand. Also, findings show that high-use customers respond significantly more in kW reduction than do low-use customers, while low-use customers save significantly more in percentage reduction of annual electricity bills than do high-use customers.
(with low-use consumers saving up to 5.5% of their annual bill). In addition, satisfaction rates across all customer segments were uniformly high, averaging between 7.7 and 8.3 out of a maximum of 10 [69].

Herter and Wayland [70] analyze data from 483 households in California that took part in a CPP experiment between July and September 2004. Results from this study confirms that residential customers can and do respond to time-varying price signals. Moreover, an analysis involving two different levels of critical-peak prices – $0.50/kWh and $0.68/kWh – indicates that households did not respond more to the higher CPP rate, suggesting that the lower incentive is sufficient to change the timing of electricity consumption, and further incentives do not lead to more drastic change in electricity consumption. A study conducted by Georgia Power found that consumers reduced demand by 20 to 30 percent when electricity prices increased between 25 to 50 cents per kWh [57]. In another study conducted by Gulf Power, consumers reduced their demand by 1.5 to 2.0 kW for approximately two hours when presented with peak prices of 30 cents per kWh [57].

Newsham and Bowker [56] provide a survey of studies relating to peak reduction via the introduction of time-based demand response programs. The authors find that the most effective strategy to reduce peak demand is a critical peak price program with enabling technology to automatically curtail loads during peak events (controllable thermostats), which show little evidence of causing substantial hardship for the occupants. CPP is shown to be able to achieve a peak load reduction of at least 30%. A simple TOU program can only expect to realize on-peak reductions of 5%. The reviewed pilot studies covered lengthy periods, in some cases several years, so it is reasonable to expect that these reductions will be maintained over time. The data analyzed by Newsham and Bowker [56] also suggest that focusing residential demand response programs on households with certain characteristics, such as higher income,
education, and underlying conservation orientation, and providing these households with excellent utility support services, might realize high peak demand reductions.

Faruqui and Sergici [59, 60] survey several experimental residential demand response programs in the United States based on time-varying electricity pricing. Results from over 15 time-varying pricing pilot programs reveal that customers do respond to price, leading to reductions in peak demand ranging from 3 to 6% for TOU programs and between 13-20% for CPP programs. According to Faruqui and Sergici [59, 60] time-of-use impacts are lower because the peak prices they charge customers are lower than the peak prices charged during critical-peak periods by CPP rates.

The City of Anaheim Public Utilities (APU) conducted a residential time-varying pricing experiment between June 2005 and October 2005, described in detail by Wolak [61]. A total of 123 customers participated in the experiment: 52 in the control group and 71 in the treatment group. Despite its name, this experiment did not provide a critical peak pricing rate to participants. Instead, it provided them a rebate for each kWh reduction during critical times. The magnitude of the peak time rebate (PTR) was $0.35 for each kWh reduction below the reference level peak-period consumption on non-CPP days. The data showed that the treatment group used 12 percent less electricity on average during the peak hours of the critical days than the control group [61].

In the summer of 2006, Xcel Energy initiated a pilot program that tested the impact of TOU and CPP rates, as well as enabling technologies, on residential consumption in the Denver metropolitan area [60]. Approximately 3,700 residential customers initially volunteered into the pilot program, with about 75% maintaining enrollment until the end. Customers were subject to different rate options and some of them were provided with programmable thermostats. Participants subject to critical peak pricing reduced demand during peak hours up to 55%, while TOU lead to on-peak
reductions of maximum 10% [60]. Xcel Energy notes in the conclusion of its report that the pilot was conducted as a proof of concept rather than a technology test [80]. While the demand reduction was significant, the meters adopted in the pilot were too expensive to make the offerings cost-effective.

Table 1.2 summarizes some of the main residential demand response programs proposed in the United States, providing references for further details.

<table>
<thead>
<tr>
<th>Program</th>
<th>Period</th>
<th>Location</th>
<th>Price Structure</th>
<th>Ref.</th>
</tr>
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<tbody>
<tr>
<td>CCC</td>
<td>February 1994 – May 1997</td>
<td>Laredo, Texas</td>
<td>TOU</td>
<td>[79]</td>
</tr>
<tr>
<td>GPU</td>
<td>June-September 1997</td>
<td>New Jersey</td>
<td>TOU/CPP</td>
<td>[81]</td>
</tr>
<tr>
<td>Gulf Power</td>
<td>Summer 2000 and 2001</td>
<td>Western Florida</td>
<td>TOU/CPP</td>
<td>[82]</td>
</tr>
<tr>
<td>SPP</td>
<td>July 2003 – December 2004</td>
<td>California</td>
<td>TOU/CPP</td>
<td>[84]</td>
</tr>
<tr>
<td>ESPP</td>
<td>2003 – 2006</td>
<td>Illinois</td>
<td>RTP</td>
<td>[85]</td>
</tr>
<tr>
<td>AmerenUe</td>
<td>June-September 2004 and June-August 2005</td>
<td>St. Louis, Missouri</td>
<td>TOU/CPP</td>
<td>[86]</td>
</tr>
<tr>
<td>ADRS</td>
<td>July-September 2004 and July-September 2005</td>
<td>California</td>
<td>CPP</td>
<td>[87]</td>
</tr>
<tr>
<td>Anaheim</td>
<td>June-October 2005</td>
<td>Anaheim, California</td>
<td>PTR</td>
<td>[61]</td>
</tr>
<tr>
<td>OPP</td>
<td>April 2006 – March 2007</td>
<td>Washington &amp; Oregon</td>
<td>RTP</td>
<td>[88]</td>
</tr>
<tr>
<td>Xcel</td>
<td>July 2006 – July 2007</td>
<td>Denver, Colorado</td>
<td>TOU/CPP</td>
<td>[80]</td>
</tr>
<tr>
<td>PowerCents</td>
<td>July 2008 – March 2009</td>
<td>District of Columbia</td>
<td>CPP/PTR</td>
<td>[90]</td>
</tr>
</tbody>
</table>

Table 1.2: Summary of residential demand response programs in the United States.

This dissertation uses highly resolved models to simulate automated residential demand response programs and to evaluate the potential impact of widespread adoption of decentralized residential energy management systems exploiting time-varying electricity prices.
1.4 Modeling Background

This section presents a review of the state-of-the-art on bottom-up modeling techniques. Particular focus is given to modeling of residential power demand and personal transportation energy consumption. Moreover, demand-side energy management strategies able to intelligently manage residential loads are reviewed. Additional extensive reviews of the specific literature on these topics are reported in various parts of the present study.

When estimating energy demand of a population, both top-down or bottom-up approaches can be exploited. Top-down models apply regression analysis to historical data in order to determine the relationship between the demand and macro variables, including Gross Domestic Product (GDP), Human Development Index (HDI), weather, prices of fuels, and rates of population and economic growth. Such models provide useful macro-level results in the form of aggregated data but they present a low level of resolution. The data are usually obtained through surveys conducted on a representative statistical sample of the population by federal agencies \[91, 18, 92\]. Besides the lack of coarseness of the data, the main drawback of this approach is the inability to model energy final use. Moreover, top-down approaches are characterized by the absence of a physically-based prediction model.

Bottom-up approaches exploit available data to calibrate a consumption model, while aggregated statistical data are used for its validation by means of large-scale simulations \[93, 94\]. In particular, the energy consumption of the entire population can be computed by aggregation of a group of individuals representing the population characteristics.

Bottom-up models provide high-resolution data (at a defined time-step level), providing the ability to model the impact of different technologies and allowing the
proper implementation of energy management and optimization techniques. The versatility of the output in the bottom-up approaches comes at a price: model complexity increases and calibration typically requires more effort than the top-down technique.

Estimation models can also be categorized according to consumption data. Following this methodology, energy demand models can be classified as sector-based or consumer-oriented. The sector-based approach, which is commonly used, divides the total energy demand among several sectors (typically residential, commercial, industrial, and transportation). Consumer-oriented approaches try to estimate the same energy demand by accounting only for the role of different consumers, and their consumption patterns [94, 95]. In particular, the energy consumption of the whole population can be computed by aggregation of a group of individuals representing the population characteristics.

For instance, in the sector-based approach the energy consumption for the production of an asset is taken into account as a direct industrial cost, whereas in the consumer-oriented approach that same energy consumption is seen as an indirect cost allocated to the consumer buying that specific asset. The advantage of the consumer-oriented approach over the sector-based is the ability to capture the total impact of consumer activities, accounting for both direct and indirect consumption.

Characterization of both direct and indirect energy use - and associated emissions - can be useful in designing more effective energy policies and incentives. Bin and Dowlatabadi [94] claim sector-based models to be limited in their capacity to mirror the total impacts of consumer activities on energy use. However, sector-based approaches offer a sector-by-sector overview of the energy demand, thus allowing for allocation of the energy demand among the various sectors according to their final use. Table 1.3 provides a summary of the advantages and disadvantages of the energy demand modeling techniques discussed in this section.
In this study, bottom-up sector-based estimation techniques are adopted to compute residential and personal transportation energy consumption. The proposed residential and transportation energy consumption models (presented in Chapter 3 and Chapter 4, respectively) are flexible in design, allowing for energy consumption to be modeled at any time resolution desired by the user. Thus, they are considered highly-resolved models. High model resolution is needed to make the models suitable to be used for the purpose of this research. In the present study a 10-minute resolution is used to model energy demand and implement dynamic energy management techniques.

Residential demand-side energy management has been extensively studied. At the beginning of the 21st century the Electric Power Research Institute (EPRI)\(^4\) pioneered research on smart grids, trying to assess the future of the electric sector [96], [97]. In particular, EPRI emphasized three critical enabling technologies needed

\[^4\text{The Electric Power Research Institute (EPRI) is an independent, non-profit company performing research, development, and demonstration in the electricity sector.}\]
to move toward realizing a smart grid: \textit{a)} integrated automation and communication, 
\textit{b)} distributed energy resources and storage development and integration, and \textit{c)} automated customer-side equipment, called consumer portal, used to intelligently monitor and manage residential energy use [96].

The smart grid technologies are enablers that permit scheduling loads at the consumer level to save energy, reduce cost, and help grid operation; however, a residential automated energy management system is needed to optimally manage such an advanced integrated system [98]. Demand-side energy management systems must allow consumers to compare costs/benefits with different load schedules and automatically make decisions to optimize energy use in the household.

Dynamic Energy Management (DEM) was first introduced in 2008 [99] as an innovative approach to managing load at the demand side. It differs from demand response and classic demand-side energy management as it transforms the local, standard energy management into a system comprising smart end-use devices and distributed energy resources with highly advanced controls and communications capabilities.

In this study, a dynamic energy management framework for a generic residential energy eco-system is developed. The objective of the dynamic energy management framework is to optimize the scheduling of all the controllable appliances and in-home charging of plug-in electric vehicles to minimize a cost function. Also, large-scale simulations are performed to simulate widespread participation to residential demand response programs and evaluate their impact of the total electric power infrastructure.
1.5 Objectives and Summary

The objectives of this dissertation are the following:

1. Develop a highly-resolved model of a residential energy eco-system able to capture the entire energy footprint of American households;
2. Develop a dynamic energy management framework to optimally schedule controllable appliances and in-home charging of plug-in electric vehicles;
3. Perform large-scale simulations to obtain aggregate-level results and allow for evaluating the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand;
4. Implement a tool that can serve as a virtual laboratory for investigating fundamental economic and policy-related questions regarding the interplay of individual consumer decisions and energy use;
5. Use the proposed tool to investigate the impact of plug-in electric vehicle on the electric power infrastructure;
6. Use the proposed tool to explore opportunities related to residential demand response programs and compare the effects of different electricity price structures.

SUMMARY

In this study a bottom-up highly resolved model of a generic residential energy eco-system in the United States is developed. The model is able to capture the entire energy footprint of an individual household, to include all appliances, HVAC (Heating, Ventilation, and Air Conditioning) systems, in-home charging of plug-in electric vehicles, and any other energy needs, viewing residential and transportation energy needs as an integrated continuum.
The residential energy eco-system model is based on a novel bottom-up approach that quantifies consumer energy use behavior. Chapter 2 reports on the development of a stochastic behavioral model able to reproduce highly-resolved behavioral patterns of individuals with a desired time resolution. Five agent types are included in this study, capturing differences in behavior. Such agent types are: working and non-working males and females and children. Also, differences between weekdays and week-ends and the influence of the time of day on the behavior of individuals are both considered in the model. The model is calibrated using data recorded in the American Time Use Survey (see Section 2.2).

Chapter 3 presents a bottom-up model used to generate highly-resolved electricity demand profiles of American households consisting of multiple individuals, considering cold appliances, HVAC systems, lighting, and activity-related power consumption. The latter component is based on highly-resolved behavioral patterns. This allows capturing the electricity consumption of each residential specific end-use (e.g. cooking, lighting, etc.), providing an accurate estimation of the actual amount of available controllable resources. This can help electric utilities study residential demand response programs. The proposed model can be used to reconstruct power consumption of a single or an aggregate group of households with desired characteristics and composition.

Chapter 4 reports on the development of a bottom-up model used to compute and compare the personal transportation energy consumption of U.S. drivers, considering a set of different vehicles. The model uses highly-resolved behavioral patterns to establish when driving events occur over the simulation time horizon and the duration/length of each event. Once driving events are defined, realistic driving profiles for each driving event are generated. These profiles are fed to a vehicle simulator to compute energy consumption of different vehicles. The main outputs of the
model are highly-resolved (10-minute resolution) consumption profiles for personal transportation in the United States, including gasoline, natural gas, and/or electricity consumption in the case of plug-in electric vehicles. In the latter case, output includes highly-resolved in-home charging profiles.

The first chapters constitute the basis of the residential energy eco-system model, to which dynamic energy management techniques are applied. Chapter 5 details the implementation of a dynamic energy management framework for a generic residential energy eco-system. The energy management framework simultaneously optimizes controllable appliances and in-home charging of plug-in electric vehicles. The dynamic energy management framework is automated, decentralized (each household receives the same signal from the electric grid, and independently optimizes its own demand), and non-disruptive, in the sense that it does not require changes in people’s behavior to optimally manage the energy consumption inside the eco-system. The management problem is solved using a numerical optimization technique called dynamic programming, and considers the behavior of household members and their energy consumption, as predicted by the highly-resolved stochastic personal energy consumption models. The algorithm proposed is flexible and robust and can include different cost functions and electricity price structures.

Chapter 6 details the integration of the residential power demand model and the personal transportation energy consumption model to create the residential energy eco-system model. Large-scale simulations of groups of residential energy eco-systems are performed to simulate aggregate-level results and allow for evaluating the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand. Two case studies are reported in this chapter: the first considers the impact of market penetration of plug-in electric vehicles on the electric power infrastructure, and the second provides a quantitative comparison of
the impact of different electricity price structures on residential demand response. Simulation results and an innovative electricity price structure, called Multi-TOU, are reported in this chapter.

Chapter 7 contains a summary of this study and some concluding remarks. Also, the contributions to the literature and to the general knowledge and suggested directions for future research on this topic are reported.

Appendix A describes the Residential Energy Consumption Survey, which contains household characteristics used as input to the residential power demand model presented in Chapter 3. Appendix B reports a practical example of simulations performed using the HVAC model introduced in Section 3.4. Appendix C and Appendix D report executive summaries of the two case studies proposed in Chapter 6.
Chapter 2

MODELING TIME ALLOCATION AND BEHAVIOR OF INDIVIDUALS

The subject of this study is energy consumption in the U.S. residential and personal transportation sectors. Transportation and residential demand profiles are, by nature, variable and depend on multiple physical factors, such as weather, ambient temperature, the characteristics of vehicles and dwellings, and on the behavior of individuals. Although human behavior has long been identified as the key determinant of energy consumption, until recent years attempts to include such behavior as a parameter in energy simulations are rare and usually without any theoretical guidance [100].

Modeling the behavior of individuals is a complex task, due to the stochastic nature of the activities performed. Factors such as age, gender, working status, life habits of each individual, number of individuals sharing the same household, as well as daily and weekly variations in behavior should all be captured.

Modeling the behavior of individuals is a key component of several models proposed in the literature [101, 100, 102], and time use data are used by researchers in a broad range of areas, including economic research (e.g. determining the value of unpaid work or changes in the time spent working), medical research, comparison of different education policies, and development of energy consumption models.

This chapter reports on the development of a stochastic behavioral model able to reproduce highly-resolved behavioral patterns of individuals with a desired time
resolution. The model is calibrated using data recorded in the American Time Use Survey, presented in Section 2.2. The implementation of the model is presented in Section 2.3, while results an a statistical validation are reported in Section 2.4.

2.1 Introduction and Review of the Literature

This chapter proposes a heterogeneous Markov chain model, based on time use data, to simulate the behavior of individuals in the United States and predict the associated energy consumption for both residential and personal transportation.

Markov chains are discrete time mathematical systems that undergo transitions from one state to another (among a finite number of possible states), thus generating sequences of random variables. They present a limited form of historical dependency (memory-less processes), meaning that each state in the chain depends only on the previous state and not on the sequence of events that preceded it [103].

The transitions between the states are determined by a so-called transition probability matrix, indicating the probability of transitioning from one state to all the others (including remaining in the current state). Figure 2.1 shows the state transition diagram illustrating the concept of the transition probabilities in a two-state Markov chain.

\[ P_{1,1} \quad P_{1,2} \quad P_{2,1} \quad P_{2,2} \]

\[ 1 \quad 2 \]

*Figure 2.1: State transition diagram for a two-state Markov chain.*
In the example in Figure 2.1, \( P_{1,1} \) represents the probability of remaining in state 1 when already in state 1. \( P_{1,2} \) represents the probability of transitioning from state 1 to state 2. Note that \( P_{1,1} + P_{1,2} = 1 \). For an \( n \)-dimensional Markov chain the transition probability matrix has size \( [n \times n] \).

Markov chains require an initial state to be chosen. Once an initial state is chosen, at each time step a uniformly-distributed pseudo-random number, \( x \), is generated and compared to the cumulative distribution of the state transitions to determine which transition takes place. This is illustrated for a two-state Markov chain in Figure 2.2. Since \( x \) is in the second interval in this example, the state will transition from state 1 to state 2.

\[
\begin{align*}
0 & \rightarrow \text{Transition}\rightarrow 1 \\
\mathcal{R}_{i,1} & \rightarrow \text{Transition}\rightarrow \mathcal{R}_{i,2}
\end{align*}
\]

*Figure 2.2: Random simulation of state transition between two subsequent time periods for a two-state Markov chain.*

In a heterogeneous Markov chain the transition probability matrix is a function of time, namely all the \( P_{i,j} \) take on different values at different moments in time.

In this study a heterogeneous Markov-chain model is developed to capture time allocation and associated energy use of individuals in the United States, based on data collected in the American Time Use Survey (ATUS). Nine states have been identified to capture the energy use of individuals (each possible activity performed by an individual is classified in one of these nine states). Transition probability
matrices are defined depending on the day type \((d, \text{ namely a weekday or a week-end day})\) and hour of the day \((h, \text{ ranging from 1 to 24})\). For example, \(P_{i,j}^{d,h}\) gives the probability of going from state \(i\) to state \(j\) on a type-\(d\) day during hour \(h\).

In order to estimate the transition probability matrices, detailed input data are required. In this study, time use records that include detailed information on the behavior of Americans – collected in the American Time Use Survey – are used to estimate the transition probabilities. Further details on the ATUS data are provided in Section 2.2. Details on the calibration of a Markov chain using survey data are provided in Section 2.3.

Pandit and Wu [104] provide details on the use of Markov chain models to reconstruct behavioral patterns and Widén et al. propose an approach based on Markov chains to construct load profiles for household electricity and hot water from time-use data [101]. That study employs time use data collected in Sweden in 1996.

Widén and Wäckelgård [105] develop a similar model to predict lighting demand in Sweden. In the stochastic model proposed, a three-state non-homogeneous Markov chain, with transition probabilities estimated from a survey on time use in Swedish households, is used to generate realistic patterns of occupancy and capture domestic lighting demand [105]. The time use data are recorded in 5 households for 3 consecutive days.
2.2 The American Time Use Survey (ATUS) Data

In the present study a highly-resolved heterogeneous Markov-chain model is developed to capture time allocation and associated energy consumption of individuals in the United States. The model is calibrated to simulate average behaviors of individuals by using time use data collected in the 2003-2009 American Time Use Survey (ATUS).¹

The American Time Use Survey measures the amount of time people spend doing various activities, such as paid work, child care, volunteering, and socializing. The ATUS is taken every year from a sub-sample of participants in the Consumer Preferences Survey (CPS) administered by the Bureau of Labor Statistics. ATUS is designed to provide researchers with detailed data on the time allocation of American adults. Though administered annually, ATUS is not a panel survey. Each annual survey is based on a different set of participants, and is therefore strictly longitudinal. ATUS respondents are interviewed on a randomly selected date about their activities on the previous day. Each activity is recorded and coded by the interviewer, along with its duration in minutes, starting at 4 a.m. and lasting until midnight.

Because this survey is administered with the CPS, extensive demographic information is also available about the respondents and others sharing the same household. Moreover, because the ATUS relies on a stratified sampling technique, each respondent has a weight placed on his responses that represents the weight of those data relative to the total population.

The ATUS data provide very detailed time use information for over 13000 respondents selected to represent the U.S. population. ATUS employs an activity coding system that categorizes daily activity into over 1000 categories. Such categories range from personal care (e.g. sleeping, dressing) and household activities (e.g. laundry, laundry,

¹The ATUS data are publicly available for download at http://www.bls.gov/tus/home.htm.
food preparation) to work-related activities, education, vehicle maintenance, child care, and care of the elderly. The fine resolution of ATUS time diary, not seen in the time use survey data of other nations, allows for very detailed analysis of the behavior of individuals in the United States, and together with its large dimension represents the strength of this survey.

An example of the time diaries reported in the 2009 ATUS is shown in Table 2.1, which illustrates the sequence of activities performed by one respondent during one day. For each respondent, each activity (labeled TRCODE in ATUS) performed during the day is identified by an activity number (labeled TUACTIVITYN in ATUS). Information on location (labeled TEWHERE in ATUS), starting time (labeled TUSTARTTIM in ATUS), and ending time (labeled TUSTOPTIME in ATUS) of each activity are reported. The ATUS time diaries contain many variables describing each activity (e.g. time allocation providing child care) not shown in Table 2.1, that are not relevant for this study.\(^2\)

In this study, respondents are stratified into five agent types: working and non-working males and females and children. Table 2.2 summarizes the number and average age of respondents corresponding to each agent type. Working and non-working male and female respondents are all between the ages of 18 and 85, whereas children are between the ages of 15 and 17. ATUS data have been collected uniformly across the year during which the survey was conducted.

ATUS data have been used by a large number of researchers for a variety of purposes [100, 102, 106]. Hamermesh et al. [107] provide an economic perspective and a description of the data available in the ATUS, including suggestions on what questions can be addressed because of the unique features of the data.

\(^2\)For more information about the structure of the ATUS time diaries, see the ATUS 2009 Interview Data Dictionary, available online at: http://www.bls.gov/tus/atusintcodebk09.pdf.
Table 2.1: Example of time use diary, as reported in the 2009 American Time Use Survey (Respondent number: 20090101090037).

<table>
<thead>
<tr>
<th>Activity Number</th>
<th>Location</th>
<th>Activity in ATUS</th>
<th>Start Time</th>
<th>End Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Home</td>
<td>Sleeping</td>
<td>04:00</td>
<td>08:00</td>
</tr>
<tr>
<td>2</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>08:00</td>
<td>08:30</td>
</tr>
<tr>
<td>3</td>
<td>Home</td>
<td>Television and movies</td>
<td>08:30</td>
<td>09:30</td>
</tr>
<tr>
<td>4</td>
<td>Home</td>
<td>Sleeping</td>
<td>09:30</td>
<td>11:00</td>
</tr>
<tr>
<td>5</td>
<td>Home</td>
<td>Reading</td>
<td>11:00</td>
<td>12:00</td>
</tr>
<tr>
<td>6</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>12:00</td>
<td>12:30</td>
</tr>
<tr>
<td>7</td>
<td>Home</td>
<td>Television and movies</td>
<td>12:30</td>
<td>13:30</td>
</tr>
<tr>
<td>8</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>13:30</td>
<td>13:35</td>
</tr>
<tr>
<td>9</td>
<td>Other store/mall</td>
<td>Shopping</td>
<td>13:35</td>
<td>14:35</td>
</tr>
<tr>
<td>10</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>14:35</td>
<td>14:45</td>
</tr>
<tr>
<td>11</td>
<td>Home</td>
<td>Household organization</td>
<td>14:45</td>
<td>15:00</td>
</tr>
<tr>
<td>12</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>15:00</td>
<td>15:05</td>
</tr>
<tr>
<td>13</td>
<td>Library</td>
<td>Reading</td>
<td>15:05</td>
<td>15:07</td>
</tr>
<tr>
<td>14</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>15:07</td>
<td>15:12</td>
</tr>
<tr>
<td>15</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>15:12</td>
<td>15:42</td>
</tr>
<tr>
<td>16</td>
<td>Home</td>
<td>Socializing with family</td>
<td>15:42</td>
<td>17:00</td>
</tr>
<tr>
<td>17</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>17:00</td>
<td>18:00</td>
</tr>
<tr>
<td>18</td>
<td>Home</td>
<td>Television and movies</td>
<td>18:00</td>
<td>22:00</td>
</tr>
<tr>
<td>19</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>22:00</td>
<td>22:30</td>
</tr>
<tr>
<td>20</td>
<td>Home</td>
<td>Food preparation</td>
<td>22:30</td>
<td>22:40</td>
</tr>
<tr>
<td>21</td>
<td>Home</td>
<td>Waiting</td>
<td>22:40</td>
<td>22:50</td>
</tr>
<tr>
<td>22</td>
<td>Home</td>
<td>Sleeping</td>
<td>22:50</td>
<td>08:00</td>
</tr>
</tbody>
</table>

Table 2.2: Summary statistics of ATUS respondents.

<table>
<thead>
<tr>
<th>Respondent Type</th>
<th>Mean Age</th>
<th>Number of Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working Male</td>
<td>43</td>
<td>3649</td>
</tr>
<tr>
<td>Working Female</td>
<td>43</td>
<td>3978</td>
</tr>
<tr>
<td>Non-Working Male</td>
<td>57</td>
<td>1706</td>
</tr>
<tr>
<td>Non-Working Female</td>
<td>56</td>
<td>3235</td>
</tr>
<tr>
<td>Child</td>
<td>16</td>
<td>565</td>
</tr>
<tr>
<td>Total Population</td>
<td>43</td>
<td>13133</td>
</tr>
</tbody>
</table>
2.3 Behavioral Model: Calibrating Heterogeneous Markov Chains with Survey Data

Detailed time use data collected in ATUS (presented in the previous section) are used in this study to calibrate a heterogeneous Markov chain to model occupant behavior and predict the associated energy consumption for both residential and personal transportation. Namely, ATUS time use data are used to estimate the transition probabilities between the states in the Markovian behavioral model for each hour of the day and for each day type (weekday or week-end).

All possible activities included in ATUS are lumped into nine broader categories, which differ in terms of the energy required to perform the activities. These activities are:

1. Sleeping;
2. No-power activity (*e.g.* reading);
3. Cleaning (*e.g.* vacuuming);
4. Laundry;
5. Cooking;
6. Automatic dishwashing;
7. Leisure (*e.g.* use of the TV, stereo, computer, or videogame system);
8. Away, working; and
9. Away, not working.

Note that these categories are intended to capture only the energy consumption of individuals directly related to performing a particular activity. For example, reading requires the use of lights at night, but no direct power consumption is required for reading. Energy consumption for lighting – and any other indirect energy use – is captured by other energy consumption sub-models presented in Chapter 3.
Table 2.3: Example of time use diary, as reported in the 2009 American Time Use Survey (Respondent number: 20090101090037).

<table>
<thead>
<tr>
<th>Activity Number</th>
<th>Location</th>
<th>Activity in ATUS</th>
<th>Activity Category</th>
<th>Start Time</th>
<th>End Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Home</td>
<td>Sleeping</td>
<td>1</td>
<td>04:00</td>
<td>08:00</td>
</tr>
<tr>
<td>2</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>2</td>
<td>08:00</td>
<td>08:30</td>
</tr>
<tr>
<td>3</td>
<td>Home</td>
<td>Television and movies</td>
<td>7</td>
<td>08:30</td>
<td>09:30</td>
</tr>
<tr>
<td>4</td>
<td>Home</td>
<td>Sleeping</td>
<td>1</td>
<td>09:30</td>
<td>11:00</td>
</tr>
<tr>
<td>5</td>
<td>Home</td>
<td>Reading</td>
<td>2</td>
<td>11:00</td>
<td>12:00</td>
</tr>
<tr>
<td>6</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>2</td>
<td>12:00</td>
<td>12:30</td>
</tr>
<tr>
<td>7</td>
<td>Home</td>
<td>Television and movies</td>
<td>7</td>
<td>12:30</td>
<td>13:30</td>
</tr>
<tr>
<td>8</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>9</td>
<td>13:30</td>
<td>13:35</td>
</tr>
<tr>
<td>9</td>
<td>Other store/mall</td>
<td>Shopping</td>
<td>9</td>
<td>13:35</td>
<td>14:35</td>
</tr>
<tr>
<td>10</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>9</td>
<td>14:35</td>
<td>14:45</td>
</tr>
<tr>
<td>11</td>
<td>Home</td>
<td>Household organization</td>
<td>2</td>
<td>14:45</td>
<td>15:00</td>
</tr>
<tr>
<td>12</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>9</td>
<td>15:00</td>
<td>15:05</td>
</tr>
<tr>
<td>13</td>
<td>Library</td>
<td>Reading</td>
<td>9</td>
<td>15:05</td>
<td>15:07</td>
</tr>
<tr>
<td>14</td>
<td>Car (driver)</td>
<td>Travel</td>
<td>9</td>
<td>15:07</td>
<td>15:12</td>
</tr>
<tr>
<td>15</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>2</td>
<td>15:12</td>
<td>15:42</td>
</tr>
<tr>
<td>16</td>
<td>Home</td>
<td>Socializing with family</td>
<td>2</td>
<td>15:42</td>
<td>17:00</td>
</tr>
<tr>
<td>17</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>2</td>
<td>17:00</td>
<td>18:00</td>
</tr>
<tr>
<td>18</td>
<td>Home</td>
<td>Television and movies</td>
<td>7</td>
<td>18:00</td>
<td>22:00</td>
</tr>
<tr>
<td>19</td>
<td>Home</td>
<td>Eating and drinking</td>
<td>2</td>
<td>22:00</td>
<td>22:30</td>
</tr>
<tr>
<td>20</td>
<td>Home</td>
<td>Food preparation</td>
<td>5</td>
<td>22:30</td>
<td>22:40</td>
</tr>
<tr>
<td>21</td>
<td>Home</td>
<td>Waiting</td>
<td>2</td>
<td>22:40</td>
<td>22:50</td>
</tr>
<tr>
<td>22</td>
<td>Home</td>
<td>Sleeping</td>
<td>1</td>
<td>22:50</td>
<td>08:00</td>
</tr>
</tbody>
</table>

Figure 2.3: Example of daily activity pattern using the nine proposed activity categories.
Table 2.3 illustrates the sequence of activities performed by one respondent during one day (as reported in Table 2.1), together with the proposed classification for the activities performed. The resulting behavioral pattern is graphically shown in Figure 2.3.

The Markov chain model assumes that each simulated individual (household member) is in one of these nine states in every discrete time step. As time proceeds from \( t \) to \( t + 1 \) a state transition occurs. These transitions are governed by transition probabilities, \( p_{i,j}^{d,h} \), which give the probability of going from state \( i \) to state \( j \) on a type-\( d \) day during hour \( h \). Diurnal behavior patterns are reproduced by allowing transition probabilities to vary over the 24 hours, which is represented by the index \( h \). Similarly, behavior differences between working and non-working days are captured by allowing the probabilities to vary between week days (\( d = 1 \)) and week-end days (\( d = 0 \)). The Markov chain model approach requires an initial state to be chosen. In this study, the initial condition is chosen so that all individuals are sleeping at 4 a.m. of the first day simulated.\(^3\) Then at each time step a uniformly-distributed pseudo-random number, \( x \), is generated and compared to the cumulative distribution of the state transition to determine which transition takes place. This is illustrated in Figure 2.4. Since \( x \) is in the fifth interval in the example shown in the figure, the state will transition to the fifth state.

Because the behavior of individuals change on an hour-to-hour and day-to-day basis, the ATUS data are used to estimate the transition probability matrices, \( P^{d,h} \), for weekdays (\( d = 1 \)) and weekends (\( d = 0 \)) and for each hour of the day (\( h = 3 \)).

---

\(^3\)Removing the first few days simulated is sufficient to eliminate the influence of the initial condition chosen. Therefore, when generating a behavioral pattern for \( N \) days, \( N + 3 \) days are actually generated and then the first 3 days are removed to eliminate the influence of the initial condition. At the beginning of the fourth day (the first day actually used in the modeling proposed) there is a variability in the activity performed by each individual simulated, thus avoiding that the behavior of all the individual is determined by the initial condition chosen.
The ATUS data are collected starting at 4 a.m. and lasting until midnight, making it impossible to directly estimate the transition probability matrices for the first four hours of the day. Thus, in this study the transition probabilities matrices for the hour going from midnight to 1 a.m. have been assumed to be equal to the ones going from 11 p.m. to midnight. The transition probabilities matrices for the hours going from 1 a.m. to 4 a.m. have been assumed to be equal to the ones of the following hour (going from 4 a.m. to 5 a.m.). For each agent type (as reported in Table 2.2), twenty four \([9 \times 9]\) matrices are computed both for weekdays and week-ends. Given ATUS data from \(K\) respondents, first their activities are classified into the nine categories enumerated above. Then, the number of transitions at one-minute intervals between the nine states is counted, yielding 60 observations per respondent per hour. The transition probability for that agent type on that hour is then calculated as:

\[
p_{i,j}^{d,h} = \frac{w_k \cdot n_{i,j,k}^{d,h}}{\sum_k \sum_i w_k \cdot n_{i,j,k}^{d,h}}
\]

where \(w_k\) is the weight of the \(k^{th}\) respondent, \(n_{i,j,k}^{d,h}\) is the number of transitions that he or she makes from state \(i\) to state \(j\) during hour \(h\) of day \(d\). The resulting transition matrices represent the probability of transitioning from one state to another at one-minute time intervals. These probabilities are computed for every hour and for the two day types (weekdays and week-ends) yielding to two \([9 \times 9 \times 24]\) matrices per
each agent type (for a total of ten $[9 \times 9 \times 24]$ transition probability matrices used in this study).

Since this study is implemented using a 10-minute time step, the transition probability matrices are raised to the 6th power and each row is scaled to sum to one, to account for the limitations of numerical precision. This gives the probability of transitioning from one state to another at 10-minute time intervals.

### 2.4 Results and Validation

An in-sample validation of the activity patterns generated by the Markov chain model is performed by comparing the modeled behavior to the underlying ATUS data used to determine the transition probabilities. The results are shown from 4 a.m. to midnight, since this is the time interval during which data have been collected in the ATUS survey.

First, time allocation of individuals is analyzed. Figures 2.5 and 2.6 compare measured and simulated time allocation of individuals.

Figure 2.5 reports a comparison between average time allocation of working males in the ATUS data (part a) and average time allocation resulting from the simulation of 40 working males for 100 week-ends (part b). The simulated results total 4000 person-days compared to 3854 working males present in the ATUS data (information on one single day are recorded per each respondent, yielding to 3854 person-days). Figure 2.6 reports the same comparison for working males during working days.

Figures 2.5 and 2.6 qualitatively show that the heterogeneous Markov chain approach is able to capture the dynamics of the behavior of these individuals. The comparison confirms that the model reproduces the underlying time allocations of

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4The author would like to thank Professor Matthew C. Roberts for the help provided in analyzing the ATUS data and generating the transition probability matrices.
a group of individuals, as reported in ATUS. Other agent types (e.g. non-working females) show similar trends.

Large-scale simulations also allow for performing a more rigorous statistical validation. Behavioral patterns for a large number of individuals are computed, and time allocation confidence intervals of these modeled patterns are generated. The underlying time allocation in the ATUS data (percentage of people engaged in each activity in each time period) can then be compared with the confidence intervals generated by the simulations.
A close relationship exists between confidence intervals and hypothesis significance tests for a specific parameter. Specifically, values in a \((1 - \alpha)\) confidence interval are plausible values for the parameter, and would be in the acceptance region of a hypothesis test with \(\alpha\)-level of significance. On the other hand, values outside a \((1 - \alpha)\) confidence interval are not plausible values for the parameter, and would be in the rejection region of a hypothesis test with \(\alpha\)-level of significance. For example, if a parameter is statistically significantly different from 0 at the \(\alpha\) level, then the \((1 - \alpha)\) confidence interval will not contain 0.
In the validation procedure proposed, the percentage of people engaged in each activity in each time step (the statistic of interest) as reported in the ATUS data is compared with a 95% confidence interval of the same statistic, generated performing large-scale simulations using the proposed behavioral model.

Figure 2.7 reports the comparison of time allocation in the ATUS data and related confidence intervals generated by the behavioral model for each of the nine different activities. Results are shown for working males during week-ends. The confidence intervals shown in the figure are created simulating 40 individuals for 100 working days for a total of 4000 person-days compared to 3854 working males present in the ATUS data.

Figure 2.7: 95% confidence intervals for the simulated activity patterns compared against underlying ATUS data for working males during week-ends.

Figure 2.7 shows that the time allocation of working males during week-ends reported in the ATUS data is well within the confidence intervals. In particular, the
ATUS data are not contained in the 95% confidence interval for 1.11% of the time periods, meaning that a hypothesis test with significance level of 5% would conclude that there is not enough evidence to indicate a statistical difference between the behavior reported in the ATUS data and the behavioral patterns generated by the model.

Figure 2.8 reports the same comparison for working males during week days.

![Figure 2.8: 95% confidence intervals for the simulated activity patterns compared against underlying ATUS data for working males during week-ends.](image)

In this case the ATUS data are not contained in the 95% confidence interval for 1.67% of the time periods, and again a hypothesis test with significance level of 5% would conclude that there is not enough evidence to indicate a difference between the underlying ATUS data and the behavioral patterns generated by the model.

Table 2.4 reports a summary of the portions of the ATUS data not contained in the 95% confidence intervals generated performing large-scale simulations with
the proposed behavioral model for all the respondent types considered in this study. For each respondent type, large-scale simulations are performed so that the number of simulated person-days is larger than the ATUS number of respondents in that category, as reported in Table 2.2.

Table 2.4: Summary of the comparison between ATUS and simulated data. Percentage of ATUS data not contained in the 95% confidence interval generated performing large-scale simulations with the proposed behavioral model.

<table>
<thead>
<tr>
<th>Respondent Type</th>
<th>Week-end days</th>
<th>Week days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working Male</td>
<td>1.1%</td>
<td>1.7%</td>
</tr>
<tr>
<td>Working Female</td>
<td>2.2%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Non-Working Male</td>
<td>2.8%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Non-Working Female</td>
<td>2.8%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Child</td>
<td>1.7%</td>
<td>3.3%</td>
</tr>
</tbody>
</table>

Results in Table 2.4 confirms that hypothesis tests with significance level of 5% would conclude that there is not enough evidence to indicate a difference between the underlying ATUS data and the behavioral patterns generated by the model.

The proposed behavioral model is shown to generate behavioral patterns that have the same features of the recorded time use data used for the calibration. Thus, the behavior of a group of individuals generated by the Markovian model has the same characteristics of the population considered in the American Time Use Survey. Also, each individual behavioral pattern is shown to have the same statistical features of the underlying ATUS data. Modeled behavioral patterns are used in this study to simulate the behavior of Americans and ultimately capture their energy consumption.
2.5 Conclusions

The heterogeneous Markov chain behavioral model described in this chapter is used in the present study to generate highly-resolved activity patterns of different Americans. Five agent types are included in this study, capturing differences in behavior and associated energy use. Such agent types are: working and non-working males, working and non-working females, and children. Also, differences between weekdays and weekends and the influence of the time of day on the behavior of individuals are both considered in the model.

The activity patterns generated by the Markov chain are shown to replicate the behavior observed in the American Time Use Survey, validating the ability of the proposed model to reproduce behavior of diverse categories of Americans during the year.

The behavioral patterns generated by the heterogeneous Markov chain behavioral model are used, together with other pertinent variables, to model the energy footprint of individuals. For this purpose, a residential power demand model and a personal transportation energy consumption model have been developed and are presented in Chapters 3 and 4, respectively. The highly-resolved (time resolution of 10 minutes) activity patterns generated by the Markov chain are used as input to both models to capture the precise time during which such a consumption occurs.
Chapter 3
RESIDENTIAL POWER DEMAND MODEL

The residential sector accounted for about 22% of total primary energy consumption in the United States in 2011, namely 21620 Trillion BTU ($2.28 \cdot 10^{19} J$) [30]. This indicates that there are major potential gains from implementing policy and technology solutions to reduce and shift energy use in residential settings.

The potential energy, cost, and emissions savings of such policies and technologies can be investigated by modeling their impacts on residential energy demand and the resulting interactions between this demand and the power grid, distributed energy storage and generation, and plug-in electric vehicles. The aim of the bottom-up model introduced in this chapter is to generate highly-resolved electricity demand profiles of American households consisting of multiple individuals. This integrates into the Residential Energy Eco-System modeling proposed in this study.

First, an introduction and general literature review are presented in Section 3.1 and Section 3.2, respectively. Section 3.3 introduces a model to capture cold appliances energy consumption. Section 3.4 presents the development of a model to simulate Heating, Ventilation and Air Conditioning (HVAC) energy consumption, including a specific review of the existing literature and a validation of the proposed model. Section 3.5 details on the use of the behavioral model introduced in Chapter 2 to capture energy use directly related to activities of household members. Section 3.6 describes the linear regression model used to estimate lighting electricity consumption
starting from metered data. A rigorous two-level statistical validation framework for the proposed residential power consumption model is presented in Section 3.7, and concluding remarks are provided in Section 3.8.

3.1 Introduction

Highly-resolved energy consumption patterns (i.e. power profiles) are more complicated to predict than energy demand, because of their random nature and acute fluctuating aspects. Accordingly, higher complexity is introduced in this type of modeling.

Residential demand profiles are, by nature, variable and depend on multiple physical factors, such as weather, temperature, and dwelling characteristics but also on the behavior of household members. Thus the modeled demand depends on physical properties and the location of the dwelling and on the number and type of individuals living in the household. Because this model is intended to generate a typical residential demand profile, individual behavior is modeled stochastically.

The total residential electricity consumption is divided into five main categories, namely cold appliances, HVAC, lighting, and energy consumed by household members’ activities. The first three components are modeled using engineering models, while the activity patterns of individuals are modeled using a heterogeneous Markov chain, using the approach presented in Chapter 2. The total electric power demand (rate of electricity consumption) of a dwelling, $\dot{W}$, is computed as:

$$\dot{W} = \dot{W}_{cold} + \dot{W}_{HVAC} + \dot{W}_{act} + \dot{W}_{light} + \dot{W}_{fix}$$  \hspace{1cm} (3.1.1)

where:

- $\dot{W}$ is the total electric power demand, expressed in W;
• $\dot{W}_{\text{cold}}$ represents the power used by cold appliances, such as refrigerators and freezers;

• $\dot{W}_{\text{HVAC}}$ is the electric power used by the HVAC system to maintain the desired thermal comfort in the house;

• $\dot{W}_{\text{act}}$ is the electricity use directly related to activities of the household members, e.g. cooking or use of dishwasher;

• $\dot{W}_{\text{light}}$ is the electric power consumption due to lighting; and

• $\dot{W}_{\text{fix}}$ is a constant time-invariant term that represents ubiquitous electric consumption, i.e. lights that are always on and appliance stand-by power.

Each of these terms includes power losses due to system inefficiencies. The power consumption categories present different dependencies, which determine the underlying structure of the modeling approach used. $\dot{W}_{\text{cold}}$ depends only on the size and number of the cold appliances in the house—the effects of external temperature and door openings are neglected. $\dot{W}_{\text{HVAC}}$ depends on the physical characteristics of the HVAC system installed, the thermal comfort required by the occupants, properties of the thermal envelope of the dwelling, and on weather conditions that the house experiences. $\dot{W}_{\text{act}}$ depends on the behavior of the household members and on the associated electricity consumption. Activities are converted into electricity consumption by use of activity-to-power conversion factors, namely the wattage of appliances used when energy-intensive activities are performed. $\dot{W}_{\text{light}}$ depends on dwelling occupancy and on the amount of natural lighting available. This is captured using different lighting power conversion parameters during the day and night.

The lighting power conversion parameters and $\dot{W}_{\text{fix}}$ are difficult to assess, and are computed using a linear regression model against actual metered data provided by American Electric Power (AEP).\(^1\)

\(^1\)AEP’s transmission system directly or indirectly serves about 10 percent of the electricity
The model proposed in this chapter is flexible, allowing energy consumption to be modeled at any time resolution desired by the user. All the examples and results presented in this study use a 10-minute time step. However, the HVAC model uses a one-second time resolution to capture the variation of the air temperature inside the building. Also, the metered data against which the residential power demand model introduced in this chapter is validated report electricity consumption at hourly time steps. Thus, the simulated 10-minute consumption profiles and the one-second HVAC consumption are aggregated to arrive at hourly values, which can be compared to metered data.

A rigorous statistical validation of the predicted electricity demand against metered data is provided. The results show highly realistic patterns that capture annual and diurnal variations, load fluctuations, and diversity between household configuration, location, and size.

3.2 Review of the Existing Literature

Two general classes of techniques are available to model residential power demand: top-down and bottom-up models [109]. Grandjean et al. provide an exhaustive review of the main models proposed to generate residential electric load profiles [110].

Top-down models use estimates of total residential sector energy consumption, together with other pertinent macro-economic variables, to attribute energy consumption to characteristics of the housing sector. This class of models can be compared to econometric models, which require little detail of the actual consumption process.
These models treat the residential sector as an energy sink and apply regression techniques to determine trends [109, 111, 112, 113]. Depending on availability, the input data required to develop these models can include the structural characteristics of the dwellings, occupants and their behavior, appliance characteristics, historical energy consumption, weather conditions, and macro-economic indicators. Stochastic predictors, based on time-series approach, such as auto-regressive moving average methods, are also used to forecast home energy consumption [114, 115, 116].

Bottom-up models, on the other hand, identify the contribution of each end-use towards the aggregate energy consumption of the residential sector [117, 118, 105]. Bottom-up approaches refine the modeling of energy consumption, allowing the simulation of the effects of technology improvements and policy decisions. These models calculate the energy consumption of an individual or group of households and extrapolate the results to a region or nation. This aggregate result is generally accomplished by using a weight for each modeled house or group of houses based on its representation of the sector [109]. Moreover, after proper calibration the bottom-up approach has the capability of determining total energy consumption of the residential sector without relying on additional historical data. Common input data to bottom-up models include dwelling characteristics (e.g. size and layout, building materials, and appliance characteristics), weather conditions, behavior of the household occupants and related use of appliances, lighting use, and characteristics of the HVAC systems. This high level of detail represents the strength of bottom-up models, providing the ability to model the impact of different technology options and allowing for an accurate implementation of energy optimization techniques (distinction between different specific end uses). On the other hand, the use of such detailed information, in particular regarding behavior of the household members, introduces significant model
complexity. The input data requirements are typically greater than that of top-down models.

A number of works propose using bottom-up techniques to model residential energy use. According to Grandjean et al. [110], Walker and Pokoski [119] are the first to use the concept of time of use with the aim of constructing a load curve model. In 1985 they included human behaviour as a factor in reconstructing load curves for a specified house or a set of different dwellings. The model was developed to assist the planning of new power plants and generates total load curves with a resolution of 15 minutes. At the base of the model are two probabilities, capturing the probability of household members being at home (called availability) and their tendency to perform an activity during the day (called proclivity).

In 1994 Capasso et al. [117] generalized the approach introduced by Walker and Pokoski and proposed a model for evaluating the impact of demand-side management on residential customers. A Monte Carlo method is used to capture the relationship between residential demand and the psychological and behavioral factors typical of the household occupants. This model was developed mainly to predict residential power consumption profiles during peak days, and results are provided for limited times. For these times, modeled and measured load curves are very similar. For other periods, comparisons are less favorable [110].

Richardson et al. [118] introduce a Markov-chain technique to generate synthetic active occupancy patterns, based upon survey data of the time use of people in the United Kingdom. The stochastic model maps occupant activity to appliance use, creating highly-resolved synthetic demand data. The same authors also include a lighting model, which accounts for natural daylight [120]. Widén et al. [105, 121] follow a similar approach to relate residential power demand to occupancy profiles in Sweden. In their model, appliance sharing between household members is taken into
consideration, and appliance power demand can occur before, during, or just after the corresponding domestic activity and even totally disconnected from it. The model is calibrated and validated against relatively small time use and electricity consumption data sets collected in Sweden. The authors show that realistic demand patterns can be generated from these activity sequences.

In this chapter a highly-resolutiond bottom-up approach is developed to model residential energy demand in the United States. The model is calibrated to simulate households in the U.S. and behaviors of household members are simulated by using a Markov process calibrated using time use data collected in the 2003-2009 American Time Use Survey (ATUS), presented in Chapter 2.

The model proposed in this study differs from existing bottom-up techniques in four important ways. One is that HVAC use and demand is modeled with much greater detail using an engineering physically-based approach. This sub-model is independently validated against aggregate electricity consumption data available in the literature and hourly metered residential load data. The second is that a large-scale time use survey is used to calibrate the behavioral model. Existing approaches rely on much smaller data sets. Third, some of the parameters of the model, which are difficult to estimate, are calibrated using actual metered residential electricity data. Finally, rigorous statistical tests are used to validate the model by comparing estimated demand profiles generated by the model against metered residential electricity demand data. In this way the stochastic features of the residential demand profiles modeled are validated.

The proposed model can be used to reconstruct power consumption of a single or an aggregate group of households with desired characteristics and composition. This model can be used as a tool to simulate the status quo of the residential sector and, ultimately, evaluate the impact of energy policies and different technology adoption
and deployment scenarios on energy use, cost, and emissions. The model can also be used as an input to detailed power system simulations, for instance determining the impacts of diurnal load patterns and renewable uncertainty and variability on day-ahead and real-time unit commitment, dispatch, and power flows. High model resolution is needed to make the model suitable to be used for such analysis.

Also, this model can be exploited in the simulation of residential demand response programs. The model allows capturing the electricity consumption of each specific residential end-use (e.g. cooking, lighting, etc.), providing an accurate estimation of the actual amount of available controllable resources. This can help electric utilities understand residential electricity consumption in the context of demand response programs and evaluating the use of price signals as a means of shaping the electricity load in order to reduce production costs and make demand more flexible to facilitate the integration of renewable energy sources. Results and use of the proposed residential power demand model for such applications and in large-scale simulations are reported in Chapter 6.

Finally, the model also can be used as an input to long-term capacity planning and expansion studies. Depending on the specific end application, the model may be used to generate a load profile for an individual household, or the load profiles of multiple households may be aggregated to simulate the load of a broader system.
3.3 Cold Appliance Energy Consumption Model

Recent estimates place the average nominal power rating of a refrigerator at about 725 W. Moreover, the U.S. Department of Energy’s Energy Information Administration reports annual per-household electricity consumption of refrigerators to be 1,243 kWh in 2010.

Assuming that a refrigerator is an on/off device that always operates at its nominal power when on, an average operating time can be estimated by dividing annual energy consumption by nominal power as:

\[
t_{op} = \frac{1243 \text{ kWh}}{0.725 \text{ kW}} = 1658 \text{ h.}
\]

Cold appliance consumption is simulated using a Bernoulli distribution, with the success probability fixed so the expected time the appliance operates is 1658 hours annually. Assuming that the use is evenly distributed during the year, this implies that a typical cold appliance operates 19% of the time. Since the model is implemented using a 10-minute time resolution, this amounts to a cold appliance running for 9 random 10-minute intervals every 8 hours. This yields a daily energy consumption of about 3.43 kWh and a yearly energy consumption of 1251 kWh (compared to 1243 kWh reported in [16]). Figure 3.1 shows an example of the resulting power profile over a one-day period.

More detailed models to capture energy consumption of cold appliance are available in the literature [122]. These models are not appropriate for the purpose of

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2 The U.S. Department of Energy publishes statistics regarding the energy use of the average U.S. appliance stock at: http://www.energysavers.gov/your_home/appliances/index.cfm?mytopic=10050. A value of 725 W was reported as of September 2013.

3 The U.S. Energy Information Administration periodically publishes the Residential Energy Consumption Survey (RECS), a national area-probability sample survey that collects residential energy-related data [16]. More details on the RECS are provided in Appendix A.
this study given their complexity, number of input parameters required, and high computation time.

3.4 Heating, Ventilation, and Air Conditioning Energy Consumption Model

Space conditioning end-use includes heating, ventilation, and air conditioning and represents almost 50% of the total residential energy consumption in the United States [16]. The main purpose of an HVAC system is to maintain indoor air quality through adequate ventilation with filtration and provide thermal comfort [123].

This section introduces a physically-based model to simulate electricity and fossil fuel consumption of residential HVAC systems during the year, starting from a limited set of characteristic parameters of a house. The purpose of the model is to generate realistic highly-resolved energy consumption profiles (including both electricity and fossil fuel consumption) for a set of different houses, that have the same statistical properties of measured HVAC consumption profiles. The model is not intended to
be used for retrofitting purposes or to model in details a specific house. The model relies on fundamental principles of thermodynamics and heat transfer applied to a control volume comprised of the air present in the house.

The HVAC model, implemented in MATLAB\textsuperscript{®}, is a stand-alone subroutine of the residential energy demand model presented in this chapter. It is easily tunable, flexible, fast, and it relies on a limited set of input parameters. For these reasons it suits the purpose of this study of simulating HVAC energy consumption for a group of residential houses.

The input parameters needed by the model (\textit{e.g.} size of the house, general thermal properties, etc.) are collected in the U.S. DOE Residential Energy Consumption Survey (RECS) [16]. RECS data provide detailed information for over 12000 households across the United States, including physical properties of each dwelling. The RECS data are presented in more detail in Appendix A.

The model flexibility not only allows different scenarios to be easily simulated but also the evaluation of the space conditioning energy consumption of residential houses at a desired time-resolution. A 1-second resolution has been chosen in this work to capture air temperature dynamics, allowing for the construction of highly-resolved consumption patterns. A two-level validation framework against aggregate electricity consumption data available in the literature and hourly metered residential load data provided by American Electric Power is provided. A detailed example of heating and cooling operations of a residential HVAC system is reported in Appendix B.

3.4.1 Introduction and Review of the Literature

Nowadays space conditioning has become ubiquitous in U.S. buildings. Except in the temperate climate regions along the West coast, air conditioners and ventilation systems are now standard equipment in most U.S. homes (see Figure 3.2).
As recently as 1993, only 68 percent of all occupied housing units in the U.S. had an Air Conditioner (AC) unit. The latest results from the 2009 Residential Energy Consumption Survey [16], show that 87 percent of U.S. households are now equipped with AC. According to the U.S. Department of Energy - Energy Information Administration [16], this growth occurred among all housing types and in every census region. Moreover, wider use has coincided with much improved energy efficiency standards for air conditioning equipment, a population shift to hotter and more humid regions, and a housing boom during which average housing sizes increased. Currently, over 70% of residential buildings in the U.S. use central forced-air distribution systems for heating and air-conditioning purposes [124].

Different techniques, varying from simple regression to detailed models that are
based on physical principles, have been proposed in the literature to compute performance and energy consumption of HVAC systems. Trka and Hensen [125] give an overview of available modeling and simulation tools. The paper summarizes current approaches used for modeling HVAC components, HVAC control, and overall HVAC systems, providing a general categorization of such tools.

Different modeling techniques are suitable to different end goals. For comparing HVAC system alternatives and evaluating different control strategies detailed HVAC system models are required. On the other hand, most design analyses do not require detailed system modeling and HVAC energy consumption can be estimated by using simpler modeling approaches [125].

In 1997 Lam et al. [126] used linear and non-linear multiple regression techniques to develop regression models and energy equations for the prediction of annual electricity use in office buildings. In 2010 Lam et al. [127] proposed a multiple regression model for office buildings in the five major climates in China. In that paper annual building energy use predicted by the regression model is compared against simulations performed with DOE-2, and the differences are shown to be within 10%. Olofsson and Sjgren [128] applied multivariate partial least square analysis to model different energy performance measures, including heating energy consumption, for a set of 112 residential multifamily buildings in Sweden. The purpose of the study was to guide real estate management. Freiere et al. [129] propose a coupled system of linear multiple-input/single-output regression models to predict indoor temperature and relative humidity. An extensive identification process, using data obtained from simulations performed with a building simulation tool, is required to calibrate the model, making this tool extremely case-specific and not general in scope. On the

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4DOE-2 is a building energy use and cost analysis software developed by James J. Hirsch & Associates in collaboration with Lawrence Berkeley National Laboratory. More information are available at: http://www.doe2.com/.
other hand, the equations derived can be easily implemented, allowing for results to be rapidly obtained for different weather conditions and interior heat gain, if known.

Artificial neural networks also have been proposed as a possible modeling technique to predict building energy consumption [130, 131, 132]. The literature has demonstrated their superior capability over conventional methods, such as times series or regression analysis, their main advantage being the high potential to model non-linear processes, such as individual buildings energy consumption [132]. Neto and Fiorelli [17] propose a neural network using only the external dry-bulb temperature as an input parameter, giving results comparable to the ones obtained using EnergyPlus.\(^5\) Also a more complex neural network is proposed by Neto and Fiorelli [17] that includes the effects of humidity and radiation on energy consumption. Still, the authors report that these added parameters are less significant than external temperature.

Accurate regression models and neural network approaches are adequate for a variety of purposes, such as approximating indoor air conditions and total energy consumption/demand of HVAC systems. Nevertheless such models are only capable of predicting the energy consumption based on previous measurements. Therefore, evaluation of strategies for reducing energy consumption can only be evaluated after they are implemented [17]. Also, this class of models provide aggregate energy consumption (\textit{e.g.} in the form of kWh per year or day) and not highly-resolved energy consumption patterns, making them unsuitable for use in this study. Finally, most energy forecasting models based on neural networks have been developed for large commercial buildings and, due to the nature of the modeling technique, cannot be readily transferred to different applications.

\(^5\)EnergyPlus is a whole building energy simulation program developed by the U.S. Department of Energy [133].
Other modeling techniques, including engineering physically-based models have been proposed in the past to predict HVAC system energy consumption.

Several simple engineering methods have been implemented that use physical principles to calculate HVAC energy consumption at the building level or for sub-level components [123]. Zhao and Magoulès [134] provide a comprehensive review.

Li et al. [135] propose a simple model to predict HVAC power consumption. The temperature inside the household is assumed to be uniform and a utility function is implemented such that the temperature inside the household is maintained at a defined value. The model relies on parameters that specify the thermal characteristics of the HVAC system and the environment in which it operates. Nevertheless, numerical values are not provided and no procedure is proposed for the calibration of such parameters.

Goyal and Barooah [136] propose a methodology for reducing the order of a class of non-linear systems that models the humidity thermal dynamics in a multi-zone building. Still, multi-zone modeling requires fairly detailed information on the building being modeled, including physical properties of the various zones (i.e. size and location of each room).

Several engineering end-use forecasting models and software tools have been developed since the mid-1970s, most of which account for space conditioning energy consumption. A survey of the earliest models developed is presented by Johnson et al. [137], where the modeling framework provided by the HVAC module in the Residential End-Use Energy Planning System (REEPS) is described in detail. The EPRI-REEPS was originally developed by the Electric Power Research Institute in 1992 [138]. This model incorporates the basic features of residential end-use forecasting into a generalized modeling framework in which the user has considerable control.
over the algorithms and model structure. The REEPS 2.1 modeling tool is data intensive, however, requiring data at the household level as well as detailed data on the characteristics of HVAC equipment and thermal shells plus simulation methodologies that are often difficult to trace due to decades of development and lack of clear documentation.

For more than 20 years, the U.S. government has supported development of two building energy simulation programs, DOE-2 and BLAST. Details on the BLAST model are provided by Al-Rabghi and Hittle [139]. In 1996, the two models were merged to create a new building energy simulation tool called EnergyPlus [140, 133].

EnergyPlus is a whole-building energy simulation program that engineers, architects, and researchers can use to model energy and water use in buildings [141]. Based on a user’s description of a building from the perspective of its physical make-up and associated mechanical and other systems, EnergyPlus calculates heating and cooling loads necessary to maintain thermal control set-points, conditions throughout a secondary HVAC system and coil loads, and the energy consumption of primary plant equipment.

As with EPRI-REEPS, to accurately predict total energy consumption using EnergyPlus requires a detailed description of the household modeled (including up to several hundred input parameters) along with several economic and geographical parameters [134]. Accordingly, this kind of model is suitable only for detailed simulations and it is difficult to customize. These shortcomings have limited the utility of many such tools, and according to Jacobs and Henderson [142] these software tools do not fit into current design efforts.

Buildings are complex systems where actual performance often deviates from the performance predicted in the design stage, and developing the right model for a simulation task at hand is still more an art than an engineering discipline [125]. Recent
studies show that the difference between the predicted and real energy consumption can be significant, up to 40% [143]. Neto and Fiorelli [17] provide a comparison of actual energy consumption data and data simulated using EnergyPlus, which is considered to be one of the most accurate physically-based energy forecasting tool. Results of such a comparison are shown in Figure 3.3. The data are spread, and only 80% is included in a ±13% region when compared to measured data [17].

![Comparison between EnergyPlus-simulated and measured daily energy consumption. From Neto and Fiorelli [17].](image)

In this work, a physically-based model has been implemented to generate highly-resolved HVAC energy consumption patterns of residential buildings. This includes a methodology for components sizing and a validation against aggregate and hourly-resolved data.
3.4.2 Heating, Ventilation, and Air Conditioning Model Development

The model developed in this work uses overall thermal resistance theory to simulate the behavior of a typical air-based HVAC system [144].

A control volume analysis, based on fundamental principles of thermodynamics and heat transfer is performed for the volume including solely the air present in the house. Air flow rates due to leakages and doors or windows openings and direct solar radiation have been neglected, to maintain model simplicity. Shown in Figure 3.4 are two systems in communication. One is the control volume comprising the air within a house. The other is the HVAC unit that provides heating or cooling to a stream of air drawn from and eventually returned to the control volume.

Figure 3.4: System considered in the HVAC analysis.
Analysis of the HVAC unit accounts for the electricity provided to it to achieve the conditioning required during the year, including electricity to service the fans (needed for both cooling and heating), the air conditioner when cooling is required, and heat pumps or electric resistor heaters, if present, when heating is required. The analysis also accounts for the energy of the fossil fuel to service a furnace, if one is adopted. In symbols:

\[ \dot{W}_{HVAC} = \text{Total rate of electricity consumed by the HVAC system.} \]
\[ \dot{W}_{fan} = \text{Rate of electricity consumed by the fans.} \]
\[ \dot{W}_{elec,cool} = \text{Rate of electricity consumed by the air-conditioning unit.} \]
\[ \dot{W}_{elec,heat} = \text{Rate of electricity consumed by the electric heating unit.} \]
\[ \dot{E}_{fuel} = \text{Rate of energy consumed by the fossil fuel furnace.} \]

Accordingly, the total rate of electricity consumed for space conditioning is:

\[ \dot{W}_{HVAC} = \dot{W}_{fan} + \dot{W}_{elec,heat} + \dot{W}_{elec,cool} \] (3.4.1)

Analyzing the control volume shown in Figure 3.4, if the temperature of the air within the control volume is uniform with position, the variation of air temperature with time is given by:

\[ m_a c_p \frac{dT_a}{dt} = \dot{m}_{HVAC} \cdot c_p (T_{HVAC} - T_a) - \frac{T_a - T_\infty}{R_{tot}} \] (3.4.2)

where the variables are defined as:

- \( m_a \) air mass inside the control volume [kg];
- \( c_p \) air specific heat, 1.005 kJ/kg K;
- \( T_a \) air temperature inside the control volume [°C];
- \( \dot{m}_{HVAC} \) HVAC air flow rate [kg/s];
- \( R_{tot} \) equivalent thermal resistance of the household envelope [K/W];
- \( T_{HVAC} \) HVAC supply air temperature [°C]; and
- \( T_\infty \) ambient temperature [°C].
The term on the left accounts for the time rate of change of the energy of the control volume. The first term on the right accounts for the rate of increase or decrease of the energy of the stream of air flowing from the control volume at temperature $T_a$ and to the control volume at temperature $T_{HVAC}$ after passing through the HVAC unit. The second term on the right accounts for the rate energy is added or removed from the control volume by heat transfer between the control volume and the external ambient at temperature $T_\infty$.

Solving Equation (3.4.2), the variation of air temperature with time inside the control volume is:

$$T_a = [T_0 - A]e^{-t/\tau} + A \quad (3.4.3)$$

where:

$$A = \frac{T_\infty + \dot{m}_{HVAC}T_{HVAC}}{\dot{m}_{HVAC}c_p + \frac{1}{R_{tot}}},$$

$$\frac{1}{\tau} = \frac{\dot{m}_{HVAC}c_p + \frac{1}{R_{tot}}}{m_a c_p},$$

and $T_0$ represents the initial condition.

The energy rate expressions used in this study to evaluate $\dot{W}_{HVAC}$ and $\dot{E}_{fuel}$ are summarized in Table 3.1.

By inspection, these energy consumption rates depends on four key quantities: the ambient temperature $T_\infty$, $\dot{m}_{HVAC}$, $T_{HVAC}$, and $T_a$. Additionally, each depends on an accompanying set of parameters capturing system characteristics and efficiencies. These energy consumption rates and accompanying parameters and the terms introduced in Equation (3.4.2) are detailed later in the present section together with discussion of the modeling employed.
Table 3.1: Key energy rate expressions.

\[ W_{fan} = \frac{\dot{m}_{HVAC} \cdot \Delta P_{tot}}{\rho_{air} \cdot \eta_{fan} \cdot \eta_{motor}} \]  
(3.4.4)

\[ W_{elec,cool} = \frac{\dot{m}_{HVAC} \cdot c_p \cdot (T_a - T_{HVAC})}{SHR \cdot COP_{cool}} \]  
(3.4.5)

\[ W_{elec,heat} = \begin{cases} 
\dot{m}_{HVAC} \cdot c_p \cdot (T_a - T_{HVAC}) & \text{for electric resistor heaters} \\
\frac{\dot{m}_{HVAC} \cdot c_p \cdot (T_a - T_{HVAC})}{COP_{heat}} & \text{for heat pumps} \\
0 & \text{for fossil fuel furnaces}
\end{cases} \]  
(3.4.6)

\[ \dot{E}_{fuel} = \frac{\dot{m}_{HVAC} \cdot c_p \cdot (T_{HVAC} - T_a)}{\eta_{furnace}} \]  
(3.4.7)

EVALUATION OF \( R_{tot} \)

The equivalent thermal resistance of the house envelope introduced in Equation 3.4.2 is computed as [145]:

\[ R_{tot} = \left[ \frac{R_{ground}}{A_{floor}} + \left( \frac{1}{h_o \cdot A_{wall}} + \frac{R_{wall}}{A_{wall}} + \frac{1}{h_i \cdot A_{wall}} \right)^{-1} + \left( \frac{1}{h_o \cdot A_{wind}} + \frac{R_{wind}}{A_{wind}} + \frac{1}{h_i \cdot A_{wind}} \right)^{-1} \right]^{-1} \]  
(3.4.8)

where \( h_o \) and \( h_i \) are the outside and inside convective heat transfer coefficients, respectively.

Typical values for convective transfer coefficients with surface infrared reflectance < 0.1 (nonmetallic) are reported in the 2009 ASHRAE (American Society of Heating, Refrigerating and Air Conditioning Engineers) Handbook [144]:

79
The convective heat transfer coefficient in unbounded natural convection along vertical walls is in general a function of several factors, including the fluid flow regime and temperature distribution (influencing fluid density and viscosity), surface roughness, surface orientation, the temperature difference between the wall and fluid, and the surface temperature distribution. Further details on the topic are available in literature [146, 147]. Physically-based engineering models – of the kind proposed here – that do not rely on computational fluid dynamics (CFD) analysis usually disregard all of these factors [148].

The 2009 ASHRAE Handbook [144] suggests correlations for $h_o$ as a function of wind speed (EnergyPlus, for example, considers only wind speed when calculating exterior heat transfer coefficient [149]). Also, for $h_i$ the 2009 ASHRAE Handbook [144] reports values for winter (room air temperature 70 °F, outdoor air temperature 0 °F, and no solar radiation) and summer (room air temperature 75 °F, outdoor air temperature 89 °F, and direct solar irradiance of 248 BTU/h · ft²) conditions. Values for different window glazing types are reported, and the average summer $h_i$ value is about 6.7% larger than the average winter $h_i$ value.

For simplicity, in this study the influence of wind speed, surface roughness, orientation, and temperature on the convective heat transfer coefficient have been neglected, and average values over the ranges provided by ASHRAE have been assumed: 25 and 6.25 W/m²K for outside and inside convective coefficients, respectively.

The specific heat of air, $c_p$, is assumed to be constant at 1.005 kJ/kgK, which is accurate for temperature ranging between 0 and 40 °C.

$A_{wall}$, $A_{wind}$, $A_{ceil}$, and $A_{floor}$ are the surface of walls, windows, ceiling, and floor in contact with the environment, respectively. These surfaces are normal to the
direction of heat transfer. $R_{\text{ground}}, R_{\text{wind}}, R_{\text{wall}},$ and $R_{\text{ceil}}$ are the thermal resistances of the ground, windows, walls, and ceiling, respectively. For each simulated house, envelope characteristics, areas, and thermal resistance values are derived from the RECS data, as detailed in Appendix A.

EVALUATION OF THE DESIRED TEMPERATURE INSIDE THE HOUSE: $T_a$

Information on desired temperatures of the air inside the control volume ($T_a$) are reported in the RECS data. The model determines whether each day is a heating or cooling day, comparing the desired temperature and the temperature of the environment. This is meant to replicate the decision made by the occupant to switch on the heating or the cooling system.

In each case, a realistic control strategy is implemented based on a relay that allows a tolerance of 1°C (1.8°F) around the desired indoor temperature. Daily and nightly desired temperatures in the house are reported for summer and winter in the RECS data (typically around 70°F, corresponding to 21.1°C), and are used as set points for each modeled household.

HVAC SYSTEM SIZING: EVALUATION OF $\dot{m}_{\text{HVAC}}$ AND $T_{\text{HVAC}}$

The HVAC model requires several assumptions regarding the physical characteristics of the system, including the size of the ducts, fans, and thermal machines. Such information is not available in the RECS data. In this work, a component-sizing methodology for selection of air ducts size, AC unit, and fossil fuel heating furnace, if any, is presented.

Generally, ductwork sizes are determined by minimizing the net present installation and operating cost [144]. In the proposed model the ducts and fans are sized to guarantee that the HVAC system is capable of maintaining the desired temperature
in the house during both the the highest and lowest ambient temperatures for the location of the building being modeled (taken from historical data). Once the air flow rate is chosen among the most common available options for residential systems, the fossil fuel furnace necessary to match the worst winter condition is selected, if one is present.

Cooling machines are scalable and a variety of models is available on the market. Therefore, in this study an AC machine is selected so that the temperature of the supply air from the HVAC system during cooling operations is constant and equal to 13°C [144]. Likewise, when heating is achieved using an all-electric system, the temperature of the supply air from the HVAC system during heating operations is constant and equal to 50°C [144].

On the other hand, when heating is achieved using a fossil fuel furnace, the selection of both air flow rate and the nominal size of the furnace lead to a fixed value of the temperature of the air returning to the household in heating mode that, depending on the specific system chosen, varies from 40 to 66 °C. The possible air flow rate and fossil fuel heating unit size combinations, as well as the returning air temperature from the HVAC system, for commercially available systems are reported in Table 3.2.6

This component-sizing procedure is applied to any household modeled to select the appropriate ducts, fans, and HVAC equipment. A detailed example illustrating the sizing procedure is reported in Appendix B.

6The values in the table are given in imperial (or English) units, since these units are used in the design and marketing of HVAC systems in the United States.
Table 3.2: Available air flow rates and fossil fuel furnace sizes for residential systems and resulting temperature of the air [°C] returning to the household in heating operations [20].

<table>
<thead>
<tr>
<th>Air Flow [cfm]</th>
<th>45</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>75</th>
<th>80</th>
<th>90</th>
<th>100</th>
<th>115</th>
<th>120</th>
<th>125</th>
<th>140</th>
</tr>
</thead>
<tbody>
<tr>
<td>800</td>
<td></td>
<td></td>
<td>50</td>
<td>53</td>
<td>59</td>
<td>66</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1200</td>
<td></td>
<td></td>
<td>40</td>
<td>42</td>
<td>47</td>
<td>51</td>
<td>53</td>
<td>55</td>
<td>59</td>
<td>64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1600</td>
<td></td>
<td></td>
<td>43</td>
<td>45</td>
<td>47</td>
<td>50</td>
<td>53</td>
<td>58</td>
<td>59</td>
<td>61</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td></td>
<td></td>
<td>44</td>
<td>47</td>
<td>50</td>
<td>52</td>
<td>53</td>
<td>57</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

EVALUATION OF THE ENERGY CONSUMPTION RATES.

HVAC energy consumption is divided into two components: the power consumed by the fans to circulate the air, $\dot{W}_{fan}$, and the rates at which energy is provided to the HVAC equipment to provide space conditioning, namely cooling and heating ($\dot{E}_{cooling}$ and $\dot{E}_{heating}$). The former is necessarily electricity consumption, and the same applies for space cooling. In the case of space heating, energy can be provided to the heating unit either in the form of electricity or by a stream of fossil fuel.

The electrical power consumed by the fans can be computed as:

$$\dot{W}_{fan} = \frac{\dot{m}_{HVAC} \cdot \Delta P_{tot}}{\rho_{air} \cdot \eta_{fan} \cdot \eta_{motor}}$$

(3.4.9)

where the total pressure drop, $\Delta P_{tot}$, is defined to equal $P_{static} + \rho_{air} \frac{v^2}{2}$. $P_{static}$ is the static pressure drop, $\rho_{air}$ is the air density, and $v$ is the air velocity. The 2009 ASHRAE handbook reports $P_{static} = 135$ Pa [144]. In this work $v$ is assumed to equal 4 m/s, the midpoint of the range of values suggested in the handbook to avoid noise [144]. Therefore $\Delta P_{tot} = 145$ Pa. $\eta_{fan}$ and $\eta_{motor}$ are the efficiencies of the fan and motor, respectively, and the product $\eta_{fan}\eta_{motor}$ is assumed to equal 0.15 [150].

The HVAC equipment energy consumption differs depending on whether the system is in cooling or heating mode. In heating operations, the energy required to maintain the desired thermal condition in the household can be obtained using two
technologies: traditional fossil fuel furnaces or all-electric heating systems. In the former case, the rate at which energy is consumed (\( \dot{E}_{\text{heating}} \)) can be computed as:

\[
\dot{E}_{\text{heating}} = \dot{E}_{\text{fuel}} = \dot{m}_{\text{HVAC}} \cdot c_p \cdot \left( T_{\text{HVAC}} - T_a \right)/\eta_{\text{furnace}} \tag{3.4.10}
\]

where \( \eta_{\text{furnace}} \) is the efficiency of the fossil fuel furnace. Furnace efficiencies are not reported in the RECS data. When dealing with new residential natural gas furnaces, there are two types of equipment to choose from: mid-efficiency furnaces that have an Annual Fuel Utilization Efficiency (AFUE) of 80%-83%, and high-efficiency furnaces that have an AFUE of 90%-98% \[151\]. The National Appliance Energy Conservation Act limits the minimum efficiency of natural gas furnaces to 80% AFUE when tested according to the DOE standard (Title 10, Code of Federal Regulations) \[151\]. In this work a conservative approach is followed, and \( \eta_{\text{furnace}} \) is assumed to equal 0.8 \[152\].

If a fossil fuel furnace heating system is used, \( \dot{E}_{\text{heating}} \) is directly obtained via combustion of fuels (\( e.g. \) natural gas, fuel oil). In such a case \( \dot{E}_{\text{heating}} \) does not contribute to the building’s electricity load, which is represented solely by the power consumed to circulate the air, namely \( \dot{W}_{\text{fan}} \).

Alternatively, space heating can be obtained using an all-electric system. In this case the rate at which thermal energy, \( \dot{E}_{\text{heating}} \), is supplied to the household is provided by electricity, and is computed as:

\[
\dot{E}_{\text{heating}} = \dot{W}_{\text{elec,heat}} = \begin{cases} 
\dot{m}_{\text{HVAC}} \cdot c_p \cdot (T_a - T_{\text{HVAC}}) & \text{for electric heaters} \\
\dot{m}_{\text{HVAC}} \cdot c_p \cdot (T_a - T_{\text{HVAC}})/\text{COP}_{\text{heat}} & \text{for heat pumps}
\end{cases} \tag{3.4.11}
\]

When an all-electric heating system is adopted, the total electricity consumption during the heating days can be obtained by summing \( \dot{W}_{\text{fan}} \) and \( \dot{W}_{\text{elec,heat}} \).

A detailed example of heating and cooling operations of a residential HVAC system is reported in Appendix B. From that case study, Figure 3.5 reports an example for
a heating day. The top part of the figure shows the evolution of the temperature of the external ambient and of the air inside the control volume during a heating day. The bottom part of the figure reports the resulting total hourly electric energy consumed by the HVAC system. This is shown for both an HVAC system coupled with a fossil fuel furnace and for an all-electric heating system using heat pumps. For the fossil fuel heating system, the total simulated electricity consumption for the day is 0.58 kWh (due to the electric consumption of the fans). Additionally, 31.2 kWh of heating is provided via the combustion of fuel in the furnace. For the all-electric system using heat pumps, the total simulated electricity consumption for the day is 6.24 kWh.

Figure 3.5: Simulated temperatures evolution and resulting HVAC electricity consumption for a heating day (see Appendix B for details).

In cooling operations the HVAC system must both cool and reduce air humidity to provide comfort in the household. Typically, moist air flows across a cooling coil
through which a refrigerant or chilled water circulates. When a moist air stream is cooled at constant mixture pressure to a temperature below its dew point temperature, some condensation of the water vapor initially present occur. As some of the water vapor initially present in the moist air condenses, a saturated moist air mixture exits the dehumidifier section. Since the moist air leaving the humidifier is saturated at a temperature lower than the temperature of the moist air entering, the moist air stream might be unsuitable for direct use in occupied spaces. However, by passing the stream through a following heating section, it can be brought to a condition most occupants would regard as comfortable [153]. Calculating the total energy requirement for this process requires the knowledge of the air properties in all the states, making this extremely case-specific. Alternatively, the total energy requirement can be computed given the proportion of sensible heat (due only to temperature difference, and easy to calculate) on the total heat.

The total energy requirement for cooling, which is proportional to the total enthalpy change, $\Delta h_{\text{total}}$, can be computed using the sensible heat ratio, $\text{SHR}$, as defined by ASHRAE. This term measures the ratio between the sensible heat load ($e.g.$ energy used to cool) and total heat load, and is defined as:

$$\text{SHR} = \frac{\Delta h_{\text{sensible}}}{\Delta h_{\text{total}}},$$

where $\Delta h_{\text{sensible}}$ is the sensible enthalpy change. Typical $\text{SHR}$ values range from 0.2 to 1 for different locations in the U.S. [154]. The rate of energy consumption in cooling operation, always provided as electricity, is then given by:

$$\dot{E}_{\text{cooling}} = \dot{W}_{\text{elec,cool}} = \frac{\dot{m}_{\text{HVAC}} \cdot c_p \cdot (T_a - T_{\text{HVAC}})}{\text{SHR} \cdot \text{COP}_{\text{cool}}}. \quad (3.4.12)$$

Note that $\text{COP}_{\text{cool}}$ (coefficient of performance during cooling operations) is defined
as the thermal energy removed from the house per unit of electric energy absorbed by the AC system (air conditioner). This can be determined from:

\[ \text{COP}_{\text{cool}} = \frac{\text{EER}}{3.412} \]

where \( \text{EER} \) represents the energy efficiency ratio, the value of which is typically labeled on HVAC equipment sold in the United States. \( \text{EER} \) represents the cooling output, measured in BTU, divided by the total electric energy input, measured in watt-hours, during the cooling season. COP and EER values are not included in the RECS data.

In general, the performance of air conditioners (\( \text{COP}_{\text{cool}} \)) and heat pumps (\( \text{COP}_{\text{heat}} \)) depend on the temperature difference between the warm and cold regions (house and environment, depending on the season). The higher this temperature difference the lower the performance coefficient.

Still, there exist seasonal values that measure the overall performance of a system during a season, which can be considered as an average performance coefficient for an entire cooling or heating season (as defined by ASHRAE in its 2008 standard AHRI 210/240). New residential central air conditioner standards went into effect on January 23, 2006. Air conditioners manufactured after January 26, 2006 must achieve a seasonal \( \text{EER} \) of 13 or higher, which is 30% more efficient than the previous minimum seasonal \( \text{EER} \) of 10. In order to simulate the current HVAC market stock, in this work \( \text{COP}_{\text{cool}} \) is approximated by the seasonal value, and conservatively assumed to be 3 \( (\text{EER} = 10.236) \). \( \text{COP}_{\text{heat}} \) is assumed to be 4 \( (\text{EER} = 13.648) \).

The total electricity consumption during the cooling days can be obtained by summing \( W_{\text{fan}} \) and \( W_{\text{elec,cool}} \).

Forecasting energy consumption for space conditioning in U.S. residences is complicated by geographical differences in climate and the associated heating and cooling requirements. In this study the geographic variation is captured by the change of both
the ambient temperature and the $SHR$ parameter. Unfortunately, $SHR$ values provided by ASHRAE are highly fragmented, including only a few specific locations in the United States. In the next sub-section, space cooling energy consumption data reported in the RECS are used to estimate average $SHR$ values for different macro locations in the United States.

The model proposed allows for long-term simulations (e.g. spanning a year or longer). Also, if the location and a few house thermal characteristics are specified, the model computes both thermal and electrical energy consumption patterns to maintain comfort in a residential dwelling with a desired time resolution. These consumption patterns contribute to the overall residential energy demand model introduced in this chapter.

### 3.4.3 Estimation of SHR Values from RECS Data

The sensible heat ratio, $SHR$, measures the ratio between the sensible heat load (i.e. energy used to cool) and total heat load in summer operations of HVAC systems. It is one of the terms used in the proposed HVAC model to predict the cooling energy consumption. Unfortunately, ASHRAE provides values for such a term only for a very limited set of locations (7 cities) in the United States. In the current study, space cooling energy consumption data reported in the RECS are used to estimate $SHR$ values for different locations (for more details on the RECS data see Appendix A). For this purpose, the RECS data set is divided into different subsets. One is used for estimating the $SHR$ parameters. Another subset is used to validate the ability of the proposed model to capture aggregate space conditioning energy consumption.

RECS data report yearly electricity consumption for space heating and cooling in 2009 for over 12000 American households, divided into 27 geographical areas. Two areas have been selected for the purpose of this study: Indiana-Ohio and Texas.
Table 3.3 reports a summary of the HVAC electricity use and consumption data for such regions.

Table 3.3: HVAC electricity consumption in Texas and Indiana-Ohio. From the RECS data.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Ohio-Indiana</th>
<th>Texas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of households</td>
<td>386</td>
<td>991</td>
</tr>
<tr>
<td>Use of AC systems</td>
<td>85%</td>
<td>97%</td>
</tr>
<tr>
<td>Use of electricity of primary heating source</td>
<td>25%</td>
<td>51%</td>
</tr>
<tr>
<td>Average electricity consumption for space heating [kWh/year]</td>
<td>1236</td>
<td>1103</td>
</tr>
<tr>
<td>St. dev. of electricity consumption for space heating [kWh/year]</td>
<td>2054</td>
<td>1193</td>
</tr>
<tr>
<td>Average electricity consumption for space cooling [kWh/year]</td>
<td>730</td>
<td>4090</td>
</tr>
<tr>
<td>St. dev. of electricity consumption for space cooling [kWh/year]</td>
<td>786</td>
<td>3159</td>
</tr>
</tbody>
</table>

Space conditioning electricity consumption in Texas and Ohio-Indiana appears to be quite different. First, AC systems are more widely used in Texas, but still largely used in both regions. Second, electricity is used as primary heating source by a substantially higher percentage of households in Texas, compared to Ohio-Indiana, where natural gas is more used for space heating purposes.

The average electricity consumption for space heating is comparable in the two regions. The reason for this is that significantly smaller percentages of households use electricity as a heating source in the colder region (Ohio-Indiana) compared to the hotter region (Texas). In other words, fewer households use electricity for space heating in Ohio-Indiana, but the colder region requires them to consume more electricity on a per-household basis, compared to households in Texas. Given a similar adoption of AC in the two regions, the average electricity consumption for space cooling is much higher in the hotter region (Texas). Both heating and cooling annual electricity consumption data present a notably high standard deviation, indicating that space conditioning consumptions vary significantly among the observed households. This
confirms the difficulties of accurately modeling HVAC energy consumption, resulting in the substantial amount of literature on the topic and many tools developed in the past.

Ohio-Indiana and Texas are used in this study to represent different HVAC use in disparate climate areas. In order to simulate space conditioning electricity consumption using the proposed HVAC model, house characteristics and ambient temperature are needed. The former are taken from the RECS data. The National Climatic Data Center (NCDC) makes historical weather and temperature data available for over 1400 locations in the United States. NCDC is part of the National Climatic and Atmospheric Administration (NOAA), an organization responsible for preserving, monitoring, assessing, and providing public access to the Nation’s treasure of climate and historical weather data and information.\textsuperscript{7} NCDC maintains the world’s largest climate data archive and provides climatological services and data to every sector of the United States economy and to users worldwide. The data include solar irradiation, wind speed, humidity and dry bulb temperature with an hourly resolution.\textsuperscript{8} Temperature data are used in this work as input to the HVAC model.

Austin, Columbus, and Indianapolis have been chosen as representative locations for Texas, Ohio, and Indiana, respectively. Figure 3.6 shows 2009 dry bulb temperature data for such locations that are used as input to estimate $SHR$ values for Ohio-Indiana and Texas.

The temperature difference between Columbus, OH and Indianapolis, IN in 2009 is small and an average temperature between these two data sets is used as input when simulating the Indiana-Ohio region.

\textsuperscript{7}More information is available online at: \url{http://www.noaa.gov/}.

\textsuperscript{8}Weather data are publicly available for download at: \url{ftp://ftp.ncdc.noaa.gov/pub/data/nsrdb-solar/station-data-2010/}
In this study, a least-squares simple linear regression model is used to estimate the \( SHR \) values for the two regions starting from aggregate electricity consumption data. This regression is performed using a first subset of the RECS data set. A second subset (including different households) of the RECS data set is then used to validate the modeling methodology, as reported in Section 3.4.4.

Regression has been widely used to predict HVAC energy consumption (see Section 3.4.1). This technique is used here to estimate \( SHR \) values used in the proposed physically-based model.

Simulations are performed for a subset including 100 households per each region, randomly selected among the ones available in the RECS data. The linear regression model has the form:

\[
y = \frac{x}{SHR} + \epsilon
\]  

(3.4.13)
where $y$ is a vector containing the cooling electricity consumption for the 100 households, as reported in the RECS data; $x$ is a vector containing the cooling electricity consumption for the 100 households, as predicted by the HVAC model; and $\epsilon$ is the vector containing the random error terms. Since the $SHR$ term is not available, $x$ is computed assuming $SHR = 1$. The least-squares linear regression model shown in Equation 3.4.13 is used to estimate the value of $SHR$. In general, there are three assumptions that justify the use of simple linear regression models:

- linearity of the relationship between $x$ and $y$ variables;
- homoscedasticity (constant variance) of the error terms;
- independence of the error terms (no serial correlation).

Moreover, the random error terms $\epsilon$ are assumed to be normally distributed. This allows computing the variance of the estimated parameters, and performing rigorous statistical tests [155].

All these four assumptions are satisfied for both cases. Diagnostics for the Texas region are reported as an example. Figure 3.7 reports a graphical summary of the linear regression diagnostics.

A t-test is run to assess the linear relationship between $x$ and $y$ variables, resulting in a p-value of 0.000 (confirming the linear relationship). The homoscedasticity assumption is confirmed by the plot of the residuals versus the fitted values, where no particular trend is shown. The plot of the standardized residuals versus the observation order confirms the independence of the error terms. The normality of the error distribution is confirmed by inspection of the normal probability plot and the histogram of the standardized residuals.

In summary, the $SHR$ is estimated to be 0.36 in the Ohio-Indiana region and 0.40 in Texas.
Figure 3.7: Diagnostics plots for the linear regression model used to estimate the SHR parameter for Texas region.

3.4.4 Heating, Ventilation, and Air Conditioning Model Validation

A two-level methodology is used to validate the proposed HVAC model. First, simulated annual electricity consumption data are compared to HVAC electricity consumption data included in the RECS data. Second, a comparison against highly-resolved hourly averaged residential per-customer electric loads provided by American Electric Power is provided. This methodology verifies that the model is both capable of accurately estimating the total space conditioning electricity consumption and generating realistic highly-resolved consumption patterns for a group of households in different locations in the United States.
VALIDATION OF THE ANNUAL HVAC ELECTRICITY CONSUMPTION

To validate the proposed model, 100 households for two regions of the United States: Ohio-Indiana and Texas, are randomly selected among the ones available in the RECS data (note that these subsets are different from the ones used to estimate the SHR parameters). The annual space conditioning energy consumption of these households is modeled and results are compared against electricity consumption data reported in the RECS (space heating and cooling annual consumption). Table 3.4 reports a summary of the HVAC electricity consumption in the two regions according to the RECS data and as predicted by the model.

Table 3.4: Comparison of HVAC electricity consumption in Ohio-Indiana and Texas.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>RECS data</th>
<th>HVAC model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average electricity consumption for space heating, Ohio-Indiana [kWh/year]</td>
<td>1353</td>
<td>1304</td>
</tr>
<tr>
<td>St. dev. of electricity consumption for space heating, Ohio-Indiana [kWh/year]</td>
<td>1955</td>
<td>1770</td>
</tr>
<tr>
<td>Average electricity consumption for space cooling, Ohio-Indiana [kWh/year]</td>
<td>675</td>
<td>609</td>
</tr>
<tr>
<td>St. dev. of electricity consumption for space cooling, Ohio-Indiana [kWh/year]</td>
<td>842</td>
<td>546</td>
</tr>
<tr>
<td>Average electricity consumption for space heating, Texas [kWh/year]</td>
<td>1117</td>
<td>1023</td>
</tr>
<tr>
<td>St. dev. of electricity consumption for space heating, Texas [kWh/year]</td>
<td>1170</td>
<td>1164</td>
</tr>
<tr>
<td>Average electricity consumption for space cooling, Texas [kWh/year]</td>
<td>4114</td>
<td>3379</td>
</tr>
<tr>
<td>St. dev. of electricity consumption for space cooling, Texas [kWh/year]</td>
<td>3367</td>
<td>2703</td>
</tr>
</tbody>
</table>

Since the overall purpose of the proposed HVAC model is to capture the features of the energy consumption for space conditioning of a group of diverse residential houses, formal statistical tests are used to assess how modeled averages and standard deviations compare to the data reported in the 2009 RECS. Analysis of the
high-order moments\textsuperscript{9} of the distribution of space conditioning energy consumption provides the basis of an alternative route to analytical results compared with working directly with probability density functions or cumulative distribution functions, which are not available in this case. In particular, a two-tailed hypothesis t-test and a two-tailed hypothesis z-test are performed to compare the average electricity consumptions and their standard deviations, respectively. A significance (level of risk) of 5\% has been chosen for all the tests. Kutner et al. \cite{155} provide more details on statistical hypothesis testing. The p-values of all the tests are reported in Table 3.5.

\begin{table}[ht]
\centering
\caption{HVAC model validation. Summary of hypothesis tests p-values.}
\begin{tabular}{|l|l|l|}
\hline
Test & \textbf{t-test (Average)} & \textbf{z-test (Standard Deviation)} \\
\hline
Electricity consumption for space heating, Ohio-Indiana & 0.854 & 0.153 \\
Electricity consumption for space cooling, Ohio-Indiana & 0.511 & 0.247 \\
Electricity consumption for space heating, Texas & 0.569 & 0.055 \\
Electricity consumption for space cooling, Texas & 0.077 & 0.075 \\
\hline
\end{tabular}
\end{table}

All the hypothesis tests show that there is not enough statistical evidence, at a 95\% confidence level, to claim a difference between the space conditioning electricity consumption simulated by the proposed HVAC model and the values reported in the RECS data, both in terms of average and standard deviation. This implies that, from an aggregate point of view, the proposed HVAC model achieves its objective: able to accurately predict the total HVAC electricity consumption of a group of diverse residential houses in different regions of the United States. The results generated by

\textsuperscript{9}In statistics, moments describe various aspects of a distribution. They are a quantitative measure of the shape of a set of points. Any distribution can be characterized by a number of features (such as the mean, the variance, the skewness, etc.), and the moments of a random variable’s probability distribution are related to these features.
the HVAC model present the same statistical features of data reported in the RECS. This confirms that the thermal modeling conducted for the air inside the household (see Equation 3.4.2) is a suitable approach for computing the energy consumption of a typical residential HVAC system.

It is worth mentioning that the estimation of only one parameter for each modeled macro-region, namely $SHR$, is required to properly capture the space cooling energy consumption. Moreover, space cooling and space heating consumptions are predicted by the proposed physical model using a limited set of input parameters, including characteristics of the house modeled and ambient temperature. The required information is readily available in the literature.

Aggregate yearly space conditioning electricity consumption (sum of heating and cooling) for the 200 modeled houses (including the two subsets used for the validation) is plotted versus the corresponding RECS data in Figure 3.8. From the figure the linear trend between simulated and RECS data is evident. Figure 3.8 can be compared to Figure 3.3, which reports a similar comparison between measured HVAC energy consumption and predictions performed using EnergyPlus. The two figures show similar trends.

VALIDATION OF THE HIGHLY-RESOLVED HVAC ELECTRICITY CONSUMPTION PROFILES

Further, the HVAC model has been validated against highly-resolved hourly averaged per-customer electric loads provided by American Electric Power. This is aimed at guaranteeing that the highly-resolved electricity consumption profiles generated by the HVAC model are in accordance with metered data.
Data reporting average hourly electric loads for fully diversified residential customers in two AEP service territories, Indiana-Michigan and Texas, were made available by AEP to validate the residential model. The data are from 2010, and include electricity demand and ambient temperature with a one-hour resolution. In particular the data for the Indiana-Michigan territory, reported in Figure 3.9, are differentiated with respect to the primary heating source, distinguishing between customers who use electricity only ($W_{\text{all-electric}}$), and customers who use a supplemental fossil fuel (typically natural gas) for heating purposes ($W_{\text{fuel-heating}}$).

The difference between the two groups of households represents the electricity used by an all-electric heating system to maintain the desired temperature in the households. Note that the two curves very closely overlap during the summer, indicating that there is no intrinsic difference between the two data sets other than the main source of energy used for space heating. The difference between the two

*Figure 3.8: Comparison between Modeled and RECS annual electricity consumption.*
Figure 3.9: Fully diversified average per customer electric loads on an hourly integrated basis for Indiana-Michigan territory.

The SHR parameter for the Indiana-Michigan region is estimated using 2009 total electricity consumption reported in the RECS, following the procedure detailed in Section 3.4.3. Given the geographical location of the AEP Indiana-Michigan territory, 2009 temperature data for Fort Wayne, IN have been used. A first subset of 100 households was randomly selected from the ones available in the RECS for this region, and the modeling proposed in this study is used with 2009 input data to estimate the SHR parameter. The result is $SHR = 0.33$. The value obtained, not surprisingly, is very similar to the value estimated for Ohio-Indiana. A second subset of 100

\[ (\dot{W}_{all-electric} - \dot{W}_{fuel-heating}) = \dot{W}_{elec,heat} \]  

"A map of the AEP territory is available online at: https://www.indianamichiganpower.com/info/facts/ServiceTerritory.aspx."
households from the same region is then selected and the HVAC model is used to simulate space conditioning electricity consumption in 2010. These results are used to validate the HVAC model against the highly-resolved AEP data.

Figure 3.10 reports the two terms of Equation 3.4.14 (electricity consumption for space heating as reported in the AEP data and as hourly-averaged prediction computed using the proposed HVAC model) for the Indiana-Michigan region in 2010.

![Figure 3.10: Comparison between electricity consumption for space heating in the AEP data and modeled all-electric heating consumption.](image)

The green line represents the difference between the two AEP data data sets (electricity used for space heating), while the blue line represents the modeled electricity consumption of an all-electric system used during heating operations, namely the right hand side of Equation 3.4.14. Note that this term does not include the electric power consumed to circulate the air, since that term is independent of the heating source. In the period from June to August, the blue line is constantly equal to 0,
since no electricity is consumed for space heating during cooling operations of the HVAC system. For the same period the green line shows some oscillations around 0, due to intrinsic differences among the different dwellings. Still, the two curves match with an $R^2 = 81\%$.

Looking at the periods during which the HVAC system operates in heating mode (January through May and September through December), the consumption patterns generated by the HVAC model matches well the trend of the AEP data. This is more clearly observed in Figure 3.11, which reports a zoom of Figure 3.10 for the month of November to illustrate better how the predicted profile generated by the proposed HVAC model follows the trend of the real data.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure3_11}
\caption{Comparison between electricity consumption for space heating in the AEP data and modeled all-electric heating consumption. Zoom for November.}
\end{figure}

Figures 3.10 and 3.11 confirm that the electricity profiles generated by the proposed HVAC model have the same time-evolution characteristics of metered data.
This allows the proposed HVAC model to be used as a subroutine of the residential energy demand model when generating highly-resolved electricity profiles of American households.

The term $\dot{W}_{HVAC}$ in Equation 3.1.1, computed as in Equation 3.4.1, represents the total rate of electricity consumption for space conditioning and accounts for electricity consumption to service the fans and the HVAC unit in both heating and cooling operations, as appropriate.

### 3.5 Occupant Activity Energy Consumption Model

Modeling the behavior of individuals is a complex task due to the stochastic nature of the activities performed. Factors such as the number of individuals in the household, personal habits of each individual, differences in energy use associated with different activities, daily and weekly variations in behavior, and load coincidence should all be captured. The behavioral model introduced in Chapter 2 is used to model occupant behavior and predict the associated energy consumption. Pandit and Wu [104] use a similar approach to model residential electricity demand and Widén and Wäckelgård [105] develop a similar model to predict residential demand in Sweden.

As a first step a synthetic activity pattern for each household member is generated by the behavioral model (a sample of daily activity pattern is shown in Figure 2.3). Then this pattern is converted into $\dot{W}_{act}$ (electricity use directly related to activities of the household members) by using power conversion factors associated with each activity (namely the wattage of the appliance used when performing a specific activity).

Figure 3.12 reports an example of a behavior pattern and corresponding power consumption profile.
Input data of the activity-related power consumption model are the number of household members and their agent types and power conversion factors. The behavioral model presented in Chapter 2 is used to generate corresponding activity patterns for each individual (based on the appropriate transition probability matrices). The transition probabilities are derived from the ATUS data for different typical agent types, such as working males and working females (with different associated transition probabilities, see Chapter 2 for more details on the behavioral model).

Table 3.6 lists the power conversion parameters used to convert activity patterns into power demands. These are based on the average wattage of the current American appliance stock. The laundry activity is divided into two parts: 30 minutes of washing cycle, which uses 425 W, followed by 60 minutes of drying, which uses

\[ \text{Power Demand [W]} \]

\[ 0:00 \quad 12:00 \quad 24:00 \quad 12:00 \quad 24:00 \quad 12:00 \quad 24:00 \]

Average values reported at http://www.energysavers.gov/your_home/appliances/index.cfm/mytopic=10050 by the U.S. Department of Energy as of September 2013 are used.
3400 W. In addition, automatic dish-washing is assumed to last for 90 minutes after
it is initiated. All of the other activities are assumed to be instantaneous, in that
the associated power is only used when the individual is engaged in the activity (e.g.
1225 W are consumed in each time step during which an individual performs the
cooking activity).

Table 3.6: Power conversion parameters used in behavioral model

<table>
<thead>
<tr>
<th>Activity</th>
<th>Power Consumption [W]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sleeping</td>
<td>0</td>
</tr>
<tr>
<td>No-power activity</td>
<td>0</td>
</tr>
<tr>
<td>Cleaning</td>
<td>1250</td>
</tr>
<tr>
<td>Laundry</td>
<td>425 + 3400</td>
</tr>
<tr>
<td>Cooking</td>
<td>1225</td>
</tr>
<tr>
<td>Automatic dish-washing</td>
<td>1800</td>
</tr>
<tr>
<td>Leisure</td>
<td>300</td>
</tr>
<tr>
<td>Away working</td>
<td>0</td>
</tr>
<tr>
<td>Away non-working</td>
<td>0</td>
</tr>
</tbody>
</table>

3.6 Lighting Energy Consumption Model and Calibration
against Metered Data

Lighting loads represent about 11% of total U.S. residential energy demand [13], and
significantly contribute to seasonal and diurnal load variations [156]. Proper mod-
eling of this component requires information on location, solar irradiance, dwelling
orientation, and lighting technology used.

Detailed models to capture residential lighting demand are available in the liter-
ature. Given the number of input parameters required they are not appropriate for
the purpose of this study [156, 157].
This study assumes different power consumption levels are required for lighting during the day (between sunrise and sunset) and at night (between sunset and sunrise). Lighting power consumption also is assumed to occur in each time step during which at least one household member is present in the house and he or she is doing an activity other than sleeping (see possible activities classification in Chapter 2).

Sunset and sunrise times are computed based on the date and coordinates of the building being modeled using an approach developed by the U.S. Geological Survey.\textsuperscript{12} Figure 3.13 reports sunrise and sunset hours for 2010 in Columbus, Ohio. The model implemented in this work accounts for Daylight Saving Time: +1 hour on the second Sunday in March and -1 hour on the first Sunday in November.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{sunset-sunrise_graph.png}
\caption{Example sunrise and sunset hours in 2010 for Columbus, Ohio.}
\end{figure}

\textsuperscript{12}This software tool, which is implemented in MATLAB, is publicly available for download at \url{http://woodshole.er.usgs.gov/operations/sea-mat/air_sea-html/index.html}.
Different lighting power conversion parameters (electric power consumption for lighting, measured in W) are used to capture the different power consumption levels for the day and night. This captures different power use depending on the amount of natural lighting available.

Daytime and nocturnal lighting power conversion parameters and the constant time-invariant term, $\dot{W}_{fix}$, are adjusted according to the household location, size, and the behavior of the building occupants. In this work a least-squares linear regression model is used to estimate these three parameters. This is done by estimating daytime and nocturnal lighting power conversion parameters and the constant time-invariant term to fit modeled consumption data to metered hourly-average per-customer electric load data provided by AEP. The AEP data report average hourly electric loads for two service territories, Indiana/Michigan and Texas. These regions differ in that Indiana/Michigan primarily has non-electric heating, whereas Texas is dominated by all-electric heating systems. This difference is captured by the HVAC model, as shown in Section 3.4. The first data set (Indiana/Michigan) is used to estimate the conversion parameters and a comparison against both data sets is reported in the next section. Temperature data, which correspond to the metered consumption data, have been provided by AEP and are used when estimating HVAC consumption.

The linear regression model has the form:\textsuperscript{13}

$$y = \dot{W}_{cold} + \dot{W}_{HVAC} + \dot{W}_{act} + \dot{W}_{fix} + X\beta + \epsilon,$$ \hspace{1cm} (3.6.1)

where $y$ is a vector containing hourly metered electricity consumption (reported by AEP), $X$ is a binary matrix, which indicates whether lighting during the day and at night is required during each hour or not, $\beta$ is the vector of lighting power conversion parameters, and $\epsilon$ is the vector containing the random error terms. With

\textsuperscript{13}The author would like to thank Professor Ramteen Sioshansi for the help provided in the development of this model.
this notation, $\dot{W}_{\text{light}} = X\beta$. $\dot{W}_{\text{cold}}$, $\dot{W}_{\text{HVAC}}$, and $\dot{W}_{\text{act}}$ are computed using the modeling proposed in the previous sections. The $\beta$ values (lighting power conversion parameter) and the constant time-invariant term, $\dot{W}_{fix}$, are estimated using ordinary least-squares.

To run the regression model a simulation including 200 households in the Indiana-Michigan region is performed (for a total of 502 individuals). Such households are randomly selected among the ones available in the RECS data set for the specific region (the RECS data are presented in more detail in Appendix A), including information on house size, heating and AC systems, and physical properties of the house.

The resulting power conversion parameters for lighting and the constant term are:

- day-time lighting power: 125 W
- night-time lighting power: 330 W
- constant electric consumption, $\dot{W}_{fix}$: 230 W

These parameters are estimated based on the proposed cold appliance, HVAC, and Markov-based activity models and the power conversion parameters given in Table 3.6 used to compute the occupant activity energy consumption ($\dot{W}_{\text{act}}$).

Figure 3.14 reports simulated power demand for the Indiana-Michigan region in 2010, compared to the metered data used for calibrating the conversion parameters. The two data sets fit with an $R^2$ of 0.49.
Figure 3.14: Daily per-household modeled electricity consumption and AEP data for Indiana/Michigan service territory.

3.7 Results and Statistical Validation

A two-step validation methodology is proposed to confirm that the proposed model is capable of generating proper highly-resolved power demand profiles. First, the model output is compared against the data set used for the calibration (Indiana/Michigan region) to verify that the simulated results have the same statistical features as the metered data. Second, the model is used to simulate power demand for a different region (Texas) and its output is compared with metered residential demand data from that region. Since the Texas data set is not used for model calibration, this provides an out-of-sample model validation. Figure 3.15 is a scatter plot showing hourly modeled residential electricity demand against metered demand for AEP’s Indiana/Michigan service territory, which is the data set used for model calibration. The figure shows a linear relationship between the modeled and metered data. Simulated data for the
Indiana/Michigan region (also shown in Figure 3.14) fit the actual data with an $R^2$ of 0.49.

\[ R^2 = 0.49 \]

\[ AEP Metered Power Demand [W] \]

\[ Modeled Power Demand [W] \]

Figure 3.15: Scatter plot of hourly modeled and metered residential electricity demand in AEP Indiana/Michigan service territory.

A non-parametric Mann-Whitney U test is performed to assess whether the distributions of two samples of independent observations are equal [158]. The test verifies if one of two samples tends to have larger values than the other, namely it checks that there is a symmetry between populations with respect to the probability of randomly drawing a larger observation. The test is unable to reject the null hypothesis at the 99% confidence (the $p$-value is 0.3755), suggesting that the modeled and metered data have the same underlying distribution. Moreover, the difference of the means of the two samples is very small (1,118 W and 1,116 W for the metered and modeled data sets, respectively).
The difference of the standard deviations of the two data sets is larger (403 W for the metered as opposed to 385 W for the modeled data). Therefore, a Levene/Brown-Forsythe test is performed to determine if the variances are statistically significantly different [155]. Again, the test does not detect significantly different variances at a 99% confidence level (the $p$-value is 0.1004).

The model is further validated by comparing simulated and metered demand data for Texas. Figure 3.16 shows modeled per-household electric power consumption in Texas and the corresponding metered data provided by AEP.

![Figure 3.16: Daily per-household modeled electricity consumption and AEP data for Texas.](image)

The figure shows that the model, when fed with typical average data, is able to replicate the trend of the actual metered data. Simulated data for the Texas region fit the actual data with an $R^2$ of 0.5829. The figure shows that the model captures diurnal load patterns as well as seasonal variations in demand.
Residential loads in the winter are rarely greater than 1.5 kW in the Indiana/Michigan area whereas demands above 2.5 kW are seen in Texas. This reflects the greater use of all-electric heating systems in Texas; the greater electricity consumption is captured by the HVAC model. Summer loads in Texas also tend to show greater peaks and span a greater number of months, showing the effect of the warmer and longer cooling period.

A Mann-Whitney U test is again unable to reject the null hypothesis that the distributions of the modeled and metered data for Texas are equal at the 99% confidence level (the $p$-value is 0.1067). In this second case there is a greater difference in the means of the metered and modeled data sets, which are 1519 W and 1507 W, respectively. The standard deviation of the metered data provided by AEP is 609 W, as opposed to 614 W for the modeled data. A Levene/Brown-Forsythe test does not detect significantly different variances at a 99% confidence level (the $p$-value is 0.6880).

The difference in standard deviations is 4.5% for the calibration case and below 1% for the out-of-sample validation case. Such differences are likely due to intrinsic differences in the residential power usage of the two regions. Such differences in the variance of simulated and metered data is in line with what is reported in the literature. Specifically, Widén and Wäckelgård [105] report descriptive statistics for the end-use-specific power demand of 14 modeled households and corresponding measurements. Their model gives means and standard deviations that differ from the metered data by 1.8% and 3.2%, respectively. Bartusch et al. [159] provide further discussion of the variance of annual electricity consumption in single-family homes as well as the impact of household features and building properties in Sweden. The overall result of the analyses is that variance in residential electricity consumption
cannot be fully explained by independent variables related to household and building characteristics alone.

This model is implemented in MATLAB® and requires about 90 seconds to generate the yearly electricity consumption profile at 10-minute resolution for a household consisting of 4 individuals. Simulations are performed using an Intel® CORE™ i5-2430M CPU @2.40 GHz and 8 GB of RAM.

3.8 Conclusions

This chapter proposes a bottom-up highly-resolved model to simulate residential electricity consumption. The model is able to simulate the power demand of households consisting of multiple individuals, considering cold appliances, HVAC systems, lighting, and activity-related power consumption. Activity patterns for individuals are modeled using a heterogeneous Markov chain presented in Chapter 2, calibrated with data collected by the U.S. Bureau of Labor Statistics. Thus, the model is based on a novel bottom-up approach that quantifies consumer energy use behavior. This allows capturing the electricity consumption of each residential specific end-use (e.g. cooking, lighting, etc.). The proposed model can be used to reconstruct power consumption of a single or an aggregate group of households with desired characteristics and composition.

A rigorous statistical framework is used to validate the modeled electricity demand against metered data provided by AEP. The results show realistic demand patterns that capture annual and diurnal variations, load fluctuations, and diversity between differing household configurations, locations, and sizes. The model generates electricity demand profiles with the same statistical features as residential metered data.

The model proposed can serve as a tool for a variety of purposes, ranging from
studies regarding energy use in the residential sector and impact of smart grid deployment to energy policy and investment decisions. The effects of different technologies can be analyzed by varying the appropriate model parameters. For instance, a more efficient HVAC system can be modeled by adjusting the \( COP \) and the potential savings of high-efficiency lighting can be captured by adjusting the lighting conversion parameters. Modeling of this nature is useful as it can guide policy decisions regarding the residential stock, both old and new. By quantifying the consumption and predicting the impact or savings due to retrofits and new materials and technologies, decisions can be made to support energy supply, retrofit and technology adoption incentives, building codes, or even demolition and re-construction. This modeling technique can also be coupled with long-term investment models to determine how energy-saving technologies might be adopted by consumers and the impact of policy and other decisions on such adoption.

The model can be used by electric utilities to study residential demand response programs and provide more accurate estimation of the actual amount of available controllable resources (see Chapter 6 for more details).

In this study, the residential power demand model introduced in this chapter is integrated with the personal transportation energy consumption model presented in Chapter 4 to simulate a Residential Energy Eco-system (REES) capturing the entire energy footprint of Americans. This is intended to evaluate the potential of integrated residential and personal transportation sectors from an energy perspective. Large-scale simulations of groups of REESs are reported in Chapter 6 to simulate aggregate-level results and allow for evaluating the impact of different energy policies.
Chapter 4
PERSONAL TRANSPORTATION ENERGY
CONSUMPTION MODEL

The intersection of energy, environmental, and national security issues that policy
makers currently face involves a complex set of trade-offs among cost, air quality,
climate change, technology, and national energy independence. Solutions for such a
complex problem cannot be obtained through simple reasoning or one-dimensional
thinking. Comprehensive and accurate models of the next-generation energy sys-
tems are needed to face this challenge. Among these models, energy consumption
prediction and optimization play key roles.

The transportation sector accounted for about 28% of total primary energy con-
sumption in the U.S. in 2011 [30], namely 27080 Trillion BTU (2.95 \cdot 10^{19} J), divided
among the following sources:

- 95.71 % from petroleum
- 3.99 % from biomass
- 2.48 % from natural gas
- 0.29 % from electricity (including transmission and distribution losses)

Petroleum is by far the largest contributor to transportation energy consumption.
70% of the petroleum consumed in 2010 in the U.S. was devoted to this end-use. Out
of the total 13.5 million barrels of petroleum per day, 8.9 represents motor gasoline,
implying that personal transportation accounts for over 65% of the transportation sector [20].

The aim of the bottom-up model introduced in this chapter is to compute and compare the personal transportation (also known as private mobility) energy consumption of U.S. drivers, considering a set of different vehicles. Output is provided as highly-resolved (10-minute resolution) consumption profiles, including gasoline, natural gas, and/or electricity consumption in the case of Plug-in Electric Vehicles (PEVs), which include Plug-in Hybrid Electric Vehicles (PHEVs) and battery Electric Vehicles (EVs). In case of PEVs, output includes highly-resolved in-home charging profiles.

In order to simulate highly-resolved consumption profiles three main modeling steps are needed: modeling the behavior of drivers, generating realistic driving profiles, and simulating energy consumption of different kinds of vehicles.

The proposed methodology allows computing fossil fuel and/or electricity consumption, which directly relates to the fuel operating cost. Nevertheless, an in-depth economic evaluation considering initial cost of the vehicle, operation and maintenance costs, financial costs, and other pertinent issues is out of the scope of the present study (Michalek et al. [160] and Hendrickson et al. [161] propose examples of such an economic analysis).

The modeling proposed allows for evaluating the impact of plug-in electric vehicles on the electric grid—especially at the distribution level. It can serve as a tool to compare different vehicle types and assist policy-makers in estimating their impact on primary energy consumption and the role transportation can play to reduce oil dependency and face the current energy issue.

The personal transportation energy consumption model, together with the residential demand model introduced in Chapter 3, constitutes the basis of the residential
energy eco-system model, to which dynamic energy management techniques will be applied. This allows capturing the entire energy consumption of individuals, seeing residential and transportation energy demand as a continuum.

Recently, PEVs introduced a first connection between the energy consumptions of residential and transportation sectors, opening up new opportunities for optimization of integrated transportation-building-grid systems. Such a connection will become tighter in the future as new technologies, use of multiple energy carriers, and distributed generation and storage are adopted. In particular, greater fuel diversity is expected for passenger vehicles (e.g. electricity, natural gas, hydrogen, bio-fuels, oil-derived fuels, and combination of them are expected to be part of the portfolio of vehicles available in the near future).

Energy diversity, integration of multiple energy carriers, and coordination among them are necessary conditions for the development of a high-efficiency energy system. Moreover, introduction of energy diversity in the residential-transportation sectors will promote national energy independence—a topic that is becoming of extraordinary relevance.

After an introductory section, provided in Section 4.1, the remainder of this chapter is structured as follows: Section 4.2 reports on the generation of driving diaries containing all driving events of modeled individuals. Individual behavior patterns are simulated by use of the stochastic behavioral model, based on heterogeneous Markov-chains, introduced in Chapter 2. A statistical model, referred to as driving profiles generator, is used to generate realistic driving cycles. This model, presented in detail in Section 4.3, is able to generate a driving profile starting from information on either trip duration or distance driven. Such information is contained in the driving diaries. Once driving profiles are known, a set of backward vehicle dynamic simulators, detailed in Section 4.4, is used to compute energy consumption for different vehicle
types. In Section 4.5, to facilitate comparison of the performance of different vehicle types, their energy consumption: gasoline, natural gas, and/or electricity produced off-board is converted to a common basis using exergy. In later discussions such values may be referred to interchangeably as primary exergy or primary energy. Results are presented in Section 4.6. Finally, concluding remarks are provided in Section 4.7.

4.1 Introduction

Personal transportation represents all travel by individuals, including trips for shopping and leisure as well as commuting to work. Personal transportation does not include commercial and industrial activities.

Currently, nearly all energy consumed in the U.S. transportation sector comes from petroleum, most of which is imported \[91\]. Personal transportation accounts for 8.9 million barrels of oil per day out of a total of 13.5 million barrels consumed \[162\]. Nowadays the transportation sector is evolving to more fuel-efficient vehicles having less environmental impact \[8\].

Such massive oil consumption leads to three main implications. First, it is clear how fossil fuels represent an enormous economic cost. Further, due to growing demand, future availability of petroleum continues to present political, economic, and environmental risks associated to oil exploration and production, as well as economic uncertainty due to price volatility.

Second, fossil fuels are responsible for a significant fraction of anthropogenic CO\(_2\) production, as well as the emissions of other pollutants. The U.S. Department of Energy estimates that in 2011 the transportation sector accounted for 36% of total CO\(_2\) emissions from energy consumption. In addition personal transportation has

\[1\] In 2011 93% of the total primary energy consumed by the U.S. transportation sector came from petroleum \[91\], 45% of which was imported.
a tremendous local impact, as vehicles are largely used in densely populated areas, where their impact on the local air pollution is critical.

Third, oil dependence is becoming a pressing issue for many countries. This sensitive issue has two main threads: the political issue of depending from foreign countries for a commodity like oil, and the economic problems that arise from it. According to Oak Ridge National Laboratory, between 2006 and 2012 the U.S. economy suffered a total loss of over 2 trillion dollars for combined wealth transfer and GDP losses related to oil dependency [163]. Displacing petroleum without penalizing personal and commercial mobility has therefore become a major objective for the automotive industry and for government agencies worldwide.

Today, viable options include fuel economy improvements in conventional vehicles (engine downsizing and boosting, direct injection and variable valve actuation, weight reduction), fuel-cell vehicles, non-electric hybrids (pneumatic, for instance), vehicle electric hybridization, plug-in electric vehicles (including renewable-based hybridizations and/or recharging), natural gas and bio-fuel vehicles, and the integration with vehicle-to-vehicle and vehicle-to-infrastructure (V2V/V2I) communication technologies. Table 1 reports a summary of transportation energy consumption by source. While petroleum accounts for the majority of transportation energy needs, the role of electricity and renewables appears to be growing [163].

In particular, here focus is given to natural gas vehicles and vehicle electrification, at several levels. Among the current available options for alternative propulsion, electricity seems the most promising, that a) addresses the simultaneous need for fuel diversity, energy security, reductions in greenhouse gas emissions, and improvements in air quality, and b) is widely available and produced domestically.

Owing to several factors, natural gas is currently plentiful in the U.S. and is expected to be so for years ahead. Accordingly, the use of natural gas to fuel vehicles,
including vehicles for personal transportation, has become an attractive option. Currently, several automakers are looking to start offering compressed natural gas (CNG) vehicles in the U.S. market [164]. Such a use for natural gas is expected to play a significant role in many residential eco-systems. Example of this is the home refueling device called Phill, that Honda began offering when starting retail sales of the natural gas Civic, the only commercially-available CNG passenger vehicle in the U.S. today. Also, with Department of Energy support, General Electric is now developing an inexpensive home refueling station that would connect to home gas lines, compress the gas and deliver it to vehicle fuel tanks [165].

The purpose of this model is to predict personal transportation energy consumption, namely the energy consumed when private citizens drive their personal vehicles. In order to compute highly-resolved personal transportation energy consumption patterns, three main modeling steps are needed:

1. Modeling the behavior of drivers in order to establish when driving events occur over the simulation time horizon and the duration/length of each event;
2. Generation of realistic driving profiles for each driving event. Profiles must be representative of actual usage of passenger vehicles (real-world driving profiles);
3. Simulation of different kind of vehicles in order to compute energy consumption starting from a velocity profile.

The main outputs of the model are highly-resolved consumption profiles for personal transportation in the United States. These consumption profiles include information on how much energy is consumed for each trip and when in time this consumption occurs.

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2 The project has been funded in July 2012 with a $2.3 million grant.
Personal transportation energy consumption has been divided into two main categories, according to driving purpose:

1. Commuting to work.
2. Driving for leisure and shopping.

Information on when a person is commuting to work and when he or she is driving for leisure/shopping are provided by a behavioral model (Presented in Chapter 2) and collected in driving diaries. Once the length or the duration of each driving event is known, a statistical model (driving profile generator) is used to generate highly-resolved velocity profiles for each trip. After realistic driving profiles representative of real-world usage of passenger vehicles in the United States are generated, a set of backward dynamic vehicle models is used to compute highly-resolved consumption profiles, to include charging time and duration for PEVs. Figure 4.1 shows a schematic of the modeling approach.

### 4.2 Driving Diaries

The behavioral model introduced in Chapter 2 generates a highly-resolved activity pattern for each individual included in the simulation. These profiles are a representation of the time-sequence of activities performed by typical U.S. drivers. Figure 4.2 shows a 10-minute resolved example of the activity pattern of a working male during 36 hours, dividing between activities performed at home, at the workplace, or somewhere else.

These activity patterns allow for the construction of a driving diary for each individual. These diaries include driving events and their duration/length as well as charging availability either at home or at the workplace. Driving events include
commuting to work and driving for leisure/shopping. Daily commutes to and from work are computed starting from the data shown in Figure 4.3.

These data report statistics of one-way commute-to-work distance in the United States. They have been collected by U.S. Department of Transportation as part of the Omnibus Household Survey, which collects data on core questions about general travel experiences, satisfaction with the system, as well as some demographic information. Data presented in OmniStats are taken from several issues of the 2003
Figure 4.2: Example of activity pattern of a working male.

Figure 4.3: Typical one-way commute to work statistics for the United States. From U.S. Department of Transportation – Omnibus Household Survey [18].

Omnibus Household Survey [18]. The target population for the survey are adults (18 years or older). Results are based on completed bi-monthly samples that are
randomly selected using a list-assisted random digit dialing (RDD) methodology. An implicit stratification on the telephone prefixes is imposed to ensure that the sample is representative of the entire nation.

As reported by OmniStats [18], to reach the workplace the average American commuter travels approximately 15 miles (24 km), one way. Two out of three commuters (68%) reported a one-way commute of 15 miles (24 km) or less, 22% traveled between 16 and 30 miles (26 – 48 km) and 11% traveled more than 30 miles (48 km). The majority of commuters (81%) used only their personal vehicle to complete their commute and most personal vehicle users (86%) drove alone [18].

For each person considered in the simulation a commute distance is drawn from the distribution shown in Figure 4.3 and two one-way trips are considered for every working day. The first trip (morning commute to work) occurs the first time in a day that a person enters the Work state while the second trip (evening commute from work) occurs the last time that a person leaves the Work state (refer to Figure 4.2).

Commute-to-work distances are converted into velocity profiles by means of a driving profiles generator and these profiles are fed to a backward vehicle dynamic simulator to compute the final energy consumption, in terms of gasoline and/or electricity.

For the second category of trips considered: driving for leisure and shopping, when an individual is in the Away state (refer to the behavioral model presented in Chapter 2) it is assumed that he/she can drive for a period of time that is no more than the time spent in the Away state. The exact driving duration is computed as:

\[ t_{driving} = \alpha \cdot t_{away} \]  

(4.2.1)

where \( \alpha \) is drawn from a random variable uniformly distributed in the interval [0, 1]. The term \( \alpha \) represents the portion of time spent driving out of the total time spent in the Away state.
Once the driving duration is known (and precisely defined in time) the driving profile generator is used to generate the corresponding velocity profile.

Table 4.1 gives an example of a driving diary corresponding to the behavior shown in Figure 4.2.

<table>
<thead>
<tr>
<th>Starting Time</th>
<th>Event</th>
<th>Trip Duration [min]</th>
<th>Trip Distance [km]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:00</td>
<td>Home</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>0:50</td>
<td>Leisure Trip</td>
<td>20</td>
<td>-</td>
</tr>
<tr>
<td>2:00</td>
<td>Home</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>9:30</td>
<td>Trip to Work</td>
<td>-</td>
<td>10.32</td>
</tr>
<tr>
<td>9:40</td>
<td>Work</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>14:20</td>
<td>Leisure Trip</td>
<td>40</td>
<td>-</td>
</tr>
<tr>
<td>15:20</td>
<td>Work</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>17:50</td>
<td>Trip to Home</td>
<td>-</td>
<td>10.32</td>
</tr>
<tr>
<td>18:10</td>
<td>Home</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>19:00</td>
<td>Leisure Trip</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>21:10</td>
<td>Home</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5:20</td>
<td>Trip to Work</td>
<td>-</td>
<td>10.32</td>
</tr>
<tr>
<td>5:30</td>
<td>Work</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

From Table 4.1 observe that:

- during the first period in the Away state (0:50 to 2:00), the individual had a leisure trip of 20 minutes ($\alpha = 0.33$).

- the individual commuted to or from work three times during the simulation horizon (9:30, 17:50, 5:20). A commute-to-work distance for the individual has been drawn from the distribution shown in Figure 4.3 of 10.32 km (6.41 miles).

- during the second period in the Away state (14:20 to 15:20) the individual had a leisure Trip of 40 minutes ($\alpha = 0.67$).
• during the third period in the Away state (19:00 to 21:10) the individual had a leisure trip of 0 minutes (no use of the vehicle during the Away time, $\alpha = 0$).

• in the case of plug-in electric vehicles, the time spent at Home (i.e. 0:00 to 0:50) or at Work (i.e. 9:40 to 14:20) can be used to charge the battery of the vehicle, if a charger is available.

4.3 Generation of Realistic Driving Profiles

Realistic driving profiles are a prerequisite for evaluating and comparing vehicle performance, energy consumption, and environmental impact. The literature includes several publications that are particularly relevant to the driving profile generator used in the present study [166, 167, 168, 169].

The literature on the driving cycles construction was first reviewed in 1996 in a survey paper by Andrè [166]. The author analyzed and characterized the development of a dozen existing certification driving cycles from different countries (United States, Australia and some European countries). These are cycles produced by different countries and organizations to assess the performance of vehicles in various ways, for example fuel consumption and polluting emissions. Examples are U.S. EPA certification procedures: FUDS (an urban driving cycle), HWFET (a highway driving cycle), the Federal Test Procedure (FTP-75); the European urban cycle (ECE-15), and extra-urban cycle (EUDC); and the 10-15 Modes, the official fuel economy and emission certification test for new light duty vehicles in Japan.

Recently, comparison studies have introduced so called real-world (or naturalistic) driving cycles to better capture the driving behaviors and evaluate more precisely consumptions and emissions [167], [168], and [169]. Raykin et al. [168] conclude that for PHEVs the length of the driving cycles affects the vehicle performance because distance influences the fraction of driving in each mode, namely charge-depleting (when
the vehicle runs on electric energy drawn from the battery) and charge-sustaining
(when the vehicle behaves like an HEV and uses fossil fuel as energy source).

Furthermore, Lee et al. describe and validate a Markov-chain approach for the
synthesis of real-world driving cycles as well as statistical methodologies for their
validation [170, 171]. Such validation methodologies are aimed at guaranteeing the
representativeness of the synthesized cycles. The real-world driving cycles synthesis
is obtained by converting the real collected driving data into Transition Probability
Matrices (TPMs) used in a Markovian process. This synthesis technique was first
introduced by Lin et al. [172] to assess energy request in the context of energy
management. The same approach has been adopted by Gong et al. [173], where
clustering techniques are exploited to obtain different TPMs for different driving
profile classes. The resulting transition probability matrices have been used in this
work for the synthesis of real-world driving profiles.

The driving profile generator is a Markovian stochastic tool based on historical
data that takes as input either a driving duration or a driving distance and generates
as output a driving profile compatible with the given duration/distance.

The data used for the calibration were collected as part of the SMART@CAR
research program at The Ohio State University - Center for Automotive Research
(CAR). The data were collected from a PEV fleet composed of nine different vehicles
for a total of over 100 thousand miles (161 thousand km) of real driving profiles.
These data capture the driving styles of different drivers for a variety of alternative
situations.

In general, the relationship between driving duration or distance and the corre-
spanding driving profile of individuals is dependent on a very large set of personal and
physical factors, such as driving style, weather, vehicle performance, road conditions
and others. The collected data are used to generate a set of transition probabilities
able to replicate the effects of several factors, including use of highways versus streets, road congestion, personal driving style, and other factors influencing the relationships between driving duration or distance and driving profiles. More details are provided by Gong et al. [174, 175]. In this work it has been assumed that for passenger vehicles these relationships for a specific trip do not depend on the particular type of vehicle [171]. Therefore the results can be applied to all classes of vehicles.

To generate a driving profile starting from a particular trip duration a corresponding trip distance must be first generated as a starting point for the stochastic process. The raw trip distance and trip duration data have been aggregated into classes of coarseness with intervals of 5 kilometers and 5 minutes, respectively. Based on the trips present in each class, a trip distance probability distribution is derived. This is shown in Figure 4.4a, where the color-coding and the y-axis indicate trip durations. Figure 4.4b is a slice from Figure 4.4a that reports the trip distance distribution for a trip duration of 50 minutes. This probability distribution matrix is then used to generate a realistic trip distance corresponding to a given trip duration.

Once the driving distance is known, a parameter called the highway ratio$^3$ can be estimated (shown in Figure 4.5).

Figure 4.5 shows the probability distribution function of the highway ratio with respect to different total driving distances, ranging from 1 to 200 km. As expected, the distribution is extremely skewed to the left for short trips, meaning that the highway ratio is likely to be 0 of very small for short trips (a few kilometers). As the total trip distance increases the highway ratio is more likely to take on higher values. For very long trips (over 100 km), it is extremely unlikely to find highway ratio lower

---

$^3$The highway ratio is defined as the proportion of the trip occurring on highways with respect to the total length of the trip, and it is determined starting from the probability distribution of collected data [175].
than 0.75, meaning that most of long trips in the United States occur on highway, according to the data collected.

Based on the trip distance and highway ratio it is possible to generate a driving profile using a Markov chain model, the PTM of which have been identified using historical data [174].

To generate the driving profile, the velocity $v$ is assumed to take on a finite
number of values: \( v \in \{ v^1, v^2, \ldots, v^N \} \). Starting from the velocity, acceleration values, \( a \), can be computed, which are also discretized into a finite set of values: \( a \in \{ a^1, a^2, \ldots, a^M \} \). All data have been clustered into one of the two classes of driving patterns considered, namely urban and highway. The state vector of the Markov chain model is defined as: \( x_k = (v_k, a_k) \), and its dynamics can be expressed by \( x_{k+1} = w_k \). Since the transition of \( a_k \) is a deterministic process, the two-dimensional Markov chain describing the probability distribution of \( w_k \) can be reduced to a one-dimensional Markov chain:

\[
Pr \{ w_k = (v^i, a^l) \mid w_{k-1} = (v^j, a^y) \} = p^l_{i,j}
\]

\[i, j \in \{1, 2, \ldots, N\}, \ l, y \in \{1, 2, \ldots, M\}\]

where \( \sum_{j=1}^{N} p^l_{i,j} = 1, \ \forall l \in \{1, 2, \ldots, M\} \) represents the one-step transition probability

Figure 4.5: Highway ratio distribution used to generate driving cycles.
associated with the acceleration $a^l$. As described in Equation (4.3.1), the acceleration has been assumed to be constant during each transition. Starting from the empirical time-synchronized velocity and acceleration data collected for a set of vehicles, nearest-neighbor quantization is used to map the sequence of continuous observations $(v, a)$ into a sequence of quantized states $(v^i, a^l)$ [172]. The transition probabilities can then be estimated by means of the maximum likelihood estimator, which counts the observation data as:

$$
\hat{p}_{i,j}^l = \frac{m_{i,j}^l}{m_i^l}
$$

(4.3.2)

where $m_{i,j}^l$ is the number of times that a transition has occurred from $v^i$ to $v^j$ given that the acceleration was in the state $a^l$, and $m_i^l = \sum_{j=1}^{N} m_{i,j}^l$ is the total number of times that a transition has occurred from $v^i$ when the acceleration was $a^l$. The procedure is repeated to calibrate a transition probability matrix for both the urban and highway portions of the trip. Accordingly, the data from the two classes of driving patterns have been exploited.

Figure 4.6 shows a representation of the transition probabilities used to generate urban and highway driving cycles, with respect to velocity and acceleration. Note the difference in the velocity scales used in the two scenarios. It is also worth noting that the range of values over which acceleration takes place shrinks as velocity increases, as expected. Moreover, values of acceleration for highway portions are more concentrated around 0 (constant speed).

In this work, the driving profile of a complete trip is obtained by composing three segments: each trip starts with an urban portion (Segment 1), followed by a highway portion (Segment 2) and a second urban portion (Segment 3). This approach has been chosen to reproduce typical driving conditions.
The proportion of the first urban portion (Segment 1) to the second urban portion (Segment 3) is drawn from a standard uniform distribution. The proportion of highway-to-urban driving is dictated by the highway ratio. This parameter has a high probability of being very small for short trips, meaning that very short trips are likely to occur entirely in urban conditions. On the other hand, the probability of having a high value of the highway ratio increases for longer trips, approaching a value of 1, meaning only highway driving for very long trips (see Figure 4.5). The model is flexible in design, meaning that different combinations of urban and highway portions can be used to generate driving cycles. The Driving Profile Generator produces velocity profiles with a resolution of 1 second.
Finally, while the Driving Profile Generator has been calibrated using historical data from a PEV fleet, the relationships between trip duration/distance and corresponding driving profile do not strongly depend on the type of vehicle. Accordingly, driving profiles generated can be used for all classes of vehicles [171].

4.4 Vehicle Energy Consumption Models

In this section, a vehicle simulator based on longitudinal dynamics is developed to compute highly-resolved energy consumption profiles of a set of different vehicles. The simulator takes as input the driving profiles generated by the model discussed in Section 4.3, and simulates the energy consumption of a set of different vehicles. Output is provided as highly-resolved (10-minute resolution) consumption profiles, including gasoline, natural gas, and/or electricity consumption in the case of Plug-in Electric Vehicles (PEVs), which include Plug-in Hybrid Electric Vehicles (PHEVs) and Electric Vehicles (EVs), also called battery electric vehicles or purely electric vehicles. In case of PEVs, output includes highly-resolved in-home charging profiles. The information is stored in a five-dimensional array, with length equal to the total number of trips simulated. The five dimensions include fossil fuel consumption (gasoline or natural gas, depending on the vehicle type), electricity consumption, starting and ending time of each trip, and final State of Charge (SOC) of the battery, when relevant.

BACKGROUND

In general, two main philosophies are used to model vehicles’ performance: backward model and forward model. In the former class, the decisions of the driver are simulated and accelerator or brake signals are sent to the different powertrain and
component controllers in order to follow the desired driving profile. On the other hand, in a backward model, the driving profile is used as input for the different pow-ertrain and component controllers and energy and pollutant emissions are computed by means of static maps. Because of this model organization, quasi-steady models can only be used and realistic control cannot be developed. Consequently, transient effects cannot be captured by backward models.

Backward models are usually used to define trends while forward-looking models allow selection and optimization of powertrain components, as well as development of control strategies that can be implemented on-board [176].

Modeling of different vehicles consumption is typically done exploiting commercially available vehicle simulation tools. More specifically forward models which target specific vehicles, are widely used in the industry to properly address the component interactions that affect fuel consumption and performance [176]. A complete review of such tools is proposed by Gao et al. [177]. Depending on the level of details of how each component is modeled, the vehicle model may be steady-state, quasi-steady, or dynamic [177]. For example, the ADVISOR [178] model can be categorized as a steady-state model, the AUTONOMIE [176] (and its predecessor, PSAT) model as a quasi-steady one, and PSIM [179] models as dynamic.

The main advantage of employing a steady-state model or quasi-steady model is fast computation, while the disadvantage is inaccuracy for dynamic simulation. On the contrary, physics-based models can facilitate high fidelity dynamic simulations at different time scales [177].

Backward models are faster in term of simulation time and allow for the flexibility needed to simulate a large number of different driving cycles. Moreover, the precision and complexity of forward-looking models is not necessary for computation of system-level and aggregate consumption, which is the purpose of this study.
VEHICLE DYNAMIC SIMULATOR

The driving profiles generated by the model discussed in Section 4.3 are used in a backward dynamic simulator developed in the MATLAB® environment to predict energy consumption. The performance and accuracy of the proposed vehicle dynamic simulator are compared against ADVISOR, a model developed by NREL [180].

Backward dynamic simulators compute the energy consumption of different vehicles using static maps, also called brake-specific fuel consumption maps. Input to backward simulator is the velocity profile driven. The power $\dot{W}$ required at the wheels to move a vehicle is given by the longitudinal vehicle dynamics expression given by Equation 4.4.1 [181]. Lateral dynamics are not taken into account, since their impact on fuel consumption during normal driving is minimal.

$$\dot{W}(t) = \left[ m \dot{v}(t) + mg \cos(\theta) [r_0 + r_1 v(t)] + \frac{1}{2} \rho_{\text{air}} A_f C_D v^2(t) + mg \sin(\theta) \right] v(t) \quad (4.4.1)$$

where $v$ is the desired velocity, $\dot{v}$ is the acceleration, $m$ is the mass of the vehicle, $r_0$ and $r_1$ are rolling resistance coefficients, $\rho_{\text{air}}$ is the air density, $A_f$ is the frontal area of the vehicle, $C_D$ is the aerodynamic drag coefficient, and $\theta$ is the road grade. The term $m \dot{v}$ in Equation 4.4.1 represents the force needed to change the longitudinal velocity and follow the desired velocity profile, the other terms represent resistances, defined as the forces impeding vehicle motion. Numerical values of the parameter used in Equation 4.4.1 are reported in Table 4.2, based on values reported by U.S. EPA [182].

This power is summed with the power consumed by the auxiliaries present on board (e.g. air conditioning system, lights, etc.), assumed to be constant at 750 W [182]. The vehicle mass varies for different vehicles, as reported in Table 4.4. Once the power needed to move the vehicle is known, torque and angular velocity of the
Table 4.2: Vehicle model: longitudinal dynamic parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g )</td>
<td>9.81</td>
<td>( m/s^2 )</td>
</tr>
<tr>
<td>( r_0 )</td>
<td>0.012</td>
<td>-</td>
</tr>
<tr>
<td>( r_1 )</td>
<td>0</td>
<td>( s/m )</td>
</tr>
<tr>
<td>( \rho_{air} )</td>
<td>1.275</td>
<td>( kg/m^3 )</td>
</tr>
<tr>
<td>( A_f )</td>
<td>2</td>
<td>( m^2 )</td>
</tr>
<tr>
<td>( C_D )</td>
<td>0.3</td>
<td>-</td>
</tr>
</tbody>
</table>

Wheels can be computed assuming a wheel radius of 0.3305 m. The torque required by the engine is then computed assuming a powertrain efficiency. The angular velocity of the engine is computed by use of transmission gear ratios.

In the vehicle simulator proposed in this study, a strategy is implemented to simulate shifting behavior, as suggested by EPA technical report 420-P-05-001 [182]. The vast majority of light duty vehicles on the road (in the United States) have automatic transmissions, and fixed shifting points. The shift points and gear ratios used in the implementation of the shifting strategy are shown in Table 4.3.

Table 4.3: Shift point and gear ratios for light duty vehicles (5 speed). From Thomas and Ross [21].

<table>
<thead>
<tr>
<th>Speed [mph]</th>
<th>Gear</th>
<th>( g/g_{top} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-18</td>
<td>1</td>
<td>4.04</td>
</tr>
<tr>
<td>18-25</td>
<td>2</td>
<td>2.22</td>
</tr>
<tr>
<td>25-40</td>
<td>3</td>
<td>1.44</td>
</tr>
<tr>
<td>40-50</td>
<td>4</td>
<td>1.0</td>
</tr>
<tr>
<td>50+</td>
<td>5</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Fuel consumption rates are then derived by use of brake-specific fuel consumption maps, that relate engine angular velocity and torque to the instantaneous consumption. Analogous maps are used to compute the consumption of electric motors.

In the present study, the vehicle simulator is used to compute the electricity and fossil fuel (gasoline or natural gas) consumption for a set of different vehicles:

1. 4-cylinder gasoline-fueled spark ignition vehicle (Conventional Vehicle)
2. Compressed natural gas-fueled spark ignition vehicle (CNG)
3. Hybrid Electric Vehicle (HEV)
4. Plug-in Hybrid Electric Vehicle with 10 miles (16 km) of all-electric range (PHEV-10)
5. Plug-in Hybrid Electric Vehicle with 40 miles (64 km) of all-electric range (PHEV-40)
6. Electric Vehicle (EV)

These vehicles have been chosen to represent the current market situation for passenger vehicles in the United States. In particular, focus is given to natural gas vehicles and vehicle electrification, at several levels, as these two technologies are expected to play a significant role in a future U.S. automotive market.

Among the currently available options for alternative types of propulsions, electricity seems the most promising for several reasons:

- electricity addresses the simultaneous need for fuel diversity, energy security, reductions in greenhouse gas emissions, and improvements in air quality;
- electricity is widely available and produced domestically.
- vehicle electrification has been proven to substantially improve vehicle fuel economy, reduce petroleum use, and potentially reduce CO$_2$ and pollutants emissions, depending on the primary energy source used to produce electricity.
Moreover, vehicle electrification attenuates the air quality issues, taking the emissions away from highly populated areas.

Natural gas is currently plentiful in the U.S. and is expected to be so for years ahead. Accordingly, the use of natural gas to fuel vehicles, including vehicles for personal transportation, has become an attractive option.

Table 4.4 reports the main specifications of the six vehicle classes considered. Note that the values of these parameters can be adjusted depending on the specific vehicle being modeled. In this table average parameters representative of the six types considered are reported, starting from characteristics of vehicles currently available on the market.

**Table 4.4: Vehicles data.**

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Curb Weight [kg]</th>
<th>Battery Capacity [kWh]</th>
<th>Electric Motor [kW]</th>
<th>ICE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>1450</td>
<td>-</td>
<td>-</td>
<td>L4 - 2.0 liters</td>
</tr>
<tr>
<td>CNG</td>
<td>1500</td>
<td>-</td>
<td>-</td>
<td>L4 - 2.0 liters</td>
</tr>
<tr>
<td>HEV</td>
<td>1550</td>
<td>1.3</td>
<td>100</td>
<td>L4 - 1.6 liters</td>
</tr>
<tr>
<td><strong>PHEV – 10</strong></td>
<td>1650</td>
<td>4</td>
<td>110</td>
<td>L4 - 1.6 liters</td>
</tr>
<tr>
<td><strong>PHEV – 40</strong></td>
<td>1800</td>
<td>16</td>
<td>110</td>
<td>L4 - 1.6 liters</td>
</tr>
<tr>
<td><strong>EV</strong></td>
<td>1525</td>
<td>24</td>
<td>80</td>
<td>-</td>
</tr>
</tbody>
</table>

10 miles *all-electric range*, 2 40 miles *all-electric range*, 3 100 miles range.

**CONVENTIONAL VEHICLE (CV) AND COMPRESSED NATURAL GAS VEHICLE (CNG)**

In conventional vehicles the amount of gasoline burned in the internal combustion engine represents the only contribution to the energy consumption. Figure 4.7 shows an example output of the conventional vehicle model.
Analogously, in a CNG vehicle natural gas is the only energy carrier used on-board. Alam et al. provide an experimental comparison of performance, fuel consumption, and exhaust emissions for gasoline and compressed natural gas passenger vehicles [183]. It is also observed that brake specific fuel consumption for CNG is always less than for gasoline throughout the speed range. This can be attributed to the fact that the heating value of natural gas is about 12% more compared to gasoline [183]. Also, natural gas presents a slower burning velocity compared to that of the gasoline [184], leading to fewer combustion losses. Alam et al. report that on average fuel consumption using CNG is about 18% lower than that of gasoline. The lower consumption of natural gas-fueled engines has been more recently confirmed by Jahirul et al. [184], where an average 15.5% saving is observed for a retrofitted spark ignition car engine run on natural gas. In the absence of detailed brake specific fuel consumption maps for light-duty CNG passenger vehicles, these results from the literature have been used to model the fuel consumption of natural gas-fueled vehicles. In this study it
is assumed that a passenger vehicle designed to run on CNG shows a reduction of 18% in brake specific fuel consumption relative to that of a comparable spark ignition gasoline engine.

**HYBRID ELECTRIC VEHICLE (HEV)**

In hybrid vehicles (HEVs and PHEV), an internal combustion engine (ICE) and an electric motor (EM) are present in the vehicle. Energy is stored on board both in a fuel tank and in a battery pack. Thus, a power-split strategy is implemented to optimize the fuel consumption and battery depletion while coping with vehicle performance requirements.

The HEV control strategy is aimed at maintaining the battery state of charge within a pre-determined range: 62% to 68%, while operating the vehicle in *charge-sustaining* mode. The electric motor is used to assist the internal combustion engine in sudden accelerations. Also, the presence of the battery allows for regenerative braking. Control strategies are implemented in the vehicle simulator developed in this study to capture these features. Again, in this class of vehicles, gasoline is the only contributor to the energy consumption, since the battery is not charged via an external source. Figure 4.8 shows an example output of the HEV simulator.

In hybrid electric vehicles the electric motor and the battery are used to assist the internal combustion engine and to perform regenerative braking, as shown by the battery power profile in Figure 4.8 (where the power is positive when the battery is discharged and negative when it is charged).
PLUG-IN HYBRID ELECTRIC VEHICLE (PHEV)

Vehicles that use electricity as a propulsion source are called Plug-in Electric Vehicles (PEVs). A PEV is defined by the U.S. Department of Energy as a vehicle that draws electricity from a battery with a capacity of at least 4 kWh and is capable of being charged from an external source [185]. The definition of PEV includes Plug-in Hybrid Electric Vehicles (PHEVs) and Electric Vehicles (EVs). The impact of PEVs on the electric grid is analyzed in detail in Section 6.3.

PHEVs are essentially HEVs with high capacity batteries that can be charged by connecting them to the electric grid. PHEVs can store enough electricity from the electric grid to significantly reduce their petroleum consumption.

As reported by Markel and Wipke [186], in a plug-in hybrid electric vehicle the control strategy will attempt to bias the power flows towards battery pack usage while the pack exhibits a high state-of-charge. Depending on the cell chemistry, a low state of charge may significantly deteriorate performance and shorten battery life.
Thus, as the SOC of the battery decreases, the control strategy will bias the power usage more towards the engine, to prevent battery damage and reduced life.

In the PHEV simulator developed in this study the power-splitting control strategy is a combination of an initial charge-depleting mode followed by a charge-sustaining mode once the state of charge of the battery reaches a certain threshold, here selected to be 30% (these vehicles are also referred to as parallel hybrids). After the first portion of the trip, where the vehicle works as a pure EV (charge-depleting), the PHEV behaves like an HEV (charge-sustaining) and the internal combustion engine allows for an indefinitely long range (assuming availability of refueling stations). A sample output of the PHEV vehicle simulator is shown in Figure 4.9, where the effects of the control strategy are graphically shown.

![Sample output of the plug-in hybrid electric vehicle dynamic simulator.](image)

PHEVs have an all-electric range, namely the distance that can be covered in charge-depleting mode. Figure 4.9 shows the operation of a PHEV with a 6 kWh
battery (allowing for an all-electric range of approximately 10 miles). At the beginning of the trip, when the battery is fully charged, the internal combustion engine is rarely used, and all the power is provided by the electric motor (charge-depleting mode). In this situation the battery is rapidly discharged. As the SOC decreases and reaches its lower limit (30%), use of the internal engine increases while that of the electric motor decreases, thus reducing the rate of decrease of the SOC (charge-sustaining mode).

The all-electric range is directly proportional to the capacity of the battery. Battery size heavily influences vehicle cost and curb weight, therefore the choice of battery size results from a compromise between initial investment and operating costs [188]. Typical Li-Ion cells for automotive applications weight about 4.5 kg/kWh [189] and cost about 400 $/kWh [190]. Such a vehicle design analysis is out of the scope of this work.

Typical all-electric range values vary from 10 to 40 miles (16 – 64 km); thus these two cases have been considered in the present study. In PHEVs, both gasoline and electricity contribute to the total energy consumption of the vehicle, since the battery can be recharged when the vehicle is parked and connected to the grid.

PHEVs combine the benefits of HEVs and EVs: they are less reliant on petroleum than HEVs, and they are a more practical alternative to pure electric vehicles because they avoid the challenges presented by EVs’ battery-only operation (limited range, high cost, lack of recharging infrastructure, and long charging time) [191].

**ELECTRIC VEHICLE (EV)**

For battery electric vehicles (EVs), electricity drawn from the grid is the only energy carrier and once the state of charge of the battery reaches a minimum value (here assumed to be 20%) the vehicle shuts down, limiting the total range of the
vehicle. Typical electric vehicles have a range of 100 to 180 miles (161 – 290 km), depending on the characteristics of the vehicle (such as curb weight, frontal area, etc.) and the size of the battery installed. Figure 4.10 shows a sample output of the EV model (electric power is assumed positive when the battery is discharged).

![Sample output of the electric vehicle dynamic simulator.](image)

**Figure 4.10: Sample output of the electric vehicle dynamic simulator.**

**VEHICLE ELECTRIFICATION**

Different levels of electrification are compared in Figure 4.11. In particular, a driving cycle, the corresponding power requirement at the wheels, and the evolution of the SOC of the battery for a HEV, a PHEV, and an EV are reported.

As previously noted, the HEV operates in charge-sustaining mode, maintaining the SOC of the battery in the range 62% - 68% (blue solid line) and exploiting regenerative braking. The PHEV-10 (purple dash-dot line) operates in charge-depleting mode until the SOC reaches the lower threshold of 30% (approximately
at 2600s). From that moment it operates as an HEV at the 30% SOC threshold (charge-sustaining mode). The same applies for the PHEV-40 (red dash-dot line), but given the higher capacity of the battery the SOC reaches 30% at 3500s, allowing for a longer period in charge-depleting mode and reducing substantially the on-board gasoline consumption. Battery SOC of the EV during the trip is reported with a green dashed line. Owing to the higher capacity of the EV battery, its SOC has the slowest dynamics among the four vehicles. At the end of this trip (about 1 hour and 15 minutes) the SOC of the EV battery is about 45%, allowing for further travel without the need for immediate recharging. Note that the slope at which SOC decreases depends on the discharging power of the battery, and in turn on the driving cycle and driving style. Increases in the battery SOC represent braking energy recovery (regenerative braking).

*Figure 4.11: Comparison of SOC evolution for a set of different vehicles.*
VEHICLE SIMULATOR VALIDATION

To validate the fuel consumption predicted by the vehicle simulator developed in this study, a comparison against ADVISOR (ADvanced VehIcle SimulatOR) is conducted for different classes of vehicles. ADVISOR is a flexible modeling tool, implemented in the MATLAB/Simulink® environment, that assesses the performance and fuel economy of conventional, electric, hybrid, and fuel cell vehicles [180]. In ADVISOR the performance of a vehicle is estimated in a combined backward-forward facing approach [192], guaranteeing accuracy but requiring long computation time.

Three specific vehicles have been selected among the ones available in the ADVISOR library: a 1.9L gasoline-fueled spark ignition vehicle, a hybrid electric vehicle, and purely electric vehicle. Parameters for such vehicles (curb weight, maximum torque curves, fuel consumption maps, etc.) are taken from the ADVISOR library to reproduce the characteristics of the vehicles reported in Table 4.4, and simulations are run to compare the two models.

No PHEV or CNG vehicle is currently available in ADVISOR. Nevertheless, CNG vehicles are essentially conventional vehicles with an adapted internal combustion engine, and PHEVs can be seen as HEVs with high capacity batteries. Thus an indirect validation can be made for CNG vehicles and PHEVs.

Recently, the U.S. Environmental Protection Agency adopted new methods to estimate fuel economy for cars and light trucks. This methods use 4 standard driving cycles to determine average fuel economy. These cycles are: the Federal Test Procedure (FTP), the Highway Fuel Economy Test (HFET or HWFET), the US06 cycle, and the Supplemental Federal Test Procedure (SFTP or SC03).

In this study, all the cycles proposed by EPA and two additional standardize cycle:

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4 ADVISOR was created by the U.S. Department of Energy’s National Renewable Energy Laboratory’s (NREL) Center for Transportation Technologies and Systems, and can be freely downloaded at: http://www.nrel.gov/transportation/analysis.
the Urban Dynamometer Driving Schedule (UDDS) and the European INRETS, are used for the purpose of comparing the dynamic vehicle simulator against ADVISOR. The driving cycles used are shown in Figure 4.12. These cycles capture different driving situations (urban and highway) and can be used to assess vehicles fuel economies for real-world driving.

![Figure 4.12: Standard Driving Cycles used for the comparison between the proposed vehicle simulator and ADVISOR.](image)

Table 4.5 reports a comparison of fuel consumption estimated by the proposed vehicle simulator and ADVISOR. Results are reported as average over the 6 driving cycles reported in Figure 4.12.

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5 The author would like to thank Chiara Fiori for the valuable assistance provided in performing this validation.
Table 4.5: Comparison of the average energy consumption estimated by the proposed vehicle simulator and ADVISOR over the driving cycles reported in Figure 4.12.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Vehicle Simulator</th>
<th>ADVISOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>29.7 MPG</td>
<td>29.2 MPG</td>
</tr>
<tr>
<td>HEV</td>
<td>43.1 MPG</td>
<td>41.9 MPG</td>
</tr>
<tr>
<td>EV</td>
<td>0.30 kWh/Mile</td>
<td>0.29 kWh/Mile</td>
</tr>
</tbody>
</table>

The results show similar values, validating the ability of the proposed dynamic vehicle simulator to capture the fuel consumption of this set of vehicles in different driving situations. The proposed dynamic vehicle simulator is on average 40 times faster compared to ADVISOR.

The vehicle simulator developed in this section has been implemented with a 1-second resolution. The electricity consumption related to residential charging of PEVs is aggregated to a 10-minute resolution, and then summed to the residential (domestic) demand predicted by the residential power demand model presented in Chapter 3 to obtain the total demand of a residential eco-system.

4.5 Exergy-based Comparison of Multiple Energy Carriers

The energy consumption of the six categories of vehicles comes from different energy carriers: fossil fuels (gasoline or natural gas) burned in the engine and electricity produced off-board, used to recharge the vehicle battery. Gasoline, natural gas, and electricity have different efficiencies of production and of use. For instance, in conventional vehicles most of the exergy destruction occurs in the engine, where the combustion takes place. For electric vehicles the greater part of the exergy destruction occurs in the power plant, where fossil fuels are burned.

Comparing powertrains using only a single input, such as gasoline, is relatively
straightforward. But when comparing vehicles where both gasoline and electricity produced off-board are used, for example, a common measure is needed to avoid misleading conclusions [193]. In this study, that measure is primary exergy. Specifically, we use the exergy that must be supplied to the refinery to produce the gasoline (or the natural gas) and to the power plant to produce electricity, as required for use by the vehicle.

Accordingly, gasoline consumed on-board is expressed as:

\[ E = V_{\text{gasoline}} \cdot \rho_{\text{gasoline}} \cdot \frac{E_{\text{gasoline}}}{\varepsilon_{\text{gasoline}}} \]  

(4.5.1)

where \( E \) represents the exergy of the crude oil entering the refinery. \( V_{\text{gasoline}} \) is the gasoline consumption, in liters, \( \rho_{\text{gasoline}} \) is the density of the gasoline, namely 0.74 kg/l, \( E_{\text{gasoline}} \) is the chemical exergy of the gasoline, namely 47.5 MJ/kg [153], and \( \varepsilon_{\text{gasoline}} \) represents the exergetic efficiency of gasoline production.

Natural gas consumed on board is expressed as:

\[ E = m_{\text{NG}} \cdot \frac{E_{\text{NG}}}{\varepsilon_{\text{NG}}} \]  

(4.5.2)

where \( E \) represents the exergy of the raw natural gas, as extracted, before entering any processing unit.\(^6\) \( m_{\text{NG}} \) is the natural gas consumption, in kg, \( E_{\text{NG}} \) is the chemical exergy of the natural gas, namely 52.0 MJ/kg [153], and \( \varepsilon_{\text{NG}} \) represents the exergetic efficiency of natural gas processing production.

Analogously, electricity produced off-board is expressed as:

\[ E = W \cdot \frac{3.6}{\varepsilon_{\text{electricity}} \cdot \varepsilon_{\text{battery}}} \]  

(4.5.3)

where \( E \) is the exergy supplied to the power plant, \( W \) is the electricity, in kWh, \( \varepsilon_{\text{electricity}} \) is a term accounting for electricity generation efficiency and transmission

\(^6\)Natural-gas processing is a complex industrial process designed to clean raw natural gas by separating impurities and various non-methane hydrocarbons and fluids to produce what is known as pipeline quality dry natural gas.
losses, $\varepsilon_{\text{battery}}$ is the exergetic efficiency of the battery, and 3.6 is a unit conversion factor used to convert kWh into MJ.

In this work average exergetic efficiencies have been assumed to be:

- $\varepsilon_{\text{gasoline}} = 0.76$
- $\varepsilon_{NG} = 0.86$
- $\varepsilon_{\text{electricity}} = 0.44$
- $\varepsilon_{\text{battery}} = 0.99$

The exergetic efficiencies of gasoline, natural gas, and electricity production are derived from GREET\textsuperscript{7} (Greenhouse gases, Regulated Emissions, and Energy use in Transportation), a full life-cycle model developed by Argonne National Laboratory and sponsored by the U.S. Department of Energy’s Office of Energy Efficiency and Renewable Energy (EERE). These efficiencies reflect current (2013) values and electricity generation mix in the United States (i.e. for electricity: 43% coal, 21% nuclear, 25% natural gas, 0.34% biomass, 11% others). Also, 31% of natural gas is assumed to come from shale gas fields. Round-cycle coulombic efficiency of Li-Ion batteries ($\varepsilon_{\text{battery}}$) is taken from the work of Smith et al. [194].

Note that the efficiency of the internal combustion engine and of the electric motor are captured by the vehicle models, where fuel and electricity consumption maps are used. The average exergetic efficiency ($\varepsilon_{ICE}$) of the internal combustion engine of the conventional vehicle listed in Table 4.4 is 21% (average MPG of the conventional vehicle over real-world use is 29.5, equivalent to 12.6 km/l or 8 l/100km); for more on this see the work of Van Basshuysen and Schafer [195]. This is intended to model the performance of a relatively new and well maintained conventional vehicle, and compare it with alternative solutions. The national average is still 23.5 MPG [196].

\textsuperscript{7}Software and publications available at: http://greet.es.anl.gov/
The average exergetic efficiency ($\varepsilon_{EM}$) of the motor of the electric vehicle listed in Table 4.4 is 84%; which is in accordance with values in the literature [197].

### 4.6 Validation and Results

In order to validate the driving diaries generated, large-scale simulations of a population of individuals are performed and results are compared against average aggregate data available in the literature. In particular, a population of 100 representative individuals is generated, such to represent the actual U.S. driving population. The representative population considers both the sex ratio (0.97 male/female [198]), and the labor force participation (73% for males and 60% for females [199]). Hence, within roundoff error the population considered is:

- 36 working males;
- 31 working females;
- 20 non-working females;
- 13 non-working males.

Figure 4.13 reports the distribution (in miles) of the total distance traveled by the individuals in the representative population, including both leisure trips and commuting to work.

The simulated average distance traveled is 13133 miles (21136 km). Historical data show that the average annual miles per driver in the U.S. is 13476 miles (21688 km) [200], which leads to a difference of about 2.5% between the simulated average and the real data. This validates the procedure used in this work to generate the distances traveled over a year by the individuals composing the representative population.

Large-scale simulations are also performed to compare the energy consumption of the six classes of vehicles considered in this study. For each of the six classes of
vehicles, the yearly average fossil fuel and electricity consumed by the representative population is evaluated in terms of primary energy. Results are reported in Tables 4.6 and 4.7, where all values are normalized with respect to the primary energy consumption of the conventional vehicle. Table 4.6 reports simulation results for a scenario where PEVs are allowed to charge solely when parked at home (no work or public charging stations available). Charging power has been selected to be 3.3 kW, which is a typical value for residential applications. The percentages of trips that purely electric vehicles were unable to complete owing to intrinsic limitations of the battery are also reported.

The results show that compressed natural gas vehicles consume almost 20% less primary energy, compared to conventional vehicles. This is due to two main reasons: first the brake specific fuel consumption of natural gas engines is assumed to be 18% lower than comparable spark ignition gasoline engines. Second, natural gas processing has a significantly higher exergetic efficiency than that of gasoline.

Figure 4.13: Annual traveled distance distribution, in miles, for the simulated population.
Table 4.6: Population average primary energy consumption. Electric charging only at home.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Average Fossil Fuel Consumption</th>
<th>Average Electricity Consumption</th>
<th>Total Primary Energy Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>100%</td>
<td>-</td>
<td>100%</td>
</tr>
<tr>
<td>CNG</td>
<td>81%</td>
<td>-</td>
<td>81%</td>
</tr>
<tr>
<td>HEV</td>
<td>65%</td>
<td>-</td>
<td>65%</td>
</tr>
<tr>
<td>PHEV – 10&lt;sup&gt;1&lt;/sup&gt;</td>
<td>41%</td>
<td>16%</td>
<td>57%</td>
</tr>
<tr>
<td>PHEV – 40&lt;sup&gt;2&lt;/sup&gt;</td>
<td>20%</td>
<td>36%</td>
<td>56%</td>
</tr>
<tr>
<td>EV&lt;sup&gt;3&lt;/sup&gt;</td>
<td>-</td>
<td>49% (3.7%&lt;sup&gt;*&lt;/sup&gt;)</td>
<td>41%</td>
</tr>
</tbody>
</table>

<sup>1</sup>10 miles all-electric range, <sup>2</sup>40 miles all-electric range, <sup>3</sup>100 miles range.

<sup>*</sup> Average percentage of trips not completed due to limited range.

Also, total primary energy consumption decreases as the electrification of the vehicle increases. The total primary energy consumption of HEVs is 35% less than that of conventional vehicles, and the two PHEVs achieve over 40% saving. The total primary energy consumption of the two PHEV is similar, but the amount of primary energy coming from fossil fuel decreases as the electrification level increases, namely as the size of the battery present on-board increases.

For PHEVs, the proportion of the equivalent electricity consumption and the fossil fuel consumption is affected by both battery size and charging strategy, in term of availability of charging stations and charging power (often referred to as charging level). The first class (all-electric range of 10 miles) presents a substantially higher consumption of gasoline, due to the limited battery capacity. Nevertheless, the lower weight, and in turn the lower power requirements, leads to a total primary energy consumption for real-world usage extremely close to that of PHEV-40. The two vehicles will show differences in fuel operating cost, depending on the cost of gasoline and electricity. Also, the capital cost of the vehicle increases with battery
size. Therefore, from an economic perspective, an optimal battery sizing problem needs to be solved during the design process of PHEVs, depending on the specific application and the cost of gasoline and electricity, and thus on the region of usage. Moreover, the design choice results from trade-offs in incremental costs and fossil fuel consumption reduction potential [201].

In this scenario, electric vehicles are unable to complete 3.7% of the trips, due to battery limitations. Considering only the completed trips, or portions of trips, EV are shown to reduce the total primary energy consumption by more almost 60%, compared to conventional gasoline vehicles.

Table 4.7 reports simulation results for a second scenario, where recharging can be performed both at home and at work. Note that the energy consumption of the conventional, natural gas, and HEV vehicles each remain the same.

Table 4.7: Population average primary energy consumption. Electric charging both at home and at work.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Average Fossil Fuel Consumption</th>
<th>Average Electricity Consumption</th>
<th>Total Primary Energy Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>100%</td>
<td>-</td>
<td>100%</td>
</tr>
<tr>
<td>CNG</td>
<td>81%</td>
<td>-</td>
<td>81%</td>
</tr>
<tr>
<td>HEV</td>
<td>65%</td>
<td>-</td>
<td>65%</td>
</tr>
<tr>
<td>PHEV − 10$^1$</td>
<td>39%</td>
<td>18%</td>
<td>57%</td>
</tr>
<tr>
<td>PHEV − 40$^2$</td>
<td>18%</td>
<td>37%</td>
<td>55%</td>
</tr>
<tr>
<td>EV$^3$</td>
<td>-</td>
<td>42% (2.6%$^*$)</td>
<td>42%</td>
</tr>
</tbody>
</table>

$^1$10 miles all-electric range, $^2$40 miles all-electric range, $^3$100 miles range.

* Average percentage of trips not completed due to limited range.

As expected, in this second scenario the proportion of gasoline consumption and electricity consumption for PHEVs moved toward higher electricity use. Also, the
number of trips that purely electric vehicles were unable to complete decreased (and the total primary energy consumption increases accordingly). However, the influence of availability of charging stations at the workplace is minimal and the percentage of trips that purely electric vehicles could not complete remains similar. This is because, regardless of the charging infrastructure, there is a small portion of trips that are longer than the range of EVs (here selected to be 100 miles, 161 km). EVs are unable to complete such trips, due to limitations of the battery, even if completely recharged at the beginning of the trip.

The results presented in tables 4.6 and 4.7 not only depend on vehicle technology (i.e. vehicle type and relative performance), but are strongly dependent on how the vehicles are used (realistic driving profiles) and on characteristics of the energy sector (i.e. production of gasoline and electricity). Results in this work are valid for current (2013) personal transportation applications in the United States.

Figure 4.14 shows the total primary energy consumption for the first scenario (charging solely at home) as a function of total miles driven during a year. The results for the 100 people simulated are aggregated into four classes with respect to the total miles driven in the year. Among each class the results are normalized with respect to the average conventional vehicle energy consumption for that specific class, to remove the influence of the total miles driven.

Results reported in Figure 4.14 show that, independent of the miles driven annually, the higher the electrification of the vehicle, the lower the primary energy consumption. This suggests that vehicle electrification would benefit every kind of driver, spanning those who rarely drive and those who drive over 30000 miles (48000 km) per year. Results for the two PHEVs are extremely similar. Still, as the size of the battery increases electricity largely replaces gasoline as propulsion source, opening
Figure 4.14: Normalized average primary energy consumption for different vehicle types per yearly distance-driven classes. * Percentage of trips not completed due to limited range.

up for opportunities to reduce oil dependency and fossil fuel consumption in general – depending on the primary energy source used to produce electricity.

From a primary energy point of view, electric vehicles are the better choice. This is due to the overall higher efficiency of generation and use of electricity compared to that for gasoline. On the other hand, EVs are burdened by their limited range owing to limitations of the battery capacity. Also, results for primary energy consumption do not include the portion of trips that EVs could not complete. In Figure 4.14, the percentages of trips that purely electric vehicles are unable to complete are reported by *. The percentage is less than 3% for driving distances up to 20000 miles (32000 km) per year, but increases dramatically above that threshold. These results are valid for the modeling used to simulate an EV: 100 miles (161 km) of all-electric range with charging solely at home with a power of 3.3 kW.
It is worth noting that the last two classes, including individuals driving more than 20000 miles (32000 km) per year, are composed solely of those who are designated as working, while non-working drivers are concentrated in the first two classes. Also, out of the representative population, just one person drove more than 30000 miles (48000 km) in one year and 91% of the population drove less than 20000 miles (32000 km) per year.

The personal transportation energy consumption model is implemented in MATLAB®. It takes about 140 seconds to generate a yearly driving diary for one individual, including the associated driving profiles for all the trips performed during the year by the simulated individual (over 1000 trips). It takes an additional 15 seconds to generate the corresponding yearly energy consumption profiles at 10-minute resolution in the case of CV, CNG vehicle, or EV (including generation of in-home charging profiles). Generating a year worth of energy consumption profiles at 10-minute resolution for hybrid vehicles (HEVs and PHEVs) requires about 400 seconds, due to the implementation of the control power-splitting strategy. Simulations are performed using an Intel® CORE™ i5-2430M CPU @2.40 GHz and 8 GB of RAM.

4.7 Conclusions

In this chapter a modeling approach for generating highly-resolved driving profiles for different individuals and related energy consumption patterns for personal transportation has been presented. Six different vehicle types have been considered: conventional gasoline-fueled spark ignition vehicles, compressed natural gas vehicles, hybrid electric vehicles, plug-in hybrid electric vehicles, and electric vehicles. Also, an approach to compare different energy carriers, based on exergy, is introduced. The
modeling developed allows performing a quantitative comparison of the energy consumption of the different vehicle types in terms of total primary energy. Moreover, the percentage of trips that purely electric vehicles are unable to complete is assessed.

For conventional vehicles, CNG vehicles, and HEVs the consumption patterns include only fossil fuels, while electricity consumption is also considered in the case of PHEVs and EVs. The personal transportation energy consumption model also generates charging consumption profiles for PEVs.

The modeling methodology introduced in this chapter is coupled to the residential power demand model to form the core of the residential energy eco-system model developed in this study. This allows capturing the entire energy footprint of an individual household, to include all appliances, Heating, Ventilation, and Air conditioning (HVAC) systems, in-home charging of plug-in electric vehicles, refueling of compressed natural gas vehicles, and any other energy needs, viewing residential and transportation energy needs as an integrated continuum.

Furthermore, the personal transportation energy consumption model is a standalone model that can serve as a tool for:

- generating realistic driving patterns for different individuals that are useful in performing statistical analysis, evaluation and comparison of different vehicles, and in deciding preferred dwelling locations relative to workplace.
- developing demographic considerations on transportation energy consumption for different classes of drivers (e.g. working and non-working).
- evaluating the impact of PEVs on the electric grid - especially at the distribution level. For this, precise information on PEV charging time and duration is crucial (Section 6.3 reports a case study on this topic).
- assisting policy-makers in evaluating incentives in the transportation sector,
such as automaker-discounts for PEVs and tax discounts for owning high-efficiency vehicles.

- assisting policy-makers in estimating impact of PEV market penetration on primary energy and crude oil consumption.
- comparing the initial cost of different vehicles and their expected fuel (fossil fuels and/or electricity) operating cost.
- bottom-up modeling of part of the transportation sector and corresponding primary energy consumption.
Chapter 5

DYNAMIC ENERGY MANAGEMENT OF
RESIDENTIAL ECO-SYSTEMS

This chapter introduces a dynamic energy management framework for a generic residential energy eco-system. The framework considered in this chapter is intended to simulate a scenario in which electric utilities send a signal to residential customers as a way to steer the aggregate demand (demand response).\(^1\) In the demand response paradigm, electric utilities provide some sort of incentive to their customers to change their consumption patterns. Utilities also provide a signal to their customers that is intended to guide the electric power consumption so as to obtain an aggregate demand that better matches the needs of the power generation. This satisfies two major needs.

First, the electricity demand that occurs during peak periods is one of the biggest drivers of costs and capacity requirement currently faced by the electric industry. To meet high demand during these peak periods, utility companies are required to maintain a significant amount of operational capacity which is often outdated, expensive, and underutilized.

\(^1\)Demand response is defined as: “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [28].
Second, the widespread adoption of non-dispatchable\textsuperscript{2} renewable energy sources limits the flexibility of power generation and its ability to follow fluctuations in demand. Traditionally, generation follows demand closely, making adjustments to keep the grid balanced. Instead of adapting electricity generation to match changes in demand, the demand itself could be made more flexible to reduce requirements on the electric power generation infrastructure and allow for easier integration of non-dispatchable renewable resources.

The overall objective of demand response programs is to improve the operation of the electric power system in one or more of the following ways:

1. reduce electricity generation and grid operation costs for electric utilities;
2. manage demand peaks (better interaction between demand and generation);
3. reduce overall pollutant and carbon dioxide emissions from electricity generation;
4. improve overall grid efficiency and minimize primary energy consumption (national energy policy).

The energy management framework introduced in this chapter simultaneously optimizes controllable appliances and in-home charging of PEVs. The proposed energy management framework is based on highly-resolved personal energy consumption models developed using a novel bottom-up approach that quantifies residential energy use. Residential and personal transportation energy consumption models are described in Chapter 3 and Chapter 4, respectively. The incorporation of stochastic consumer behaviors provides more accurate estimation of the actual amount of available controllable resources, allowing for a better understanding of the potential of residential demand response programs. By definition, demand response involves

\textsuperscript{2}A term for an energy system that cannot be expected to provide a continuous output to furnish power on demand, because production cannot be correlated to load. From The Energy Library \cite{159}.
changes in the electricity consumption patterns, potentially leading to inconvenience for the user. The level of the inconvenience is significantly dependent on the specific activity performed.

The dynamic energy management framework introduced in this chapter is decentralized, in the sense that each single household receives the same signal from the electric grid, and independently optimizes its own demand. Even though this leads to a local optimum, the signal sent from the electric utility can be constructed in such a way as to achieve one or more of the four system-level objectives mentioned earlier.

Also, the dynamic energy management framework is non-disruptive, meaning that household members are not required to change their behavior. Namely, when a user performs an activity, he or she enables the controllable appliance associated with it (i.e. pushing the start button on a controllable appliance). The controllable appliance may in fact run later, depending on the energy management decision, but this has no direct impact on the activities performed by the user.

Several companies are currently selling smart appliances in the American market, that enable consumer participation to residential demand response programs (e.g. GE Brillion™ [202], LG SMART THINQ™ [203], Siemens-Bosch [204], and others). Smart appliances can be monitored and controlled from mobile devices, are equipped with innovative device-to-device connectivity features, and can be integrated in a home energy management system. This opens up a new era in convenient and efficient home management. PEV residential charging equipment, or charging stations, are considered smart appliances and have the same connectivity features.

In this work, the behavioral model introduced in Chapter 2 predicts activity patterns of individuals. These activity patterns are associated with energy consumption, and in particular with use of appliances. Some appliances may be controllable, in
which case the energy management system makes decisions aimed at achieving one or more of the objective mentioned earlier, without requiring any direct intervention from the consumer. Smart appliances require no direct human input to start their run-cycles, other than being enabled, thus simulating an automated system. For example, a plug-in electric vehicle is enabled when a consumer connects it to the residential charging station. At that moment, the user also selects a deadline for the completion of the charging. The management framework decides the charging schedule for the vehicle so as to minimize a cost function, while respecting the deadline selected.

The management problem thus formulated is solved using a numerical optimization technique called Dynamic Programming (DP), and considers the behavior of household members and their energy consumption, as predicted by the highly-resolved stochastic personal energy consumption model of Chapter 3 and 4. The DP algorithm computes the optimal schedule for all controllable appliances, including plug-in electric vehicle charging, where a schedule is considered optimal when it minimizes a specific cost function intended to achieve one or more of the four objectives mentioned earlier. The optimization algorithm is flexible enough to accommodate different cost functions, and could respond to different signals, used to achieve different objectives (e.g., electricity price, instantaneous CO$_2$ emissions, or others).

This chapter is structured as follows: first a general introduction on demand-side energy management, residential demand response programs, and dynamic energy management is given in Section 5.1. Section 5.2 provides an introduction to dynamic programming. Section 5.3 provides a review of the state-of-the-art on residential demand response programs, with particular focus on energy management algorithms and optimization techniques. The proposed dynamic energy management framework is presented in Section 5.4, and results are reported in Section 5.5. Section 5.6
presents some conclusions. Large-scale simulations aimed at capturing the impact of widespread adoption of decentralized energy management on the aggregate demand are provided in Chapter 6.

5.1 Introduction

In the next decades, the world electric grid may see the largest change since the beginning of the industrial revolution, as a centralized system based on fossil fuels may be progressively replaced by a diversified system including renewables, energy storage, and distributed generation. All of these resources are connected via a smart grid, allowing for advanced communication and distribution management.

Demand-side management is a critical and necessary element for the efficient operation of the smart grid and is a key enabling technology for the integration of renewable generation, contributing to the sustainable operation of the entire energy system. Advanced modeling, simulation, and optimization methods are needed to understand, study, develop, and operate such a complex system, which includes interactions among humans, environmental conditions, and electric power generation, transmission, and distribution infrastructure.

Residential energy management has been studied extensively in the literature, and time-varying electricity price appears to be the most commonly adopted tool to influence residential energy consumption. The electricity price is intended to be a signal to convey time-varying production cost, and to guide consumer consumption to better match the aggregate demand with the power generation. Consumers voluntarily adjust their electricity consumption based on time-varying electricity prices, typically Time of Use Pricing (TOU), Critical Peak Pricing (CPP), Peak Time Rebates (PTR), or Real Time Pricing (RTP) [33, 56, 57, 58].

TOU rates are defined as different electricity prices for different periods of the day
or of the year. For instance, consumers might see a higher price during the day than during the period between midnight and 6 in the morning. Consumers know prices paid for energy consumed during different periods in advance, allowing them to vary their usage in response to such prices and manage their energy costs by shifting usage to a lower cost period or reducing their overall consumption. TOU programs can be characterized by two or more price tiers.

CPP is essentially a TOU program, with a significantly higher price tier during peak periods. Two variants of this type of price structure exist: one where the time and duration of the peak periods are predetermined and another where the time and duration of the peak periods may vary based on the needs of the electric power infrastructure. Outside these peak periods TOU prices are typically in effect. When critical peak events are established by the electric utility in response to an emergency, they shall not exceed a defined number per calendar year, typically 10 to 15 events. Customers are notified a few hours prior to a critical peak event, that cannot last for more than a few hours. The objective of CPP is to enhance a TOU price structure with the ability to promptly respond to emergency events.

In the PTR paradigm customers receive electricity bill rebates for reducing their electricity consumption during peak periods (established \textit{a priori} by the electric utility) relative to a previously established baseline, which is determined for each individual customer. The baseline is usually identified using historical household electricity consumption. PTR are similar to CPP in some instances, but do not provide a time-varying price, in general.

RTP is a dynamic electricity price structure that adjusts electricity prices on an ongoing basis throughout the day, following the wholesale electricity generation cost, on an hourly or sub-hourly basis (generally 10-15 minutes). RTP is intended to convey actual generation cost to the final consumer allowing for optimal use of generation
resources. In this scenario, when the electricity price drops and consumers start increasing their demand, the generation infrastructure will be confronted with a cost increase and convey this to the consumer, who adjust their demand consequently. In a residential demand response program, some of the deferrable loads cannot be interrupted once started (i.e. dishwasher cycle) but some others will (i.e. PEV battery recharging). Thus, RTP-based residential demand response introduces fluctuations in the system, since a decrease in demand would lead again to lower generation cost. Such oscillations might be very dangerous and hard to control, calling for further investigation on the use of real-time price.

While time-varying electricity pricing is often used as an effective method to incentivize customers to change the timing of their electricity consumption, it has been recently shown that purely relying on pricing is often insufficient to provide reliable operation of smart energy assets and may lead to undesired demand dynamics, especially for large-scale deployment of demand response programs, or when automated decentralized energy management systems are used [1, 5].

LeMay et al. [205] suggest that there is a threat of rebound peaks in which consumers delay their demands to avoid a peak, but cause a new peak when trying to satisfy delayed demand. Similar trends are observed in an experiment performed by Pacific Gas and Electric to monitor the substation-level load impacts of end-use load control [206]. Lenhoff et al. [207] reports that if many consumers react to time-varying electricity pricing in an un-coordinated manner, the coincidence factor of load increases significantly and the electric system may face strongly increased load fluctuations.

Mishra et al. [208] suggest that current pricing plans incentivize all consumers to shift their energy consumption during low-price periods. Thus, at large scales, simultaneous energy request during off-peak periods will trigger rebound peaks if prices
do not change to reflect the resulting increases in off-peak demand. In particular, a simulation study has been performed to assess the potential savings of using distributed energy storage to take advantage of a TOU pricing scheme. Simulations results show that doing so leads to a 20% peak power reduction when 22% of homes use distributed storage, as long as the homes randomize when they begin overnight charging. If everyone begins charging at the same time, the peak reduction is shown to decrease to a maximum of only 8%. Even using randomized charging, Mishra et al. [209] show that if more than 22% of consumers install energy storage devices to take advantage of TOU electricity pricing, then the peak reduction benefits begin to decrease, due to a nighttime rebound peak. Once 45% of consumers use the system the evening rebound peak actually becomes larger than the original peak. Assuming that 100% of residential consumers install 24 kWh of energy storage, then the peak demand period will migrate to the (previously) off-peak period and actually increase, rather than decrease, peak demand by nearly 120% [209].

Load “pickup” effects are observed in several studies and pilot projects. For example, results from the EV Project\(^3\) show how the introduction of a time-of-use rate plan does not necessarily prevent the charging demand from peaking [210].

If anything, the TOU rate plan increases and shifts the peak demand, as shown in Figure 5.1, where weekdays-charging demand profiles normalized per Electric Vehicle Supply Equipment (EVSE) for two locations are reported. Figure 5.1a shows how in Nashville, where the project participants do not have access to any time-of-use rate, the charging demand starts to increase gradually after 4 p.m. and peaks around 8 p.m. when residents are mostly at home. On the other hand, Figure 5.1b shows charging demand profiles in San Francisco where a special TOU rate plan is available.

\(^3\)The EV Project is the largest deployment of electric vehicle charge infrastructure in history. Further details are available at: http://www.theevproject.com.
In this case, the introduction of the TOU rate plan has the effect of synchronizing the demand exactly at the moment when electricity price changes. Therefore, the demand increase is steeper and presents a higher peak value (note the different scale on the y-axis).

These examples show that the time-of-use electricity plan successfully shifted the charging demand, but also incurred a large demand rebound peak when the electricity price decreases, around midnight.

In addition to the undesired rebound dynamics, there are also unsolved real-world challenges for demand-side energy management, such as meeting end-use constraints (e.g. keeping temperature within a certain range, or meeting a charging deadline), understanding user preferences, heterogeneous loads dynamics, and stochastic end-user behavior.

Recently, Plug-in Electric Vehicles (PEVs) have introduced a connection between the energy consumptions of residential and transportation sectors, creating a Residential Energy Eco-System (REES) that comprises energy consumption inside the household and residential charging of PEVs’ batteries. This opens up new opportunities to improve energy efficiency of integrated transportation-building-grid systems.

A high-performance demand-side energy management system to optimally manage the energy consumption of integrated residential and personal transportation energy systems – aimed at improving the overall system performance – is conspicuously missing.

Dynamic Energy Management (DEM) was first introduced in 2008 [99] as an innovative approach to managing load at the demand side. It differs from demand response and classic demand-side energy management as it transforms the local, standard energy management into a system comprising smart end-use devices and distributed energy resources with highly advanced controls and communications capabilities. In
DEM, all components interact with one another to contribute to an infrastructure that is dynamic, fully-integrated, highly energy-efficient, and automated [99]. A dynamic energy management system is a demand-side energy resource that integrates energy efficiency and load management from a dynamic, whole-systems or networked perspective [99].

In the present study, a DEM framework is proposed based on a highly-resolved
The REES model generates residential and personal transportation highly-resolved energy consumption and behavior patterns, with a 10-minute resolution, that are used as inputs for the DEM tool. The models have been validated against real measured data. The proposed DEM framework is solved by use of a dynamic programming algorithm, implemented in MATLAB®. More details on DP are provided in Section 5.2.

The present study is the first that systematically considers stochastic correlations among different end-use activities in the design of a residential energy management framework. The incorporation of stochastic consumer behaviors provides more accurate estimation of the actual amount of available controllable resources in the population, and hence enables better interactions with the grid. Moreover, the proposed study of integrated load modeling for both PEVs and other smart appliances represent a significant advance over most existing works in aggregate load modeling that have mainly focused on first-order thermostatically controlled loads.

5.2 Fundamentals of Dynamic Programming

The term Dynamic Programming (DP) was originally used in the 1940s by Richard Bellman to describe the process of solving problems where decisions can be made sequentially. Such problems can be divided into time periods (time discretization), or stages, and a decision is made at each stage. The word dynamic was chosen by Bellman to capture the time-varying aspect of the problems.  

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4Bellman explains the reasoning behind the term dynamic programming in his autobiography, Eye of the Hurricane: An Autobiography (1984): “In the first place I was interested in planning, in decision making, in thinking. But planning, is not a good word for various reasons. I decided therefore to use the word “programming”. I wanted to get across the idea that this was dynamic, this was multistage, this was time-varying. I thought, lets kill two birds with one stone. Lets take a word that has an absolutely precise meaning, namely dynamic, in the classical physical sense. It also has a very interesting property as an adjective, and that is its impossible to use the word dynamic in
Dynamic programming algorithms are used as a solution algorithm for many optimization problems. A dynamic programming algorithm evaluates all possible ways to solve the problem and finds the best solution. Therefore, dynamic programming can be seen as a brute-force method that intelligently goes through all feasible solutions to find the best one. DP is faster compared to traditional brute-force methods (e.g., enumeration of all possible solutions) that go through all possible solutions, in that after one decision is made all suboptimal courses of action from that point forward are eliminated, making the problem smaller and easier to solve.

In general, an optimization problem, or mathematical programming problem, consists in the selection of a best element (with regard to some criteria) from a set of available alternatives. The decision maker has control over some parameters, called decision or control variables, and makes a decision following some criteria (i.e., to achieve an objective). Mathematically this translates into minimizing or maximizing a function, called objective function or cost function.

Considering a deterministic discrete-time dynamical system, at any given time $t$ (or stage) the system has a state, $x_t$, given by a set of real numbers. The state represents the information that is needed at any time $t$ to make an optimal decision. The evolution rule of the dynamical system is a fixed rule that describes what future states follow from the current state. Here this rule, called state dynamics, is assumed to be deterministic. Thus, a general optimization problem takes the form:

$$
\begin{cases}
\min_{u_t} \sum_{t=0}^{\infty} g(t, x_t, u_t) \\
x_{t+1} = f(t, x_t, u_t)
\end{cases}
$$

(5.2.1)

where $u_t$ is the control variable (because it is under the control of the decision maker), $x_t$ is the state variable (that describes the state of the system at the beginning of a pejorative sense. Try thinking of some combination that will possibly give it a pejorative meaning. It’s impossible. Thus, I thought dynamic programming was a good name”.}

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time-step $t$, when the decision is made), $g$ is the cost function, and $f$ is the state
dynamic equation.

Bellman’s idea for solving the problem in Equation 5.2.1 is to define a value
function, or cost-to-go function, in a recursive way at each time step $t$:

$$V(t, k_t) = \min_{u_s} \sum_{s=t}^{\infty} g(s, x_s, u_s) \mid x_{s+1} = f(s, x_s, u_s)$$

At the base of dynamic programming is the idea of breaking a complex problem
into simpler subproblems in a recursive manner. This is done based on the Bellman’s
principle of optimality, which states that: “an optimal policy has the property that
whatever the initial state and initial decision are, the remaining decisions must con-
stitute an optimal policy with regard to the state resulting from the first decision”
[211]. Thus:

$$V(t, k_t) = \min_{u_t} [g(t, x_t, u_t) + V(t + 1, f(t, x_t, u_t))]$$

Equation 5.2.3, called Bellman equation or Hamilton-Jacobi equation, restates the
optimization problem in recursive form. This reduces an infinite-period optimization
problem to a two-period optimization problem. The Bellman equation is classified
as a functional equation, because solving it means finding the unknown function $V$,
which is the value function. Note that the value function describes the best possible
value of the objective, as a function of the state $x$. By calculating the value function,
one will also find the function $u(x, t)$ that describes the optimal control action as a
function of the state and time. $u(x, t)$ is called policy function, and it is generally
indicated by $\mu$.

When applicable, dynamic programming takes far less time than naive methods
that do not take advantage of a recursive problem structure, and that solve the same
subproblem over and over. DP exploits the advantage of the subproblem overlap, a
property exhibited by problems that can be broken down into subproblems which are reused several times, to solve optimization problems more quickly.

Winston et al. [212] summarize the characteristics that are common to most applications of dynamic programming:

1. The problem can be divided into stages (time periods) with a decision required at each stage;
2. Each stage has a number of states associated with it. The state represents the information that is needed at any stage to make an optimal decision;
3. The decision chosen at any stage describes how the state at the current stage is transformed into the state at the next stage;
4. Given the current state, the optimal decision for each of the remaining stages must not depend on previously reached states or previously chosen decisions;
5. If the states for the problem have been classified into one of the $T$ stages, there must be a recursion that relates the cost or reward earned during stages $t, t+1, \ldots, T-1$ to the cost or reward earned from stages $t+1, t+2, \ldots, T$

The Bellman equation can be solved by backwards induction\(^5\), either analytically in a few special cases, or numerically. To illustrate the concept of using backwards induction to solve an optimization problem consider an unemployed person who will be able to work for ten more years $t = 1, 2, \ldots, 10$. Suppose that each year in which he remains unemployed, he may be offered a “good job” that pays $100, or a “bad job” that pays $40, with equal probability. Once he accepts a job, he will remain in that job for the rest of the ten years. Assume for simplicity that he cares only about his monetary earnings, and that he values earnings at different times equally (i.e. the

\(^5\)Backward induction is the process of reasoning backwards in time, from the end of a problem or situation, to determine a sequence of optimal actions.
discount rate is zero). Should this person accept “bad job” offers? To answer this question, backwards induction from time $t = 10$ can be used:

- At time 10, the value of accepting a “good job” is $100; the value of accepting a “bad job” is $40; the value of rejecting the job that is available is zero. Therefore, if he is still unemployed in the last period, he should accept whatever job he is offered at that time.

- At time 9, the value of accepting a “good job” is $200 (because that job will last for two years). The value of accepting a “bad job” is $80. The value of rejecting a job offer is $0 now, plus the value of waiting for the next job offer, which will either be $40 with 50% probability or $100 with 50% probability, for an expected value of $70. Therefore regardless of whether the job available at time 9 is good or bad, it is better to accept that offer than wait for a better one.

- At time 8, the value of accepting a “good job” is $300 (it will last for three years). The value of accepting a “bad job” is $120. The value of rejecting a job offer is $0 now, plus the value of waiting for a job offer at time 9. Since we have already concluded that offers at time 9 should be accepted, the expected value of waiting for a job offer at time 9 is $0.5 \cdot (\$200 + \$80) = \$140. Therefore at time 8, it is more valuable to wait for the next offer than to accept a bad job.

It can be verified by continuing to work backwards that bad offers should only be accepted if one is still unemployed at times 9 or 10; they should be rejected at all times up to $t = 8$. This simple example illustrates the use of backwards induction to solve an optimization problem.

Numerical backwards induction is applicable to a wide variety of problems. Still, the objective function must be computed for each combination of values and this may be infeasible when the dimension of the state variable is large. Computational
complexity of the DP algorithm increases exponentially with dimensionality of the state, which makes it impractical in large-scale applications. Given that dynamic programming is highly computationally demanding, it is hard to use such a solution algorithm for complex real-world problems. This problem is known as the “curse of dimensionality”.

Many researchers are interested in finding accurate and fast approximation techniques to improve the performance of dynamic programming algorithms [213]. Powell is a major contributor to the development of Approximate Dynamic Programming (ADP) [214], which is both a modeling and algorithmic framework for efficiently solving stochastic optimization problems.

Dynamic programming can also be applied to solve stochastic problems, in which case it is called stochastic dynamic programming. The incorporation of stochasticity exacerbates the issues related to the curse of dimensionality, making approximate methods a Hobson’s choice. Further details on dynamic programming can be found in several books [212, 215, 216, 214].

5.3 Review of the Existing Literature

Residential demand response programs can be classified into incentive-based and price-based programs [48, 53]. Both are established by electric utilities to change consumption patterns by effectively changing the cost of electricity for consumers, and increase overall system performance. Incentive-based demand response programs provide financial compensation to consumers to change their consumption. Price-based programs provide a varying electricity price that is intended to be a signal to guide consumer consumption to better match generation. Consumers are expected to voluntarily adjust their electricity consumption based on such prices, typically TOU, CPP, or RTP [33, 56, 57, 58]. Both incentive-based and price-based mechanisms can
be used at the same time. Albadi and Saadany provide a detailed overview of these mechanisms [54].

Time-varying electricity pricing has been shown to effectively shift electricity demand by varying amounts [51, 75, 76, 78, 79]. Cappers et al. [62] provide empirical evidence on the evolution of demand response resources in U.S. electric power markets. This evidence shows that demand response is a growing industry in the United States, as evidenced by the increasing number of entities that offer demand response programs and dynamic pricing tariffs and the emergence of wholesale market programs.

Herter [69] found that consumers in California were very responsive to critical peak pricing during a 15-month experiment, with participants with programmable communicating thermostats using 25% less electricity during 5 hour critical events and 41% less during 2-hour critical events. Even those participants without programmable communicating thermostats reduced their consumption during these periods by an average of 13%, showing that even an awareness of critical conditions can help reduce demand. Also, findings show that high-use customers respond significantly more in kW reduction than do low-use customers, while low-use customers save significantly more in percentage reduction of annual electricity bills than do high-use customers (with low-use consumers saving up to 5.5% of their annual bill). In addition, satisfaction rates across all customer segments were uniformly high, averaging between 7.7 and 8.3 out of a maximum of 10 [69].

Herter and Wayland [70] analyzes data from 483 households in California that took part in a CPP experiment between July and September 2004. Results from this study confirms that residential customers can and do respond to time-varying price signals. Moreover, an analysis involving two different levels of critical-peak prices – $0.50/kWh and $0.68/kWh – indicates that households did not respond more to
the higher CPP rate, suggesting that the lower incentive is sufficient to change the timing of electricity consumption, and further incentives do not lead to more drastic change in electricity consumption. A study conducted by Georgia Power found that consumers reduced demand by 20 to 30 percent when electricity prices increased between 25 to 50 cents per kWh [57]. In another study conducted by Gulf Power, consumers reduced their demand by 1.5 to 2.0 kW for approximately 2 hours when presented with peak prices of 30 cents per kWh [57].

Newsham and Bowker [56] provide a survey of studies relating to peak reduction via the introduction of time-based demand response programs. The authors found that the most effective strategy to reduce peak demand is a critical peak price program with enabling technology to automatically curtail loads during peak events (controllable thermostats), which show little evidence of causing substantial hardship for the occupants. CPP is shown to be able to achieve a peak load reduction of at least 30%. A simple TOU program can only expect to realize on-peak reductions of 5%. The reviewed pilot studies covered lengthy periods, in some cases several years, so it is reasonable to expect that these reductions will be maintained over time. The data analyzed by Newsham and Bowker [56] also suggest that focusing residential demand response programs on households with certain characteristics, such as higher income, education, and underlying conservation orientation, and providing these households with excellent utility support services, might realize high peak demand reductions.

Faruqui and Sergici [59, 60] survey several experimental residential demand response programs in the United States based on time-varying electricity pricing. Results from over 15 time-varying pricing pilot programs reveal that customers do respond to price, leading to reductions in peak demand ranging from 3 to 6% for TOU programs and between 13-20% for CPP programs. According to Faruqui and Sergici
time-of-use impacts are lower because the peak prices they charge customers are lower than the peak prices charged during critical-peak periods by CPP rates.

Smart grid technologies are enablers that permit scheduling loads at the consumer level to save energy, reduce cost, and help grid operation; however, a residential automated Energy Management System (EMS) is needed to optimally manage such an advanced integrated system [98]. Demand-side EMSs must allow consumers to compare costs/benefits with different load schedules and automatically make decisions to optimize energy use in the household. As the electric world is evolving towards the future smart grid, demand-side management will play a key-role to help reduce peak load, increase reliability, and allow more widespread integration of fluctuating non-dispatchable renewable energy sources [217].

Many demonstration projects have been launched recently to evaluate the performance of different pricing strategies in terms of peak shaving and/or demand shifting [218, 219]. The expected time-varying retail electricity price motivates the studies of various algorithms to schedule smart appliances to maximize economic gains for the users [98, 217, 220, 221, 222, 223, 224, 225, 226].

In particular, Li et al. [217] presents a demand response approach based on utility maximization for households that operate different appliances including PHEVs and batteries. In the paper the existence of time-varying prices that can align individual optimality with social optimality (i.e. under such prices, when the households selfishly optimize their own benefits, they automatically also maximize the social welfare) is shown.

Pedrasa et al. [217] implement a co-evolutionary version of particle swarm optimization (CPSO) to find the optimal schedules of the controllable appliances. However, the algorithm is capable of finding only a near-optimal schedule. In addition,
because coordination of all the appliances greatly enhances the computation complexity, finding the overall optimal schedules remain a challenge for CPSO.

This optimization problem has also been solved using iterative approaches [222, 227]. Pedrasa et al. [222], present an optimization algorithm that enables end-users to assign values to desired energy services and schedules the available distributed energy resources to maximize net benefit. Mohsenian-Rad and Leon-Garcia [223], propose a residential energy consumption scheduling framework which attempts to achieve a desired trade-off between minimizing the electricity payment and minimizing the waiting time for the operation of each appliance in household in presence of a real-time pricing tariff by doing price prediction based on prior knowledge. Kishore and Snyder [226] extend the optimal energy management across multiple homes. This would extend the single-household framework to a broader management system, able to intelligently manage energy consumption of a neighborhood.

The capability of scheduling thermostatically-controlled loads is at the core of several appliance commitment algorithms proposed in the literature. This includes the scheduling of an electric water heater [98], and a two-stage cost- and energy-efficient HVAC load control strategy under a dynamic price setting [228]. Most of the research and implementation of advanced control schemes for the HVAC systems, however, focus on commercial or industrial buildings. Moreover, American customers might be hardly willing to see interference in their choices when it comes to personal comfort, like automatic control of space conditioning systems for residential applications.

In this chapter a dynamic energy management framework is proposed to simultaneously find the optimal schedule for all the controllable appliances and PEVs charging. The optimization framework is general, and different cost functions (e.g. minimization of electricity-related expenditures, carbon footprint, or total primary energy consumption) or combinations of costs functions could be adopted. The choice
of the cost function will determine the input requirement of the DEM tool. For instance electricity price or carbon dioxide (CO$_2$) emission signals can be used by electric utilities to steer and re-shape the aggregate residential power demand. The optimal solution is found using the dynamic programming method. DP allows finding the optimal schedules considering stochastic users’ behaviors.

Many numerical optimization techniques, such as gradient descent, convex optimization, and integer programming, rely crucially on the structure of cost function and on the system dynamics. When applying these techniques to energy management problems, an optimization problem needs to be solved at each discrete time instant, whenever a new state measurement arrives. DP solves for a control policy rather than for a particular control sequence. The policy maps each system state to an optimized control action, and therefore DP is capable of finding globally optimal solution. Its performance is limited by the curse of dimensionality rather than by the structure of the cost function and state dynamics. Once the optimal control policy is determined, the decision-making process simply involves plugging-in state measurements to obtain the optimal control action, which requires no further nontrivial on-line computations.

Dynamic programming is adopted here to find the global optimum solution that can serve as a means for evaluation and comparison of different residential demand response programs and as a benchmark for other energy management tools. The proposed algorithm is not intended to be a tool for real-time implementation.

Dynamic programming has been proposed to solve residential appliances scheduling problem in several forms. Hatami and Pedram [229] propose a mathematical formulation of the electrical energy bill minimization problem for cooperative networked consumers, such as those working in a commercial/industrial building. Two
frameworks, one based on nonlinear programming, the other based on dynamic programming, are proposed. The DP approach is reported to be more efficient in obtaining the optimum solution, but its memory requirements are higher compared to nonlinear programming. Arthur [230] proposes an algorithm for scheduling residential appliances directly controlled by electric utilities using an approximate forward dynamic programming procedure. Huang and Liu [231], apply adaptive dynamic programming (thus avoiding the curse of dimensionality problem) to obtain a learning neural network scheme capable of solving the residential energy management problem, with an emphasis on home battery use connected to power grids. Nevertheless, these approaches do not focus specifically on solving a decentralized (not coordinated) residential energy management problem, and do not properly capture stochastic user behavior.

The proposed automated, decentralized, non-disruptive energy management framework relies on highly-resolved models of all the components in a residential eco-system, providing a more accurate estimation of the actual amount of available controllable resources in the population. DP guarantees finding the global optimum, while other algorithms might find sub-optimal solutions. Users’ random behavior is captured by the proposed highly-resolved models and the DP is run off-line, which relaxes the complexity constraint. The framework proposed is flexible enough that different cost functions (e.g. minimization of carbon footprint or total primary energy consumption) and different price structure (e.g. time-of-use rates, real-time price, or others) can be easily simulated to reproduce different policy decisions and evaluate their impact on the residential/personal transportation sector.
5.4 Dynamic Energy Management Model

The energy management problem is solved by use of a dynamic programming algorithm that considers household members’ behavior, as predicted by the highly-resolved REES model presented in the previous chapters, and manages controllable appliances and PEV charging to minimize a chosen cost function. The algorithm is flexible enough to accommodate diverse costs functions and price structures (e.g., time-of-use price, critical peak price, real-time price, or others). The cost function is also used to capture users’ inconvenience, giving some sort of monetary value to the waiting time before a scheduled activity is completed. This can be used by the users to weight their flexibility towards load postponements.

Starting from the REES model, an optimal control problem for the scheduling of all the controllable appliances (i.e. laundry appliances and dishwasher) and charging of plug-in electric vehicles, when present, is defined in a non-disruptive fashion (users are not required to change their behavior). A possible scheduling configuration for a residential eco-system is shown in Figure 5.2.

The enabling time $E^i$, the completion time $C^i$, the deadline $D^i$, and the maximum waiting time $W^i$ for each controllable appliance are computed by the REES model, and could differ for different appliances executions or charging events. Take the charging of a PEV as an example: the enabling time, $E^i$, corresponds to the moment in which the driver plugs in the vehicle; the completion time $C^i$ is the time required to fully charge the battery. $C^i$ varies depending on the capacity of the battery installed in the vehicle, and on its state of charge (SOC) at the time the vehicle is plugged in. Deadlines are set by the user and may be the result of a compromise between cost and convenience. In this study it has been assumed that each PEV must finish charging before the next driving event, when possible, while dish-washing and laundry appliances are given an 8-hour window to complete their execution. The maximum
waiting time ($W^i$) is computed as the difference between the time interval between the enabling of the appliance by the user, the deadline at which the appliance must complete its run-cycle ($D^i - E^i$), and the time required to complete the run of the appliance ($C^i$). In summary: $W^i = D^i - E^i - C^i$. A numerical example is given later in the chapter.
The state vector of the optimal control problem is defined as:

\[
x = \begin{bmatrix}
    x_a^1 \\
    \vdots \\
    x_a^N \\
    x_t^1 \\
    \vdots \\
    x_t^{M_{\text{mint}}} \\
    x_t^{M_{\text{mint}}+1} \\
    \vdots \\
    x_t^{M_{\text{mint}}+M_{\text{int}}}
\end{bmatrix} = \begin{bmatrix}
    x_a \\
    x_t
\end{bmatrix}
\] (5.4.1)

where \( \forall j \in \{1, 2, \ldots, N\} \), \( x_a^j \in \{1, 2, \ldots, 9\} \) and \( \forall i \in \{1, 2, \ldots, L_c\} \), \( x_t^i \in \mathbb{N} \).

The first \( N \) components of the state vector, namely \( x_a \), indicates which activity is currently performed by each of the \( N \) household’s members, as predicted by the REES model. All the possible activities have been classified in 9 categories, depending on the corresponding energy use (see Chapter 2 for the details of the behavioral model).

The second part of the state vector, namely \( x_t \), represents the timing dynamics of the controllable appliances.

The dynamics of the state variable and the output function are:

\[
\begin{align*}
    x(k+1) &= f(x(k), k, u(k)) \\
    y(k) &= h(x(k))
\end{align*}
\] (5.4.2)

where \( u(k) \) is the control vector for all the controllable appliances. Accordingly, \( u^i(k) = 1 \) when the \( i^{th} \) appliance is running and \( u^i(k) = 0 \) when it is not.

The dynamics of the first component of the state vector is the following:

\[
x_a(k+1) = A(x_a(k), k)
\] (5.4.3)
where $A$ is a function that represents the heterogeneous Markovian process used in the REES model to simulate the behavior of the household members (see Chapter 2).

The controllable appliances timing dynamics, $x_t$, are different for non-interruptible and interruptible appliances. In the former case, $x_t$ represents a counter that keeps track of the state of the controllable appliance. When $x_t = -\infty$ the appliance has not been enabled by any household member and sits waiting. When it is negative, and finite ($-\infty < x^i_t(k) \leq 0$), its value represents the maximum waiting time before the appliance must start running to satisfy the deadline constraint (time at which the execution of the appliance must be completed). Finally, when the timing state of a controllable non-interruptible appliance has a positive value ($x^i_t(k) > 0$), it represents the portion of the appliance execution that has been already completed, terminating with $C^i$, the completion time required to run the non-interruptible appliance. The timing dynamics for the $M_{nint}$ non-interruptible controllable appliances ($\forall i \in \{1, 2, \ldots, M_{nint}\}$) are given by:

$$
x^i_t(k+1) =
\begin{cases} 
-W^i & \text{if } (x_a(k) = i) \land (u^i(k) = 0) \land (x^i_t(k) = -\infty) \\
1 & \text{if } (x^i_t(k) < 0) \land (u^i(k) = 1) \\
x^i_t(k) + 1 & \text{if } (-\infty < x^i_t(k) \leq 0) \land (u^i(k) = 0) \\
x^i_t(k) + 1 & \text{if } (0 < x^i_t(k) < C^i) \\
-\infty & \text{if } (x^i_t(k) = C^i)
\end{cases}
\quad (5.4.4)
$$

In Equation 5.4.4 $x_a$ is the vector representing the activities in which the $N$ household members are engaged at each time-step. The notation, $(x_a(k) = i)$ is so defined as:

$\exists \ t \in \{1, 2, \ldots, N\}$ such that $x^i_a(k) = i$,

meaning that at least one household member ($t \in \{1, 2, \ldots, N\}$) is performing activity $i$ during time-step $k$.

The first case of Equation 5.4.4 represents the enabling $(x_a(k) = i)$ of a waiting
(i.e. $x^i_t(k) = -\infty$) controllable appliance by a household member. In this case, the control strategy decides not to start running the appliance in this time step ($u^i(k) = 0$). The timing state is set to be the maximum waiting time ($W^i$), computed as the difference between the time interval between the enabling of the appliance by the user, the deadline at which the appliance must complete its run-cycle ($D^i - E^i$), and the time required to complete the run of the appliance ($C^i$). $W^i = D^i - E^i - C^i$.

The second case of Equation 5.4.4 represents the case in which the control strategy decides to start running the $i^{th}$ appliance that was waiting ($u^i(k) = 1$). Independent of the activity component of the state vector ($x_a$), if the appliance timing state was negative in the previous time step ($x^i_t(k) < 0$), which indicates that the appliance was waiting for the control strategy to trigger the run-cycle, the state is set to 1. A constraint is implemented that prevents the control strategy from starting the execution of an appliance that has not yet been enabled ($x^i_t(k) = -\infty$). This case represents the moment in which the management framework decides to start running the controllable appliance.

The third case of Equation 5.4.4 represents the case in which during the waiting time ($-\infty < x^i_t(k) \leq 0$) the control strategy decides not to run the appliance ($u^i(k) = 0$). The value of the state is incremented by 1. These state dynamics simulate a countdown, starting from the maximum waiting time. Once the state reaches the value 0, the control strategy knows that the appliance must start running in the next time-step in order to complete the execution before the deadline. This case does not depend on the activity component of the state vector ($x_a$), meaning that an individual performing again an activity already enabled will not influence the control strategy (i.e. re-enabling a dishwasher before it finishes running will not have any practical effect). Still, the algorithm accounts for multiple household members performing the same activity within the same day by reducing the deadline to accommodate the
additional run cycles (e.g. if two household members perform the laundry activity one 4 hours after the other the first run cycle must be completed in 4 hours).

The fourth case of Equation 5.4.4 represents the case in which the controllable appliance has started its execution. As the appliance is non-interruptible, the value of the timing state is set to increase by 1 at each time step until it reaches the total time required to complete the run of the appliance ($C^i$).

Once the state reaches the value of the completion time (i.e. $C^i$), the state is set to $-\infty$, as reported in the fifth, and last, case of Equation 5.4.4. This is intended to model an unknown waiting time. The state sits at $-\infty$ until the activity is enabled again by a household member ($x_a(k) = i$). Note that whenever a household member enables a controllable appliance, he or she has the possibility of overriding the DEM tool and immediately start the run cycle.

For all the interruptible appliances ($\forall i \in \{M_{\text{int}} + 1, \ldots, M_{\text{int}}\}$), the timing dynamics are divided into two counters, an up counter and a down counter. Equation 5.4.5 explains these counters, as described below.

$$x_{i,1}^i(k + 1) = \begin{cases} x_{i,1}^i(k) & \text{if } (u^i(k) = 0) \\ x_{i,1}^i(k) + 1 & \text{if } (u^i(k) = 1) \\ 0 & \text{if } (x_{i,1}^i(k) = C^i) \end{cases}$$

$$x_{i,2}^i(k + 1) = \begin{cases} -W^i & \text{if } (x_a(k) = i) \land (u^i(k) = 0) \land (x_{i,2}^i(k) = -\infty) \\ -(W^i + 1) & \text{if } (x_a(k) = i) \land (u^i(k) = 1) \land (x_{i,2}^i(k) = -\infty) \\ x_{i,2}^i(k) & \text{if } (u^i(k) = 1) \\ x_{i,2}^i(k) + 1 & \text{if } (u^i(k) = 0) \\ -\infty & \text{if } (x_{i,1}^i(k) = C^i) \end{cases}$$

The first part of Equation 5.4.5, $x_{i,1}^i$, is an up counter that increases whenever the appliance is on (e.g. battery of a plug-in electric vehicle is being charged), until
reaching the completion time $C^i$ required to complete the run-cycle (fully charging PEV battery) of the $i^{th}$ interruptible controllable appliance. When $x^i_{t,1} = C^i$ the job is completed and the states are re-initialized: $x^i_{t,1} = 0; x^i_{t,2} = -\infty$.

The second part of Equation 5.4.5, $x^i_{t,1}$, is a down counter that, starting from the maximum waiting time $-W^i$, increases until reaching the value of 0, threshold at which the appliance (e.g. PEV charging station) must start running in order to complete its run-cycle before the deadline. The count-down state increases by 1 in the time-steps in which the battery is not recharged ($u^i(k) = 0$) in order to decrease the maximum waiting time while it remains constant when the battery is being recharged ($u^i(k) = 1$), as the waiting time before charging must begin remains unchanged.

The first part of the state vector, $x_a(0)$, is initialized in the REES model to reflect actual people behavior, the second part of the state vector is initialized as:

$$\forall i \in \{1, 2, \ldots, M_{\text{mint}}\}, \quad x^i_0(0) = -\infty \quad (5.4.6)$$

$$\forall i \in \{M_{\text{mint}} + 1, \ldots, M_{\text{int}}\}, \quad x^i_{t,1}(0) = 0 \quad (5.4.7)$$

$$\forall i \in \{M_{\text{mint}} + 1, \ldots, M_{\text{int}}\}, \quad x^i_{t,2}(0) = -\infty \quad (5.4.8)$$

Figure 5.3 shows an example of the dynamic evolution of the timing state of one controllable interruptible appliance (e.g. PEV battery charging) in a household composed of one person ($N = 1$ and $M = 1$). The control signal (represented in purple in Figure 5.3) is composed of a sequence of time pulses whose total duration coincides with the $i^{th}$ appliance completion time, namely $C^i$. In this example, the execution of the $i^{th}$ appliance starts after 3 time-steps from the moment in which it had been enabled, and its execution finishes at the deadline.
Figure 5.3: Example of the dynamic evolution of a controllable interruptible appliance timing state. First, the two timing states are initialized: $x_{t,1}(0) = 0$ and $x_{t,2}(0) = -\infty$.

The appliance is enabled by a user at $k = 3$: $x_a(3) = 1$. Following Equation 5.4.5 $x_{t,2}(4) = -W^i$. $u^i$ represents the control signal; in this example the interruptible appliance runs for two time periods: $k = 7, 8, 9$ and $k = 12, 13, 14$. Note that in the time-steps during which the appliance runs $x_{t,1}^i$ is increased by 1 until reaching the completion time $C^i$. The two timing states are then re-initialized.
Table 5.1 summarizes the constants used in the example of Figure 5.3 (numerical values have been arbitrarily chosen to represent a realistic situation). The maximum waiting time, $W^i$, is computed as $W^i = (D^i - E^i - C^i)$. Note that $-W^i \leq x^i \leq C^i$.

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Time-Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W^i$</td>
<td>4</td>
<td>-</td>
<td>Maximum waiting time to start the execution of the $i^{th}$ appliance</td>
</tr>
<tr>
<td>$C^i$</td>
<td>6</td>
<td>-</td>
<td>Completion time required to run the $i^{th}$ appliance</td>
</tr>
<tr>
<td>$E^i$</td>
<td>-</td>
<td>3</td>
<td>Enabling time for the $i^{th}$ appliance</td>
</tr>
<tr>
<td>$D^i$</td>
<td>-</td>
<td>13</td>
<td>Deadline to complete the execution of the $i^{th}$ appliance</td>
</tr>
</tbody>
</table>

Table 5.1: Summary of the constants used in the example of Figure 5.3.

**OPTIMAL CONTROL PROBLEM FORMULATION**

In the preceding section the dynamic energy management model has been introduced, together with the definition of the states and their dynamics. With this background, an optimal control problem, that is the selection of the control sequence $u(k)$ that will result in the minimization of the chosen cost function, can be formulated in the following form:

Evolution of state vectors:  
$$x_t(k + 1) = f_k(x_t(k), u(k))$$

Control constraints:  
$$u(k) \in U_k(x_t(k))$$

Class of policies:  
$$\pi = \mu(0), \ldots, \mu(K - 1)$$

Expected cost starting from $x_t(0)$:  
$$J_\pi(x_t(0)) = \mathbb{E}\{g_K(x_t(K)) + \sum_{k=0}^{K-1} g_k(x_t(k), u(k))\}$$  
(5.4.9)

Optimal cost function:  
$$J_{\pi^*}(x_t(0)) = \min J_\pi(x_t(0))$$
which can be solved by applying the DP method outlined in Section 5.2. The evolution of the states of the appliances \( f_k(x_t(k), u(k)) \) are described in Eq. 5.4.4 and Eq. 5.4.5, which govern the transition of the states of non-interruptible and interruptible appliances, respectively. The control constraints \( U_k(x_t(k)) \) are also different for non-interruptible and interruptible appliances. For a non-interruptible controllable appliance (\( \forall i \in \{1, 2, \ldots, M_{\text{int}}\} \)):

\[
U_k^i(x_t^i(k)) = \begin{cases} 
    \{1\} & \text{if } (0 \leq x_t^i(k) < C^i) \\
    \{0\} & \text{if } (x_t^i(k) = C^i) \lor (x_t^i(k) = -\infty) \\
    \{0, 1\} & \text{if } (-W^i \leq x_t^i(k) < 0)
\end{cases}
\]  

(5.4.10)

where \( x_t^i \in \mathbb{Z} \). This constrains the control \( u \) to be 1 (appliance running) after the execution of the non-interruptible appliance has started (\( 0 \leq x_t^i(k) < C^i \)). The control signal is forced to be 0 (appliance waiting) when the execution is completed (\( x_t^i(k) = C^i \)) or the appliance is not enabled (\( x_t^i(k) = -\infty \)).

The control constraints for an interruptible controllable appliance (\( \forall i \in \{M_{\text{int}} + 1, \ldots, M_{\text{int}}\} \)) is:

\[
U_k^i(x_t^i(k)) = \begin{cases} 
    \{0\} & \text{if } (x_t^{i_1}(k) = -\infty) \lor (x_t^{i_1}(k) = C^i) \lor (x_t^{i_2}(k) = D^i) \\
    \{1\} & \text{if } (x_t^{i_2}(k) = 0) \\
    \{0, 1\} & \text{other cases}
\end{cases}
\]  

(5.4.11)

where \( x_t^i = [x_t^{i_1}, x_t^{i_2}]^T \in \mathbb{Z}^2 \forall i \in \{M_{\text{int}} + 1, \ldots, M_{\text{int}}\} \).

The expected cost \( J \) is represented by \( \pi \), a collection of control policies from \( k = 0 \) to \( k = K - 1 \). In this way, \( J \) conveniently depends only on \( \pi \) and \( x_t(0) \). The DP algorithm computes the optimal policies \( \mu_0, \mu_1, \ldots, \mu_{(K-1)} \) off-line and sends them to each controllable appliance. The appliances find their optimal control \( u^*(k) \) based on their current states \( x_a(k) \), and \( \mu_k \). The cost of the power consumption of the appliances from \( k \) to \( k + 1 \) is described by \( g_k(x_t(k), u(k)) \).
An exogenous signal, sent by the electric utility, is needed as input to the DEM tool. In this case, the price of electricity \( p(k) \) is used to define the function of \( k \in \{0, 1, \ldots, K - 1\} \) in the following form:

\[
g_k(x_t(k), u(k)) = \frac{1}{6} \sum_{i=1}^{M} \{ u^i(k) \cdot p(k) \cdot \Upsilon^i + \Phi(k) T_i^* \}
\]

where \( \Upsilon^i \) is the wattage of the \( i^{th} \) appliance, expressed in [W]. \( \Phi^i \) is a term that represents the monetary value of the waiting time, expressed in [$/h], namely the value a user gives to the time he or she has to wait before a controllable appliance finishes its running cycle after being enabled. Since the problem has been implemented on a 10-minute time basis, the term \( \frac{1}{6} \) is used to convert the electric energy consumption to [kWh]. The term \( \Phi \) can be seen as a flexibility factor capturing the willingness of a user to delay the appliances’ execution in order to save money. \( T_i^* \) represents the time to be waited until the execution of the \( i^{th} \) appliance is started. The second term in the cost function increases as \( \Phi \) increases and as the time that the users have to wait increases. Note that this term is non-zero only when \( k = T_i^* \).

The cost function described by Equation 5.4.12 represents a scenario in which electric utilities send electricity price signal to residential customers as a way to steer the demand. Each consumer sees the same price and tries to optimally manage his/her electricity consumption to minimize cost without undue inconvenience. The electric utility uses the electricity price as a signal to re-shape the aggregate demand and operate the overall power system in a more efficient and cost-effective way. In this approach, electric utilities are giving an economic incentive to their customers to change their consumption pattern so as to obtain an aggregate demand that more easily matches the needs of the power generation, and that eventually brings the utility a monetary benefit greater than the total incentive provided.

The cost function described in Equation 5.4.12 is general and is intended to capture a variety of different scenarios. The signal sent by the electric utility (electricity
price, \( p(k) \)) can reflect not only the cost of generating electricity, but also other pertinent quantities. The selection of a price signal could, for example, be driven by a number of policy- or economics-driven incentives.

Among the possible options, consider the effect of a carbon tax: a tax levied on the carbon content of the fossil fuels used to produce electricity. In this case, electricity generators are charged an extra cost proportional to the amount of \( \text{CO}_2 \) emitted in generating electricity. This cost can be included in the retail price sent to the residential customers \( (p(k)) \), that are indirectly responsible for the carbon emission. Currently, there is no nationwide carbon tax leveled in the United States, although a few states and localities have introduced such a tax. In a similar fashion, the electric utilities could indirectly cause the residential consumers to respond to a signal designed to reward specific sources, such as low-carbon sources, renewables, or others.

The term \( \Phi \) is seen as a flexibility factor that the user can exploit to leverage his/her attitude towards deferring controllable appliance execution. Demand response models are based on the assumption that consumer demand is elastic and, thus, that consumers will respond to higher prices by reducing or shifting demand. Studies have shown that under certain conditions and in some markets this is the case. Espey and Espey [50] summarize several studies of residential electricity demand elasticities, confirming the elasticity of residential demand for electricity in the United States. Caves and Christensen [51] use data from five experimental implementations of residential TOU rates in the United States, and concluded that customers responded to higher prices during the peak period by reducing peak period usage and/or shifting it to less expensive off-peak periods. The results were consistent around the country. Furthermore, Faruqui and Sergici report that several studies have consistently demonstrated that direct feedback alone (namely informing the residential consumer
of high generation cost during peak periods) motivates behavior change, resulting in energy savings ranging up to 20 percent [52].

Currently, no definitive information is reported in the literature on the attitude of American customers towards deferring controllable appliance execution, and the associated inconvenience cost perceived by residential customers. In this study, this is controlled by the term \( \Phi \), which remains a subjective choice of each residential customers. A comparative analysis of the effects of \( \Phi \) is reported in Section 5.5. The term \( \Phi \) is set to be 0 in the remainder of this work, assuming that residential customers are willing to relinquish control to the DEM tool, as long as the constraints are respected (PEV charged before the following trip, and other controllable appliances complete their run-cycle within 8 hour from the enabling time). This term is included in the cost function for generality, and its importance is expected to increase as residential demand response programs are more broadly deployed.

Starting from the formulation defined in Equation 5.4.9, the optimal control for every possible state-time pair can be found. The optimal control policy \( \mu^*(k, x_t(k)) \) is defined as the optimal control \( u^*(k) \) with the initial state being \( x_t(k) \), and it is found by solving the cost-to-go function, \( V_k(x_t(k)) \):

\[
V_k(x_t(k)) = \min_{u(i) \in U(x_t(i)), k \leq i \leq K-1} E \left\{ g_K(x_t(K)) + \sum_{i=k}^{K-1} g_k(x_t(i), \mu(i, x_t(i))) \right\} \\
= \min_{u(k) \in U(x_t(k))} E \left\{ g_k(x_t(k), \mu(k, x_t(k))) + V_{k+1}(f_k(x_t(k), \mu(k, x_t(k)))) \right\}
\]

(5.4.13)

Note that the DP method solves \( \mu^*(k, x_t(k)) \) backward in time. The cost-to-go function – \( V_K(x_t(K)) \) – is exactly \( g_K(x_t(K)) \). Since each controllable appliance is required to complete its run-cycles before the end of the simulation, in case \( \exists \ i : U_{K}^{i}(x_t^{i}(K)) \neq \{0\}, \) then \( g_K(x_t(K)) \) is set to \( \infty \). This satisfies \( U_{K}^{i}(x_t^{i}(K)) = \{0\}, \forall i \in 192 \).
\{1, 2, \ldots, M_{\text{int}} + M_{\text{int}}\}, meaning that in the last time-step of the simulation \((k = K)\) all the controllable appliances must have completed their run-cycles or be inactive. For those \(x_t(K)\) such that \(g_K(x_t(K)) < \infty\), \(g_K(x_t(K))\) is set to be zero. The algorithm proceeds from \(k = K - 1\) to \(k = 0\) considering every possible state \(x_t(k)\) per each time-step \(k\). Thus, the optimal control policy \(\mu^*(k, x_t(k))\) for every state-time pair is found. Given the optimal policy \(\mu^*(k, x_t(k))\), the optimal control sequence for every possible state-time pair is then derived. Starting from the initial state \(x_t(0)\), the optimal control is found to be \(u^*(0) = \mu^*(0, x_t(0))\). The state vector at the next time step is computed by the state evolution equation: \(x_t(1) = f_0(x_t(0), u^*(0))\). The optimal control signal at the following time-step \((k = 1)\) is then \(u^*(1) = \mu^*(1, x_t(1))\). This process is repeated recursively to find the optimal control sequence that minimizes the expected cost \(J_\pi(x_t(0))\), which is found to be: \(\{u^*(0), \ldots, u^*(N - 1)\}\).

The proposed automated optimization framework finds the optimal schedule for all the controllable appliances so as to minimize the cost function—based on the dynamic programming algorithm. The framework is based on the highly-resolved modeling of household members behavior and related electricity consumption presented in the previous chapters. The management framework proposed is flexible enough to accommodate different cost functions and electricity price structures.

5.5 Results

This section reports results on the application of the proposed dynamic energy management framework to a single residential energy eco-system. Large scale simulations of a group of residential energy eco-systems and related results, together with an evaluation of the overall impact of demand response programs, are reported in Chapter 6.

The developed dynamic management framework is flexible and allows for the simulation of different scenarios, cost functions, and electricity price structures. In
the following, the term \( \Phi \) in the cost function reported in Equation 5.4.12 is set to 0, assuming that the consumers decide to add no cost associated with the waiting time, letting the energy management tool optimally schedule the controllable appliances. Still a set of constraints is used to guarantee consumer convenience: non-interruptible appliances (laundry and dish-washing) are constrained to complete their running-cycles within 8 hours from the enabling time; and PEVs are fully charged before the following trip (as simulated by REES model), whenever possible. The underlying assumption is that residential customers are willing to participate in demand response programs, namely consumers will respond to higher prices by reducing and/or shifting demand. Several empirical evidence support such an assumption [56, 54, 69, 51, 50, 52, 61]. Espey and Espey [50] summarize several studies of residential electricity demand elasticities, confirming the elasticity of residential demand for electricity in the United States. Caves and Christensen [51] use data from five experimental implementations of residential TOU rates in the United States, and concluded that customers responded to higher prices during the peak period by reducing peak period usage and/or shifting it to less expensive off-peak periods. The results were consistent around the country. Also, some additional incentive (monetary or in terms of service quality) may be provided by the electric utilities.

When finding the optimal schedule for the controllable appliances, more than one solution may result in the same minimum cost. If this is the case, the DEM framework implemented in this study schedules the controllable appliances to run as early as possible during lowest price periods. This is illustrated in Figure 5.4, that shows an example of optimal scheduling of one laundry run-cycle given a time-varying electricity price. Note that the laundry activity cannot be interrupted once started.

Moreover, the laundry activity presents a multi-power run-cycle. Namely, the activity is divided into two parts: 30 minutes of washing cycle, which uses 425 W,
followed by 60 minutes of drying, which uses 3400 W (as reported in Chapter 3). Therefore, the part of the run-cycle corresponding to the higher power consumption must be scheduled during lowest electricity price periods. This is illustrated in Figure 5.5, where a short price drop is simulated.

As expected, the proposed DEM schedules the laundry activity so that the most power-intensive part of the run cycle occurs during the price drop, minimizing the total cost.

Figure 5.6 reports an example of optimization of a residential eco-system composed by a working couple and two children with one PEV under a 2-tier TOU electricity price. Simulation results are reported for a period of one week. For the purpose of this example, the electricity price has been chosen to be 18 c/kWh between 7 a.m. and 10 p.m. (high daily price), and 7 c/kWh between 10 p.m. and 7 a.m. (low night price).

As expected, the deferrable loads are postponed to periods of low electricity price,
resulting in a total monetary saving of about 10% compared to the non-optimized case (still applying the 2-tier TOU electricity price), which is in line with what reported in the literature [56]. The saving heavily depends on the price structure selected (namely the price of electricity during day-time and night-time).

Figure 5.7 reports the weekly cumulative electricity-related monetary expenditure for the same residential eco-system reported in Figure 5.6. Three scenarios are shown in the figure: first a flat electricity rate of 14 c/kWh is considered, representing the current reference scenario. Then the 2-tier TOU electricity price is introduced both in case of non-optimized system and applying the dynamic energy management strategy.

From Figure 5.7 it appears that the introduction of TOU electricity rates might lead to a higher expenditure, if electricity consumption is not somehow optimized, while the optimization algorithm allows for a cost reduction. These results are dependent on the specific price structures, that must therefore be carefully chosen. Such a tool can be used to compare and qualitatively evaluate different electricity price structures.
Figure 5.6: Example of dynamic energy management of a REES composed of 4 people under 2-tier electricity price.

Figure 5.7: Cumulative electricity-related economic expenditure.
Figure 5.8 shows the same example reported in Figure 5.6 when real-time electricity price is adopted. Real-time marginal generation cost has been taken from PJM\textsuperscript{6} for the simulated week to approximate the real-time price seen by consumer.

![Figure 5.8: Example of dynamic energy management of a REES composed of 4 people under real-time electricity price.](image)

Again, results shown that the introduction of the DEM tool is effective at shifting the demand towards periods of low electricity price. In this example the electricity expenditure is reduced by about 15\% by introducing dynamic energy management, while guaranteeing that the PEV is fully charged before the following trip and smart appliances complete their running within 8 hours from the enabling time.

\textsuperscript{6}PJM is a regional transmission organization that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia. Daily real-time electricity prices are freely available for download at: http://www.pjm.com/markets-and-operations/energy/real-time/lmp.aspx
Even though such an economic saving might not impact substantially the single household’s energy-related expenditures (in the United States with current energy prices), the savings are substantial when considering widespread adoption of demand response programs (see Chapter 6 for large-scale simulations and results). More importantly, electricity cost and generation capacity requirements are driven by demand that occurs during peak periods, therefore even a small change in such a demand would be extremely beneficial for electric utilities and could help operate the whole system in a more efficient and economic way. For example, it is estimated that a 5% demand reduction would have resulted in a 50% price reduction during the peak hours of the California electricity crisis in 2000/2001 [26]. Incentives and rebates from electric utilities are needed to favor the adoption of residential demand response programs.

The proposed dynamic energy management framework has been implemented in the MATLAB® environment. The simulations shown in Figure 5.6 and Figure 5.8 have been performed using an Intel® CORE™ i5-2430M CPU @2.40 GHz and 8 GB of RAM. The DP implementation took about 70 seconds to find the optimal schedule of controllable appliances and PEV charging for one week. Finding the optimal energy management strategy for a REES without PEVs requires about 10 seconds per week. This framework is not intended for real-time implementation and can be used as a tool to evaluate opportunities related to residential energy management and demand response. The optimized policy is computed off-line and the time requirement is acceptable for the application proposed.

**PARAMETRIC ANALYSIS OF THE TERM Φ IN THE COST FUNCTION**

The impact of the monetary value given to the time that a user must wait for the completion of deferrable activities is analyzed in this section. The term Φ in the
cost function (Equation 5.4.12) represents the monetary value (in \[$/h\]) given by a user for the time that has to be waited before a controllable appliance completes its running cycle. This term is added to the cost of the electricity consumed. Figure 5.9 reports a comparison of the electricity cost and waiting time required for charging a PEV battery as different monetary values are given to the waiting time (different values of $\Phi$).

![Graph comparing electricity cost and waiting time](image)

*Figure 5.9: Comparison of price and waiting time for the charging of a PEV as function of the monetary value given to the waiting time, $\Phi$."

From Figure 5.9 it appears that when no value is given to the waiting time ($\Phi=0$), the electricity-related expenditure are kept at a minimum but almost 8 hours are required to fully charge the vehicle. As more value is given to the waiting time, the energy management schedules the PEV to be charged sooner, bearing higher electricity prices and incurring higher electricity expenditures. The term $\Phi$ can be
seen as a flexibility factor selected by the user to trade-off between expenditure and convenience (appliances complete their run-cycles sooner). The trend in Figure 5.9 depends on the price of electricity. For the purpose of this simulation, real-time marginal generation cost has been taken from PJM to approximate real-time prices seen by the consumer. In this example, the real-time price for the period between 6 p.m. and 2 a.m. has been taken. The price changes on an hourly level, explaining the jumps in price.

The selection of $\Phi$ is a subjective choice of each residential customers. The term $\Phi$ is set to be 0 in the remainder of this study, assuming that residential customers are willing to relinquish control to the dynamic energy management tool, as long as the constraints are respected.

5.6 Conclusions

This chapter describes the development of a dynamic energy management framework aimed at optimally managing deferrable loads in a single residential energy eco-system. This includes all controllable appliances and charging of PEVs, when present.

Residential energy eco-systems capture the entire energy footprint of individual households, to include all appliances, HVAC systems, in-home charging of plug-in electric vehicles, and any other energy needs, viewing residential and transportation energy needs as an integrated continuum.

The proposed automated management framework is based on highly-resolved personal energy consumption models developed using a novel bottom-up approach that quantifies consumer energy use behaviors. The incorporation of stochastic consumer behaviors will provide more accurate estimation of the actual amount of available
controllable resources in the population, and hence enables better interactions with the grid.

The dynamic energy management framework is automated, decentralized (each single household receives the same signal from the electric grid, and independently optimizes its own demand), and non-disruptive, in the sense that it does not require changes in people’s behavior to optimally manage the energy consumption inside the eco-system.

Dynamic programming is used to find the optimal solution for the energy management problem. The algorithm proposed is flexible and robust and can include different cost functions and electricity price structures. This work is the first that systematically considers stochastic correlations among different end-use activities in the design of an energy management framework.

Examples are reported for the application of the dynamic energy management with time-varying electricity price. Results show that the introduction of the dynamic energy management tool is effective in shifting the demand towards periods of low electricity price.

This framework can serve as a tool to evaluate the impact of residential and personal transportation automated demand response. Also, trade-offs between cost and waiting time can be evaluated from a user perspective.

In particular, the dynamic energy management framework presented in this chapter is applied in the following chapter to perform large scale simulations aimed at simulating and studying residential demand response programs, and evaluate their impact on the electric power infrastructure.

Electric utilities can use demand response programs to improve the operation of the electric power system in several ways, including reducing electricity generation
and grid operation costs and managing demand peaks. The dynamic energy management tool presented in this chapter is used as a tool to better understand large-scale and local impact of residential demand response programs. It can serve as a tool to compare different alternative scenarios and quantitatively evaluate the effect of alternative electricity price structures, thus providing guidance and advice to electric utilities.
Chapter 6

RESIDENTIAL ENERGY ECO-SYSTEMS (REES):
LARGE SCALE SIMULATIONS

In this chapter the residential power demand model and the personal transportation energy consumption model presented in Chapter 3 and Chapter 4, respectively, are integrated to simulate the energy use in a Residential Energy Eco-system (REES). Figure 6.1 shows a representation of a REES. The REES model captures the entire energy footprint of an individual household, viewing the residential and personal transportation energy consumption as a continuum.

Section 6.1 details the integration of the residential power demand model and the personal transportation energy consumption model. Moreover, in this chapter large-scale simulations of groups of REESs are performed to simulate aggregate-level results and allow for evaluating the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand. To simulate a group of REESs representative of the current status quo of the residential and transportation sector in the United States, detailed information on household characteristics are needed. Such information appear in the Residential Energy Consumption Survey (RECS), described in Appendix A. Section 6.1 of this chapter reports on the use of the information included in the RECS data set as input to the REES model.

The dynamic energy framework presented in Chapter 5 is applied to manage the energy consumption of each REES, finding the optimal schedule for all the controllable
appliances and in-home charging of plug-in electric vehicles to minimize the chosen cost function. Details on the use of the dynamic energy framework in large-scale simulations are reported in Section 6.2, together with considerations on residential demand response programs.

Furthermore, two case studies are reported in this chapter: the first considers the impact of market penetration of plug-in electric vehicles on the electric grid and the second provides a quantitative comparison of the impact of different electricity price structures on residential demand response. These case studies appear in Section 6.3 and Section 6.4, respectively. Executive summaries of the two case studies are provided in Appendix C and Appendix D, respectively. Concluding remarks are provided in Section 6.5.
6.1 Large-Scale Simulations: Model Integration and Input Parameters

The residential power demand model and the personal transportation energy consumption model presented in Chapter 3 and Chapter 4, respectively, are integrated to simulate a Residential Energy Eco-system (REES). The integrated model proposed in this study captures the entire energy footprint of an individual household, to include all appliances, HVAC systems, in-home charging of plug-in electric vehicles, and any other energy needs, viewing residential and transportation energy needs as an integrated continuum.

The REES model is based on a novel bottom-up approach that quantifies consumer energy use behaviors. The development of integrated energy consumption models allows for the simulation of different “what-if?” scenarios and the evaluation of technology adoption, so as to provide answers and guidance towards a sustainable future for energy systems.

Figure 6.2 shows a scheme of the sub-components included in the REES model, their connections, and the inputs required for the development and calibration of the modeling proposed in this study.

The REES model is highly-resolved, generating electricity consumption profiles with a time resolution of 10 minutes. Also, fossil fuel consumption for space heating and personal transportation is computed.

The behavioral model, introduced in Chapter 2, is a heterogeneous Markov chain that generates highly-resolved activity patterns of different Americans. Five agent types are included in this study, capturing differences in behavior and related energy use. Such agent types are: working and non-working male, working and non-working
female, and child. Also, differences between weekdays and week-ends and the influence of time of day on the behavior of individuals are both considered in the model. The American Time Use Survey (ATUS) is used to calibrate the Markovian model (see Section 2.2).

The activity patterns generated by the Markov chain are used as input to both the residential power demand model and the personal transportation energy demand model to capture the precise time of energy consumption of different activities.

The personal transportation energy demand model (presented in Chapter 4) generates highly-resolved consumption profiles for personal transportation in the United States.
States. In particular, for plug-in electric vehicles, the model predicts residential charging events that add to the residential electricity demand.

The behavior of drivers, as predicted by the behavioral model, is used to establish when driving (and charging) events occur over the simulation time horizon, and the duration/length of each event. Once each driving event is known, a stochastic tool calibrated with driving data collected at The Ohio State University - Center for Automotive Research, is used to generate realistic driving profiles for each driving event. Profiles are representative of actual usage of passenger vehicles (real-world driving profiles). These profiles are used in a backward dynamic simulator (see Section 4.4) to predict energy consumption, and therefore the electrical energy required when PEVs are charged.

The personal transportation energy demand model takes as inputs the number and type of vehicles present in a specific household, and their characteristics (e.g., curb weight, frontal area, battery capacity, etc.). Six vehicle types are considered in this study: conventional gasoline vehicles, compressed natural gas vehicles, hybrid electric vehicles, plug-in hybrid electric vehicles (with two different battery capacities), and battery electric vehicles. Average characteristics of these vehicles are assumed to represent passenger vehicles currently available in the market.

To simulate the electricity demand of a specific household, the residential power demand model (presented in Chapter 3) requires as inputs characteristics of the dwelling (e.g., size, building materials, heating equipment, desired temperature inside the house, appliances’ characteristics, etc.) and weather data. The former are taken from the Residential Energy Consumption Survey (RECS), and weather data are taken from the National Climatic Data Center (see Chapter 3 for more details).

The residential power demand model is able to simulate the power demand of
a household consisting of multiple individuals, considering cold appliances, HVAC systems, lighting, and activity-related power consumption.

To simulate a group of REES representative of the current status quo of the residential and transportation sector in one region of the United States, detailed information on household characteristics in that region are needed. Such information are reported in the Residential Energy Consumption Survey (RECS), described in Appendix A.

To simulate aggregate energy consumption of a group of household a subset of households can be randomly selected among the ones available in the RECS data, and their characteristics are used as input parameters to the demand model developed in this study. This allows for reconstructing the aggregate demand of a specific region of the United States.

6.2 Aggregate Results and Considerations on Residential Demand Response Programs

The REES model generates highly-resolved electricity consumption profiles with a resolution of 10 minutes. Large-scale simulation can be performed to reconstruct the power consumption of an aggregate group of households with desired characteristics and composition.

Section 6.3 reports a case study to illustrate the use of the proposed REES modeling, where large-scale simulations are performed to evaluate the impact of in-home recharging of PEVs on the electric grid, both at the aggregate and local levels. The case study includes a literature review on the topic, and simulation results.

In this first case study, no control nor coordination is used to manage vehicle charging, so as to evaluate the impact of PEV adoption in a scenario in which a
smart grid has not been fully deployed. Each PEV is charged as soon as connected to the grid, until the battery is fully charged. The amount of electricity required to fully charge the battery depends on the previous trips and charging events, which are accounted for by the personal transportation energy demand model.

When performing large-scale simulations, the dynamic energy management framework presented in Chapter 5 can be used to manage the energy consumption of each REES, finding the optimal schedule for all the controllable appliances and in-home charging of plug-in electric vehicles to minimize the chosen cost function. This approach simulates widespread adoption of residential demand response programs, and permits simulating, studying, and evaluating the impact of residential demand response programs on the electric power infrastructure.

Section 6.4 reports a second case study aimed at simulating the impact of residential demand response programs on the aggregate electricity demand, and at quantitatively comparing different electricity price structures. Also, an innovative electricity price structure is proposed in this case study.

Electric utilities can use demand response programs to improve the operation of the electric power system in several ways, including reducing electricity generation and grid operation costs and managing demand peaks. Time-varying rate plans have been proposed by electric utilities with the objective of re-shaping the demand. As of today, these plans have been successfully implemented in relatively small-scale pilot programs with a low degree of automation. Nevertheless, the use of time-varying electricity price structures could lead to undesired rebound effects in case of widespread adoption of demand response programs, together with automated energy management systems. Previous studies suggest that there is a threat of rebound peaks in which consumers delay their demands to avoid a peak, but cause a new peak when trying to satisfy delayed demand [205, 206, 208]. This study confirms
that when each household independently optimizes its demand leveraging off-peak electricity prices in order to reduce its own cost, the resulting aggregate demand may be affected by an even higher rebound peak shifted toward the off-peak period.

The case study reported in Section 6.4 illustrates the use of the proposed REES model coupled to the dynamic energy framework presented in Chapter 5 to investigate residential demand response programs. The case study includes a quantitative comparison of different electricity price structures. Section 6.4 also proposes an electricity price structure, called Multi-TOU, that solves the issues related to rebound peaks created by traditional time-varying electricity pricing.

A review of the substantial body of literature on residential Demand Response (DR), indicates that a further exploration of this topic is warranted. The goal of DR programs is to influence consumers to change their electricity consumption patterns, or demand, in response to the needs of the supplier [48]. Demand response models are based on the assumption that consumer demand is elastic and, thus, that consumers will respond to higher prices by reducing demand. Studies have shown that under certain conditions and in some markets this is the case [50, 51, 52, 62, 66, 56, 67, 61]. Cappers and his colleagues [62] found that DR programs have significant potential in terms of peak load reduction.

Residential demand response programs can be classified into incentive-based and price-based programs [48, 53]. Both are established by electric utilities to change consumption patterns by effectively changing the cost of electricity for consumers. Consumers are not likely to be the drivers for the adoption of these technologies, as the monetary savings are not dramatic. On the other hand, the aggregate impact can be significant, and noteworthy opportunities arise for electric utilities, especially to alleviate capacity constraints and deal with peak demand management. Thus, electric utilities can provide further economic incentives and benefits to customers.
participating in such programs. Other than overall reduction of electricity-related expenditures, residential customer would also benefit from a series of advantages deriving from a better operation of the system, including reduced power sags and interruptions, better service continuity and reliability, and improved power quality (reduced voltage and frequency variations and transients phenomena).

Incentive-based demand response programs provide financial compensation to consumers to shift their consumption. Price-based programs provide a varying electricity price that is intended to be a signal to guide consumer consumption to better match generation. Consumers voluntarily adjust their electricity consumption based on time-based electricity prices, typically Time of Use pricing (TOU), Real Time Pricing (RTP) or a Critical Peak Pricing (CPP).

Smart grid technologies are enablers that permit scheduling loads at the consumer level to save energy, reduce cost, and help grid operation; however, a residential automated Energy Management System (EMS) is needed to fully manage such an advanced integrated system [98]. Demand-side EMSs must allow consumers to compare costs/benefits with different load schedules and automatically make decisions to optimize energy use in the household. As the United States evolves towards a future smart grid, demand-side management will play a key role to help reduce peak load, increase reliability, and allow more widespread integration of fluctuating renewable energy sources [217]. The dynamic energy management framework presented in Chapter 5 is used in this study to simulate a residential automated EMS.

The use of smart grid technologies requires that the consumer relinquish some operational control, at least within certain limits. For instance, the consumer can request that a dishwasher runs sometime during the night so as to complete its cycle by 7 a.m. when the consumer wants to use the dishes. Many consumers are ambivalent as to when the dishwasher cycle occurs during the night, as long as the end-time
constraint is met. The EMS schedules the run cycle to meet the constraint of the end
time and optimize the energy use, namely, minimizing a cost function. This type of
operation is known as a demand response program because the demand responds to
the needs of the power generation.

Many consumers have expressed an interest in and support for smart meters, smart
appliances, and other smart grid technologies. On the other hand, many have also
expressed significant reservations about relinquishing control of the operation of their
appliances to an external controller, even when they have the ability to override this
external control [232, 233]. Consumers have also expressed concerns about privacy
issues as consumption data and patterns are transmitted to the electricity supplier
[234]. Due to consumer concerns and the limited deployment of infrastructure, the
deployment and implementation of smart grid technologies have been generally lim-
ited to one-way communication, where electric utilities send some sort of signal to
customers, typically a sub-hourly electricity price at 10- or 15-minute intervals. In
such a scenario, control and operation of smart appliances remain with the consumer.
Consumption can be locally shifted or reduced in response to the price signal, but the
electricity provider is still obliged to meet load demand and cannot directly control
or alter it.

The relinquishment of the control and convenience of starting and using the ap-
pliance at one’s own discretion typically requires some sort of an incentive, since
consumers are often unwilling to change their electricity consumption voluntarily
[235]. Several different incentives are proposed and tested, including a) compensat-
ing customers for reducing their electric demand in case of a grid contingency, b)
sending consumers signals to encourage them to reduce demand during peak hours,
c) initiating brief grid-initiated curtailment events with very short notification. The
latter are typically 10 to 30 minute reductions with a 10-minute warning and qualify
as *ancillary services*\(^1\), which help the grid operator to maintain reliable operations of the electric system.

One of the most common forms of incentive is to provide a tiered pricing system, where electricity prices are lower during low-use times. The EMS would then automatically delay the consumption of electricity to minimize the overall cost of electricity for the consumer. By introducing automatic energy management, the expectation is that the electric power system would operate more efficiently. That is, that the electricity demand can be better coupled with generation, so as to reduce the peak demand and reduce the need for higher-cost capacity.

The modeling proposed in this study allows for exploring the implications of residential demand response, considering the impact of time-varying tiered pricing on residential demand response. The goal of the simulations presented in this chapter, and in particular of the case study in Section 6.4 is to assess the impact of decentralized residential demand response. That is, each single customer optimizes energy consumption so as to minimize cost, while also minimizing the disruption and interference with individual decisions. The impact of electricity price structures on the aggregate residential demand is analyzed and quantitatively assessed via large-scale simulations.

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\(^1\) The United States Federal Energy Regulatory Commission (FERC) defines the ancillary services as: “those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system”.

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6.3 Case study 1: Impact of Plug-in Electric Vehicles on the Electric Power Infrastructure

Among the currently available options for alternative propulsion, electricity seems the most promising, in that a) it addresses the simultaneous need for fuel diversity, energy security, reductions in greenhouse gas emissions, and improvements in air quality, and b) it is widely available and produced domestically. Moreover, vehicle electrification has proven to substantially improve vehicle efficiency and reduce CO$_2$ and pollutants emissions [7].

Vehicles that use electricity as a propulsion source are called Plug-in Electric Vehicles (PEVs). A PEV is defined by the U.S. Department of Energy as a vehicle that draws electricity from a battery with a capacity of at least 4 kWh and is capable of being charged from an external source [185]. The definition of PEV includes Plug-in Hybrid Electric Vehicles (PHEV) and Electric Vehicles (EV), also called battery electric vehicles or purely electric vehicles.

PHEVs are vehicles that run using fossil fuels, electricity, or a combination of both, leading to a great level of flexibility and to a variety of advantages. Energy is stored on-board both in a battery pack and in a fuel tank. One or more electric motors and an internal combustion engine are used to power the vehicle.

EVs are vehicles that store electricity on-board in a battery pack and are powered by one or more electric motors. Electricity drawn from the grid is the only energy carrier present on board, and once the state of charge of the battery reaches a minimum value the vehicle shuts down, limiting the total range of the vehicle. Typical electric vehicles have a range of 100 to 180 miles (161 – 290 km), depending on the characteristics of the vehicle (such as curb weight, frontal area, etc.) and on the size of the battery pack installed.
PEVs represent an additional electric load that affects the operation of the electric grid. While several studies analyze technical and economic benefits of PEVs, it is also important to understand what impact PEVs will have on the electric power generation, transmission, and distribution infrastructure.

In this section, a case study is presented that uses the modeling proposed in Chapters 3 and 4 to evaluate the impact of in-home recharging of PEVs on the electric grid, both at the aggregate and local levels (impact on electricity generation and distribution infrastructure, respectively).

In this case study, no control nor coordination is proposed for vehicle charging, so as to evaluate the impact of PEV adoption in a scenario in which a smart grid has not been fully deployed. Each PEV is charged as soon as connected to the grid, until the battery is fully charged. The amount of electricity required to fully charge the battery depends on the previous trips and charging events, which are simulated by the personal transportation energy demand model presented in Chapter 4.

This section is structured as follows: Subsection 6.3.1 reports a review of the existing literature on the topic. The aggregate impact of PEVs on the electric power generation infrastructure is evaluated in Subsection 6.3.2, and Subsection 6.3.3 reports on the local impact on the residential electric power distribution infrastructure. Concluding remarks are provided in Subsection 6.3.4. An executive summary of this case study is provided in Appendix C.

6.3.1 Review of the Existing Literature

Several works in the literature attempt to evaluate the overall impact of plug-in electric vehicles on the electric power infrastructure.

Liu et al. survey the impact of PEVs on electric utilities [236]. They report that although PEV charging demand on overall power generation capacity may not be
significant, the possible impacts on power delivery systems, especially the distribution system, can be an issue if the charge is totally uncontrolled.

Galus et al. [237] and Srivastava et al. [238] analyze general challenges, opportunities, and policy options for integrating PEVs into the electric grid. Galus et al. [237] focus on long- and short-term planning activities. Techno-economic issues of plug-in electric vehicles and their options to connect to the power grid within a system-level view are reviewed by Srivastava et al. [238]. In both papers the potential of coordinated charging and vehicle-to-grid (V2G) services is stressed, including considerations on the policies needed to integrate such services in the electricity market.

In V2G applications, the vehicles can discharge as well as charge, and this can be exploited by owners of PEVs to generate revenue by taking advantage of fluctuating electricity price and providing high-value electric system services. This integrates in energy policies aimed at moving towards distributed power generation and storage.

The National Renewable Energy Laboratory (NREL) concluded in 2006 that large-scale deployment of PEVs will have limited, if any, negative impacts on the electricity generation infrastructure [191]. According to their study, even though a high penetration of PEVs (up to 50% market share) would lead to a significant increase in the system minimum load, the majority of PEV charging energy would be still supplied by base-load units. Only a very small amount of electricity would be provided by intermediate load plants, mostly during summer nights when air-conditioning demand stays high until late in the evening. In particular, at 50% PEV market share, more than 80% of the charging electricity is derived from units meeting the bottom two-thirds of the load duration curve.\(^2\) Therefore, there would be no need

\(^2\)A load duration curve is used in electric power generation to illustrate the relationship between generating capacity and capacity utilization. It is similar to a load curve but the demand data are ordered in descending order of magnitude, rather than chronologically. The load duration curve shows the utilization of each increment of capacity.
for installing additional generation capacity. According to these results, the presence of PEVs would positively impact the electric power system by increasing the overall load factor.

In all regions of the U.S. considered in the study by NREL, the increase in total electric demand stays below 5% for a PEV market share up to 25%, and below 10% for a PEV penetration of 50% [191].

The Electric Power Research Institute (EPRI) concluded in 2007 that if PEVs displaced half of all vehicles on the road by year 2050, they would require only an 8% increase in electricity generation (4% increases in required capacity) [239].

Even though the impact of PEVs on electric power generation and transmission is expected to be minimal, local distribution is the part of the electric infrastructure that can be adversely affected by PEV charging. Several studies focus on the impact of PEV charging on the electric distribution network [240, 241, 242, 243, 244].

Green et al. [240] propose a review and outlook of the impact of PHEVs on the electricity distribution network. The authors identify the key factors needed to determine the impact of PHEVs on the distribution network as: driving patterns, charging characteristics, charge timing, and PHEV adoption. In the paper, average mileage driven during any given day and random location of PEVs during charging events are used to capture the impact of driving patterns. Different scenarios for charge characteristics (charging level) and charge timing are considered, without any precise justification. Finally, assumptions are made for PEV market share and average data are used to estimate load increase due to PEV adoption. Overall, the authors underline the need for further research to assess the main factors influencing the impact of PHEVs on the distribution network.

In the present study, the impact of driving patterns and charging time is captured by the personal transportation energy consumption model presented in Chapter 4,
allowing for a more precise estimation of the impact of PEVs on the electric distribution infrastructure. Also, detailed vehicle models are used to compute energy consumption of PEVs on real driving conditions. Assumptions are made only for vehicle adoption (market share of PEVs) and charging infrastructure availability.

Clement-Nyns et al. [241] propose the use of coordinated charging to minimize the impact of PHEVs charging in terms of transformer and feeder overloads, power losses, and power quality (e.g. voltage profile, unbalance, harmonics, etc.) with the objective of maximizing the main grid load factor. In this paper unidirectional energy flow is considered, and no vehicle-to-grid application is explored. Power losses and voltage deviations are reported for uncoordinated charging of PHEVs, given hourly trip distribution and assuming that vehicles are charged during fixed time windows and are completely discharged when plugged-in. Also, average residential loads are assumed.

Results indicate that improvements can be achieved using coordinated charging (sending signals to each individual vehicle). In this scenario owners of PHEVs can only select the point in time when the batteries must be fully charged. In the paper the optimal charging profile of PHEVs is computed by minimizing the power losses. Both quadratic programming and dynamic programming are proven to be effective tools to solve this problem. Stochastic programming is also introduced to represent an error in the forecasting which increases the power losses, as no forecasting tool for the residential loads is used in the paper. Impact of a 30% market share of PHEVs on the distribution infrastructure is given for the average of 1000 samples: uncoordinated charging increases the peak load by 57%, while in case of coordinated charging the peak load is increased by 9%.

Clement-Nyns et al. [241] conclude that coordinated PHEV charging can lower power losses and voltage deviations by flattening out peak power. However, when the
choice of charging periods is rather arbitrary, the impact of the PHEV penetration level can still be significant. These results are based on average assumptions regarding residential and PHEV charging demand (e.g. daily mileage driven).

Pieltain Fernández et al. [242] study the impact of PEVs on large-scale real distribution networks, including over 61000 customers. The authors assumed that 85% of the PEVs are connected to the grid during off-peak hours (12 a.m. - 6 a.m.). During peak hours (4 p.m. - 9 p.m.), it is assumed that 40% of the PEVs are connected to the grid, 90% of which are charging, and 10% are injecting power into the grid (V2G application).

A large-scale distribution planning model is used in the paper to build the optimal base case distribution network to supply the demand to the area of interest. Results show that for 62% market share of PEVs in areas with high population density, investment costs can increase up to 20% of total actual distribution network investment costs, totaling about $8000/PEV. This value is computed assuming that the charging of all PEVs coincides in time (PEVs load factor equals 1). The authors claim that if PEV smart charging strategies are implemented, hence decreasing charging simultaneity factors, up to 60% - 70% of the required incremental investment can be avoided. In addition, if strategies are defined so that some of the PEVs that were charged at peak hours are charged at off-peak hours instead, up to 5% - 35% of the required investment can also be avoided.

Pieltain Fernández et al. [242] report that energy losses can increase up to 40% in off-peak hours for a scenario with 62% market share of PEVs. The authors assumed a single load condition for off-peak hours and another for peak hours.

Gong et al. [243] propose a study to evaluate the impact of PEV charging on the life of a local residential distribution transformer. Starting from real data on residential load, ambient temperature, and vehicle parameters, a case study for a 25
kVA transformer connected to 6 households is developed and a transformer thermal model is used to estimate transformer loss of life due to PEV charging. Different PEV penetrations are simulated, considering up to 6 PEVs connected to the same distribution transformer. In the paper PEVs are assumed to be completely discharged when plugged-in, and Level-2 charging (from SAE J1772 standard) is considered, namely 6.6 kW (220 V, 30 A).

Results show that, for peak charging (7 p.m.), expected transformer insulation life is reduced to less than 7 years when 2 PEVs are connected to it. The transformer is completely inadequate to sustain 4 or more PEVs. In case of off-peak charging (12 a.m.) no loss of life is reported when 2 PEVs are connected to the transformer. However, the transformer is still inadequate to sustain more PEVs. Results are improved in case of controlled charging, and an expected transformer insulation life of 25 years is reported for a case in which even charging is performed between 7 p.m. and 6 a.m. and 6 PEVs are connected to the transformer. Transformer life also improves if PEVs do not need to be fully recharged.

Masoum et al. [244] study the use of smart grid technologies to manage PEV charging, with particular focus on the impact on distribution infrastructure. Findings indicate that the PEV charging rate and time scheduling have a significant impact on the system load curve, while moderate voltage deviations are reported. Also, fast PEV charging (11.4 kW) results in extreme overloads that will significantly deteriorate the lifetime of the high voltage (23 kV) distribution transformer.

Masoum et al. use an average residential load curve to model the residential load of each household. PEVs are assumed to use 16 kWh batteries that are charged for 80% of their capacity every day. While such general assumptions might be appropriate for preliminary evaluation of the aggregate impact of PEV penetration on the electric
infrastructure, they are not suitable to evaluate the local impact of PEV charging on
the distribution infrastructure.

In general, all the works in the literature rely on average statistics to estimate
PEV charging loads and assess their impact on the electric system, rather than on
local data or bottom-up models. For instance, the total charging requirement of PEVs
is often estimated using the average daily vehicle miles traveled (e.g. by Morrow et al. [245]),
together with the average vehicle energy consumption (kWh of electricity
consumed per mile traveled). Alternatively, per capita electric transportation demand
is used for the same purpose [191]. Charging time is typically estimated starting from
assumed vehicle availability. These general average information come from national
surveys (e.g. National Household Travel Survey [92]) or from assumptions made by
the authors of the studies proposed (e.g. all vehicles charge during a predetermined
time period). Several works simply assume a PEV market share and a time of the
day during which all vehicles are fully charged (i.e. Masoum et al. [244]). While this
approach can be useful to establish general trends, the results obtained are strongly
dependent on such general assumptions.

In this case study, detailed bottom-up models of all the components, validated
against real data in the previous chapters, are used to simulate a real-word scenario
in order to accurately assess the impact of PEVs on the electric power system. This
is done both at the aggregate level and at the local level. In particular, the modeling
proposed allows for better capturing charging times and energy consumption of PEVs
in the United States. Results of this work refine the knowledge on this topic, and can
be used as inputs to other engineering or economic models.

Note that several studies include V2G applications, where vehicle batteries are
discharged as well as charged. Tuttle and Baldick [246] predict that various grid-
to-vehicle (G2V) configurations will be developed well before the advent of V2G.
The use of V2G is still controversial, given that charging and discharging cycles would impact the life and performance of PEVs’ batteries. V2G provides a service to the electric utilities, and possibly to the owners of the PEVs, relying on resources for which automakers are responsible (PEV battery life is guaranteed by vehicle manufacturers), making the use of V2G arguable.

In the present study V2G interaction, namely power flow from PEV batteries to the grid, has not been considered.

6.3.2 Aggregate Impact of PEV Charging on the Electric Power Generation Infrastructure

The introduction of PEVs changes the aggregate electricity demand, leading to a twofold effect on the electric power generation and transmission infrastructures: first the overall demand is increased, given that an additional load in introduced. Second, the shape of the demand is modified. Both these effects must be considered to properly evaluate the impact of PEV adoption on the electric power generation and transmission infrastructures.

To estimate the aggregate impact of in-home PEV charging on the total residential demand, a simulation including 200 households in the Midwest region of the United States is performed (characteristics of the households are taken from the RECS data set, and environmental data for Columbus, Ohio in 2010 are used as input to the model). Details of the population considered are provided in Table 6.1.

According to SAE J1772-standard two AC charging levels for plug-in electric vehicles are currently available on the market: Level-1 and Level-2. Characteristics of these charging levels are defined in Table 6.2.

Level-1 charging operates at 1.92 kW. Depending on the charging equipment, the Level-2 option can operate at up to 19.2 kW. However, most residential AC Level 2
Table 6.1: Population used to estimate the aggregate impact of PEV charging.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of households</td>
<td>200</td>
</tr>
<tr>
<td>Number of individuals</td>
<td>502</td>
</tr>
<tr>
<td>Number of vehicles</td>
<td>348</td>
</tr>
</tbody>
</table>

Table 6.2: Plug-in electric vehicle charging levels according to SAE J1772 standard.

<table>
<thead>
<tr>
<th>Charging Level</th>
<th>Voltage</th>
<th>Phase</th>
<th>Peak Current</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC Level-1</td>
<td>120 V</td>
<td>Single phase</td>
<td>16 A</td>
</tr>
<tr>
<td>AC Level-2</td>
<td>240 V</td>
<td>Split phase</td>
<td>up to 80 A</td>
</tr>
</tbody>
</table>

applications will operate at lower power. In this study Level-2 charging is assumed to operate at 6.6 kW.

Figure 6.3 shows the per-household aggregate residential power demand for the simulation detailed in Table 6.1 during a summer week for two cases: 10% and 50% PEV market share. Also, the average residential demand when no PEVs are present is shown for comparison. Results are computed assuming that SAE J1772-standard Level-2 residential charging is adopted (each vehicle is recharged at 6.6 kW), but no substantial difference on the aggregate demand is noted if Level-1 charging is adopted. From Figure 6.3 the impact of significant PEV market share on the residential demand appears to be fairly limited and the impact on the electric generation infrastructure small.
Figure 6.3: Per-household average residential power demand during a summer week.

ESTIMATION OF THE INCREASE IN THE AGGREGATE DEMAND

Numerical results of the impact of in-home PEV charging on residential aggregate electricity demand are reported in Table 6.3 for a set of scenarios considering different PEV market shares: 3%, 10%, 25%, and 50%. Also, a reference scenario with no PEVs is reported. Results are normalized with respect to the peak power for the reference scenario, namely a 0% PEV market share. In Table 6.3, $\alpha(x)$ is a severity term, introduced in this study, defined as the percentage of time during which the demand is higher than $x$ times the average demand. For example, $\alpha(1.5)$ represents the percentage of time during which the aggregate residential demand was higher than 1.5 times its average. This severity term can be used to rapidly evaluate the “peakiness” of a power profile.

From the results in Table 6.3, the impact of different PEV market penetration on the aggregate residential demand is estimated. Recent estimates by the U.S. Energy Information Administration report residential electricity demand to account for 37%
Table 6.3: Case study 1: impact of in-home PEV charging on the residential aggregate electricity demand.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>PEV Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>Peak Demand [kW]</td>
<td>100%</td>
</tr>
<tr>
<td>Minimum Demand [kW]</td>
<td>14%</td>
</tr>
<tr>
<td>Average Demand [kW]</td>
<td>45%</td>
</tr>
<tr>
<td>Standard Deviation [kW]</td>
<td>15%</td>
</tr>
<tr>
<td>Average/Peak [-]</td>
<td>0.45</td>
</tr>
<tr>
<td>Average Day Demand [kW]</td>
<td>50%</td>
</tr>
<tr>
<td>Average Night Demand [kW]</td>
<td>39%</td>
</tr>
<tr>
<td>$\alpha_{(1.25)}$ [%]</td>
<td>22.92</td>
</tr>
<tr>
<td>$\alpha_{(1.75)}$ [%]</td>
<td>2.52</td>
</tr>
</tbody>
</table>

of total electricity demand [30]. Therefore, the increase in total electricity demand due to the adoption of PEVs can be computed by multiplying the increase in the residential demand by 0.37.

Thus, with the modeling proposed in this study, assuming a PEV market share of 50% the minimum of the total demand would increase by about 4%. The average demand would increase by about 8%, and the peak demand is estimated to increase by about 7%. Assuming a PEV market share of 25%, the minimum of the total demand would increase by about 3%. The average demand would increase by about 4%, and the peak demand is estimated to increase by about 4%.

The National Renewable Energy Laboratory concluded that the increase in total electric demand would stay below 5% for a PEV penetration up to 25%, and below 10% for a PEV penetration of 50% [191]. The Electric Power Research Institute concluded that the increase in total electric demand would stay below 8% for a PEV penetration up to 50% [239]. The results reported in this study are in line with what was predicted by NREL and EPRI in 2006 and 2007, respectively. The impact of
PEVs on the electricity generation infrastructure is confirmed to be fairly limited, in terms of overall demand increase.

**ESTIMATION OF THE CHANGE IN THE DEMAND SHAPE**

The introduction of PEVs also has the effect of changing the shape of the aggregate electricity demand, which could significantly affect the electric power generation infrastructure. Figure 6.4 shows the statistical distribution of the aggregate residential electricity demand assuming different PEV market shares.

![Figure 6.4: Per-household hourly power demand distribution.](image)

From the results shown in Figure 6.4, the distribution of the aggregate residential electricity demand is significantly affected by un-coordinated charging of a large number of PEVs. In particular, a PEV market share of 10% or more would lead to a distribution significantly translated towards higher power consumption. A 3% PEV
market share does not appear to impact the aggregate residential electricity demand. This is also confirmed by the $\alpha$ terms in Table 6.3.

Thus, even though PEV adoption will lead to a limited total demand increase, the electricity generation infrastructure will be impacted by widespread adoption of plug-in electric vehicles, and both additional capacity and greater flexibility of the electric infrastructure will be required. Still, a high PEV market share ($>3\%$) is unlikely to happen in the near and medium future, and the impact of 3% PEV market share (leading to a total of over 7.5 million PEVs in the United States) on the electricity generation infrastructures can be confidently assessed as minor.

6.3.3 Local Impact of PEV Charging on the Electric Power Distribution Infrastructure

To evaluate the local impact of PEV adoption on the electric power distribution infrastructure, a local residential scenario is simulated. Typically, in the Midwest region of the United States, 25 kVA transformers are used to feed up to 10 residential dwellings. In this case study, a 25 kVA residential distribution transformer, connected to 6 households selected among the ones available in the RECS data for the region modeled, is considered. Weather data for Columbus, Ohio in 2010 are used as input to the residential power demand model to run this case study. Table 6.4 details the characteristics of the 6 households used in this case study.

The residential power demand model presented in Chapter 3 and the personal transportation energy consumption model presented in Chapter 4 are used to compute the electric load of the group of households simulated, including in-home PEV charging.
Table 6.4: Population used to estimate the local impact of PEV adoption on the electric distribution infrastructure.

<table>
<thead>
<tr>
<th>Household</th>
<th>Number of Residents</th>
<th>House Size</th>
<th>Number of Vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household 1</td>
<td>6</td>
<td>254 m²</td>
<td>3</td>
</tr>
<tr>
<td>Household 2</td>
<td>1</td>
<td>73 m²</td>
<td>1</td>
</tr>
<tr>
<td>Household 3</td>
<td>2</td>
<td>133 m²</td>
<td>1</td>
</tr>
<tr>
<td>Household 4</td>
<td>4</td>
<td>91 m²</td>
<td>2</td>
</tr>
<tr>
<td>Household 5</td>
<td>4</td>
<td>337 m²</td>
<td>2</td>
</tr>
<tr>
<td>Household 6</td>
<td>2</td>
<td>106 m²</td>
<td>2</td>
</tr>
<tr>
<td>TOTAL</td>
<td>19</td>
<td>994 m²</td>
<td>11</td>
</tr>
</tbody>
</table>

IMPACT ON THE DISTRIBUTION INFRASTRUCTURE ASSUMING RESIDENTIAL LEVEL-1 CHARGING

The impact of in-home charging of PEVs on the electric power distribution infrastructure is summarized in Table 6.5 assuming that SAE J1772-standard Level-1 residential charging is adopted (each vehicle is recharged at 1.92 kW).

Table 6.5: Case study 1: local impact of PEV charging assuming Level-1 residential charging.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>PEV Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>Peak Demand [kW]</td>
<td>24.5</td>
</tr>
<tr>
<td>Minimum Demand [kW]</td>
<td>1.6</td>
</tr>
<tr>
<td>Average Demand [kW]</td>
<td>8.0</td>
</tr>
<tr>
<td>Average Day Demand [kW]</td>
<td>9.0</td>
</tr>
<tr>
<td>Average Night Demand [kW]</td>
<td>7.0</td>
</tr>
<tr>
<td>Transformer Peak Load Factor</td>
<td>0.98</td>
</tr>
<tr>
<td>Transformer Average Load Factor</td>
<td>0.32</td>
</tr>
</tbody>
</table>

The second column of Table 6.5 reports results of a scenario where no PEVs are
present (0% PEV market share). In this scenario the entire electric load is due to residential consumption, as predicted by the residential power demand model. Results report an average transformer load factor (average power/transformer nominal power) of 0.32 and a peak transformer load factor (peak power/transformer nominal power) of 0.98. These results, computed on hourly demand, are in line with real data provided in the literature [243].

The remaining columns report the impact of different PEV market penetration on the residential distribution transformer, up to 100% PEV market share. Note that the adoption of innovative technologies is often spatially clustered, namely a technology is more likely to be adopted in areas where its market share is already significant. This is justified by consumer behavior dynamics, and similar conditions (income, commuting distance, etc.). Therefore, it is reasonable to assume that even if the total PEV market share is expected to remain well below 10% in the near and medium future, high market penetration can be reached for certain residential areas.

As reported in Table 6.4, 11 vehicles are included in the residential area considered. Results for 3% PEV market share are given as a range between 0 and 1 PEV connected to the distribution transformer. Values for 10% PEV market share are computed assuming 1 PEV, and values for 50% and 100% PEV market share are computed assuming that 6 and 11 PEVs are connected to the distribution transformer, respectively. Results show that the introduction of plug-in electric vehicles, even considering the less powerful charging infrastructure (Level-1), leads to a significant increase in peak demand on the distribution transformer, that could be as high as 60% for 100% PEV market share. The increase in the peak demand is less than linear compared to the number of PEVs connected to the transformer, given that not all PEVs are charged at the same time (vehicles charging timing is predicted by the personal transportation energy consumption model presented in Chapter 4). In
this case study, for 50% PEV market share up to 5 out of the total 6 plug-in electric vehicles are charged at the same time during the simulated year, while up to 8 out of 11 PEVs are contemporaneously charged for 100% PEV market share.

The average demand increases proportionally to the number of PEVs introduced, both during daytime and nights. The increase is approximately 0.4 kW per vehicle, leading to an average of about 3500 kWh consumed per year to recharge the battery of each PEV. The transformer load factor increases accordingly. In particular, the introduction of 1 PEV is tolerated by the transformer without excessively diminished life, while more plug-in electric vehicles lead to an excessive burden for the residential distribution transformer.

Figure 6.5 shows the total demand at the distribution transformer during a summer week for two cases: 10% and 50% PEV market share. These are chosen to represent the minimum impact (1 PEV connected to the distribution transformer) and a high-penetration scenario, where one plug-in electric vehicle is present in each of the 6 households considered. Also, total demand at the distribution transformer when no PEVs are present is shown for comparison.

Figure 6.6 shows a box plot\(^3\) of the statistical distribution of residential transformer hourly load factor assuming Level-1 residential PEV charging.

The figure illustrates the load factor distribution for each hour of the day over one year. Namely, per each hour of the day 365 observations are considered, including all the days of the simulated year. Two cases are represented: no PEV is connected to

---

\(^3\)A box plot is a graphical representation of groups of numerical data. On each box, the central mark is the median, and the edges of the box are the 25\(^{th}\) and 75\(^{th}\) percentiles. The lines extending vertically from the boxes (whiskers) reach the most extreme data points not considered outliers, indicating variability outside the upper and lower quartiles. Outliers are plotted as individual points. Points are classified as outliers if they are larger than \(q_3 + 1.5 \cdot (q_3 - q_1)\) or smaller than \(q_1 - 1.5 \cdot (q_3 - q_1)\), where \(q_1\) and \(q_3\) are the 25\(^{th}\) and 75\(^{th}\) percentiles, respectively. Box plots are non-parametric, in that they display differences between populations without making any assumptions of the underlying statistical distribution.
Figure 6.5: Total residential power demand at the distribution transformer during a summer week assuming Level-1 residential PEV charging.

Figure 6.6: Box plot of the distribution of residential transformer hourly load factor assuming Level-1 residential PEV charging.
the transformer (reference case) and 100% PEV market share (worst case scenario). All the other PEV market share cases are bounded between these two extreme cases. From the figure the stress on the distribution transformer due to unregulated PEV charging is quantitatively assessed and the in-home charging of PEVs is shown to make the load factor more likely to reach values of 1 or greater.

**IMPACT ON THE DISTRIBUTION INFRASTRUCTURE ASSUMING RESIDENTIAL LEVEL-2 CHARGING**

The impact of in-home charging of PEVs on the electric power distribution infrastructure is summarized in Table 6.6, assuming that SAE J1772-standard Level-2 residential charging is adopted (each vehicle is recharged at 6.6 kW).

*Table 6.6: Case study 1: local impact of PEV charging assuming Level-2 residential charging.*

<table>
<thead>
<tr>
<th>Parameter</th>
<th>PEV Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>Peak Demand [kW]</td>
<td>24.5</td>
</tr>
<tr>
<td>Minimum Demand [kW]</td>
<td>1.6</td>
</tr>
<tr>
<td>Average Demand [kW]</td>
<td>8.0</td>
</tr>
<tr>
<td>Average Day Demand [kW]</td>
<td>9.0</td>
</tr>
<tr>
<td>Average Night Demand [kW]</td>
<td>7.0</td>
</tr>
<tr>
<td>Transformer Peak Load Factor</td>
<td>0.98</td>
</tr>
<tr>
<td>Transformer Average Load Factor</td>
<td>0.32</td>
</tr>
</tbody>
</table>

Figure 6.7 shows the total demand at the distribution transformer during a summer week for two cases: 10% and 50% PEV market share.

Results show that the use of Level-2 charging significantly exacerbates the impact of PEVs on the residential distribution infrastructure; the increase in peak demand could be as high as 110% for 100% PEV market share, and reaches over 60% for 50% PEV market share. Availability of Level-2 charging infrastructure, compared to
Level-1, leads to higher peaks in the residential demand. Still, charging events are shorter. Figure 6.8 reports a comparison of the total residential demand assuming Level-1 and Level-2 charging for a scenario with 50% PEV market share. The higher and shorter peaks introduced by Level-2 charging can be seen noting that the red areas (PEV charging) are steeper and shorter, when Level-2 charging is adopted.

Assuming Level-2 residential charging, for a PEV market share of 50% up to 4 out of the total 6 plug-in electric vehicles are charged at the same time in the simulated year, while up to 7 out of 11 PEVs are contemporaneously charged for 100% PEV market share. This is because increasing the charging power leads to reduced charging times, and thus fewer vehicles are contemporaneously charged.

The transformer peak load factor increases substantially (above 10% increase) also at 10% PEV market share (only 1 PEV added to the neighborhood considered). The introduction of more plug-in electric vehicles leads to an excessive burden for the transformer, which would rapidly need to be replaced.
Figure 6.8: Comparison of the total residential power demands at the distribution transformer during a summer week assuming Level-1 and Level-2 residential PEV charging.

These results can be compared with the study of Clement-Nyns et al. [241] that reports a 57% increase in the peak load at the distribution transformer level with 30% PEV market share. Clement-Nyns et al. overestimate the impact of the PEV adoption on the electricity distribution infrastructure, since the distribution of charging times and energy required by each vehicle is not properly captured.

Figure 6.9 shows a box plot of the statistical distribution of residential transformer hourly load factor assuming Level-2 residential PEV charging. The figure illustrates the load factor statistical distribution for each hour of the day over one year for two cases: no PEV is connected to the transformer (reference case) and 100% PEV market share (worst case scenario). Results confirm that the introduction of Level-2 charging exacerbates the issues related to residential peak demand.

In all the simulations performed in this case study, un-coordinated charging is
Figure 6.9: Box plot of the distribution of the residential transformer hourly load factor assuming Level-2 residential PEV charging.

assumed, meaning that each plug-in electric vehicle starts charging as soon as connected to the grid until fully charged (as predicted by the personal transportation energy demand model introduced in Chapter 4).

6.3.4 Case Study 1: Conclusions

In this case study, detailed bottom-up models of all the components, validated against real data in the previous chapters, are used to simulate a real-word scenario in order to accurately assess the impact of PEVs on the electric power system. This result greatly advances the results available in the literature on this topic, that are based on general statistics and broad assumptions regarding charging requirement and time.

The impact of PEVs on the electric power generation network in terms of overall demand increase has been shown to be to be fairly limited. This confirms results reported in previous studies (e.g. by NREL in 2006 [191] and by EPRI in 2007
Based on the models developed in this dissertation, the increase in total electric demand is estimated to be 4% for a PEV market share of 25%, and 8% for a PEV market share of 50%. Peak demand is estimated to increase by 4% and 7%, respectively for 25% and 50% PEV market shares.

Previous studies neglected the effect of un-coordinated PEV charging on the shape of the residential demand, which could significantly affect electricity generation and transmission infrastructures. From the results of the case study reported in the present section, the statistical distribution of the aggregate residential electricity demand is shown to be significantly affected by un-coordinated charging of a large number of PEVs. In particular, a PEV market share of 10% or more leads to significantly higher power consumption at the distribution level.

The change in the shape of the aggregate residential demand is quantitatively assessed in this study, and should be carefully considered by electric utilities to evaluate the impact on the electric power generation infrastructure. Both additional capacity and higher degree of flexibility might be required to accommodate un-coordinated charging of a large number of PEVs. These results are not affected by the PEV charging infrastructure considered (Level-1 or Level-2). Still, high PEV market share (>3%) is unlikely to happen in the near and medium term, and the impact of 3% PEV market share on the electricity generation infrastructure can be confidently assessed as minor.4

On the other hand, this case study estimates the impact of PEVs on the electric power distribution infrastructure to be significant even for low adoption of PEVs, both in case of Level-1 and Level-2 charging.

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4Since 2008 over 150,000 plug-in electric cars have been sold in the United States through October 2013 [247]. In his 2011 State of the Union address, President Obama called for putting one million electric vehicles on the road by 2015. A 3% PEV market share translates into approximately 7.5 million PEVs.
Since the adoption of innovative technology can be spatially correlated, namely a technology is more likely to be adopted in areas where its market share is already significant, high PEV market shares and cluster effects are expected for certain residential areas. Thus, even low overall PEV market share presents significant impact at the distribution level. These effects are exacerbated as more powerful charging infrastructure is made available. The industry is constantly working to increase PEV charging power, to reduce charging time, and allow for practical use of larger batteries that guarantee a longer all-electric range.

The results of the case study conducted in this section can be summarized in two main take-away points:

• From an aggregate point of view, even widespread adoption of PEVs will have a limited impact on the electricity generation network in terms of overall demand increase. A widespread adoption of PEVs will, however, re-shape the overall electricity demand, leading to a significant impact on the electricity generation infrastructure. The choice of PEVs charging infrastructure (Level-1 or Level-2) does not significantly affect the electricity generation infrastructure. The impact of 3% PEV market share on the electricity generation infrastructure is estimated to be negligible.

• From a local residential perspective, the adoption of PEVs substantially affects the residential electricity distribution infrastructure. Also the PEV charging infrastructure is shown to play a significant role. One PEV connected to a typical residential distribution transformer leads to a 7% increase in peak demand when Level-1 charging is used. This increase is estimated to be 16% if Level-2 charging is used. If one plug-in electric vehicle was present in every household connected to a distribution transformer, these increases would be 31% and 67%, for Level-1 and Level-2 charging respectively. The increase in demand is shown
to substantially change the hourly load factor of the distribution transformer, suggesting that the distribution transformers are the most affected part of the electric infrastructure by un-coordinated PEV charging.

The adoption of plug-in electric vehicles opens up new opportunities for electric utilities to operate the system in a more effective way, reducing electricity generation and grid operation costs and improving demand peak management. This is because PEVs represent a significant load that can be postponed without excessive customer inconvenience. Coordinated re-charging of PEVs can increase the loading of base-load power plants and smooth their daily cycle or avoid additional generator start-ups, thus increasing the overall system efficiency and decreasing power generation costs. In order to coordinate the charging of PEVs, coordinated residential demand response programs can be adopted, which are beyond the scope of this case study.

6.4 Case study 2: Comparison of Different Electricity Price Structures and Related Impact on Residential Electricity Demand

For the purpose of this case study the REES model is coupled to the dynamic energy management framework introduced in Chapter 5 to simulate automated residential demand response via optimization of the schedule of controllable appliances and in-home charging of plug-in electric vehicles, when present. The dynamic energy management framework is used to minimize consumer electricity-related expenditure exploiting time-varying electricity price, simulating a scenario in which electricity utilities provide a guiding signal intended to steer the aggregate demand.

The objectives of this case study are to evaluate residential demand response programs, and to quantitatively assess and compare the impact of different electricity
price structures on the aggregate electricity demand. An executive summary of this case study is provided in Appendix D.

One of the goals in the deployment of demand response programs is to smooth the electricity demand, reducing its overall “peakiness”. However, as the results show, decentralized energy management that optimizes individual consumption without any sort of coordination does not necessarily lead to a system-level optimum. In fact, in this case, individual optimization may actually exacerbate the very problem that the smart grid solution was designed to address.

For the purpose of this study, the power demand of 100 residential eco-systems in the Midwest region of the United States is simulated using the proposed REES model. Input parameters for the REES model are taken from the RECS data, as detailed in Section 6.1. This is aimed at representing the total residential electric load of a heterogeneous group of households and related PEVs and exploring the impact of demand response.

In this case study, dishwasher and laundry machines are considered to be deferrable loads. The DEM algorithm schedules these appliances to complete their run-cycles within 8 hours from the enabling time, namely the moment in which the user activates them. PEVs are also considered as deferrable loads, and are charged before the following driving event, as predicted by the REES model. This is intended to simulate the behavior of a driver, who selects a deadline for the charging when plugging-in the vehicle.

Two scenarios are considered, namely a case where no PEVs are present (reference scenario representing the current situation), and a second case assuming 10% PEV market penetration, equally subdivided between PHEVs and EVs. Figure 6.10 shows the average power demand resulting from the aggregation of these 100 residential eco-systems for the first week of January 2010.
Figure 6.10: Simulation of 100 residential energy eco-systems. First week of January 2010, Midwest region.

Figure 6.10 shows the typical attributes of aggregate residential electricity demand, characterized by significant daily fluctuations. This provides opportunities for electric utilities to send signals aimed at reshaping the total power profile to better match the electricity generation. In particular, electric utilities are interested in reducing the electric demand at critical periods (peak reduction), allow for a more constant operation of base-load power plants (valley filling), and ultimately regulate the aggregate residential demand to accommodate intermittent renewable generation (load flexibility).

To simulate the impact of residential demand response programs on the aggregate electricity demand, and quantitatively assess the impact of different electricity price structures, the dynamic energy management framework introduced in Chapter 5 is used to optimize the electricity demand in each simulated REES. An exogenous signal,
sent from the electric utility, is needed as input to the energy management tool. Time-varying electricity price is used in this study as the exogenous input signal to the energy management framework. Different electricity price structures are considered, and their impact on the aggregate demand is evaluated.

### 6.4.1 Impact of TOU Electricity Price Structures

First, a two-tier time-of-use (TOU) electricity pricing system is assumed, where price of electricity is 20¢/kWh between 7 a.m. and 10 p.m. (high day price), and 11¢/kWh between 10 p.m. and 7 a.m. (low night price). Figure 6.11 shows the same simulation depicted in Figure 6.10, after each household optimizes its own demand to minimize electricity-related expenditure.

![Figure 6.11: Simulation of 100 residential energy eco-systems using automated energy management assuming TOU electricity price. First week of January 2010, Midwest region.](image)

Even though the demand has been deferred towards low cost periods, thus filling...
the load valleys (this phenomenon would be accentuated if more loads were deferrable or distributed energy storage were present), Figure 6.11 also shows that whenever the electricity price drops a peak appears in the aggregate demand. Such peaks, called rebound peaks, are higher and steeper than the original peaks that the time-of-use electricity pricing structure was intended to eliminate. This occurs because all the deferrable activities wait for the price to drop before starting, leading to a contemporaneous request of power when the electricity price changes.

Previous studies suggest that there is a threat of rebound peaks in which consumers delay their demands to avoid a peak, but cause a new peak when trying to satisfy delayed demand [205, 206, 208]. Lenhoff et al. [207] reports that if many consumers react to time-varying electricity pricing in an un-coordinated manner, the coincidence factor of load increases significantly and the electric system may face strongly increased load fluctuations. For example, results from the EV Project show how the introduction of a time-of-use rate plan leads to a steeper and higher peak in the average demand of automated electric vehicles charging equipment (see Figure 5.1) [210].

The creation of rebound peaks in these simulations is driven by some key modeling assumptions:

- There is a widespread participation of residential customers to the proposed demand response program;

- Each individual customer uses an automated energy management framework aimed at minimizing his electricity-related expenditure and inconvenience (waiting time). Thus, the deferrable electric power consumptions are scheduled as early as possible during low-cost periods;
The energy management frameworks are decentralized, and no form of coordination among the customers is assumed.

Figure 6.12 shows the impact of such a time-of-use electricity price on the distribution of the electricity demand when an automated energy management system is introduced. Whether or not plug-in electric vehicles are present, dynamic energy management changes the statistical distribution of the residential electricity demand, with the effect of shrinking the demand towards lower power regions, while introducing peaks of higher demand that were not present before.

Figure 6.12: Distribution of the average aggregate electric power demand assuming TOU electricity price.

Overall, the introduction of TOU electricity pricing eliminates the smoothing effect due to the natural stochastic features of residential demand, forcing demand synchronization among all the REESs. Even though the demand is being effectively
deferred toward night periods, results show that pronounced rebound peaks are created in the aggregate demand, that are higher and steeper than the original demand peaks that the time-of-use electricity pricing structure was intended to eliminate.

6.4.2 Impact of CPP Electricity Price Structures

Second, a critical-peak-pricing (CPP) electricity pricing system is assumed, where price of electricity is structured in a four-tiered fashion:

- Midnight – 7 a.m. and 9 p.m. – Midnight: 13¢/kWh
- 7 a.m. – 1 p.m. and 7 p.m. – 9 p.m.: 15¢/kWh
- 1 p.m. – 7 p.m.: 17¢/kWh
- Critical event: 70¢/kWh

Critical peak events are called by the electric utility in response to an emergency, and shall not exceed a defined number per calendar year, typically 10 to 15 events. Customers are notified a few hours prior to a critical peak event, which cannot last for more than a few hours. The objective of CPP is to enhance a TOU price structure with the ability of promptly responding to emergency events.

Figure 6.13 shows the same simulation depicted in Figure 6.10, after each household optimizes its own demand to minimize the electricity-related expenditure assuming CPP electricity price. In this case no critical event was called in the week simulated.

The introduction of CPP shows effects similar to those obtained using TOU electricity rates, given that electricity price behaves in a similar way in both cases. Still, under the CPP assumption, the electric utility has the opportunity of calling a critical peak event in case of emergency, with the objective of drastically reducing the demand and relieving the electricity generation infrastructure.
Figure 6.13: Simulation of 100 residential energy eco-systems using automated energy management assuming CPP electricity price. First week of January 2010, Midwest region.

This is shown in Figure 6.14, where the same simulation depicted in Figure 6.13 is reported but a critical event was called. In this simulation, customers are notified 24 hours prior to a critical peak event. The introduction of a critical event is proven to be effective at removing the highest peak in the demand. Overall, CPP can be considered as a case of TOU price structure, leading to the creation of similar rebound peaks, but with the ability of effectively dealing with a few emergency events during the year.

The introduction of a critical event is extremely effective at reducing the aggregate demand, which is essential for guaranteeing the reliable operation of the electric grid in case of emergency.

Figure 6.15 shows the impact of CPP electricity price considering a critical event on the statistical distribution of the electricity demand when an automated energy management system is introduced.
Figure 6.14: Simulation of 100 residential energy eco-systems using automated energy management assuming CPP electricity price. First week of January 2010, Midwest region.

Figure 6.15: Distribution of the average aggregate electric power demand assuming CPP electricity price.
Again, whether PEVs are present or not, dynamic energy management reshapes the electricity demand distribution with the effect of shrinking the demand towards lower-power regions (shift towards lower-price periods), while introducing higher demand peaks that were not present before.

### 6.4.3 Time-Varying Electricity Price Structures: Summary

This subsection summarizes results of the application of time-varying electricity price structures in residential demand response programs. Table 6.7 summarizes the statistical features of the per-household aggregate residential electricity demand (averaged over the total number of households) in the six scenarios considered so far: residential eco-systems with only conventional vehicles (REES CV) versus residential eco-systems with 10% market penetration of plug-in electric vehicles (REES 10% PEV) assuming flat electricity price, two-tier time-of use (TOU) price, and critical peak price (CPP). In the table, \( \alpha(x) \) is a severity term, introduced in this study, defined as the percentage of time during which the demand is higher that \( x \) times the average demand.

*Table 6.7: Statistical features of the per-household aggregated residential electricity demand in the six scenarios considered.*

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean [kW]</th>
<th>St. Dev. [W]</th>
<th>Min. [kW]</th>
<th>Max. [kW]</th>
<th>( \alpha(1.25) ) [-]</th>
<th>( \alpha(1.75) ) [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>REES CV</td>
<td>1.02</td>
<td>270</td>
<td>0.53</td>
<td>1.70</td>
<td>20.1</td>
<td>0</td>
</tr>
<tr>
<td>REES CV TOU Price</td>
<td>1.02</td>
<td>257</td>
<td>0.52</td>
<td>2.02</td>
<td>9.9</td>
<td>0.9</td>
</tr>
<tr>
<td>REES CV CPP Price</td>
<td>1.02</td>
<td>287</td>
<td>0.52</td>
<td>2.18</td>
<td>15.2</td>
<td>1.5</td>
</tr>
<tr>
<td>REES 10% PEV</td>
<td>1.08</td>
<td>305</td>
<td>0.54</td>
<td>1.88</td>
<td>22.8</td>
<td>0</td>
</tr>
<tr>
<td>REES 10% PEV TOU Price</td>
<td>1.08</td>
<td>296</td>
<td>0.54</td>
<td>2.28</td>
<td>9.2</td>
<td>3.0</td>
</tr>
<tr>
<td>REES 10% PEV CPP Price</td>
<td>1.08</td>
<td>326</td>
<td>0.56</td>
<td>2.36</td>
<td>14.8</td>
<td>3.3</td>
</tr>
</tbody>
</table>
The results summarized in Table 6.7 suggest that when an automated decentralized (un-coordinated) dynamic energy management system is introduced, the adoption of time-of-use electricity price decreases the overall demand variability and pushes the demand toward the average load. $\alpha(1.25)$ is significantly reduced compared to the reference case of flat electricity price. This partially achieves the provider’s goal of having a residential demand as flat as possible, filling demand valleys and reducing peaks. Nevertheless, higher demand peaks are introduced, and $\alpha(1.75)$ increases compared to the reference case.

The adoption of a critical-peak electricity price produces results similar to those achieved with time-of-use rates, but CPP can be used as a means for effectively dealing with a few emergency events. These effects are accentuated by the presence of plug-in electric vehicles, that represent a substantial portion of deferrable load. Note that in this analysis it has been assumed that the change in residential and personal transportation demand does not affect the electricity price.

One of the goals in the deployment of demand response programs is to smooth consumption and reduce overall “peakiness” of the aggregate demand. However, as the results show, introduction of either TOU or CPP rates in a system where each individual consumer optimizes demand responding to the same signal may actually exacerbate the very problem that the demand response program was designed to address. Still, CPP rates are proven to be extremely effective in dealing with a limited number of emergencies.
6.4.4 Introduction of Multi-TOU and Multi-CPP Electricity Price Structures

To cope with the rebound peaks created by time-varying electricity pricing that leads to synchronization of the individual residential demands, two solutions are explored: first a way of sending diverse signals to the residential customers is proposed, and second adoption of real-time price is analyzed.

In the present study an innovative electricity price structure, named Multi-TOU, is introduced. Again, a two-tier time-of-use (TOU) electricity pricing system is assumed, where the price of electricity is 20 c/kWh during day hours, and 11 c/kWh during night hours. In this scenario, though, all the residential customers are divided into four groups, and each group sees a different TOU price, leading to a multi-time-of-use price structure. The moment at which price changes between low and high is deferred by one hour going from one group of customers to the following. For example, for the first group of customers the daily price goes from 6 a.m. to 9 p.m., for the second group it goes from 7 a.m. to 10 p.m. and so forth. In this way each customer sees a TOU rate, but not all the customers are synchronized. To avoid disparities between customers, each can rotate among the four groups during the year, so that each residential customer faces the same overall electricity price during a calendar year. Similar Multi-TOU electricity price structures are used by EDF to introduce demand diversity between customers connected to the same area of the grid, and to avoid high demand peaks at the beginning of off-peak periods [248].

Results of the introduction of this Multi-TOU rate are shown in Figure 6.16, in

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5The author would like to thank Professor Beth-Anne Schuelke-Leech for suggesting this solution.
which the simulations described in Figure 6.10 are repeated, after each household optimizes its own demand in order to minimize electricity-related expenditures assuming Multi-TOU electricity price.

![Graph](image)

**Figure 6.16:** Simulation of 100 residential energy eco-systems using automated energy management assuming Multi-TOU electricity price. First week of January 2010, Midwest region.

The adoption of Multi-TOU pricing does not lead to the creation of any rebound peak when automated energy management is introduced. Moreover, the natural “peakiness” of the demand shown in Figure 6.10 appears to be significantly reduced, leading to a substantially smoother aggregate demand. This achieves the objective for which residential demand response programs are designed, which is to alleviate the requirements on electric utilities to follow the fluctuations in the demand. That is, instead of adapting electricity generation to match changes in the demand, the
demand itself is made more flexible to reduce requirements on power generation and allow for an easier integration of non-dispatchable renewable resources.

Figure 6.17 shows the impact of Multi-TOU electricity price on the statistical distribution of the electricity demand when an automated energy management system is introduced.

![Figure 6.17: Distribution of the average aggregate electric power demand assuming Multi-TOU electricity price.](image)

Figure 6.17 confirms that the introduction of a Multi-TOU electricity price is effective in reducing the variability in the demand, with the effect of shrinking the demand towards lower-power regions (shift of demand toward lower-price periods). In this case no rebound peak is introduced.

Table 6.8 summarizes the statistical features of the per-household aggregate residential electricity demand (averaged over the total number of households) when Multi-TOU electricity rates are introduced.
Table 6.8: Statistical features of the per-household aggregated residential electricity demand assuming Multi-TOU electricity price.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean [kW]</th>
<th>St. Dev. [W]</th>
<th>Min. [kW]</th>
<th>Max. [kW]</th>
<th>$\alpha(1.25)$</th>
<th>$\alpha(1.75)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>REES CV</td>
<td>1.02</td>
<td>270</td>
<td>0.53</td>
<td>1.70</td>
<td>20.1</td>
<td>0</td>
</tr>
<tr>
<td>REES CV Multi-TOU Price</td>
<td>1.02</td>
<td>214</td>
<td>0.52</td>
<td>1.50</td>
<td>12.0</td>
<td>0</td>
</tr>
<tr>
<td>REES 10% PEV</td>
<td>1.08</td>
<td>305</td>
<td>0.54</td>
<td>1.88</td>
<td>22.8</td>
<td>0</td>
</tr>
<tr>
<td>REES 10% PEV Multi-TOU Price</td>
<td>1.08</td>
<td>211</td>
<td>0.58</td>
<td>1.56</td>
<td>9.0</td>
<td>0</td>
</tr>
</tbody>
</table>

From the table it appears that when an automated decentralized (un-coordinated) dynamic energy management system is introduced, the adoption of multi-time-of-use electricity pricing (Multi-TOU) decreases the overall demand variability and pushes the demand toward the average load. $\alpha(1.25)$ is significantly reduced compared to the reference case of flat electricity price. Also, peaks in the demand are significantly reduced, and $\alpha(1.75)$ is maintained at 0. The maximum demand during the week simulated is reduced by 12% when no PEV are considered, and by 17% when a PEV market share of 10% is considered.

The simulated results suggest that Multi-TOU electricity pricing could be an effective policy to achieve the objective of electric utilities to have residential demand as flat as possible, filling demand valleys and reducing peaks. A multi-CPP price structure would have the same effects, also providing the ability of dealing with emergency events, as shown previously.

6.4.5 Impact of Real-Time Electricity Pricing

Real-time pricing has also been suggested as a possible time-varying pricing structure, where an hourly price is sent to each decentralized dynamic energy management system. Technical, communication, and customer service (e.g. billing, privacy) issues related to real-time pricing are outside the scope of this study.
Figure 6.18 shows the same simulation depicted in Figure 6.10, after each household optimizes its own demand to minimize the electricity-related expenditure assuming real-time electricity price. The real-time price, shown in Figure 6.18, has been taken from PJM\textsuperscript{6} for the simulated week.

![Figure 6.18: Simulation of 100 residential energy eco-systems using automated energy management assuming real-time electricity price. First week of January 2010, Midwest region.](image)

In this scenario the deferrable demand closely follows the real-time electricity price. In this case, less valley filling seems to be accomplished, and even though the rebound peaks typically reach lower values their number is increased. This is justified by the shape of the electricity price, which presents several periods of low

\textsuperscript{6}PJM is a regional transmission organization that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia. Daily real-time electricity prices are freely available for download at: http://www.pjm.com/markets-and-operations/energy/real-time/lmp.aspx
value. Rebound peaks are formed also during the night periods, introducing further complexities for the electric utilities, as these demand peaks must be matched by the power generation infrastructure.

Note that in this analysis it has been assumed that the changes in the residential demand do not affect the electricity price. While this assumption holds for small deployments of residential demand-response programs, a comprehensive analysis – including modeling of the electricity generation, transmission and distribution infrastructure – should be performed to evaluate the global effect of large-scale deployments of demand response programs. This is particularly relevant in case of real-time price, where the change in demand drives the changes in price.

In the case shown in Figure 6.18 the real-time electricity price is not updated based on the changes in the demand, leading to an incomplete answer on the overall potential of real-time electricity pricing. The results shown are appropriate only if real-time price is exploited by a group of residential customers representing a small portion of the overall demand, which will have a limited impact on the electricity generation cost.

Still, one of the problems in using real-time pricing is that electricity generation cost is passed-on to final consumer on a short time-scale (electricity price may be adjusted every 10-15 minutes). Thus, every time that the electricity price drops, each consumer increases demand. This leads to increased aggregate demand and higher generation costs, which are passed-on to consumers, and that will tend to reduce their demand. This may introduce fluctuations in the system, since interruptible loads will presumably be delayed in response to increased prices, and then restarted once the price drops again. Such oscillations might be very dangerous and hard to control, calling for further investigation.

Also, with real-time pricing, consumers may not be able to follow rapid changes
in electricity price, since some of the deferrable activities cannot be interrupted once started (e.g. dishwasher cycle), even if electricity price increases significantly.

6.4.6 Case Study 2: Conclusions

In the context of residential demand response, time-varying electricity pricing is an attempt to provide an economic incentive for the consumer to delay consumption until the price of electricity drops, after the peak consumption period has passed. From this perspective, the incentive is successful because it does indeed result in consumers delaying consumption. Several studies and pilot projects demonstrate the positive outcome of residential time-based demand response in the United States [51, 56, 60, 62, 69, 70, 71]. Nonetheless, these studies are relatively small-scale projects with a low degree of automation, where demand response is mainly driven by change in behavior of participating customers.

In case of widespread adoption of demand response, coupled with automated decentralized energy management, simple applications of time-varying pricing – such as TOU or CPP – could lead to undesired dynamics, exacerbating the original problem of the “peakiness” of the aggregate demand. In fact, when each household optimizes its demand leveraging off-peak lower electricity prices in order to reduce its own cost, the resulting aggregate demand may be affected by an even higher rebound peak shifted toward the off-peak period. Previous studies suggest that there is a threat of rebound peaks [205, 206, 207, 208]. For example, results from the EV Project show how the introduction of a time-of-use rate plan leads to a steeper and higher peak in the average demand of automated electric vehicles charging equipment (see Figure 5.1) [210].

The simulations performed in this chapter confirm that significant rebound peaks are created when a large portion of residential costumers take advantage of TOU
or CPP electricity pricing using decentralized energy management tools. These re-
bound peaks originate from the synchronization of the demand that was originally
smoother due to the stochastic request for power of independent consumers. The use
of automated systems eliminates the stochastic smoothing effect inherent in human
behavior, leading to abrupt contemporaneous requests of power.

In order to solve the problems associated with the generation of rebound peaks,
the requests of power of different consumers must be de-synchronized, reintroducing
some smoothing effects. This can be achieved using direct load control (the power
consumption of each individual consumer is established by the electric utility or the
system operator), coordination among the customers, or introducing technical solu-
tion that provide stochastic smoothing effects. Direct load control is not appealing
in the U.S. residential market. Multi time-of-use electricity pricing is introduced in
this study as one possible technical solution that can be used to solve the problems
associated with the generation of rebound peaks. Another conceivable technical solu-
tion might be to introduce a random delay in the scheduling of deferrable electricity
consumptions performed by decentralized energy management tools. This solution,
however, requires the agreement of private costumers in seeing their electricity con-
sumption potentially deferred for longer periods, or some specific regulation.

Multi time-of-use electricity rates are not currently adopted in the industry and
have not been previously proposed in the literature. As shown in the results, Multi-
TOU is effective at achieving the objective of the electric utilities, which is to make
the residential demand as flat as possible, performing valley filling and peak reduc-
tion. Also, peaks in the aggregate demand are significantly reduced compared to a
reference case, where flat electricity price is considered. The introduction of Multi-
TOU significantly reduces the variability in the demand, and maximum demand is
reduced by more than 10% when no PEV are considered, and by more than 15% when
a PEV market share of 10% is considered. A Multi-CPP price structure leads to the same positive effects, also providing the ability of dealing with emergency events. Multi-TOU and Multi-CPP are very promising solutions to cope with the problem of rebound peaks introduced by simpler time-varying electricity price structures. All simulations reported in this section assume that all the residential customers actively participate to the proposed demand response program using automated decentralized energy management tools, representing a upper-bound of the effects of introducing such programs on the aggregate electricity demand.

The modeling in this study also allows simulating different scenarios and evaluating how to properly exploit the opportunities introduced by a smart grid, and in particular by residential demand response programs. This can be used by electric utilities as a tool to develop residential demand response programs that are successful at achieving the objective of smoothing the aggregate demand, and compare the effects and implication of different alternatives.

### 6.5 Conclusions

In this chapter, the residential power demand model presented in Chapter 3 and the personal transportation energy consumption model presented in Chapter 4 are integrated to simulate a Residential Energy Eco-system (REES). The REES model is based on a novel bottom-up approach that quantifies consumer energy use behaviors. The incorporation of stochastic consumer behaviors provides more accurate estimation of the actual amount of available controllable resources, allowing for a better understanding of the potential of residential demand response programs.

The dynamic energy framework introduced in Chapter 5 is used to manage the energy consumption of each REES, finding the optimal schedule for all the controllable appliances and in-home charging of plug-in electric vehicles to minimize the chosen
cost function. The objective of the decentralized energy management framework is to minimize consumers electricity-related expenditures, exploiting time-varying electricity prices provided as a guiding signal by the electric utilities.

The modeling tool proposed in this study can be seen as a virtual laboratory for investigating fundamental economic and policy-related questions regarding the interplay of individual consumers with energy-use. Large-scale simulations of groups of REESs are performed to simulate aggregate-level results and allow for evaluating the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand. This can serve as tool to guide electric utilities and energy policy makers on topics regarding the residential electric power system, including plug-in electric vehicles. The development of integrated energy consumption models allows for the simulation of different “what-if?” scenarios and the evaluation of different technology adoption cases, to provide answers and guidance towards a sustainable future for integrated residential energy systems.

Two case studies are proposed to illustrate the use of this model to answer fundamental questions and quantitatively compare different alternatives. The first case study is aimed at evaluating the impact of plug-in electric vehicles on the electric power infrastructure, both at the local and aggregate level. Results show that even widespread adoption of PEVs (up to 50% market share) will have a limited impact on the electricity generation network in terms of overall demand increase. Still, such a widespread adoption of PEVs will contribute to re-shape the overall electricity demand, leading to a significant impact on the electricity generation infrastructure. PEVs charging infrastructure (Level-1 or Level-2) does not significantly affect the electricity generation infrastructure.

From a local perspective, the adoption of PEVs substantially impacts the residential electricity distribution infrastructure. Also the PEV charging infrastructure
available (Level-1 or Level-2) is shown to have a significant impact. One PEV connected to a typical residential distribution transformer leads to a 7% increase in peak demand when Level-1 charging is used. This increase is estimated to be 16% if Level-2 charging is available. The increase in demand is shown to substantially change the hourly load factor of the distribution transformer, suggesting that the distribution transformers are the most affected part of the electric infrastructure by un-coordinated PEV charging.

The second case study is aimed at studying different electricity price structures and comparing their impact on residential electricity demand. This can be used to evaluate the role and the potential benefits of residential demand response programs. Results show that the introduction of simple time-varying pricing (i.e. TOU or CPP), which has often been proposed as a way to smooth residential demand, may create several rebound peaks in the aggregate demand in case of widespread adoption of decentralized automated energy management tools. The rebound peaks are created by the contemporaneous request of power of all the deferrable activities triggered when the electricity price drops. The aggregate demand is thus synchronized, removing the original smoothness due to the stochastic request for power of independent residential consumers. These rebound peaks are steeper and higher than the peaks in the original demand that demand response programs are intended to eliminate. The simulation results are in agreement with previous studies and available experimental data. Still, the introduction of CPP rates is extremely effective at eliminating a few peaks in the aggregate demand during the year, which is essential at guaranteeing the reliable operation of the electric grid in case of emergency.

In this study, a technical solution is proposed that solves the problems associated with the generation of rebound peaks, which is the introduction of residential multi-time-of-use electricity rates. Such pricing structures are not currently adopted in the
United States, and have not been extensively investigated in the literature. EDF uses similar electricity price structures to avoid the formation of high peaks in the aggregate demand at the beginning of off-peak periods [248].

As shown by the results, Multi-TOU is effective at achieving the electric utilities’ objective of having a residential demand as flat as possible, performing valley filling and peak reduction. Also, peaks in the aggregate demand are significantly reduced compared to a reference case, where flat electricity price is considered.

The modeling developed in this study is flexible, allowing for the simulation of different scenarios. Also, the dynamic energy management framework can be used to optimize different cost functions, aimed at achieving different objectives. For example, future studies can consider limited customer participation in residential demand response programs, assuming that not all REESs considered in a simulation exploit energy management. Also, the environmental impact of different residential demand response programs can be evaluated, integrating the electricity price signal with a “CO₂ emission signal”. Other scenarios can be simulated, and electric utilities can use this tool to accurately evaluate options for several regions of their service territory characterized by different needs of the electric power infrastructure.
Chapter 7

CONCLUSIONS

This dissertation has developed a bottom-up highly resolved model of a generic Residential Energy Eco-System (REES) in the United States. The model is able to capture the entire energy footprint of an individual household, to include all appliances, HVAC (Heating, Ventilation, and Air Conditioning) systems, in-home charging of Plug-in Electric Vehicles (PEVs), and any other energy needs, viewing residential and transportation energy needs as an integrated continuum. The residential energy eco-system model is based on a novel bottom-up approach that quantifies consumer energy use behavior. The incorporation of stochastic consumer behaviors provides more accurate estimation of the actual amount of available controllable resources, allowing for a better understanding of the potential of residential demand response programs.

A dynamic energy management framework is then proposed to manage electricity consumption inside each residential energy eco-system. The objective of the dynamic energy management framework is to optimize the scheduling of all the controllable appliances and in-home charging of plug-in electric vehicles to minimize a cost function. Such an automated energy management is used to simulate residential demand response programs, and evaluate their impact on the electric power infrastructure.

In the demand response paradigm, electric utilities provide some sort of incentive to their customers to change their consumption pattern. Utilities also provide
a signal to their customers that is intended to guide the power consumption so as to obtain an aggregate demand that better matches the needs of the power generation. This satisfies two major needs: first the electricity demand that occurs during peak periods is one of the biggest drivers of costs and capacity requirement currently faced by the electric industry. To meet the high demand during these peak periods utility companies are required to maintain a significant amount of operational capacity, which is often outdated, expensive, and underutilized. Second, the widespread adoption of non-dispatchable renewable energy sources limits the flexibility of power generation and its ability to follow the fluctuations of the demand. Traditionally, generation follows demand extremely closely, making adjustments to keep the grid balanced. Instead of adapting electricity generation to match changes in the demand, the demand itself could be made more flexible to reduce requirements on the electric power generation infrastructure and allow for easier integration of non-dispatchable renewable resources.

Demand response, is the key application that allows efficient interaction between electricity demand and supply. The ability to reduce electricity demand and shift peak loads through better demand-side management is currently one of the most promising approaches to solve the problems related to peak demand. Beginning in the mid-1970s, several utilities have successfully applied time-varying (often called dynamic) electricity price structures to their largest commercial and industrial customers, exploiting demand elasticity.

In the U.S. the residential sector accounts for 37% of the total electricity consumption, and for a disproportional amount of peak electricity use, that can reach up to 60% for some areas of the United States. The vast potential of residential energy management is still untapped, especially considering the significant future possibilities arising as home automation and smart appliances become standardized.
and the smart grid is fully deployed. Currently, electric utilities and regulators are extremely interested in complementing industrial and commercial demand response with programs targeted towards a large number of small residential consumers.

Many studies and pilot projects have shown that U.S. residential customers are willing to participate in properly designed demand response programs. Nevertheless, this research shows that such programs could lead to unintended consequences. To understand, evaluate, and develop effective large-scale demand response programs, comprehensive and accurate modeling of the next-generation power system, like the one proposed in this dissertation, is needed. These models can be used by governments, policymakers, and the utility industry to realize and guide energy system development.

7.1 Summary of the Work Developed

This section summarizes the 6 chapters that comprise this dissertation.

CHAPTER 1

After a general introduction, Chapter 1 provides a brief overview of the current energy situation in the United States, with focus on residential electricity consumption. In this chapter the motivation for this research is analyzed in detail, and the problem under consideration is clearly defined. This includes a review of the current status of the electric power infrastructure and an analysis of the electricity markets in the United States. Demand response is identified as one possible solution to convey electricity generation costs to final consumers, making wholesale electricity market fluctuations visible in the retail market. This helps electric utilities cope with the high cost associated with peak generation. In this chapter a review of demand
response programs is provided, along with results of several pilot projects. In particular, residential demand response programs implemented in the U.S. are extensively reviewed.

Chapter 1 also includes a review of the state-of-the-art on bottom-up modeling and demand-side energy management strategies able to intelligently manage residential loads.

CHAPTER 2

In Chapter 2 a heterogeneous Markov-chain model is developed to capture time allocation and associated energy use of individuals in the United States. This behavioral model is able to reproduce highly-resolved behavioral patterns of individuals with a desired time resolution, based on data collected in the American Time Use Survey (ATUS), a detailed survey administered by the Bureau of Labor Statistics. The ATUS measures the amount of time people spend doing various activities, such as paid work, child care, volunteering, and socializing. Five agent types are included in this study, capturing differences in behavior: working and non-working males, working and non-working females, and children. Also, differences between weekdays and weekends and the influence of the time of day on the behavior of individuals are both considered in the model.

An in-sample validation of the activity patterns generated by the Markov chain model is performed by comparing the modeled behavior to the underlying ATUS data. The activity patterns generated by the Markov chain are shown to replicate the behavior observed in the American Time Use Survey, validating the ability of the proposed model to reproduce the behavior of diverse categories of Americans during the year.
Chapter 3 reports on the development of a residential power demand model, a bottom-up model used to generate highly-resolved electricity demand profiles of American households consisting of multiple individuals. This model considers cold appliances, HVAC systems, lighting, and activity-related power consumption. In the chapter, an extensive review of the existing literature on modeling of residential energy consumption is presented. The input parameters needed (e.g., size of the house, thermal properties, number of occupants, etc.) are collected in the U.S. DOE Residential Energy Consumption Survey (RECS) [16]. The RECS includes detailed information for over 12000 households across the United States, including physical properties of each dwelling. The RECS data are presented in more detail in Appendix A.

Cold appliance consumption is simulated using a Bernoulli distribution, with the success probability fixed, so that the expected on-time of the appliance matches the average operating time of cold appliances in the United States, as reported in the literature. In this study refrigerators are assumed to be on/off devices that always operate at their nominal power when on.

A physically-based model is implemented to simulate electricity and fossil fuel consumption of residential HVAC systems during the year, starting from a limited set of characteristic parameters of a house. The HVAC model relies on fundamental principles of thermodynamics and heat transfer applied to a control volume including solely the air present in the house. The HVAC model requires several assumptions regarding the physical characteristics of the system, including the size of the ducts, fans, and thermal machines. Such information are not available in the RECS data, thus a component-sizing methodology for selection of air ducts size, AC unit, and fossil fuel heating furnace (or heating unit), if any, is introduced. A two-level validation framework against aggregate electricity consumption data available in the
literature and hourly metered residential load data provided by American Electric Power is provided. The proposed HVAC model is shown to accurately predict the total HVAC electricity consumption of a group of diverse residential houses in different regions of the United States. Also, the highly-resolved electricity consumption profiles generated by the HVAC model are in accordance with metered data. A detailed example of heating and cooling operations of a residential HVAC system is reported in Appendix B.

Modeling behavior of individuals is a complex task, due to the stochastic nature of the activities performed. To model energy consumption related to people’s activities, factors such as the number of individuals in the household, life habits of each individual, differences in energy use associated with different activities, daily and weekly variations in behavior, and load coincidence should all be captured. The behavioral model introduced in Chapter 2 is used to generate synthetic activity patterns for each household member. Electricity use directly related to activities of the household members is then computed by using power conversion factors associated with each activity (namely the wattage of the appliance used when performing a specific activity).

Different lighting power conversion parameters for the day and night are used in this study to capture different power use depending on the amount of natural lighting available. This study assumes that lighting power consumption occurs in each time step during which at least one household member is present in the house and he or she is doing something other than sleeping. Sunset and sunrise times are computed based on the date and coordinates of the building being modeled using an approach developed by the U.S. Geological Survey. Day and night time lighting power conversion parameters and a fixed time-invariant term are adjusted according to the household location, size, and the activity-related energy consumption of the
building occupants. In this work a least-squares linear regression model is used to estimate these parameters. This is done by estimating these coefficients to fit modeled consumption data to metered hourly-average per-customer electric load data provided by AEP.

A rigorous statistical framework is used to validate the modeled electricity demand against metered data provided by AEP. The results show realistic demand patterns that capture annual and diurnal variations, load fluctuations, and diversity between household configuration, location, and size. The model generates electricity demand profiles with the same statistical features as residential metered data.

The model allows capturing the electricity consumption of each residential specific end-use (e.g. cooking, lighting, etc.), providing an accurate estimation of the actual amount of available controllable resources. This can help electric utilities study residential demand response programs. The proposed model can be used to reconstruct power consumption of a single or an aggregate group of households with desired characteristics and composition.

The proposed model differs from existing bottom-up techniques in four important ways. One is that HVAC use and demand is modeled with much greater detail using an engineering physically-based approach. This sub-model is independently validated against aggregate electricity consumption data available in the literature and hourly metered residential load data. The second is that a large-scale time use survey is used to calibrate the behavioral model—existing approaches rely on much smaller data sets. Third, some of the parameters of the model, which are difficult to estimate, are calibrated using actual metered residential electricity data. Finally, rigorous statistical tests are used to validate the model by comparing estimated demand profiles generated by the model against metered residential electricity demand
data. In this way the stochastic features of the residential demand profiles modeled are validated.

CHAPTER 4

Chapter 4 reports on the development of a bottom-up model used to compute and compare the personal transportation energy consumption of U.S. drivers, considering a set of different passenger vehicles. The model uses highly-resolved behavioral patterns to establish when driving events occur over the simulation time horizon and the duration/length of each event.

Once driving events are defined, realistic driving profiles for each driving event are generated. Realistic driving profiles are a prerequisite for evaluating and comparing vehicle performance, energy consumption, and environmental impact. The driving profile generator used in this study is a Markovian stochastic tool based on historical data that takes as input either a driving duration or a driving distance and generates as output a real-world driving profile compatible with the given duration/distance. The data used for the calibration were collected as part of the SMART@CAR research program at The Ohio State University - Center for Automotive Research (CAR).

These driving profiles are used in a backward dynamic simulator to predict energy consumption of different passenger vehicles. For the purpose of this research six vehicles are considered: gasoline-fueled spark ignition vehicle (Conventional Vehicle), compressed natural gas spark ignition vehicle (CNG), Hybrid Electric Vehicle (HEV), Plug-in Hybrid Electric Vehicle with 10 miles of all-electric range (PHEV-10), Plug-in Hybrid Electric Vehicle with 40 miles of all-electric range (PHEV-40), and Electric Vehicle (EV). These vehicles have been chosen to represent the current market situation and possible future solutions in the American market. In particular, focus is given to natural gas vehicles and vehicle electrification, at several levels.
The performance and accuracy of the proposed vehicle dynamic simulator are compared against ADVISOR, a model developed by NREL [180]. The results show a good agreement, validating the ability of the proposed dynamic vehicle simulator to capture the fuel consumption of this set of vehicles in different driving situations. The proposed dynamic vehicle simulator, implemented in MATLAB, is on average 40 times faster compared to ADVISOR.

The energy consumption of the six categories of vehicles comes from different energy carriers: fossil fuels (gasoline or natural gas) burned in the internal combustion engine and electricity produced off-board used to recharge the vehicle battery. To compare the different vehicles considered an approach based on exergy is proposed. The modeling developed allows performing a quantitative comparison of the energy consumption of the different vehicle types in terms of total primary energy. Moreover, the percentage of trips that pure (battery) electric vehicles are unable to complete is assessed.

The main outputs of the model reported in Chapter 4 are highly-resolved (10-minute resolution) consumption profiles for personal transportation in the United States, including gasoline, natural gas, and/or electricity consumption in the case of plug-in electric vehicles. In the latter case, output includes highly-resolved in-home charging profiles, and different recharging equipments can be considered.

This chapter includes a review of several publications that are particularly relevant to the driving profile generator used in the present study and a literature review focused on modeling vehicles’ performance and energy consumption.
CHAPTER 5

Chapter 5 describes the implementation of a dynamic energy management framework for a generic residential energy eco-system. The energy management framework simultaneously optimizes controllable appliances and in-home charging of plug-in electric vehicles. This management framework is intended to simulate a scenario in which electric utilities send a signal to residential customers as a way to steer the aggregate demand. A literature review of the state of the art on optimization techniques to find the optimal schedules of controllable appliances is also reported in the chapter.

The proposed dynamic energy management framework is decentralized, in the sense that each single household receives the same signal from the electric grid, and independently optimizes its own demand. Also, the dynamic energy management framework is non-disruptive, meaning that household members are not required to change their behavior. Smart appliances require no direct human input to start their run-cycles, other than being enabled, thus simulating an automated system.

The management problem thus formulated is solved using a numerical optimization technique called Dynamic Programming (DP) and considers the behavior of household members and their energy consumption, as predicted by the highly-resolved stochastic personal energy consumption model of Chapters 3 and 4. A brief review of the theory of dynamic programming is included in the chapter. DP guarantees finding the global optimum, while other optimization algorithms might find sub-optimal solutions. The optimization algorithm is flexible enough to accommodate different costs functions, and could respond to different signals, used to achieve different objectives (e.g. electricity price, instantaneous CO$_2$ emissions, or others). Examples are reported for the application of the dynamic energy management with time-varying electricity price. Results show that the introduction of the DEM tool is effective in shifting the demand towards periods of low electricity price.
Chapter 6 details the integration of the residential power demand model and the personal transportation energy consumption model to create the residential energy eco-system, REES, model. Moreover, in this chapter large-scale simulations of groups of REESs are performed to simulate aggregate-level results and to evaluate the impact of different energy policies, technology adoption, and electricity price structures on the total residential electricity demand.

To simulate a group of REESs representative of the current status quo of the residential and transportation sector in the United States, detailed information on household characteristics are needed. Such information are reported in the Residential Energy Consumption Survey (RECS), described in Appendix A. A review of the substantial body of literature on residential demand response is also reported in this chapter. Two case studies are reported in Chapter 6: the first considers the impact of in-home charging of Plug-in Electric Vehicles (PEVs) on the electric power infrastructure, and the second provides a quantitative comparison of the impact of different electricity price structures on residential demand response.

In the first case study, no control nor coordination is used for the vehicle charging. Each PEV is charged as soon as connected to the grid, until the battery if fully charged. The amount of electricity required to fully charge the battery depends on the previous trips and charging events, which are accounted by the personal transportation energy demand model. PEVs represent an additional electric load that will affect the operation of the electric grid. This case study uses the REES model to evaluate the impact of in-home recharging of PEVs on the electric grid, both at the aggregate and local levels (impact on electricity generation and distribution infrastructure, respectively). Also, a review of the existing literature on the topic is reported. In general, all the works available in the literature rely on average statistics
to estimate PEV charging load and assess their impact on the electric system, rather than on local data or bottom-up models. While this approach can be useful to establish general trends, these assumptions make the studies proposed not appropriate for properly evaluating the local impact of PEV charging on the electric distribution infrastructure. In this case study, detailed bottom-up models of all the components, validated against real data in the previous chapters, are used to simulate a real-world scenario in order to accurately assess the impact of PEVs on the electric power system. Results of this work refine the knowledge on this topic, and can be used as input to other engineering or economic models.

The impact of PEVs on the electric power generation infrastructure in terms of overall demand increase has been shown to be fairly limited. This confirms results reported in previous studies (e.g. by NREL in 2006 [191] and by EPRI in 2007 [239]). Previous studies neglected the effect of un-coordinated PEV charging on the shape of the residential demand, which could significantly affect electricity generation and transmission infrastructures. Widespread adoption of PEVs will contribute to re-shape the overall electricity demand, leading to a significant impact on the electricity generation infrastructure. PEV charging infrastructure (Level-1 or Level-2) does not significantly affect the electricity generation infrastructure. The impact of 3% PEV market share on the electricity generation infrastructure is estimated to be negligible.

From a local residential perspective, the adoption of PEVs substantially affects the residential electricity distribution infrastructure. Also the PEVs charging infrastructure is shown to play a significant role. One PEV connected to a typical residential distribution transformer leads to a 7% increase in residential peak demand when Level-1 charging is used. This increase is estimated to be 16% if Level-2 charging is used. If one plug-in electric vehicle was present in every household connected to a distribution transformer, these increases would be 31% and 67%, for Level-1 and
Level-2 charging, respectively. The increase in demand is shown to substantially change the hourly load factor of the distribution transformer, suggesting that the distribution transformers are the most affected part of the electric infrastructure by un-coordinated PEV charging.

The second case study illustrates the use of the proposed REES model coupled to the dynamic energy framework presented in Chapter 5 to investigate residential demand response programs. One of the goals in the deployment of demand response programs is to smooth the electricity demand, reducing its overall “peakiness”. When an automated decentralized dynamic energy management system is introduced, the adoption of time-of-use electricity price (TOU or CPP) decreases the overall demand variability and pushes the demand toward the average load. Even though the demand is being effectively deferred toward night periods, results show that pronounced rebound peaks are created in the aggregate demand when decentralized automated energy management is largely adopted. Such rebound peaks are higher and steeper than the original demand peaks that the time-of-use electricity pricing structure intended to eliminate. These effects are accentuated by the presence of plug-in electric vehicles, that represent a substantial portion of deferrable load. CPP electricity pricing is shown to be able to effectively deal with a few emergency events during the year.

To cope with the rebound peaks created by time-varying electricity pricing that leads to synchronization of the individual residential demands, an electricity price structure, named Multi-TOU, is used. In a Multi-TOU price structure, all the residential customers are divided into groups, and each group sees a different TOU price. The moment at which electricity price changes between different tiers (low off-peak price and high on-peak price) is deferred by one hour going from one group of customers to the following. In this way each customer sees a TOU rate, but not all
the customers are synchronized. The adoption of Multi-TOU pricing does not lead to the creation of any rebound peak when automated energy management is introduced. Moreover, the natural “peakiness” of the demand appears to be significantly reduced, leading to a substantially smoother aggregate demand. This achieves the objective for which residential demand response programs are designed, which is to alleviate the requirements on electric utilities to follow the fluctuations in the demand. A multi-CPP price structure would have the same effects, also providing the ability of dealing with emergency events.

APPENDIXES

Appendix A describes the Residential Energy Consumption Survey, which contains household characteristics used as input to the residential power demand model presented in Chapter 3. Appendix B reports a practical example of simulations performed using the HVAC model introduced in Section 3.4. Appendix C and Appendix D report executive summaries of the two case studies proposed in Chapter 6.

All the models developed in this work are implemented in MATLAB®, and are coded in a flexible and modular fashion, allowing for easy integration with other computation tools, and for simulating different scenarios and performing case studies.
7.2 Concluding Remarks

In this dissertation, highly-resolved modeling of residential and personal transportation are developed to capture the entire energy footprint of American households. Also, a state-of-the-art dynamic energy management framework is introduced to optimally schedule controllable appliances and in-home charging of plug-in electric vehicles.

The modeling tools developed in this study can serve as a virtual laboratory to investigate fundamental economic and policy-related questions regarding the interplay of residential consumers and energy use. Large-scale simulations are performed to simulate aggregate-level results and allow for evaluating the impact of different energy policies, technology adoption, and electricity price structures on the residential electricity demand. This can serve as tool to guide electric utilities and energy policy makers on topics regarding the residential electric power system, including in-home charging of plug-in electric vehicles. The development of integrated energy consumption models allows for the simulation of different “what-if?” scenarios and the evaluation of technology adoption, so as to provide answers and guidance towards a sustainable future for integrated residential energy systems. For example, the impact of plug-in electric vehicles on the electric power infrastructure is analyzed in detail.

Moreover, the models make it possible to simulate a scenario in which electric utilities provide some sort of incentive to their residential customers to change their consumption pattern. Utilities also provide a signal to their customers that is intended to guide the power consumption so as to obtain an aggregate demand that better matches the needs of the power generation. This signal is typically electricity price. The overall objective of this is to improve the operation of the electric power system in one or more ways, including reduce electricity generation and grid operation costs for
electric utilities, manage demand peaks, reduce overall pollutant and carbon dioxide emissions from electricity generation, and others.

Recently, simple time-varying electricity rate structures (e.g. TOU, CPP) have been proposed by electric utilities with the objective of smoothing the electricity demand, reducing its overall “peakiness”. Results presented in this dissertation show that, even though the introduction of such electricity rates is effective at deferring residential demand toward night periods, pronounced rebound peaks could be created in the aggregate demand, that are higher and steeper than the original demand peaks that the time-varying electricity pricing was intended to eliminate. These rebound peaks are created by the widespread adoption of automated decentralized energy management systems, that lead to contemporaneous request of power. The aggregate demand is thus synchronized, removing the original smoothness due to the stochastic request for power of independent residential consumers.

The models and methods developed in this dissertation permit the quantitative evaluation and comparison of different electricity price structures. Time-varying electricity rates can be used by electric utilities to guide the residential demand to better match the needs of the electric power generation infrastructure in different parts of their service territory. Further, a technical solution is proposed, that solves the problems associated with the generation of rebound peaks by introducing residential multi-time-of-use electricity rates. Similar electricity rates are currently used by EDF to avoid high demand peaks at the beginning of off-peak periods [248]. As shown by the results, Multi-TOU is effective at achieving the electric utilities objective of having residential demand as flat as possible, performing valley filling and peak reduction.

The models developed in this study are flexible and allow simulating a different scenarios and capture the effects of various assumptions. For example, future studies could consider limited customer participation into residential demand response
programs, assuming that not all REESs considered in a simulation exploit energy management. Also, the environmental impact of different residential demand response programs can be evaluated, for example by augmenting the electricity price signal with a \( \text{CO}_2 \) emission signal”. Furthermore, different cost functions can be used in the dynamic energy management framework proposed in this study, aimed at achieving different objectives.

### 7.3 Contributions to the Literature and General Knowledge

The research summarized in this dissertation contributes to the state of the art in several ways, and has been published in peer-reviewed conference proceedings and international journals. Publications related to this research include:

1. **Residential Power Demand Model**
   - Presented at ECOS 2011 [12]
   - Presented at IEEE PES General Meeting 2012 [9]
   - Published in Applied Energy (impact factor: 4.8) [4]

2. **Personal Transportation Energy Consumption Model**
   - Presented at ECOS 2012 [10]
   - Published in Energy (impact factor: 3.7) [3]

3. **Dynamic Energy Management Strategy**
   - Presented at ECOS 2013 [8]
   - Presented at ASME Dynamic System and Control Conference 2013 [6]
   - Invited publication in Energy and Buildings (impact factor: 2.7) [5]
4. *Model Integration and Large-Scale Simulations*

Published in *IEEE Computing in Science & Engineering* (impact factor: 1.7)

[2]

5. *General Result and Policy Considerations*

Published in *Renewable and Sustainable Energy Reviews* (impact factor: 5.6)

[1]

Moreover, dissemination of this research to appropriate industries in the sector is expected. This project will benefit from an existing research program at The Ohio State University – Center for Automotive Research: SMART@CAR. The SMART@CAR program was created to merge academic research with the insights and experience of: automotive manufacturers and suppliers; electric utilities; transmission system operators; electricity generation companies; intelligent metering systems companies; and others. Over the years, SMART@CAR has seen the participation of American Electric Power, Buckeye Power, Inc.; Dayton Power and Light; Duke Energy; FirstEnergy; PJM Interconnection; General Motors; Ford; Chrysler; Renault; Eaton; TE Connectivity; Clean Fuels Ohio, PlugSmart, Inc.; RechargePower LLC; and others.

SMART@CAR members and affiliates played advisory role and reviewed the study presented in this dissertation adding their expertise and advice, where appropriate and solicited. Clearly, SMART@CAR members are likely to be the first users of the tools developed.
7.4 Suggested Direction for Future Research

Energy-related technologies are increasingly important. Reliance on fossil fuels has significant environmental, geopolitical, energy supply, and macroeconomic effects. A number of technologies, including renewable energy sources, plug-in electric vehicles, and efficient and smart appliances, have been and are being proposed to mitigate these issues. These are not panacean solutions, however, and their use can have unintended consequences. Moreover, most modern energy systems are not centrally planned. Rather, energy technologies are adopted and used by individuals, based on cost and other considerations. Thus, governments, policymakers, and the utility industry often rely on indirect policy measures to guide energy system development [2].

Understanding interactions between new and existing energy technologies, and policy impacts therein, is key to driving sustainable energy use and economic growth. With more complex technologies and greater resource constraints, understanding the complete electricity generation, distribution, and consumption picture is a daunting task. Fully understanding the intricacies of how renewable energy sources, an aging electricity infrastructure, increasing global energy demand, and PEVs interact is complex, involving multiple domains of expertise. This multifaceted problem can benefit from the design and implementation of a large-scale, interactive simulation that allows users to gain insights into these topics to help inform their decision making [2].

A key concern of policy makers is to steer a path towards a new energy ecosystem that is decentralized, cost-effective, environmentally-benign, and that can lead to energy independence for the nation. Achieving this target will require that policy makers have access to a comprehensive and accurate model of the next-generation electric power system that allows the exploration of “what-if?” scenarios over large regional areas as well as over long time scales.
Such a model is currently under development at The Ohio State University. A new computational tool, called Integrated Computational System for Energy Pricing and Policy (ICS-EPP), is being developed to assist the formulation of energy policy, pricing, and investment decisions. The ICS-EPP will include multiple interacting sub-models of: 

a) the behavior of individuals; 
b) the electric power grid with distributed and stochastic power generation and consumption; 
c) the energy profile of individual vehicles based on driving patterns; 
d) long-term investment decisions; and 
e) economic policy. Such sub-models are sufficiently robust to be applicable to the major power grids in the United States. The development of this computation tool is supported by the U.S. National Science Foundation with a four year, $1.7M grant (Grant No. 1029337).

The models developed in this dissertation are a key part of the ICS-EPP, and will be used to construct large-scale economic and operational models that describe the interactions of present and future energy technologies and individuals on the power system, and to integrate these models over large time scales to determine the impacts of policy and investment decisions on the long-term development of the power system. Results from this project are expected to lead to transformational changes in the fields of energy system modeling, computational steering, and energy economics.

Some of the questions that have not yet been adequately answered in this dissertation, but will be addressed by the ICS-EPP include:

- what effect do different electricity rate structures, vehicle purchase subsidies, and gasoline taxes have on adoption of PEVs?
- what is the cost of adding PHEVs, EVs, and variable renewables in terms of generation capacity needs?
- what is the value of V2G services or other grid services provided by distributed
generation and energy storage, and does it exceed the cost of individuals providing these services? Can the accelerated equipment depletion caused by these services be internalized to the payments?

- do the benefits of the grid choosing when to charge PEVs outweigh the cost of infrastructure improvements and customer incentives required to support it?

Moreover, the research presented in this study can be expanded to several different fields of study. In particular, five research topics are identified:

1. Integrate the REES modeling with a power generation model (unit commitment and dispatch).
3. Development of a dynamic energy management system capable of optimizing the use of energy resources regardless of the energy carrier used.
4. Model distributed electric power generation and storage and include them in the energy management framework.
5. Develop a hierarchical energy management system to cooperatively manage the energy consumptions of a large population of residential eco-systems.

Coupling the demand models developed in this study with electric power generation models, considering unit commitment and dispatch, allows simulating system-level scenarios. This, for example, would allow for a proper comprehensive evaluation of the impact of real-time electricity pricing.

Owing to several factors, natural gas is currently plentiful in the U.S. and is expected to be so for years ahead. The second research topic suggested would allow capturing energy consumption related to in-home charging of compressed natural gas vehicles.

The third research topic would extend the proposed dynamic energy management
framework to include multiple energy carriers, namely electricity, natural gas, and other.

The fourth research topic allows for a deeper evaluation of distributed electric power generation and storage, which is proposed as a valuable solution to cope with the current issue of the electric power system.

The fifth research topic consists of the development of a higher-level non-pricing-based energy management system with the objective of coordinating multiple residential energy management systems (like the one introduced in this study) to achieve effective collective response via coordination of individual end-users. The goal of this higher-level framework is to achieve high performance control of the aggregated energy consumption without affecting end-use performances. Such a framework can be used to address a variety of sustainability issues, such as increase system flexibility via grid-friendly demand response, minimize the total primary energy consumption or the carbon footprint, or minimize energy-related economic expenditures.

The last four research topics proposed are going to be explored in a project called “Hierarchical Energy Management for Sustainable Residential and Mobility Ecosystems”. The proposal for this project originated from the research developed as part of this dissertation. The project was funded in September 2013 by the U.S. National Science Foundation with $300k through grant CCF-1331752.
Appendix A

RESIDENTIAL ENERGY CONSUMPTION SURVEY (RECS)

This Appendix reports details on the Residential Energy Consumption Survey (RECS), a survey periodically administered by the U.S. Energy Information Administration to a nationally representative sample of housing units.¹

In the context of the RECS data collection, specially trained interviewers collect energy characteristics on housing units, usage patterns, and household demographics. This information is combined with data from energy suppliers to these homes to estimate energy costs and usage. All housing units in the 50 States and the District of Columbia that are occupied as primary residences are eligible to be included in the RECS sample and a multi-stage design is applied to assure that the entire population of occupied housing units in the United States is represented. RECS is unique because it is the only survey that provides reliable, accurate and precise trend comparisons of energy consumption between households, housing types, and areas of the country. The 2009 RECS (the last survey available) collected data from 12,083 households in housing units statistically selected to represent the 113.6 million housing units that are occupied as a primary residence.

¹The RECS data are publicly available for download at [http://www.eia.gov/consumption/residential/](http://www.eia.gov/consumption/residential/).
The RECS data provide information on two broad categories: housing characteristics and residential consumption and expenditures. In the first category, information ranging from household demographics, structural and geographic characteristics, square footage (housing unit size) to appliances, HVAC system used, and other electronics are provided. In the second category detailed information on energy consumption by end-use and by fuel are provided.

In the present study, household characteristics included in the RECS data set are used as inputs to the residential power demand model presented in Chapter 3. Also, energy consumption data are used for validation purposes of the proposed HVAC model (see Section 3.4.3).

In particular, when simulating a household in a region of the United States, one of the households available in RECS for that region is randomly selected and the following variables are taken as input parameters to the residential power demand model:

- Household location (based on Census regions);
- Number of household members and age;
- Heated and cooled areas [m$^2$];
- Presence of an air conditioning system (0-1 flag);
- Space heating equipment (fossil fuel furnace, heat pump, or pure-resistance heating);
- Wall types, and accordingly wall thermal resistances;
- Types of windows (e.g. single pane, double pane, etc.), and accordingly window thermal resistance;
- Desired temperature in the house, during summer/winter and day/night.

Each individual present in the household is classified into one of the five agent types considered in the behavioral model introduced in Chapter 2: working and
non-working male, working and non-working female, and child. Individuals with an age below 17 are considered as children (as for ATUS classification). All the other individuals are classified as male or female based on the average U.S. sex ratio (0.97 male per female [198]). Individuals with ages between 18 and 65 are divided between working and non-working based on the average US labor force participation (73% for males and 60% for females [199]).

The information included in the RECS data set allow simulation of a group of households representing a specific region of the United States, providing all the necessary inputs to the residential power demand model.

Subsets of the RECS data from specific regions are used in the present study to simulate the energy consumption of those regions. For example, the region Ohio-Indiana in the RECS data set contains 386 different households. A subset of these 386 household can be randomly selected to represent the Ohio-Indiana region.
Appendix B

HVAC MODEL EXAMPLE

This Appendix reports a practical example of simulations performed using the HVAC model introduced in Section 3.4. In particular, the heating and cooling by a residential HVAC system of a detached house located in the state of Ohio is considered. For the purpose of this simulation, actual historical ambient temperature data are used. The procedure for generating highly-resolved energy consumption patterns of residential HVAC systems is also detailed.

STEP 1: House envelope and HVAC system characteristics

In this example, a house in Ohio is randomly selected among the ones available in the RECS data (the RECS data are presented in more detail in Appendix A). The house has a total floor area of 223 m² (2400 ft²) and a height of 2.44 m (8 ft). Accordingly, assuming air density \( \rho_{\text{air}} \) to be 1.2 kg/m³, the air mass in the control volume is

\[
m_a = \text{Area} \cdot \text{Height} \cdot \rho_{\text{air}} = 653 \text{ kg}.
\]

Table B.1 summarizes the house envelope characteristics used in this example, as reported in the RECS data. The equivalent thermal resistance of the house envelope, \( R_{\text{tot}} \), is computed according to Equation 3.4.8 as:
Table B.1: House characteristic values used in the HVAC model example.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>House size</td>
<td>223</td>
<td>m²</td>
</tr>
<tr>
<td>$R_{ground}$</td>
<td>3.88</td>
<td>m²/K/W</td>
</tr>
<tr>
<td>$R_{wall}$ (R-15)</td>
<td>2.64</td>
<td>m²/K/W</td>
</tr>
<tr>
<td>$R_{window}$ (single-pane)</td>
<td>0.183</td>
<td>m²/K/W</td>
</tr>
<tr>
<td>$R_{ceil}$</td>
<td>5.28</td>
<td>m²/K/W</td>
</tr>
<tr>
<td>WWR (windows-to-wall ratio)</td>
<td>17%</td>
<td>[-]</td>
</tr>
<tr>
<td>$A_{wall}$</td>
<td>124</td>
<td>m²</td>
</tr>
<tr>
<td>$A_{wind}$</td>
<td>21</td>
<td>m²</td>
</tr>
<tr>
<td>$A_{ceil}$</td>
<td>223</td>
<td>m²</td>
</tr>
</tbody>
</table>

\[
R_{tot} = \left[ \frac{R_{ground}}{A_{floor}} + \left( \frac{1}{h_o \cdot A_{wall}} + \frac{1}{h_i \cdot A_{wall}} \right)^{-1} + \left( \frac{1}{h_o \cdot A_{wind}} \right)^{-1} \right]^{-1}
\]

where $h_o = 25$ W/m²K and $h_i = 6.25$ W/m²K are outside and inside convective coefficients, respectively. With these values, $R_{tot} = 0.0051$ K/W.

Information on the HVAC system of the house is also available in the RECS data: the house uses a traditional electric air conditioning system with a $COP_{cool} = 3$ for cooling and a natural gas furnace for heating purposes. Following the discussion of Section 3.4, $\eta_{furnace}$ is assumed to equal 0.8.

STEP 2: Desired temperature inside the house: $T_o$

Daily and nightly desired inside temperatures are reported for summer and winter in the RECS data, and are used as set points for the simulated house. In this example a summer desired inside temperature of 70 °F, corresponding to 21.1 °C, is reported for both diurnal and nocturnal operations and is used during cooling operations. Likewise, a winter desired indoor temperature of 70 °F is reported in the RECS data.
for both diurnal and nocturnal operations and is used during heating operations. Therefore, in this example $T_a$ is constant throughout the year and set to 21.1 °C.

**STEP 3: HVAC system sizing: $\dot{m}_{HVAC}$ and $T_{HVAC}$**

Following the discussion of Section 3.4, the ducts and fans are sized such that the air flow rate suffices for the highest ambient summer temperature and the lowest ambient winter temperature for the location of the house being modeled. Table B.2 reports a summary of the temperatures used in this example.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desired temperature</td>
<td>21.1</td>
<td>°C</td>
</tr>
<tr>
<td>Highest ambient temperature</td>
<td>38</td>
<td>°C</td>
</tr>
<tr>
<td>Lowest ambient temperature</td>
<td>-30</td>
<td>°C</td>
</tr>
</tbody>
</table>

Table B.2: Desired house temperature and the extreme ambient temperatures assumed in the HVAC model example.

Cooling machines are scalable and a variety of models is available on the market. Therefore, in this study an AC machine is selected so that the temperature of the return air from the HVAC system during cooling operations is constant and equal to 13°C [144]. Likewise, when heating is achieved using an all-electric system, the temperature of the return air from the HVAC system during heating operations is assumed to be constant and equal to 50°C [144].

At steady state $\left(\frac{dT_a}{dt} = 0\right)$, Equation 3.4.2 reduces to give:

$$\dot{m}_{HVAC} = \frac{1}{c_p(T_{HVAC} - T_a)} \cdot \frac{T_a - T_\infty}{R_{tot}} \tag{B.0.1}$$

where the specific heat of air, $c_p$, is assumed to be constant at 1.005 kJ/kgK, which is accurate for temperature ranging between 0 and 40 °C.
Accordingly, inserting $T_a = 21.1 \, ^\circ C$, $T_\infty = 38 \, ^\circ C$, and $T_{HVAC} = 13 \, ^\circ C$ into Equation B.0.1, the mass flow rate necessary to match the highest ambient temperature for the house under consideration is $\dot{m}_{HVAC} = 0.41 \, \text{ks/s (circa 720 cfm)}$.

When heating is achieved using a fossil fuel furnace, the selection of both air flow rate and the nominal input capacity of the furnace lead to a fixed value of the temperature of the air returning to the house in heating mode that, depending on the specific system chosen, varies from 40 to 66 $^\circ C$. The possible air flow rate and fossil fuel heating unit size combinations, as well as the returning air temperature from the HVAC system, for commercially available systems are reported in Table B.3.\footnote{The values in the table are given in imperial (or English) units, since these units are used in the design and marketing of HVAC systems in the United States.}

\hspace{1cm} \textbf{Table B.3: Available air flow rates and fossil fuel furnace sizes for residential systems and resulting temperature of the air [^\circ C] returning to the house in heating operations [20].}

\begin{center}
\begin{tabular}{c|cccccccccccc}
\multicolumn{1}{c|}{Input Capacity [kBTU/h]} & 45 & 50 & 60 & 70 & 75 & 80 & 90 & 100 & 115 & 120 & 125 & 140 \\
\hline
\text{Air Flow} [cfm] & 800 & 50 & 53 & 59 & 66 & 53 & 59 & 64 & 59 & 61 & 59 & 64 \\
& 1200 & 40 & 42 & 47 & 51 & 53 & 55 & 59 & 64 & 59 & 61 & 59 & 64 \\
& 1600 & 43 & 45 & 47 & 50 & 53 & 58 & 59 & 57 & 59 & 57 & 57 & 57 \\
\end{tabular}
\end{center}

The use of Table B.3 data is best illustrated by means of a sample calculation. Taking the first entry of the first line of the table, $T_{HVAC} = 50 \, ^\circ C$. Then, with $T_a = 21.1 \, ^\circ C$, $T_\infty = -30 \, ^\circ C$ from Table B.2, Equation B.0.1 gives $\dot{m}_{HVAC} = 0.35 \, \text{ks/s (circa 600 cfm)}$. Observe that:

\begin{itemize}
  \item the calculated air flow rate necessary to match the lowest ambient temperature for the house under consideration is less than the nominal flow rate of 800 cfm.
\end{itemize}
• the flow rate determined previously to match the highest ambient temperature (cooling operation) for the house under consideration is also less than the nominal flow rate.

Thus, this operating point in Table B.3 is feasible for sizing the HVAC system. To explore that further, consider the 53 °C table entry for the same 800 cfm flow rate. At this operating point the input capacity (furnace size) increases from 45 to 50 kBTU/h, which is larger than necessary. Consider next the 40 °C table entry at the input capacity of 45 kBTU/h. At this operating point the air flow rate increases from 800 cfm to 1200 cfm, which is larger than necessary.2

Therefore, to ensure that the HVAC system of the house under consideration is capable of maintaining the desired temperature inside the house during both the extreme winter and summer ambient temperatures, an HVAC system is adopted with an air flow rate of 0.46 kg/s (800 cfm), consisting of a furnace providing a nominal input capacity of 13.2 kW (45 kBTU/h) and a return air temperature of 50 °C together with an AC system having a return air temperature of 13 °C. Once $\dot{m}_{HVAC}$ is determined, it is considered constant during the year.

STEP 4: Evaluation of the SHR parameter

The simulated household is located in Ohio, and therefore an $SHR$ value of 0.36 is assumed (see Section 3.4.3 for further details and the $SHR$ parameter).

---

2In the general case, iteration with Table B.3 data is required for sizing the HVAC system. The iteration process is done proceeding line by line, incrementing first the input capacity of the furnace, and then the nominal air flow rate, so to select the smallest feasible ducts and then the smallest feasible fossil fuel furnace.
STEP 5: Computation of highly-resolved energy consumption patterns

The rate of energy consumption of the HVAC system considered in this example is computed according to the formulae summarized in Table 3.1. The control strategy implemented determines whether the HVAC system is on or off in each simulation time-step (with a resolution of 1 second). In particular the rates of energy consumption whenever the HVAC system is running are:

\[
\dot{W}_{\text{fan}} = \frac{m_{\text{HVAC}} \cdot \Delta P_{\text{tot}}}{\rho_{\text{air}} \cdot \eta_{\text{fan}} \cdot \eta_{\text{motor}}} = \frac{0.46 \, \text{kg/s} \cdot 145 \, \text{Pa}}{1.22 \, \text{kg/m}^3 \cdot 0.15}
\]
\[
\dot{W}_{\text{elec,cool}} = \frac{m_{\text{HVAC}} \cdot c_p \cdot (T_a - T_{\text{HVAC}})}{SHR \cdot COP_{\text{cool}}} = \frac{0.46 \, \text{kg/s} \cdot 1005 \, \text{J/kgK} \cdot (T_a - 13 \, ^\circ \text{C})}{0.36 \cdot 3}
\]
\[
\dot{W}_{\text{elec,heat}} = 0
\]
\[
\dot{E}_{\text{fuel}} = \frac{m_{\text{HVAC}} \cdot c_p \cdot (T_{\text{HVAC}} - T_a)}{\eta_{\text{furnace}}} = \frac{0.46 \, \text{kg/s} \cdot 1005 \, \text{J/kgK} \cdot (50 \, ^\circ \text{C} - T_a)}{0.8}
\]

The evolution of the temperature of the air inside the house \(T_a\) with time is captured by Equation 3.4.2. For details on the assumptions and the values used in these formulae, readers should refer to Section 3.4.

Figure B.1 reports an example for a heating day. The top part of the figure shows the evolution of the ambient temperature and of the temperature of the air inside the control volume for 9 May, 2010. The bottom part of the figure reports the resulting total hourly electric energy consumed by the HVAC system. This is shown for both an HVAC system including a fossil fuel furnace (as considered in this example) and for an all-electric heating system using a heat pump. For the fossil fuel heating system, the total simulated electricity consumption for the day is 0.58 kWh (due to the electric consumption of the fans), and 31.2 kWh of heating is added via the combustion of fuel in the furnace. For the all-electric system using a heat pump, the total simulated electricity consumption for the day is 6.24 kWh.

Figure B.2 reports an example for a cooling day for the same house.
Figure B.1: Simulated temperature evolutions and resulting HVAC electricity consumption for the Ohio house on 9 May, 2010.

Figure B.2: Simulated temperature evolutions and resulting HVAC electricity consumption for the Ohio house on 11 July, 2010.

The top part of Figure B.2 shows the evolution of the ambient temperature and
of the temperature of the air inside the control volume for 11 July, 2010. The bottom part of the figure reports the resulting total hourly electric energy consumed by the HVAC system (air conditioning). The total simulated electricity consumption for the day is 17.81 kWh.
CASE STUDY 1: EXECUTIVE SUMMARY

Plug-in electric vehicles (PEVs) are vehicles that use electricity as a propulsion source. PEVs represent an additional electric load that affects the operation of the electric power grid. The models developed in this study are used to properly evaluate the impact of in-home recharging of PEVs on the electric power infrastructure, both at the aggregate and local levels (impact on electricity generation and distribution infrastructure, respectively).

In this case study, vehicle-to-grid (V2G) interaction, namely power flow from PEV batteries to the grid, has not been considered. Also, no control nor coordination is proposed for vehicle charging, so as to evaluate the impact of PEV adoption in a scenario in which a smart grid has not been fully deployed. Each PEV is charged as soon as connected to the grid, until the battery is fully charged. The amount of electricity required to fully charge the battery depends on the previous trips and charging events, which are simulated by the personal transportation energy demand model presented in Chapter 4.

The introduction of Plug-in Electric Vehicles (PEVs) changes the aggregate electricity demand, leading to a twofold effect on the electric power generation and transmission infrastructure: first the overall demand is increased, given that an additional load is introduced. Second, the shape of the demand is modified. The results of this case study show that even widespread adoption of PEVs will have a limited impact on
the electricity generation and transmission networks in terms of overall demand increase. A widespread adoption of PEVs will, however, re-shape the overall electricity demand, leading to a significant impact on the electricity generation infrastructure. The choice of PEVs charging infrastructure (Level-1 or Level-2) does not significantly affect the electricity generation and transmission infrastructures. The impact of 3% PEV market share on the electricity generation and transmission infrastructures is estimated to be negligible.

From a local residential perspective, the adoption of PEVs is shown to substantially affect the residential electricity distribution infrastructure. Also the PEV charging infrastructure is shown to play a significant role. One PEV connected to a typical residential distribution transformer leads to a 7% increase in peak demand when Level-1 charging is used. This increase is estimated to be 16% if Level-2 charging is used. If one plug-in electric vehicle was present in every household connected to a distribution transformer, these increases would be 31% and 67%, for Level-1 and Level-2 charging respectively. The increase in demand is shown to substantially change the hourly load factor of the distribution transformer, suggesting that the distribution transformers are the most affected part of the electric infrastructure by PEV un-coordinated charging.

Figure C.1 summarizes the expected impact of PEV charging on the electric power infrastructure.
Figure C.1: Impact of plug-in electric vehicles on the electric power infrastructure.
Appendix D

CASE STUDY 2: EXECUTIVE SUMMARY

The objectives of this case study are to evaluate residential demand response programs, and to quantitatively assess and compare the impact of different electricity price structures on the aggregate electricity demand.

In the context of residential demand response, time-varying electricity pricing is an attempt to provide an economic incentive for the consumer to delay consumption until the price of electricity drops, after the peak consumption period has passed. From this perspective, the incentive is successful because it does indeed result in consumers delaying consumption. Several studies and pilot projects demonstrate the positive outcome of residential time-based demand response in the United States [51, 56, 60, 62, 69, 70, 71]. Nonetheless, these studies are relatively small-scale projects with a low degree of automation, where demand response is mainly driven by change in behavior of participating customers.

In case of widespread adoption of demand response, coupled with automated decentralized energy management, simple applications of time-varying pricing – such as TOU or CPP – could lead to undesired dynamics, exacerbating the original problem of the “peakiness” of the aggregate demand. In fact, when each household optimizes its demand leveraging off-peak lower electricity prices in order to reduce its own cost, the resulting aggregate demand may be affected by an even higher rebound peak.
shifted toward the off-peak period. Previous studies suggest that there is a threat of rebound peaks [205, 206, 208, 207].

The simulations performed in this chapter confirm that significant rebound peaks are created when a large portion of residential costumers take advantage of TOU of CPP electricity pricing using decentralized energy management tools. These rebound peaks originate from the synchronization of the demand that was originally smoother due to the stochastic request for power of independent consumers. The use of automated systems eliminates the stochastic smoothing effect inherent in human behavior, leading to abrupt contemporaneous requests of power.

In order to solve the problems associated with the generation of rebound peaks, the requests of power of different consumers must be de-synchronized, reintroducing some smoothing effects. This can be achieved using direct load control (the power consumption of each individual consumer is established by the electric utility or the system operator), coordination among the customers, or introducing technical solution that provide stochastic smoothing effects. Multi time-of-use electricity pricing is introduced in this study as a technical solution that can be used to solve the problems associated with the generation of rebound peaks. Such rates are not currently adopted in the industry and have not been previously proposed in the literature. As shown in the results, Multi-TOU is effective at achieving the objective of the electric utilities, which is to make the residential demand as flat as possible, performing valley filling and peak reduction. Also, peaks in the aggregate demand are significantly reduced compared to a reference case, where flat electricity price is considered. The introduction of Multi-TOU significantly reduces the variability in the demand, and maximum demand is reduced by more than 10% when no PEV are considered, and by more than 15% when a PEV market share of 10% is considered. A Multi-CPP
price structure leads to the same positive effects, also providing the ability of dealing with emergency events.

Multi-TOU and Multi-CPP are very promising solutions to cope with the problem of rebound peaks introduced by simpler time-varying electricity price structures. All simulations reported in this section assume that all the residential customers actively participate to the proposed demand response program using automated decentralized energy management tools, representing a upper-bound of the effects of introducing such programs on the aggregate electricity demand.


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