Distribution Grid Response Monitor (DGROM)

A Thesis

Presented in Partial Fulfillment of the Requirements for the Degree
Master of Science in the Graduate School of The Ohio State
University

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2018

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Abstract

The penetration level of Plug-in Electric Vehicles (PEVs) is projected to continue to rise in the future, which will lead to significant stress to the power grid due to frequent charging behaviors and their high power density requirements. While many studies have demonstrated the static pressure caused by PEVs for specific scenarios, there is no software platform available for the visualization of the PEVs' dynamic impacts at the distribution level of the power grid. This thesis presents a Distribution Grid RespOnse Monitor (DGROM) that fills this gap. DGROM allows for easy parameter definition, including driving habits, PEV types, and penetration levels. Its back end allows fast integration and data processing for scattered PEV charging over wide areas. DGROM also considers mitigation efforts by providing built-in algorithms for coordinated charging and location planning of charging stations. By coordinating PEV charging, we can flatten load spikes over time and space, and thus mitigate PEV's impact. This paper presents the optimization basis and algorithms for PEV coordination. In addition to reducing distribution grids' stress, these algorithms will allow the maximization of end-user benefits under varying retail electricity prices. DGROM is demonstrated on the IEEE 8500 node test case and power systems within Columbus, OH ranging from 81 to 1230 nodes.

This is dedicated to my dearest fiancee. Thanks for her support all the time.

Acknowledgments

First, I would express my appreciation to my advisor, Prof. Jiankang Wang, for his guidance and help during my Master study. She gave me so many advice about my writing, research, and career planning. These two years studying in Professor Jiankang Wang's group is an unbelievable experience. Hope all people here can be the one in their dream.

I am grateful to my other committee member Prof. Mahesh Illindala and Prof. Antonio Conejo. It's my honor to have a committee with such wonderful professors.

The special and dearest thanks goes to my fiancee, Ms. Kun Zhang. Every time I feel lost, you will give me a hand. I would be an entirely different person if I never met you. I learned courage, confidence, and belief from you and they will be with me forever. I hope to spend my whole life with you.

Thanks to Mr. Daijiafan Mao for helping me a lot from the first day I joined Professor Jiankang Wang's group. I learned a lot of research technique and writing skill from him.

Thanks also go to Mr. Christian Moya for his help in my first semester. Thanks go to Ms. Danielle Meyer for always encouraging me about my writing. Also thanks for the help from Mr. Rich Alexander and Mr. Gonzalo Constante.

Finally, my love and gratitude go to my dear parents. Thanks a lot for their support during all these years. It's the time for me to live on my own.

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Chapter 1: Introduction

1.1 Overview of Plug-in Electrical Vehicles (PEVs)

Since their introduction to the market, due to their various advantages in environmental protection, PEV stock has continued to rise. It has almost tripled itself between 2013 and 2016, growing from 171 to 564 thousand [2]. Recent trends indicate that the size of the PEV fleet will keep increasing for the foreseeable future while automobile manufacturers continue to release new PEV models and efforts within many countries incentivizing customers to purchase these models [2]. Not only are PEVs consistently improved and introduced, so too are their charging levels. Currently, the public charging station can provide DC level charging to PEVs, which has the peak power of 96 kW. Residential charging can also require 19.2 kW power from the distribution power grid, which equals the sum of using ten ovens together. However, it still can't satisfy the need of charging while a typical PEVs needs 30 minutes at the public charging station before their car is charged at the moment. Thus, ultra-fast charging under development, which is projected to consume upwards of 300kW per vehicle [13]. Table 1.1 shows the comparison of the power demand between PEVs and typical household appliance. Thus, the impact of this newly introduced load on the power grid becomes an interesting topic.

PEVs and typical appliance power consumption			
Appliance	Power(kW)	PEV Charging Level	Power(kW)
25” colour TV	0.15	AC Level 1	2
Hair Blow dryer	1.8	AC Level 2	19.2
Home Air Conditioner	1-4	DC Level 1	36
Toaster	1-2	DC Level 2	96
Oven	2	Ultrafast Charging	300

Table 1.1: Comparison of the power demand between PEV charging level and typical home appliance.

1.2 Problem Background and Prior Work

As described in the previous section, the massive power consumption of PEVs can cause overloading while many PEVs charge together. At the same time, different from other steadily connected massive loads, e.g., factories, hospitals, and electric railways, the connection time of PEVs is very flexible and stochastic, which let the attempt to predict their charging behavior becomes hard. Thus, their massive power consumption, paired with their load characteristics, which manifests as impulses [17], can result in severe faults to the power grid, e.g., voltage deviations and power quality reductions, both of which can cause blackouts [4]. Except for the short-term impact, massive PEVs can also cause accelerated aging of distribution grid infrastructure in the long term, which further results in the significant financial loss. Thus, it is likely that the grid will become the bottleneck of the development of PEV.

Prior Work. Many past works have demonstrated the effects of PEV charging on the grid. Mostly, these analyses are focused on long-term evaluation for grid planning [25], where charging impacts are often presented concerning static time periods [12].

These static methods, however, fail to capture the duration and frequency of grid events caused by increasing levels of PEV charging. Simulation, which allows for the visualization of the effects of PEV charging, has also been popular within the literature, with many demonstrating these effects within real systems [8]. However, the individual characteristic of each vehicle is ignored in most papers, instead choosing to model all PEVs as a single entity [30]. This approach may be sufficient for a general result, but a diverse fleet of PEVs should be considered for a realistic view of the impacts. Further, these simulations often focus on one type of charging impact, e.g., thermal loading [23], or voltage drops [8]. These individual scenarios do not accurately characterize the wide range of impacts that PEVs can have on the grid. Thus, it is necessary to allow for robust analysis, consisting of a simulation that allows for the visualization of various impact metrics a system will experience under increased PEV charging.

On the other side, the mitigation of the impact of PEV charging on the distribution power grid is also a wide-discussed topic. Mainly, the whole process of mitigation can be described as an optimization problem to determine when and how PEVs should charge. which will be detailed discussed in chapter 3.

Based on the description above, plenty of commercial software has been developed to analyze the status of the power grid. However, existing commercial software packages for distribution systems (Alstom, GridlabD, OpenDss, etc.) only allow for the estimation of static load impact, which ignores the inter-temporal change of load. Visualization and evaluation of dynamic load impact are only available in the software at the transmission level (CYME, PSS/E, PSAT, etc.). However, these results are not applicable to the distribution level, where the discreteness of impulsive loads' characteristics and grid switch-gears' response is magnified. At the same time, no software offers methods of mitigating the impact of impulsive loads on the power grid (e.g., The charging of PEV). However, such methods are essential because it can reduce the stress on the power grid, providing more time for the utility to prepare through the grid reinforcement. It is also important for reducing the capital investment by prolonging the life cycles of grid assets (e.g., transformers, voltage regulators) The mitigation effort can also improve grid efficiency, power quality, and reliability by reducing the possibility of coincidental overloading which can lead to electricity supply interruptions.

1.3 Distribution Grid Response Monitor (DGROM)

To overcome the deficiencies mentioned before, we have invented Distribution Grid RespOnse Monitor (DGROM) that can monitor, assess, visualize and mitigate the impact of PEVs on the distribution power grid. In this software, time-series power flow is employed to allow for the consideration of both the frequency and duration of PEV impacts, helping to obtain both long- and short-term impact analysis. Further, DGROM is compatible with all power systems in the format of distribution power system simulator. Thus, utilities and grid planners can use this software to obtain insight into the impact PEVs will have within their systems, allowing them to prepare via grid reinforcement. To achieve realistic results, DGROM models each PEV within the system as an individual, instead of aggregating them, and allows users to easily obtain various impact indices, including voltage unbalance and line loading. A coordinated charging algorithm is also implemented, illuminating the value of this mitigation effort. Currently, DGROM can also perform charging station planning, enabling the automatic selection of the optimal charging station locations based on traffic flow within a geographical region. In conclusion, DGROM is uniquely positioned as a way to simulate generic cases of PEV penetration levels within a system of the users choice, while also presenting these impacts regarding various impact indices, resulting in a more holistic view.

1.4 Organization of this Thesis

The rest of this thesis is organized as follows.

Chapter 2 introduces the architecture of DGROM, and the function and technical details for all modules embedded in DGROM.

Chapter 3 detailed introduces the attempt to mitigate the impact of PEVs on the distribution power grid.

Chapter 4 summarizes the results of the thesis and gives pointers to future research that can be based on this exemplary work.

Chapter 2: Architecture of the DGROM

The architecture of this software can be viewed in Fig. 2.1. In DGROM, several MATLAB modules were coded to integrate, transmit, and analyze the data input by the user through the GUI, which is detailed in Fig.2.2. However, except for the external definition, the internal data integration effort is essential. DGROM creates a set of searching algorithms based on the alphabetic string analysis of imported files. Once the integration process is completed, the PEV load profile is generated and transmitted to perform time-series power flow analyses where currently OpenDSS was employed as its solver. The result is then integrated with the selection of the performance indices to show the visualization result of the system. A detailed description of the various customizable modules of DGROM is provided below.

2.1 Input Circuit Requirement

The most fundamental component within DGROM is the system under study. Currently, DGROM is compatible with all systems in the format of OpenDSS, which is capable of doing time-series power flow analysis. The ability to perform time-series power flow is of critical importance for users interested in studying both dynamic short- and long-term impacts. This part is shown in part 1 of Figure 2.2.

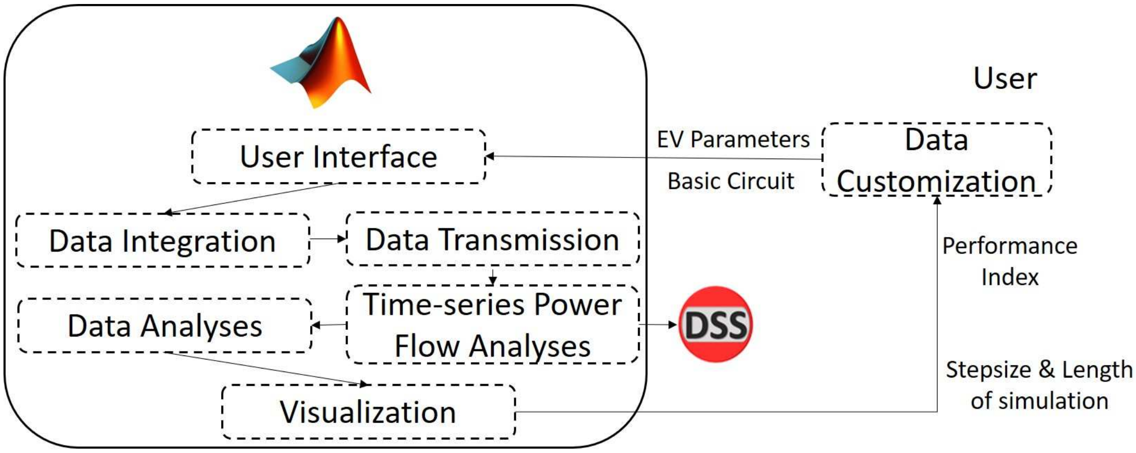

Figure 2.1: Architecture of the software

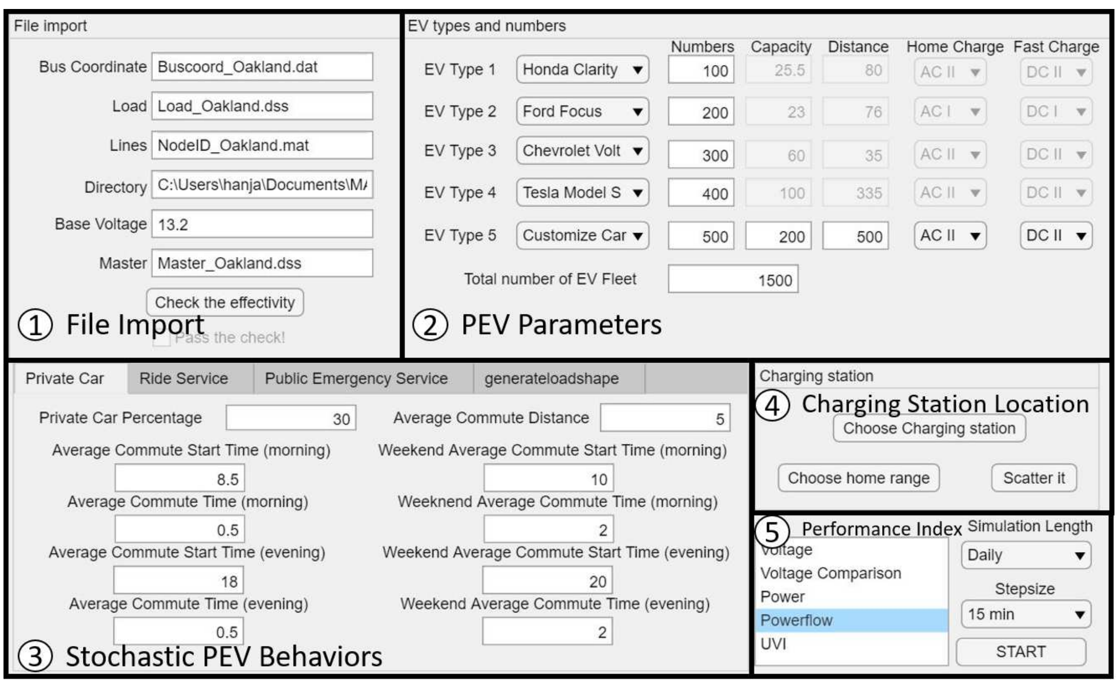

Figure 2.2: Dashboard of DGROM

However, merely inputting the system files is not enough for adequate analysis; when the simulation is performed the data conversion effort is substantial. Due to the concern of compatibility, and the fact that there's never a specific rule of how different users name their components. A comprehensive string analysis algorithm is essential to link every component together. In DGROM, we have created a set of string analyze algorithms. The example of an alphabetic string analysis of imported files is shown in Part B of fig.2.3. In this example, we extract the identical part of the name of each component components. The sorting label is then added to the remaining different part based on their geographical location. This algorithm allows us to divide the whole system based on the different labels, decreasing the range of searching for each component, resulting in a 75% reduction of searching time. Afterward, we can run time-series power flow analysis based on the searching result. The power flow result is then plotted onto the system diagram.

2.2 Load Creator (LC)

The primary load we concerned in DGROM is PEV. Thus, the design of the parameter of PEV is of critically important. In DGROM, we use Load Creator (LC) to define the parameters of PEVs, which can be divided into the electrical characteristic, the temporal characteristic, and the geographical characteristic. Thus, the connection time, duration, location and power demand can be fully defined via LC. At the same time, all parameters in LC allowed customization, which will enable users to create a system that entirely under control.

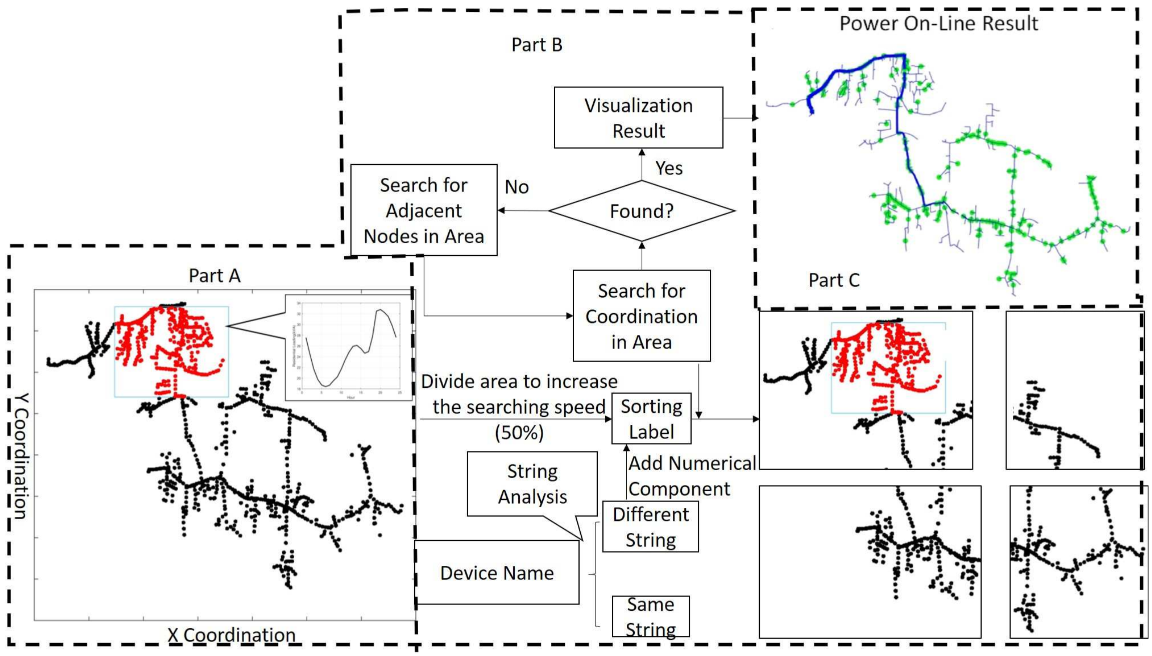

Figure 2.3: Overview of a running process of the software: Part A shows how the residential range is selected in this software, with the typical load profile of baseline load shown in the inset. Part B describes the mapping process of a certain component onto the coordination, where the coordination was divided into several parts to enhance the searching speed up to 75%. Part C shows the power on-line result for the Oakland Power system in Columbus, OH.

2.2.1 Electrical Characteristic Hub of Load (ECHL)

The electrical characteristic of PEVs (e.g., the power demand) is defined in DGROM via ECHL, as shown in block 2 of Figure 2.2. In DGROM, PEVs are defined by different models which contains description of battery and charging level, which can define the maximum charging rate and maximum energy. These two characteristics, together, allow for DGROM to determine each PEVs power draw from the grid, enabling representation of the charging load. In DGROM, the model of PEVs can be defined in two ways: a built-in model for specific PEVs or a user-definable section, in which users can represent any PEV under study. This individual representation for each PEV and the multiple charging levels within the system results in a simulation that accurately depicts the effect of varying charge levels coinciding. The range of each PEV allows for the determination of SOC based on distance traveled, allowing for a more complex representation of each PEV's electrical needs at the time of their charge. In the future, real-time traffic flow data representing travel within a geographical area will be enabled, which will increase the critical importance of the definition range, i.e., when the trip distance is known, SOC at each charging station is more accurately represented.

This model does not consider the characteristics of the charge event itself, i.e., the ramp up and down rates of charge because it is negligible while the minimum step size of DGROM is 15 minutes. However, the ramp up and down rates is helpful to show the discreteness of the PEV loads. Thus, this behavior will be included in future iterations of this software based on the interpolation algorithm to provide solutions with higher time-resolution.

2.2.2 Temporal Characteristic Hub of Load (TCHL)

Except for the power demand we have from ECHL, we still need the charging time and duration of every PEV. Thus, we create Temporal Characteristic Hub of Load (TCHL) to define these temporal characteristics. In reality, two PEVs of the same model can have different charging scenario based on its daily routine. Thus, it is necessary to consider individual differences between PEVs stochastically, not only regarding their charging parameters but also concerning different daily usage patterns. Stochastic charging behaviors are thus integrated within the TCHL, within block 3 of Fig. 2.2. PEVs are divided into three types of DGROM: Private Commuter, Ride Service, and Emergency Vehicle.

Private Commuter

PEVs, same as other vehicles, are most commonly used as daily commute vehicles, which will tend to charge at home overnight. Thus it is important to characterize the times at which they arrive at and leave their homes, as well as their SOC upon arrival. According to [31], a normal distribution, with an average commuting duration of 25.4 minutes and a variance of 7.34 minutes can be used to present the random variable describing the daily commute time. Combining with the traditional working time in the U.S., from 9:00 am to 5:00 pm, the actual period of arrival is thus defined. Based on the commute data from the Bureau of Transportation, a normal distribution with mean 15 miles and variance 5 miles is used represent their commute distance [20]. By assuming that each PEV needs to start their commutation at full charge, the final SOC can thus be calculated using the range of their vehicles and their driving distance.

In DGROM, these private commuters will charge under two scenarios: (i) they charge via residential charging level after having arrived home after a workday or (ii) they charge via public charging level while their SOC is below their pre-determined SOC threshold during their commuting process. In DGROM, such SOC threshold at which drivers choose to charge is dependent on personal preference, random variables according to a normal distribution, with mean 0.35 and variation 0.15 is used to represent such behavior. It is set to a value of 0.05 if the generated value is less than 0. Thus, this random variable allows DGROM to determine the SOC threshold for each PEV. The optimal charging algorithm, detailed in chapter 3 is applied here to minimize the owners' cost or the impact on the power grid and determine the actual period during which charging occurs.

Ride Service

Ride service vehicles are another common kind of electric vehicle, especially in large metropolitan areas. Currently, many cities worldwide, e.g., London [9] and Montreal [18], have introduced PEV cabs. A distinguishing characteristic of these vehicles is that they are for on the road for long periods. Thus, they tend to use the public charging stations with the charging level based on their model to achieve faster-charging speeds. Different from the strategy defining the characteristic of private commuters, we cannot use average trip distance while ride service vehicles drive all the day. Speed is instead used to allow for the determination of when a ride service vehicle will be charged. This platform using an average driving speed of 27 mph, which is also customizable [19]. Their start driving time are earlier than commuters' because many people use cabs to commute, so is their end driving time. Ride Service vehicles will charge while their SOC falls below their pre-determined SOC threshold, which is defined as same as the one in Private Commuter. They will continue to provide ride service after charging in the public charging station until they are out of charge again. Thus, their charging time dan duration can be defined. DGROM is embedded with the charging station planning algorithm, which enables the vehicle to charge at specific charging station based on its current location, which will be detailed described in later sections. In DGROM, TCHL generates the temporal characteristic of commuters and ride service vehicles using the same code, which is shown in Figure 2.4.

Emergency Vehicles

The final type of PEV, defined regarding its driving characteristics, consists of electric emergency vehicles. Currently, no electrical emergency vehicles are running on the road, but several have been introduced. BMW has introduced electrical emergency vehicles with ranges of 100 miles or more [6]. Ford has also been actively researching and creating concepts of electrical ambulance [32]. Thus, within the promotion of smart cities, it is reasonable to assume emergency vehicles will be electrified in the future. Within the platform, fleets of emergency vehicles can consist of all types of cars, with different charge levels. When simulating the driving behavior of such vehicles, routines relating to arrival time and distance no longer apply due to the stochastic behavior of emergency vehicles. Thus, in DGROM, a probability model is used to describe the emergency vehicles' behavior, regarding the probability of an emergency vehicle leaving the station to perform its duty, wherein each vehicle has a 5% chance of leaving the station. Emergency vehicles should never run out of charge during their trips, so there's no optimized charging sequence within the road network for vehicles of this type. The average driving speed of 67 mph, with a variation of 23

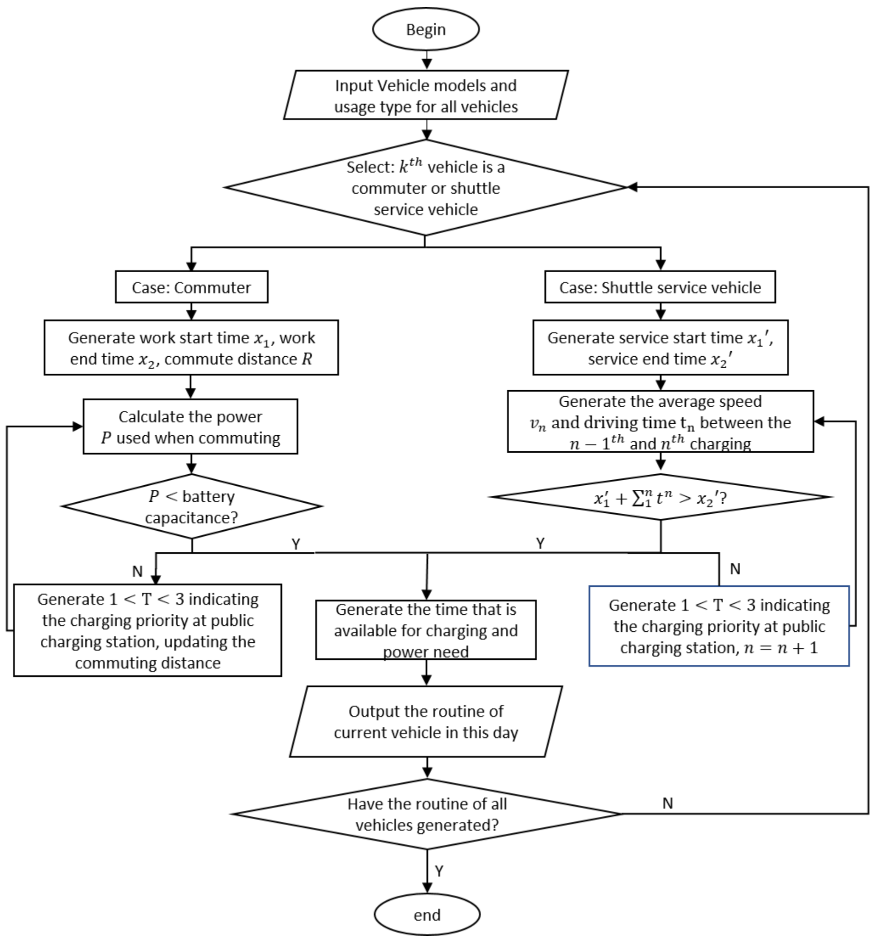

Figure 2.4: Flowchart of how DGROM Create Temporal Characteristic for Commuters and Ride Service Vehicles

mph, and an average trip time of 8 min, with variation 4.3 min, are used together to determine SOC upon return.

2.2.3 Geographical Characteristic Hub of Load (GCHL)

With the definition of PEV charge parameters and power requirements, along with knowledge of when charging will occur, the software must be able to determine *where* the charge event interacts with the grid. Thus, selection of charging station locations in the software, shown in part 4 of Fig. 2.2 is critically important. In this software, we use Geographical Characteristic Hub of Load (GCHL) to define the locations of charging stations. In GCHL, all charging locations are divided into residential charging locations, which are designed for private commuters, and the public charging stations, which are designed for ride service vehicles. Currently, in DGROM, the location of residential charging locations are user-defined by dragging ideal area on a 2-D plot of the system, shown in part A of Fig. 2.3. This allows us to accurately depict the impacts of charging based on residential charging level. However, when it comes to the selection of public charging station, the planning of the location of it becomes critical. The core problem of public charging station planning is a mixed-integer problem, with an indicator variable corresponding to the decision to build or not [10, 36]. In this software, such mix-integer optimization algorithm for charging station planning is adopted [34].

In DGROM, we made assume the distance we need to travel between two nodes equals to their linear length due to the consideration that we only have the coordination data with distinct, independent nodes. For each ride service vehicles, which is designed to charge at the public charging station. We have developed one specific trip chain for each of them. The trap chain data is defined by the following steps:

1. Define a start node and steps, which is a Gaussian distributed variable with an average step of 12 [7] and a variation of 3. Each step means the driver has completed a ride.

2. For each step, the next destination is randomly chosen in all nodes within certain range, which is a Gaussian distributed variable with an average mileage of 10 miles [7] and a variation of 5.

3. Follow this process until all steps are completed. This depicts a complete trip chain for a ride service vehicle per day.

We consider all nodes are candidate location of public charging station. Thus, this problem can be formed as a mix-integer problem:

$$\max_{x,y} \quad \sum_{q \in Q} y_q \tag{2.1}$$

$$\begin{aligned} s.t. \quad & \sum_{k \in N_q} x_k \leq y_q \\ & \sum_{k \in K} x_k \leq M \\ & x_k \in \{0,1\}, \forall k \in K \\ & y_q \in \{0,1\}, \forall q \in Q \end{aligned} \tag{2.2}$$

In the function above, M is the maximum possible number of charging station, which is input by the user. Q is the set of trip chains we defined previously. K is the set of all nodes. N_q is the set of candidate charging station locations that are capable of capturing EVs traveling on trip chains q. Here, this "capture" has two requirements. The first one is the route will pass the node within a range of 1 mile [34]. The second one is the PEV is in need to charge while it passes the node. Thus, we can define the

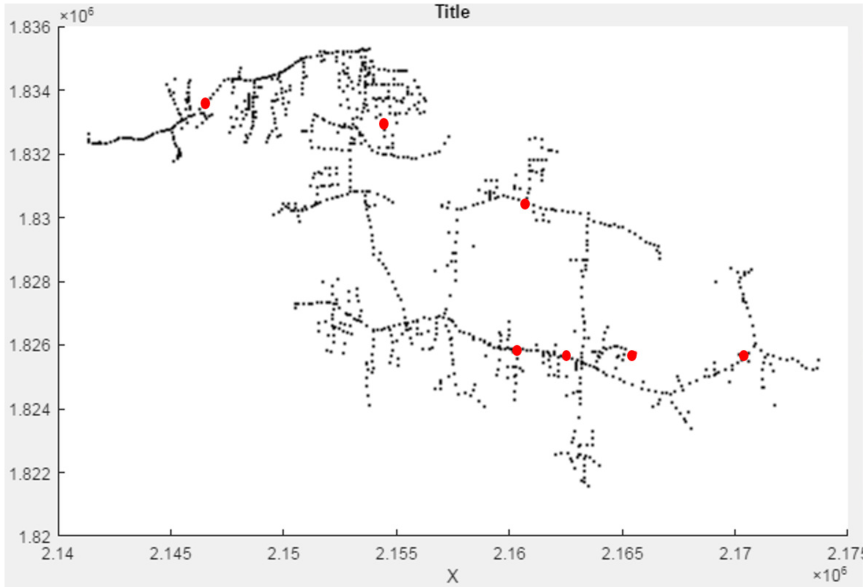

Figure 2.5: Nodes selected for Oakland power system in Columbus, Ohio.

decision variables in equations above: x_k is a binary variable that only equals to one when the station is placed at node k; y_q is a binary variable that only equals to one when the PEV on route q is "captured" by a charging station; An example result of the automatic node selection is shown in Figure 2.5 when the system needs 7 public charging stations.

2.3 Performance Indices

The ultimate goal of this software is the ability to visualize key impacts to the distribution grid caused by the defined PEV parameters, charge behavior, and charging stations. This platform is created in a way such that various impacts can be simulated, as shown in Block 5 of Fig. 2.2.

2.3.1 Voltage

PEV charging behaviors have a direct impact on the voltage profile within the system, regarding both under- and over-voltage [8]. System overloading will cause voltage drops at the end of feeders, tripping the circuit breaker and causing blackouts. This will directly impact the customers and can cause huge loss. For example, outages in the brokerage operations industry can lead to costs over $6 million [22]. Costs corresponding to outages can outrage customers and lead to consequences for critical infrastructures, such as hospitals that must switch to back-ups. The voltage tolerance of $\pm 5\%$ at the furthest end, based on the ANSI standard, is built-in [26]. DGROM will run the simulation and help users see this effect via a 3-D plot indicating the node voltage, shown in Fig. 2.6. Different colors are used to show the status of the node voltage. Results can also show the differences in system performance before and after PEV addition.

2.3.2 Voltage Unbalance Index

Voltage impacts can also be visualized according to a Voltage Unbalance Index (VUI). Load unbalance will cause under-voltage in the overloading phase and over-voltage in other phases, both of which are detrimental to grid operation. AC Levels I and II can cause voltage unbalance due to their single-phase charging, making it critical to conduct this simulation in areas where charging at these levels occur, as selected in the home range portion of the dashboard. In this paper, we use the voltage unbalance index (VUI) which defines the degree of unbalance present as

$$VUI = \frac{MAX(V_A, V_B, V_C)}{(V_A + V_B + V_C)/3},$$

where V_A, V_B, V_C are the voltage for each phase for a three-phase node. Within DGROM, the tolerance of the UVI within the system is defined according to ANSI Standards to be $\pm 3\%$ [26]. The results are presented in the form of a 3-D plot indicating the VUI at each node using various colors.

2.3.3 Load Power

Impacts relating to load power can also impact power quality, with overloading leading to blackouts, brownouts, and frequency deviations. These impacts result in costs to users, and frequency deviations can impact devices connected to the grid, even devices as small as clocks [37]. In the long-term, load power can shorten the lifetime of grid assets, such as the transformer, and replace them can lead to costs over $ 20,000 for one transformer [17]. This software addresses this impact by demonstrating the load power within the system. Load values connected to each node are also considered, enabling the user to identify where overloading occurs. Visually, the platform will produce a 3-D plot indicating the amount of load. The color of the line will change when the load power at a specific node exceeds the user-defined power threshold.

2.3.4 Loading On-Line

Overloading, as described above, can also be seen via the loading on line. All conductors within the grid have their operation limits concerning current [1]. If the current on a line exceeds its defined limit, there is an overcurrent fault, which can cause overheating, fire damage, and increased losses of power. This platform considers loading on-line, creating a 2-D plot indicating the power flow through each line, wherein the thickness of the line shows the amount of power. Part C in Fig. 2.3 shows an example of this visualization index.

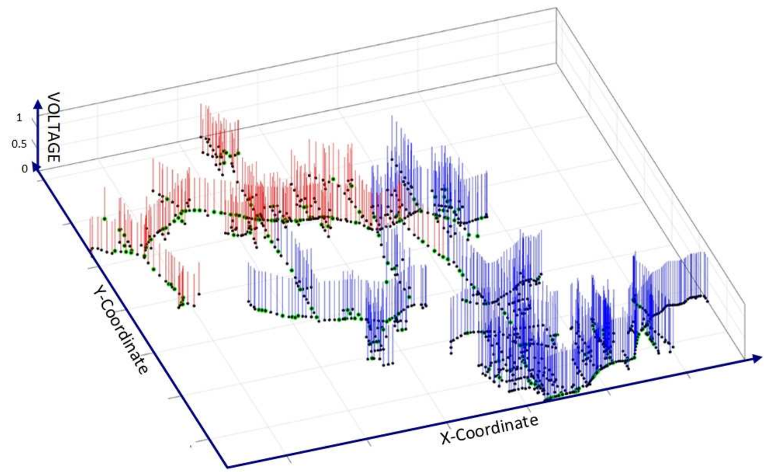

Figure 2.6: Result of Voltage Index simulation. The red areas indicate under-voltage.

2.4 Visualization Result

Figure 2.6 shows the voltage condition of Oakland Power System in Columbus, Ohio. 1000 Tesla Model S is connected to the system using the public fast-charging charger. We can see from the figure that the voltage of far end has dropped below 0.95, which is prohibited by the power grid. Thus, the increment of the penetration level of PEVs can cause serious problems.

Figure 2.7 shows the power status of Oakland Power System in Columbus, Ohio. 300 Tesla Model S is connected to the system using the public fast-charging charger. We can see from the figure that the power demand on some nodes exceeds 100kW, which will cause serious overload problem.

Figure 2.8 shows the comparison of the voltage between original system and PEV added system of Oakland Power System in Columbus, Ohio. 500 Tesla Model S is connected to the system using the public fast-charging charger. We can see from the figure that the PEVs affect the voltage of far end severely.

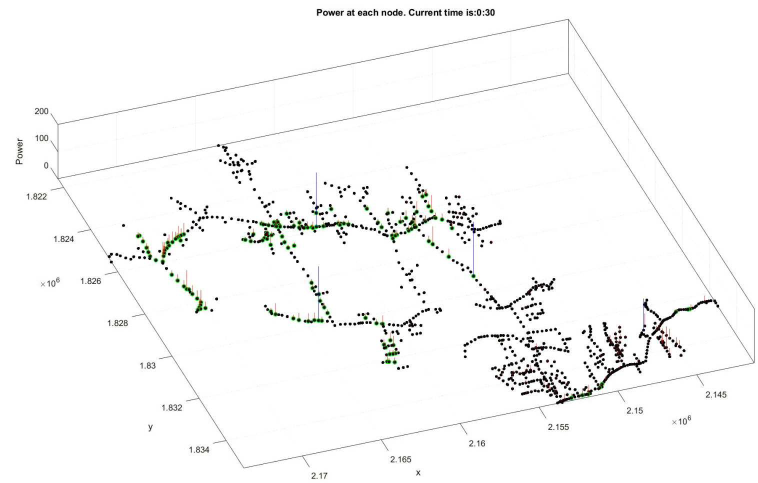

Figure 2.7: The result of Power Index simulation. Blue areas indicate the load connected to this node is more than 100kW.

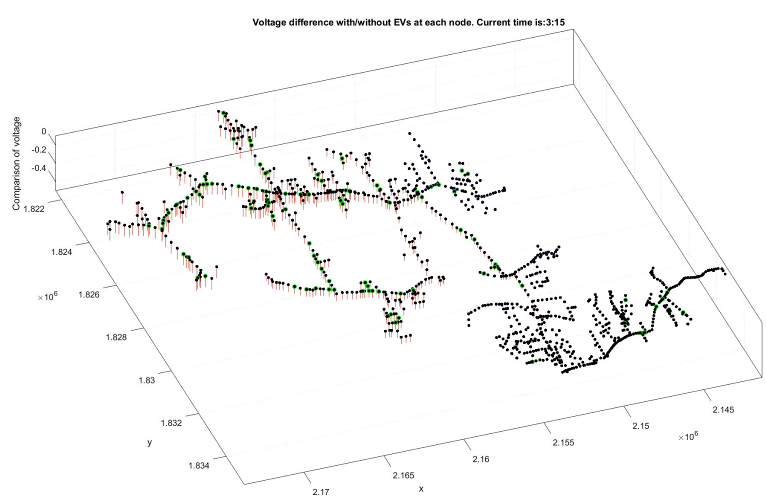

Figure 2.8: The result of the comparison of the voltage between original system and PEV added system.

Chapter 3: Mitigating PEV's Impact on Distribution Power Grids

In previous chapters, we discussed the negative impact of PEV charging on distribution power grid. Several performance indices are employed to help users visualize the negative impacts of PEV charging. However, the negative impact of PEV charging can be reduced while they are properly guided, e.g., if PEVs are guided to charge at off-peak hours, then they can act as a "valley filler." This whole process can be described as an optimization problem to determine when and how PEVs should charge.

Load coordination has been well studied in literature of demand-engaged electricity markets [21] and frequency control [27] in transmission systems. However, these results cannot be migrated to the distribution level, at which the discreteness of PEV's charging profile and grid switch-gears' response are magnified. When it comes to specific PEV load control, the charge optimization framework has been well studied through both convex and non-convex problems. The Non-convex problem, which includes Mixed-Integer Programs (MIP) with indicator variables [14] and dynamic programs [24] are widely used. However, in DGROM, convex optimization is chosen to solve coordinating charging problem for many reasons. First, their relatively simple solution algorithms help to reduce computational costs when simulating large-scale systems. Secondly, the system itself can be described as a convex problem.

Though some studies [3, 11, 14, 29], use MIPs with integer status variables to build up the problem, which can, in fact, be replaced with a continuous variable representing transmitted power. Game theory is also employed by some papers [15, 27, 33, 38] by describing the problem into a non-cooperative, zero-sum game. However, the system that is suitable to perform game theoretical approach is limited to the small-scale system while the process of solving a game can be increasing in exponential. [38].

To overcome the deficiencies mentioned before and the real need of DGROM, we propose a suite of algorithms based on convex and nonlinear optimization methods. While the convex-based algorithms present fast convergence, the nonlinear-based algorithms promise consistent optimization performance over increasing system scales. The algorithms consist three parts: TCHL, optimization formulations, and Solver Selector.

3.1 Temporal Characteristic Hub of Load (TCHL)

In chapter 2, we have introduced that TCHL is capable of generating the temporal characteristic of PEVs including charging time and duration as shown in Figure 2.4. These parameters are essential for coordinate charging. Thus, the data from TCHL will be imported and further edited by TCHL while the coordinate charging function is enabled in DGROM. TCHL also includes a time-dependent electricity price model when the user needs to concern about the price of charge a PEV. A typical price function embedded is [5, 28]

$$f(Q) = \alpha(\frac{Q}{C})^k, \tag{3.1}$$

where α and k are constants, C is the total load of the whole grid, and Q is the power absorbed by the PEV. This function can be edited, improved, or replaced by the user to achieve a better result.

3.2 Formulation

As described in previous chapters, commuters and ride service vehicles have different routines and charging locations. In DGROM, every vehicle needs to report its current status $[SOC, CAP, t_1, t_2]$ to the system before charging, where SOC is the remaining battery energy, CAP is the capacity, and $[t_1, t_2]$ is the charging start and end time. For commuters, t_2 is their time to leave home. For shuttle service vehicles, t_2 is defined by:

$$t_2 = rand \times \frac{(1 - SOC) \times CAP}{p_{nmax}} + t_1, \tag{3.2}$$

where $1 \leq rand \leq 3$ is a uniformly distributed random variable referring to the charging priority, p_{nmax} is the maximum charging rate based on charging level. The default step size of optimization is 15 min, and the length of simulation is 24 hours, resulting in 96 time periods corresponding to charge start and end times. For example, assume a PEV is leaving at 8 a.m in the morning and arrives home at 9 p.m. We have $t_1 = 21 \times 4 = 84$; $t_2 = 8 \times 4 + 96 = 128$. Thus, the time period corresponding to this PEVs charge time is $[t_1, t_2] = [84, 128]$.

For PEV owner, who are particularly interested in his benefit, a price-minimizing objective function is designed. Previous day's load data is used to calculate the electricity price curve for the next day. Thus, the objective function minimizing owner's charging cost is:

$$\min_{p_n} \qquad \sum_{n=t_1}^{t_2-1} \int_{n}^{n+1} f(p_n) dp_n, \tag{3.3}$$

where p_n is the charging power at the n^{th} slot.

For utility, an objective function minimizing the load variance is designed.

$$\min_{p_n} \qquad \mathrm{Var}\,[C_n + \sum_{i=1}^{K} p_{i,n}], \tag{3.4}$$

where C_n is the base load at the n^{th} slot, K is the total number of PEVs.

This algorithm offers series of system constraints. From owner's perspective, they want their vehicles are ready when they need to leave. Thus,

$$\sum_{n=t_1}^{t_2-1} p_n \times 0.25 = (1 - SOC) \times CAP, \tag{3.5}$$

From the utility's perspective, a limitation of the system's total power is necessary [35]:

$$C_n + \sum_{i=1}^{K} Q_{i,n} \leq L, \tag{3.6}$$

where L is the maximum value of the total load. The node voltage needs to be constrained to prevent overloading [29]:

$$V_{N,k} = V_{1,k} - \sum_{i=1}^{N-1} [P_{i(i+1),k} R_{i,i+1} + Q_{i(i+1),k} X_{i,i+1}] \geq V_{min}, \tag{3.7}$$

where $P_{i(i+1),k}$ and $Q_{i(i+1),k}$ are the active and reactive power flow from bus_i to bus_{i+1} in period k $R_{i,i+1}$ and $X_{i,i+1}$ are the resistance and reactance from bus_i to bus_{i+1}.

The implementation of this algorithm is currently limited to day-ahead pricing within DGROM. In the future, real-time pricing will be integrated to allow for decision making with respect to changing prices in real-time. Public charging will also

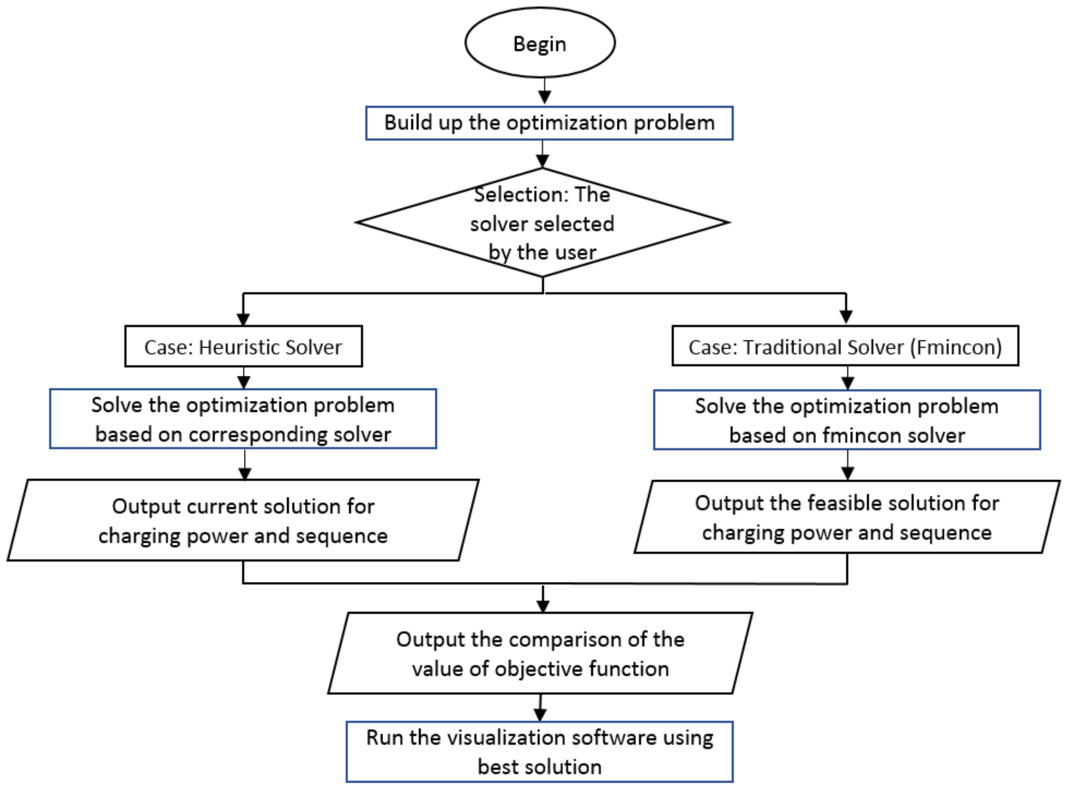

Figure 3.1: This flow chart shows how DGROM select the solver. Here, both solvers are selected, and a comparison is provided. However, such comparison is not mandatory. DGROM will ask for change a solver when: 1. The heuristic solver has solved the problem. 2. The Traditional solver takes more than 10 minutes to solve.

be considered from the perspective of the station itself, with an aggregator seeking to maximize their profit considering an unexpected ending of charge event by the user. Bidirectional power flow will also be considered, allowing for the simulation of ancillary services provided by PEVs.

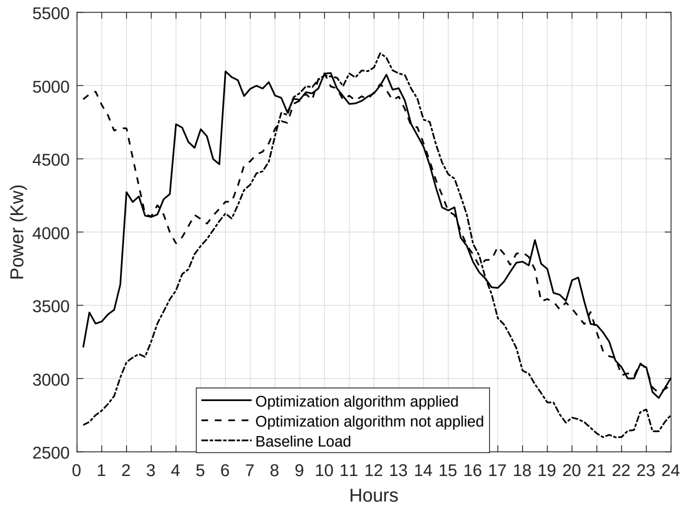

Figure 3.2: The effect of coordinated charging within a test system.

3.3 Solver Selector

DGROM supports both mathematical solvers and heuristic solvers. Mathematical solvers, e.g, interior points method and active set methods, provide global optimal solution when the problem is convex. However, As the optimization framework becomes more complex, mathematical solvers may fail to deliver results within a reasonable time, while heuristic methods can result in over 75% reductions of CPU time [16]. Among different heuristic methods, Genetic Algorithms work well with highly non-linear formulations and an expanded optimization framework will take non-linear forms. Particle Swarm Optimization works best for task scheduling, a form of the problem being addressed. Further, DGROM allows for the comparison of optimal results obtained from different solvers. The flowchart of how solver selector select between different solvers is shown in Figure 3.1.

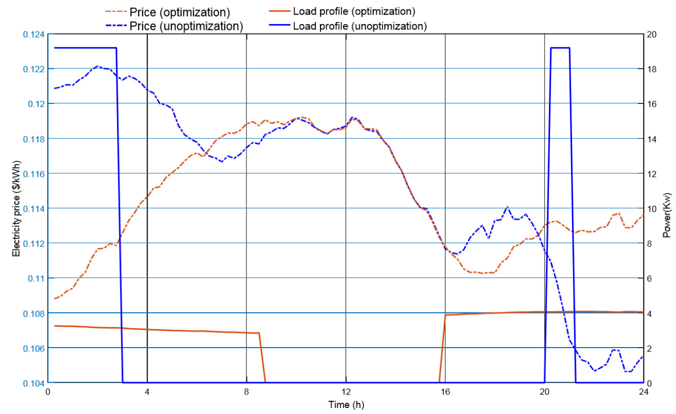

Figure 3.3: The price reduction when focusing on minimizing charging cost.

3.4 Results

The coordinated charging algorithm performed well. A numerical example using interior-point method with the objective function (3.3) and constraints (3.5)-(3.7) are shown in Figure 3.2.

Figure 3.3 shows the charging strategy for a commuter and corresponding electricity power price. From the figure, we can find that DGROM can reduce the charging cost by 23% when we choose to minimize the charging cost. When the coordinated charging algorithms applied, comparing to the original charging process, the charging power reduced while charging time increases. More generically, most of the vehicles in this case is daily commuters, who tend to charge at home using residential level. From the figure, we can see that massive charging of PEV can have huge effect on the price curve. Thus, it is likely to predict that the public charging can save more money while it needs more power from the power grid. In the future, more cases discussion the charging cost and public charging station and residential charging will be provided.

Chapter 4: Conclusion and Future Works

As PEVs continue to become a larger portion of fleets on the road, the ability to visualize impacts to the grid caused by their charging becomes more important. In this paper, a software platform, DGROM, was presented to address the deficiencies present in past works, which focus on static impact analysis for specific test cases. DGROM's graphical user interface allows for easy parameter definition, including driving habits, PEV types, and penetration patterns. Its back end allows fast integration and processing of data for scattered PEV charging over wide areas through the improvement of commercial solvers. This software also considers mitigation efforts by providing built-in algorithms for coordinated charging, presenting the optimization basis and algorithms for PEV coordination. Distinct from studies of PEV coordination at the transmission level, the proposed algorithms embrace the discreteness of PEV charging profile and grid asset response, allowing accurate estimation of coordination's cost-effectiveness. In addition to reducing distribution grids' stress, these algorithms allow the maximization of end-user benefits under varying retail electricity prices. The proposed PEV coordination algorithms are integrated with DGROM, which analyzes and visualizes the dynamic load response of distribution grids.

In the future, the update and improvement of DGROM will focused on following parts.

1. Better coding structure. Currently, the coding structure is constrained by the communication between MATLAB and OpenDSS while the parallel computing function embedded, which can greatly increase simulation speed, is not available. Thus, the efficiency of the code can be improved while we use other distribution grid simulator, especially these embedded in MATLAB.

2. In the future, DGROM will provide more analyses about asset depreciation, which greatly enhance the ability for DGROM to analyses the long-term impact of charging and corresponding countermeasure.

3. In the future, users can import their coordination charging algorithms or charging station planning algorithms. At the same time, DGROM will provide

Bibliography

[1] Ieee standard power cable ampacity tables. *IEEE Std 835-1994*, pages 1–3151, Dec 1994.

[2] International Energy Agency. Global ev outlook 2017: Two million and counting. `https://www.iea.org/publications/freepublications/publication/GlobalEVOutlook2017.pdf`. Accessed 2017.

[3] Ali T Al-Awami and Eric Sortomme. Coordinating vehicle-to-grid services with energy trading. *IEEE Transactions on smart grid*, 3(1):453–462, 2012.

[4] O. Beaude, S. Lasaulce, M. Hennebel, and I. Mohand-Kaci. Reducing the impact of ev charging operations on the distribution network. *IEEE Transactions on Smart Grid*, 7(6):2666–2679, Nov 2016.

[5] Hendrik Bessembinder and Michael L Lemmon. Equilibrium pricing and optimal hedging in electricity forward markets. *the Journal of Finance*, 57(3):1347–1382, 2002.

[6] BMW. Bmw introduces series of electric-powered emergency vehicles. `https://www.ems1.com/ems-products/specialty-vehicles/articles/54355048-BMW-introduces-series-of-electric-powered-emergency-vehicles/`. Accessed 2017.

[7] Artyom Dogtiev. Uber revenue and usage statistics 2017. `www.businessofapps.com/data/uber-statistics/`. Accessed 2017.

[8] C. Farkas, K. I. Szab, and L. Prikler. Impact assessment of electric vehicle charging on a lv distribution system. In *Proceedings of the 2011 3rd International Youth Conference on Energetics (IYCE)*, pages 1–8, July 2011.

[9] Anmar Frangoul. With new electric vehicle, london's iconic black cabs are about to go green. `https://www.cnbc.com/2017/07/12/with-new-electric-vehicle-londons-iconic-black-cabs-are-about-to-go-green.html`. Accessed 2017.

[10] Z. Hu and Y. Song. Distribution network expansion planning with optimal siting and sizing of electric vehicle charging stations. In *2012 47th International Universities Power Engineering Conference (UPEC)*, pages 1–6, Sept 2012.

[11] Chenrui Jin, Jian Tang, and Prasanta Ghosh. Optimizing electric vehicle charging with energy storage in the electricity market. *IEEE Transactions on Smart Grid*, 4(1):311–320, 2013.

[12] B. J. Johnson, M. R. Starke, and A. D. Dimitrovski. Examining the potential impact of plug-in electric vehicles on residential sector power demand. In *2015 IEEE Power Energy Society General Meeting*, pages 1–5, July 2015.

[13] J. C. G. Justino, T. M. Parreiras, and B. J. Cardoso Filho. Hundreds kw charging stations for e-buses operating under regular ultra-fast charging. *IEEE Transactions on Industry Applications*, 52(2):1766–1774, March 2016.

[14] Mohammad E Khodayar, Lei Wu, and Mohammad Shahidehpour. Hourly coordination of electric vehicle operation and volatile wind power generation in scuc. *IEEE Transactions on Smart Grid*, 3(3):1271–1279, 2012.

[15] Zhongjing Ma, Duncan S Callaway, and Ian A Hiskens. Decentralized charging control of large populations of plug-in electric vehicles. *IEEE Transactions on Control Systems Technology*, 21(1):67–78, 2013.

[16] Belkacem Mahdad, Kamel Srairi, and Tarek Bouktir. Optimal power flow for large-scale power system with shunt facts using efficient parallel ga. *International Journal of Electrical Power & Energy Systems*, 32(5):507–517, 2010.

[17] D. Mao, D. Meyer, and J. Wang. Evaluating pev's impact on long-term cost of grid assets. In *2017 IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pages 1–5, April 2017.

[18] Zach Mcdonald. Electric taxis are on their way. `https://www.fleetcarma.com/electric-taxis-on-their-way/`. Accessed 2017.

[19] NHTSA. 2011 national survey of speeding attitudes and behaviors. `https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/2011_n_survey_of_speeding_attitudes_and_behaviors_811865.pdf`. Accessed 2017.

[20] Bureau of Transportation. From home to work. `https://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/omnistats/volume_03_issue_04/pdf/entire.pdf`. Accessed 2017.

[21] Miloš Pantos. Exploitation of electric-drive vehicles in electricity markets. *IEEE Transactions on Power Systems*, 27(2):682–694, 2012.

[22] M. Pipattanasomporn, M. Willingham, and S. Rahman. Implications of on-site distributed generation for commercial/industrial facilities. *IEEE Transactions on Power Systems*, 20(1):206–212, Feb 2005.

[23] P. Richardson, D. Flynn, and A. Keane. Optimal charging of electric vehicles in low-voltage distribution systems. In *2012 IEEE Power and Energy Society General Meeting*, pages 1–1, July 2012.

[24] Niklas Rotering and Marija Ilic. Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets. *IEEE Transactions on Power Systems*, 26(3):1021–1029, 2011.

[25] Soroush Shafiee, Mahmud Fotuhi-Firuzabad, and Mohammad Rastegar. Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems. *IEEE Transactions on Smart Grid*, 4(3):1351–1360, 2013.

[26] ANSI Standard. C84. 1-2011, electric power systems and equipment-voltage ratings (60 hertz).

[27] Jun Tan and Lingfeng Wang. A game-theoretic framework for vehicle-to-grid frequency regulation considering smart charging mechanism. *IEEE Transactions on Smart Grid*, 2016.

[28] Chen Wang and Martin De Groot. Managing end-user preferences in the smart grid. In *Proceedings of the 1st International Conference on Energy-Efficient Computing and Networking*, pages 105–114. ACM, 2010.

[29] Miao Wang, Hao Liang, Ran Zhang, Ruilong Deng, and Xuemin Shen. Mobility-aware coordinated charging for electric vehicles in vanet-enhanced smart grid. *IEEE Journal on Selected Areas in Communications*, 32(7):1344–1360, 2014.

[30] X. Wang and R. Karki. Exploiting phev to augment power system reliability. *IEEE Transactions on Smart Grid*, 8(5):2100–2108, Sept 2017.

[31] WNYC. Average commute times. `https://project.wnyc.org/commute-times-us/embed.html#5.00/42.000/-89.500`. Accessed 2017.

[32] Chris Woodyard. Ford unveils first 'pursuit rated' hybrid police car for high-speed chases. `https://www.usatoday.com/story/money/cars/2017/04/10/fords-new-hybrid-police-car-fights-smog----and-crime/100234812/`. Accessed 2017.

[33] Chenye Wu, Hamed Mohsenian-Rad, and Jianwei Huang. Vehicle-to-aggregator interaction game. *IEEE Transactions on Smart Grid*, 3(1):434–442, 2012.

[34] Fei Wu and Ramteen Sioshansi. A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows. *Transportation Research Part D: Transport and Environment*, 53:354–376, 2017.

[35] Zhiwei Xu, Wencong Su, Zechun Hu, Yonghua Song, and Hongcai Zhang. A hierarchical framework for coordinated charging of plug-in electric vehicles in china. *IEEE Transactions on Smart Grid*, 7(1):428–438, 2016.

[36] H. Zhang, S. Moura, Z. Hu, and Y. Song. Pev fast-charging station siting and sizing on coupled transportation and power networks. *IEEE Transactions on Smart Grid*, PP(99):1–1, 2017.

[37] Yao Zhang, Wenxuan Yao, Shutang You, Wenpeng Yu, Ling Wu, Yi Cui, and Yilu Liu. Impacts of power grid frequency deviation on time error of synchronous electric clock and worldwide power system practices on time error correction. *Energies*, 10(9):1283, 2017.

[38] Suli Zou, Zhongjing Ma, Xiangdong Liu, and Ian Hiskens. An efficient game for coordinating electric vehicle charging. *IEEE Transactions on Automatic Control*, 62(5):2374–2389, 2017.