MINIMIZING PARKING SEARCH TIME ON URBAN UNIVERSITY
CAMPUSES THROUGH PROACTIVE CLASS ASSIGNMENT

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Ali Moradkhany

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Ali Moradkhany

Dissertation

Approved:

Accepted:

Advisor
Dr. Ping Yi

Department Chair
Dr. Wieslaw K. Binienda

Committee Member
Dr. Hamid R. Bahrami

Dean of the College
Dr. Rex D. Ramsier

Committee Member
Dr. Linda R. Barrett

Dean of the Graduate School
Dr. Chand Midha

Committee Member
Dr. Ala R. Abbas

Date

Committee Member
Dr. Junliang Tao

Committee Member
Dr. Patrick J. Wilber

ABSTRACT

Cars cruising to find a parking space represent a key component of the traffic on urban university campuses. This study introduces a bi-objective optimization algorithm to demonstrate the feasibility of minimizing the parking search time and the number of parking trials to find a free space on urban university campuses due to daily commuters. An activity-based model is developed to assess the variation in the parking search time and the number of parking trials due to different classroom assignment methods. This model is able to investigate the effect of different arrival-departure conditions as well as different parking search methods. The University of Akron campus was selected in a case study to show the parking search time reduction under variety of conditions by using the proposed optimization approach. According to the results, using this approach, the parking demand can be efficiently distributed and the search time can be effectively reduced by around 18%. Moreover, the finally optimized class assignments will result in effective mitigation of the cruising flow due to around 14.5% reduction in the total number of parking trials. The application of developed search model is not limited to the campus parking and can be expanded to many other problems. To show this flexibility, the proposed search model was applied to a special event parking search problem and the sensitivity of parking search time to various modeling parameters was investigated.

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CHAPTER I

INTRODUCTION

1.1 Parking Demand Management

Traditionally, adding more supply - through adding new parking facilities to meet the increasing demand has been a common practice to overcome the parking shortage. However, that approach has become less effective due to several land-use, financial and environmental costs and limitations. In addition, providing more free parking for the incoming demand results in more driving over time. Therefore, parking capacity expansion approach that originally intended to reduce congestion, may be worsening it, and may have other unintended negative impacts as well. The primary alternative to increasing supply is managing demand; changing the ways people travel has proven to be a quite effective way to manage congestion and make more efficient use of existing facilities.

Parking demand management works as a balancing act; Too much parking, particularly if provided in surface lots, uses valuable land resources and often results in widely-spaced and disconnected development patterns. Too little parking - or poorly designed or located parking - can result in parking spillover to adjacent areas, lead travelers to choose alternate destinations, and/or inhibit development [1].

Parking facilities can be considered as critical nodes in the traffic network with major effect on overall performance of every urban transportation system. During recent years, due to considerable increase in private car use, providing enough parking spaces for emerging demand has been a challenging issue. High construction costs of new parking facilities, as well as several land use limitations, has enforced policy makers to find a way to use existing facilities as efficient as possible.

Parking pricing, access restrictions, change in time and location of different activities, and real-time parking information are common examples of parking demand management strategies. These solutions provide the policy makers with the opportunity to predict and change drivers' behavior, and utilize parking spaces based on desirable predefined patterns.

Traditional parking demand management strategies such as pricing, time-based and location-based access restriction are based on reactive approaches that suppress the parking demand. Due to the change in parking price and/or accessibility, drivers will either change their parking location or shift to other travel modes that results in more efficient utilization of existing supply. However, they do not guarantee the convenient access since commuters may be enforced to select a parking location which are far from their final destination.

Other parking demand management strategies include parking taxing, parking maximums, reserved parking, shared parking, park and ride facilities, etc. Feasibility and effectiveness of each strategy depends on the demand characteristics, travel mode choice behavior, land use pattern, and other supply constraints. For example, shared parking works best where multiple destinations are within walking distance of the same parking

facility, and when those destinations either share patrons, or have different periods when parking demand is highest. However, in areas with sparse local transit service but with proven regional transit connections to downtowns, park and ride strategy can help to reduce the number of people who drive into downtown, especially during the critical peak hours [2].

During recent years, parking guidance information (PGI) system has been commonly used by policy-makers as an innovative and effective solution to the parking problems. The system performs based on the combination of various traffic monitoring and communication technologies, and contributes to the parking search time reduction by disseminating dynamic and real-time parking information to users. Although several research and practices have proved the efficiency of this technology, still similar to the traditional approaches, there is no guarantee for convenient access to the final destination. Additionally, PGI system is a considerably expensive alternative due to the required equipments, technical elements, and high maintenance costs.

1.2 Problem Statement

Parking search time has been identified as a significant contributor to urban congestion. Several studies have found that parking search time can constitute higher than 25% of the average total travel time. The same studies also indicated that drivers value parking search time at about 1.5 to 2 times of the value of driving time [3]. Shoup (2007) found that 30% of vehicles on the road in the downtown area of major cities are cruising for a parking spot and it takes an average of 7.8 minutes to find one [4]. Thus, policy-makers have been relying more and more on parking demand management strategies to mitigate this substantial increase in the generalized cost of travel.

Parking demand management on urban university campuses plays a key role in providing convenient access to campus facilities and consequently has a considerable effect on the academic and cultural activities at every university. Inefficient parking demand distribution results in unnecessary cruising over the traffic network as commuters look for convenient spaces near their activity location. In addition to increase in the search time, cars cruising on campus for parking may create congestion, restrict different levels of accessibility, cause traffic accidents, affect pedestrians, generate noise, pollute the air, and waste fuel [5]. Thus, both the parking search time and the traffic flow cruising for parking are key operation and management efficiency indicators of the parking system.

University campuses have a lot of challenging issues related to parking management. Every year, due to increase in number of students, universities allocate a huge budget to build new parking facilities which is followed by the long-term costs of maintenance costs. The problem is more crucial when the existing supply exceeds the total demand, but the demand is not well distributed.

Campus parking demand is commonly heavy in an urban university. Generally, commuters of an activity search for spaces within an acceptable walking distance to the same activity location. On the other hand, individual activity schedules among commuters yield different arrival-departure distributions, leading to different parking search processes and parking utilization patterns on university campuses. Therefore, using an activity-based approach, it is possible to efficiently distribute the demand over the parking facilities such that the collective parking search time and the correspondent cruising flow may be properly minimized.

1.3 Research Objective

Corroborating the reactive techniques, this study proposes a novel activity-based approach as a proactive way to redistribute the parking demand in support of efficient parking demand management. An optimization algorithm is introduced to demonstrate the feasibility of minimizing campus parking search time by changing class schedule as the major input in the optimization process. In a given campus environment, the developed algorithm investigates the effect of different classroom assignment options (assigning classes to different classrooms and buildings) on the overall parking search time. Additionally, to further improve the results, for each assignment, the proposed model takes into account the total number of parking trials to find a free spot as the measure of cruising flow. In other words, the finally optimized class assignment(s) will result in the lowest levels of both the parking search time and the cruising flow simultaneously.

Class schedule can be described as class location and time. Although the class time is initially established by the university, it might change by the faculty based on their personal schedule. Therefore, this study is mainly focused on the class location assignment. That is, the proposed methodology shows how to assign classes to possible locations to effectively decrease the parking search time and cruising flow. A simulation methodology is introduced to consider various situations and evaluate the effectiveness of different alternatives.

Thanks to the increase in the processing power and storage capacity of modern computers, many computationally complex optimization techniques have gained considerable popularity in network analysis and facility allocation problems. These methods work based on the simple concept of random search, and can be easily coded in

different programming platforms. Moreover, in many cases, the solution set is discrete, and continuous optimization approaches are far less tractable.

In this study, a discrete optimization approach is carried out using the direct random search method. In optimization problems with a very large search space, application of this method may reduce the convergence rate and result in a phenomenon called ‘combinatorial explosion’. However, by controlling the search space (solution set) during repetitive calculations and defining appropriate termination criteria, suitable results are obtainable in a reasonable time [6][7][8][9]. Additionally, by defining appropriate constraints, the size of the search space can be reduced, and consequently, the convergence rate can be improved.

In addition to the class schedule, both the parking search time and the number of parking trials on university campuses depend on many other factors such as arrival and departure distributions, parking search behavior, and rational location of different buildings and parking facilities. Defining some parameters, the developed model considers the effect of mentioned factors on the optimization results under different conditions.

Application of the proposed model is not limited to the campus parking and can be applied to variety of problems in parking demand management. In order to show this capability, the developed model was applied to a special event parking problem. and the feasibility of reducing parking search time under different combination of modeling parameters was investigated.

1.4 Dissertation Outline

This dissertation is organized in several chapters. The second chapter is devoted to the literature review. In the third chapter, the mathematical model (objective function) is proposed and explained. The fourth chapter includes different steps in developed search model to estimate the parking search time and number of parking trials (as the measure of the cruising flow). The optimization algorithm is discussed in the fifth chapter. The sixth chapter describes the application of proposed model on a case study. In the seventh chapter, the feasibility of applying proposed search model to the special event parking search problem is investigated. Finally, the eighth chapter presents the conclusion of the study and the way forward.

CHAPTER II

LITERATURE REVIEW

2.1 Parking Search Model

For many years, researchers have used aggregated approaches to model the parking search process. However, in the recent decades, activity-based models have gained high popularity in parking studies. Activity-based simulation approaches have high temporal and spatial resolution where individual drivers are at the core of the simulation. They can potentially simulate in detail the change by a policy measure both from the driver's perspective (e.g. change in search time, walk distance, cost) or from the overall systems perspective (e.g. change in travel mode, parking revenue or traffic counts) [10]. Studies carried out by Young (1986) for parking search inside parking lots and Axhausen (1990) for an activity-based parking model including parking type choice and search were early efforts in this area [11][12].

PARKAGENT developed by Benenson et al. (2008) can be considered as the first complex and detailed activity-based parking search model. It was applied to residential parking considering different groups of drivers (e.g. residential and visitors). The destination of the drivers were fixed at the beginning of the simulation. The model was able to estimate the parking utilization by tracking each individual driver and following his/her decision to park.

In this model, the main modeling factor to select a parking facility was considered as its distance to the final destination. If the driver does not find any parking after reaching the destination, it continues driving and just takes any parking it can get. If the search time is more than 10 min, driver will select the closest paid off-street parking to the destination. The model was applied to a neighborhood in Tel Aviv with severe parking shortage and where the impact the addition of one/several parking facilities is investigated [13].

The second activity-based parking model was developed by Spitaels et al. (2009) and called SUSTAPARK. It was applied to the city centre of Leuven, Belgium containing 14'000 drivers. The model is more complex than PARKAGENT due to the ability to simulate the traffic network. A multinomial logit (MNL) model was defined to simulate switching between parking types. Furthermore, the model is able to differentiate between visitors and local commuters who have prior knowledge about the parking availability [14].

Previously described activity-based models lack the capability of feedback to the traffic simulation and are therefore incapable of simulating parking policies, which might affect mode choice or location choice. More recently, Waraich and Axhausen (2012) developed more powerful activity-based parking search model using an existing activity-based traffic simulation called MATSim [10]. Comparing to SUSTAPARK and PARKAGENT, the model has many advantages as it can consider different parking strategies, travel mode choice, and change in travel time through the modeling process.

2.2 Parking Pricing and Access Restriction

According to the literature, majority of parking studies have been focused on pricing strategies to mitigate the demand for single occupancy vehicles and encourage travelers to use other transportation modes. Teknomo and Hokao (1997) carried out a research to model the mode choice behavior of travelers encountering different levels of parking pricing, in Surabaya, Indonesia [15]. A similar case study was performed in the Central Business District (CBD) of Athens by Tsamboulas (2001) to analyzes drivers' parking behavior when confronting various parking prices policies [16]. Developed model was able to investigate the change in private car usage due to the increase in parking price.

Finding the optimum price level is a key to the efficiency of parking pricing strategies. Anderson and Palma (2004) developed a parking congestion model to assess the effect of parking pricing policy on the overall market equilibrium [17]. The research showed that without an appropriate and competitive pricing patterns, the congestion resulted from cruising for parking will substantially reduce the benefits from pricing strategies. The research by D'Acierno et al. (2006) is a good example of finding an optimum parking price. They developed an optimization approach with three different objective functions; System Optimum; Accessibility Optimum and Social Optimum, as well as various mode-specific and mode-abstract variables [18].

Logit models have been commonly used to analyze the parking choice behavior. Van der Waerden et al. (2006) used Multinomial Logit analysis to assess the attitudes and behavioral responses of Eindhoven campus commuters to parking measures such as pricing and access restriction [19]. Another Logit model developed by Aflaki et al. (2010) considers the effect of various parameters on the travel mode choice of Tehran

Central Business District (CBD) travelers. They found that the parking price has a significant effect on the travelers behavior and there is a parking fare threshold above which all passengers will select the transit modes [20].

Parking demand affects the traffic network from different perspectives. An effective parking policy such as pricing results not only in efficient usage of existing parking supply, but also helps to mitigate the traffic by redistribution of existing demand. Recently, Qian and Rajagopal (2014) assessed the effect of dynamic pricing and information provision on the morning commutes. They formulated the parking choices under the User Equilibrium (UE) conditions using the Variational Inequality (VI) approach and showed that any optimal flow pattern can be achieved by charging parking prices in each area that only depend on the time or occupancy, regardless of origins and destinations of users of this area [21].

2.3 Parking Guidance Information System

Parking Guidance Information (PGI) system has been commonly used as a novel and effective solution to increase the efficiency of parking system. The system works based on the combination of various traffic monitoring and communication technologies, and contributes to the parking search time reduction by disseminating dynamic parking information to the users. The first implementation of the system was in Aachen, Germany in early 1970's based on displaying parking information on variable message signs (VMS). Though, up to now, this type has been the most widely used form of PGI system, the provision of in-vehicle parking information system has been significantly under development since early 1990's [3].

Many studies have assessed the effect of PGI system on the parking search process. Thompson et al. (2001) developed a mathematical program based on simple genetic algorithm (GA) to determine the optimal display of Parking Guidance Information (PGI) signs and minimize queue lengths and vehicle kilometers of travel [22]. Vianna et al. (2004) assessed the feasibility of implementing an integrated parking system based on telematics resources [23]. Caicedo (2010) used GA to investigate the possibility of finding the optimum information conditions that can be translated into lower emissions of toxic greenhouse gases and consequently lower search time [24].

Another study by Caicedo (2009) proposed two different strategies to manage availability information in parking facilities, and found around 16 percent potential parking search time reduction [25]. Shin and Jun (2014) developed a smart parking guidance algorithm, considering different factors such as driving distance to the guided parking, walking distance to the final destination, and parking cost. The goal was to maximize the utilization of space resources of the city and reduce the traffic congestion due to the parking search process [26].

2.4 Special Event Parking

There is little research contributing to the special event parking management. Sattayhatewa and Smith (2003) developed a lot choice model for special events using Logit function. They formulated the joint parking lot destination choice and assignment model using the concepts of User Equilibrium traffic assignment and entropy maximization for trip distribution. The parking lot choice model was applied to a basketball game event at the Kohl Center in Madison, Wisconsin to estimate the impacts of opening a new private parking lot [27]. Another study by Yan et al. (2005) proposed a

bicycle parking search model in special events based on the utility model, and used the maximum likelihood estimation to calibrate the utility of each component [28]. Lu et al. (2009) tried to model the special event parking search using a Logit based utility model with the travel time, parking fees, public transportation fees, and walking distance as the variables [29].

2.5 Parking Policies and Activity Schedule

Parking system parameters such as utilization ratio, price, type and location are key factors that influence the travel and activity schedule of trip-makers. On the other hand the activity schedule as an important factor to travel mode and destination choice is critical to parking choice and duration of drivers.

A few research has been conducted to assess the relationship between parking demand and activity scheduling. Hess and Polak (2004) used stated preferences data to model travelers' responses to change in parking attributes. They concluded that journey purposes have a strong impact on parking choice [30]. Washbrook et al. (2006) used simulated data to model parking behavior, and found that trip purpose has a significant effect on different elements of parking choice [31]. Khandker et al. (2012) developed a Generalized Extreme Value (GEV) model to investigate the relationship between parking type choice and activity scheduling process (start time choice) in Greater Montreal Area [32]. Recently, Riggs (2014) conducted a study at the University of Berkley, one of the largest regional employers in the San Francisco Bay Area, to assess the participants' responsiveness to changes in pricing and information to reveal how a campus population can search less for parking, drive fewer days per week and switch modes entirely. Results

indicates that social factors and incentives can have a strong pull on driving behavior [33].

According to the literature, research in this area has been limited to the effect of parking-related parameters on activity selection of travelers. Unfortunately, there is no research to consider activity scheduling (time and location) as a policy tool to redistribute the parking demand and make more efficient use of existing resources.

2.6 Campus Parking Management

From the modeling standpoint, transportation systems of modern university campuses provide several interesting and challenging research opportunities. On one hand, a university campus system can serve as an excellent, micro-scale example of regional transportation systems, which allows the researcher to focus on the fundamental research questions without needing to spend a disproportionate amount of time in the labor-intensive phases of data collection, model coding and debugging of a large-scale system. On the other hand, university campuses have unique features that do not often receive sufficient attention when modeling regional networks. These include trip making characteristics that significantly differ from those of individuals living in a typical single-family household, as well as issues pertaining to providing an adequate supply of parking spaces [34].

Several research work have been done to investigate the efficiency of parking demand management policies on university campuses. McIntyre (1990) conducted a comprehensive survey in several colleges in California and suggested some measures to improve the efficiency of campus parking system [35]. Carl and Davis (2001) investigated the performance of different parking policies by developing a mathematical

model [36]. Leng and Yan (2003) proposed an approach to improve the parking system in Tongji University, China [37]. Song and Wang (2004) conducted several relevant surveys in Chinese universities [38]. Shang et al. (2007) conducted a statistical analysis on parking-related parameters in Beijing University and made some suggestions to increase the efficiency of campus parking system [39].

Unfortunately, little work has been done up-to-date to link campus parking demand management with class scheduling on university campuses. The only effort found in the literature on activity-based modeling of the campus parking demand is a recent study done by Gua et al. on the north campus of University of Buffalo, in which the authors used the game theory to simulate the parking search process and investigate its environmental effects [34]. However, the research has not discussed the effect of campus activity scheduling on parking search process.

CHAPTER III

MATHEMATICAL MODEL

3.1 Objective Function

The main goal of this mathematical model is to find the class assignment that leads to both the minimum parking search time and the minimum number of parking trials of campus commuters, simultaneously (Pareto optimal solution). For this purpose, a bi-objective function is formulated as follows:

$$\text{minimize } (ST_{ave}, PT_{ave}) \quad (3-1)$$

$$ST_{ave} = \frac{1}{M} \sum_{m=1}^M ST_{m,n} = \frac{1}{M} \sum_{m=1}^M \sum_{g=1}^G st_{g,m,n} \quad (3-2)$$

$$PT_{ave} = \frac{1}{M} \sum_{m=1}^M PT_{m,n} = \frac{1}{M} \sum_{m=1}^M \sum_{g=1}^G pt_{g,m,n} \quad (3-3)$$

where ST_{ave} and PT_{ave} are the average overall parking search time and the average total number of parking trials respectively, under a certain type of class assignment, considering different parking utilization patterns. $ST_{m,n}$ and $PT_{m,n}$ are the overall parking search time and the total number of parking trials respectively, for parking utilization pattern m , and classroom assignment n . $st_{g,m,n}$ and $pt_{g,m,n}$ are the parking search time and the number of parking trials to find a free spot respectively, for commuter g under parking utilization pattern m , and classroom assignment. Finally, M and G represent the number of considered parking utilization patterns and the number of commuters, respectively.

A class assignment represents one way in which all the required classes are assigned to different buildings and classrooms on campus. Considering the randomness in both the space searching (in addition to the rational response of commuters) and their arrivals and departures, different parking search and utilization results can be expected from any unique class assignment.

Basically, the model works based on averaging search times and number of parking trials achieved from different parking utilization patterns. Each parking utilization pattern presents one way in which the parking facilities can be utilized by commuters under a specific class assignment. The details to model parking search and utilization are discussed in the next sections.

3.2 Constraints

Developed objective function is subject to constraints as follows:

$$(CLS)_i \leq (RC)_{r,b} \quad (3-4)$$

$$(Req)_i \subseteq F_{r,b} \quad (3-5)$$

$$(Av)_{r,b,t} = 1 \quad (3-6)$$

$$\min(WD_{b_i b_{di}}) \leq WDMAX \quad (3-7)$$

$$\min(WD_{P_g b_{Tg}}) \leq WDMAX \quad (3-8)$$

$$O_{p,t} \leq C_p \quad (3-9)$$

$$st_{g,m,n} \leq st_{max} \quad (3-10)$$

$$pt_{g,m,n} \leq pt_{max} \quad (3-11)$$

where $(CLS)_i$ is the size of class i and $(RC)_{r,b}$ is the room capacity (number of seats) in room r , located in building b . $(Req)_i$ is the required level of instructional facility support

for class i and $F_{r,b}$ is the instructional facility support of room r , located in building b . $(Av)_{r,b,t}$ is the availability indicator for room r , located in building b at time t . b_i is the building to which the class i is assigned. b_{di} is the building of the academic department which offers class i . $WD_{b_i b_{di}}$ is the walking distance between b_i and b_{di} . P_g is the parking facility selected by commuter g . b_{Tg} is the target building of commuter g . $\min WD_{p_g b_{Tg}}$ is the minimum walking distance between P_g and b_{Tg} . $WDMAX$ is the maximum acceptable walking distance based on the preference of campus commuters. $O_{p,t}$ is the occupancy of parking facility p . C_p is the capacity of parking facility p at time t . Finally, st_{max} and pt_{max} are the maximum acceptable parking search time and number of parking trials by campus commuters, respectively.

The first three constraints apply when assigning classes to classrooms. Data related to class size, number of seats, and classroom facility requirement are obtained from different university offices. During the assignment process, the Boolean variable $(Av)_{r,b,t}$ is set to 1 if the classroom is available and 0 if the classroom is occupied.

Every commuter is assumed to be associated with a major department. The fourth constraint guarantees the convenient access between the class location and the departmental building of the commuters where they spend their inter-class time. The maximum acceptable walking distance to classes on campus is set by the university office in classroom scheduling.

The last four constraints correspond to the parking search, parking utilization, and number of parking trials; the fifth constraint states that all commuters search for parking spaces within the acceptable walking distance from their target buildings. In addition, campus survey results showed that once parked, commuters attend classes and other

campus activities without moving their vehicles from one parking facility to another. This study determines the target building for each commuter based on her/his activity schedule and associated academic department in case of students and faculty, and work unit in case of university staff.

CHAPTER IV

PARKING SEARCH MODEL

4.1 Activity-based modeling of parking search

The activity-based approach to travel demand analysis views travel as a derived demand; derived from the need to pursue activities distributed in space. The approach adopts a holistic framework that recognizes the complex interactions in activity and travel behavior. The conceptual appeal of this approach originates from the realization that the need and desire to participate in activities is more basic than the travel that some of these participations may entail. By placing primary emphasis on activity participation and focusing on sequences or patterns of activity behavior (using the whole day or longer periods of time as the unit of analysis), such an approach can address congestion-management issues through an examination of how people modify their activity participations (for example, will individuals substitute more out-of-home activities for in-home activities in the evening if they arrived early from work due to a work-schedule change?) [40].

This study introduces an activity-based approach to analyze the parking search behavior of campus commuters. That is, the proposed model processes the parking selection sequence of each commuter based on the walking distance to the final destination (activity location). Driving distance between available parking facilities and prior knowledge about the parking occupancy are secondary parameters to influence the parking search behavior and will be discussed by this chapter in more details.

Overall, Parking search of campus commuters is often a complicated process. In this study, we assume no parking guidance information is provided and the commuters select their parking locations spontaneously according to the class schedule as a master plan of university campus activities.

4.2 Arrivals and Departures

Obviously, the parking search process is influenced by the availability and utilization of parking facilities based on different arrivals and departures of campus commuters. Campus wide traffic data investigation at the University of Akron indicates that the incoming traffic for campus parking is primarily determined by the number of commuters who need to be on campus during a specific time window based on class schedule. Similarly, the exiting traffic from campus is also found to depend on course completions of the commuters. Collectively, two main factors are considered over this problem, arrival/departure rate and arrival/departure sequence.

4.2.1 *Arrival and Departure Rate*

To estimate accurate arrival-departure rates, appropriate surveys must be conducted. Commonly, some predefined distributions such as Poisson distribution are commonly used for this purpose [41][42]. It has to be considered that the arrival-departure time distribution of campus commuters depends on their activity schedule and academic status. Undergraduate students usually come before their first class and leave the campus after their last class. Staff has to be on campus for a specific time period, due to strict activity start and end times. The situation for the faculty and graduate students is more complicated. For example, if they have their first class in the early morning, they

need to be on campus before the class start time. But, if their first class starts in the afternoon, the arrival time is not influenced only by the class start time. Even, if they have no classes, they usually come to the campus to attend other daily activities. To assess different situations, this study considers campus commuters in three different categories as follows, and makes appropriate assumptions accordingly.

- Undergraduate Students: The arrival-departure time distribution for this category strictly depends on their class time schedule. In this study, it is assumed that the arrival-departure rates of undergraduate students follow the Poisson distribution. The mean value for arrival and departure rates, as an essential parameter of the Poisson distribution, must be estimated based on the defined problem and appropriate surveys.
- Staff: Similar to undergraduate students, Poisson distribution can be used to estimate the arrival-departure rates of this category. However, they have distinct activity hours, based on official campus working hours.
- Faculty and Graduate Students: Usually they have no official activity start and end times. Also, in many cases their arrival-departure distribution is not influenced by class time schedule. Generally, if they have their first class before a specific time in the morning, the approach to estimate the arrival rates is similar to undergraduate students. similarly, if they have their last class after a specific time in the afternoon, the departure time distribution can be considered as same as departing undergraduates. In other cases, arrival-departure time distribution for

this category cannot be related to the class time schedule. Therefore, instead of Poisson distribution, this study uses uniform distribution to estimate arrival-departure rates of this category.

More specifically, campus surveys found that undergraduate students usually come before their first class and leave the campus after their last class with a particular lead/lag time interval. On the other hand, university staff come to and leave campus at a specific time period in the morning and in the afternoon.

Equation 12 shows the probability density function for Poisson distribution that has been used in this study to model arrival/departure rates:

$$P\{N(t) = n\} = \frac{(\mu t)^n}{n!} e^{-\mu t} \quad (4-1)$$

where $N(t) = n$ is the number of arrival events in a finite interval of length t .

Now, consider the waiting time until the first arrival. Clearly that time is more than t if and only if the number of arrivals before time t is 0. Combining this latter property with the above probability distribution for the number of arrival events in a fixed interval gives:

$$P(T > t) = P\{N(t) = 0\} = P\{N(t) - N(0) = 0\} = \frac{(\mu t)^0}{0!} e^{-\mu t} = e^{-\mu t} \quad (4-2)$$

and accordingly:

$$P(T \leq t) = P\{N(t) > 0\} = 1 - e^{-\mu t} \quad (4-3)$$

Therefore, the arrival time probability distribution function (PDF) and cumulative distribution function (CDF) can be shown as Equations 4-4 and 4-5 respectively. Resulted formulations represent negative exponential distribution [43]:

$$A(t_a) = 1 - e^{-\mu t_a} \quad (4-4)$$

$$a(t_a) = \mu e^{-\mu t_a} \quad (4-5)$$

where, t_a is the arrival time, $a(t_a)$ is the probability of arrival at t_a , and $A(ta)$ is the probability of arrival before t_a .

To model the departure time distribution, we assume each parking facility as a M/M/1 system. M/M/1 system has been commonly used for queue analysis and presents queuing process with the Poisson arrival process, exponentially distributed service times, and a single server [44]. That is, each facility works based on the Markovian input process with Markovian service distribution and single server. Accordingly, following assumptions are necessary:

- Average parking duration is known and the parking occupancy times follow the negative exponential distribution [45][46][47][48]. In other words, the parking duration is treated as the service time/visit length with known average value.
- Parking system works on the first-come, first-served (FCFS) basis.
- There is no queue congestion at entrance, exit, and inside parking facilities.

At this point, relying on the Burke theorem, departure times will follow the Poisson process (negative exponential distribution) with the same rate as arrivals, μ [49]. Therefore, the probability functions for departures can be shown as:

$$D(t_d) = 1 - e^{-\mu t_d} \quad (4-6)$$

$$d(t_d) = \mu e^{-\mu t_d} \quad (4-7)$$

where, t_d is the departure time, $d(t_d)$ is the probability of departure at t_d , and $D(ta)$ is the probability of departure before t_d .

To better fit the real-world situation, the walking distance between the parking facility and the activity location is considered as a modeling parameter. Figure 3-1 presents different parameters included in the arrival/departure modeling process.

Figure 4-1 Arrival and departure modeling parameters

Developed algorithm uses the length of arrival-departure time window as the input and relates it to the correspondent rate parameter (μ) based on the time needed for 99% accumulation (Equation 19):

$$1 - e^{-\mu\Delta T} = 0.99 \rightarrow \mu = -\frac{\ln(0.01)}{\Delta T} \quad (4-8)$$

As mentioned before, the situation for faculty and graduate students can be different, as some of them may not have a scheduled class during the study period and in most cases their arrivals departures are determined by complicated reasons other than class time. In general, this group of commuters represents only a very small portion of the parking demand; therefore, we simply use uniform distribution to model their arrivals and departures.

4.2.2 *Sequence of Arrival and Departure*

The parking system works on the first-come, first-served (FCFS) basis. The instant occupancies in a parking facility depend on the activity schedule of commuters who choose to park or leave there.

For the purpose of modeling the order of arrivals and departures, a random headway Poisson distribution assignment procedure is applied to each type of commuters described before. If A_t is an array of the arriving commuters in time interval t , the designated process generates a number of arrival times based on Poisson headway distribution, and stores them in a new array T_t (A_t and T_t have the same number of elements). In case of uniform arrivals for faculty/graduate students without class commitment, each element of A_t is assigned randomly to an arrival time to develop an order of arrivals for the considered time interval. A similar approach is taken for the departures.

4.3 Parking Choice

Only a few studies have been reported in the literature on how campus commuters search for parking. In general, commuters choose their parking spots within the acceptable walking distance from their activity location. If there is no significant difference in the walking distances between candidate parking facilities and the target building, we found that commuters would choose the next location randomly if the driving distance is within an acceptable range from the current facility where no space is found. Hence, to model this process, two new parameters are introduced:

- Insignificant difference in walking distance, $\Delta(WD)_0$
- Insignificant difference in driving distance, $\Delta(DD)_0$

For example, suppose commuter g wants to make the first parking selection between alternatives p_i and p_j which are located within the acceptable walking distance from the target building b_{Tg} . The following condition states that the walking distance does not influence the decision of this commuter to select a parking location:

$$\left| \min WD_{p_i b_{Tg}} - \min WD_{p_j b_{Tg}} \right| \leq \Delta(WD)_0 \quad (4-9)$$

where, $WD_{p_i b_{Tg}}$ and $WD_{p_j b_{Tg}}$ are minimum walking distances between b_{Tg} and facilities p_i and p_j , respectively. Further, assuming commuter g has found no space at parking facility p_f and needs to select between two other alternatives p_i and p_j within the acceptable walking distance from the target building b_{Tg} , the following condition states that the commuter is indifferent to the driving distance in the parking facility selection:

$$\left| \min DD_{p_f p_i} - \min DD_{p_f p_j} \right| \leq \Delta(DD)_0 \quad (4-10)$$

where $DD_{p_f b_i}$, and $DD_{p_f b_j}$ are minimum driving distances between p_f and facilities p_j and p_j respectively. Parameters $\Delta(WD)_0$ and $\Delta(DD)_0$ are defined based on the relative locations of the parking facilities and the target building. Using these parameters, the parking facility search sequence of commuters can be established.

4.4 Parking Search Time and Number of Parking Trials

The parking search time is defined as the time difference between arrival and successfully finding a parking space. Since a commuter may need to check different parking facilities to find an available space, two components for the parking search time are considered:

- Time needed to check a parking facility to find a free space
- Time needed to switch from one parking facility to another

This study utilizes the relationship introduced by Caicedo to estimate the time needed to check a parking facility [18]:

$$(t_{ch})_{p,t} = \alpha_p \left(1 + \beta_p u_{p,t}^{\gamma_p} \right) \quad (4-11)$$

where $(t_{ch})_{p,t}$ is the time needed to check facility p at time t and $u_{p,t}$ is the percentage occupancy (utilization) of facility p at time t . α_p , β_p , and γ_p are parameters related to the parking facility.

Assuming no major delay on the campus road network, such as traffic congestion, the second component of parking search time can be formulated as follows:

$$(t_{sw})_{p_i p_j} = \frac{\min DD_{p_i p_j}}{v} \quad (4-12)$$

where $(t_{sw})_{p_i p_j}$ is the time needed to switch from p_i to p_j , $minDD_{p_i p_j}$ is the minimum driving distance between facilities p_i and p_j , and V is the average driving speed.

Accordingly, if commuter g has checked θ parking facilities to find a parking space the parking search list for this commuter can be simply shown as follows:

$$P_{g,n,m} = \{1^{st} \text{ facility}, 2^{nd} \text{ facility}, \dots, \theta^{th} \text{ facility}\} \quad (4-13)$$

where n and m represent the type of class assignment and parking utilization as defined before. The total search time and the number of parking trials for commuter g can be calculated as:

$$st_{g,m,n} = \sum_{i=1}^{\theta} (t_{ch})_{P(i),t_i} + \sum_{i=1}^{\theta-1} (t_{sw})_{P(i),P(i+1)} \quad (4-14)$$

$$pt_{g,m,n} = \sum_{i=1}^{\theta} P(i) \quad (4-15)$$

where $P(i)$ is the i th element of array $P_{g,n,m}$ and t_i is the time at which the parking facility $P(i)$ is checked.

The search list and the order of parking facilities to be checked by each commuter is specified based on the search criteria as well as the assigned activity location (target building). The system assigns commuters to the parking facilities indicated in the search list, monitors the changes in available spaces of each facility, and tracks the parking search time and the number of parking trials for each commuter.

4.5 Prior knowledge about Parking Availability

Generally, commuters start their search from the nearest facilities to their activity location. However, in many cases, commuters may use their prior knowledge about the space availability of the parking garages/lots to minimize search time. In other words,

during specific time intervals, commuters may not all go to the nearest facilities if they know those facilities may possibly be full.

To address this consideration in the search process, we have introduced different levels of prior knowledge based on current space utilization condition in the facilities. This factor specifies the percentage of the commuters who will switch to other locations from the nearest parking facility based on prior knowledge about its current utilization condition.

CHAPTER V

OPTIMIZATION

5.1 Optimization Algorithm

The minimization algorithm, including the discussed parking search process, is shown in a flowchart in Figure 5-1. Steps labeled by letter R indicate application of random assignment. The direct random search method is used to perform the optimization process.

Direct random search method is based on testing all the possible solutions within the search space and logically guarantees the global optimization. For the problems with a large search space and a huge amount of repetitive calculations (imposed by arrival time variations from using different random seeds vs. different types of class assignment vs. various parking utility patterns, etc.), this method can be quite time consuming and computationally complex. This issue is the major deficiency of the described method to solve this type of problem but so far we have not found an alternative method.

Nevertheless, this search method can still be applied to a limited set of candidate solutions in order to investigate the feasibility of the optimization algorithm and the impact of classroom assignment on parking search time and number of parking trials during the search process. To improve convergence of the solution process, once a type of class assignment has been considered, it is removed from the search list to avoid any repetition. In addition, the types of classroom assignment as well as parking utilization patterns can be restricted depending on how fast a plausible solution can be found.

Figure 5-1 Optimization algorithm

Since the objective value is based on the average parking search time resulted from different utilization patterns, a higher number of parking utilization patterns considered may lead to the better result. This approach logically guarantees the global optimization if all possible class assignment methods are considered. However, this may result in a phenomenon called “combinatorial explosion” due to a huge amount of repetitive calculation works leading to time and computational power waste and extremely low efficiency. This issue is the major deficiency of the described method to solve this type of problem with a very large random search space (number of candidate solutions) but so far there is no real solution to this problem. In practice, researchers try to include as large as possible the number of candidate solutions in the comparison and increase the number and restrictiveness of optimization constraints to reduce the size of search space and consequently improve the convergence of the solution process.

During the process, the first four constraints (Equations 4, 5, 6, and 7) determine the eligibility of a random solution (class assignment) as a candidate for the further. Then, using the fifth and sixth constraints (Equations 8 and 9) the developed model estimates the parking search time and the number of parking trials for an eligible solution. Once a solution satisfies the seventh and eighth constraints (Equation 10 and 11), it will be included into a list to identify if it can improve the total parking search time and/or the total number of parking trials in comparison with other types of class assignment. The entire process continues until the termination criteria is met. Based on the processing system capability, a pre-set processing time or number of tested candidate solutions can be considered as the termination criteria. Here, the process stops once a pre-set number of possible class assignments are tested.

5.2 Numerical Simulation

To evaluate the feasibility and performance of the proposed optimization model, a numerical simulation has been designated. To simplify the process, total parking search time is considered as the only objective function, and the number of parking trials as the secondary objective function will be considered in the case study chapter. Different parameters of this model are summarized in Table 5-1, and the schematic scaled plan of the campus being considered, including buildings and parking facilities, is presented in Figure 5-2. To simplify the problem, the walking routes are assumed to be straight lines connecting all buildings and parking facilities. Also, parking check time parameters are calibrated, assuming the minimum check time ($u_{p,t}=0\%$), the maximum check time ($u_{p,t}=100\%$), and the check time when the half of the parking facility is utilized ($u_{p,t}=50\%$). Tables 5-2 and 5-3 present the walking distance between buildings and the driving distance between parking facilities.

Table 5-1 Parameters and Variables of Numerical Simulation

Class schedule and enrolment information					
Number of classes			112		
Class size			20-80		
Number of departments			7		
Class start times			8:30-17:00		
Class end times			10:00-18:00		
Offset between class start times			30 min.		
Number of undergraduate students (car ownership)			2865 (2260)		
Number of graduate students (car ownership)			85 (80)		
Number of staff			320 (298)		
Number of faculty			150 (145)		
Arrival-departure characteristics					
Commuter	Time distribution	Arrival interval	Arrival peak	Departure interval	Departure peak
Undergrads	Poisson	30 min before first class	4th five-minutes	30 min after last class	3rd five-minutes
Staff	Poisson	8:00-8:30	4th five-minutes	17:00-17:30	3rd five-minutes
Grad/Faculty	Uniform	Variable	Variable	Variable	Variable
Modeling assumptions and criteria					
Maximum acceptable walking distance inside the campus (WD _{max})			1500 ft.		
Maximum acceptable search time, st _{max}			5 min.		
Insignificant difference in walking distance, Δ(WD) ₀			150 ft.		
Insignificant difference in driving distance, Δ(DD) ₀			800 ft.		
Average driving speed			20 mph		
Random search parameters					
Number of considered parking utilization patterns, M			20		
Number of candidate solutions (termination criterion)			100000

Figure 5-2 Schematic campus map

Table 5-2 Walking Distance between Buildings

Walking Distance (ft.)	Building 6	Building 5	Building 4	Building 3	Building 2
Building 1	1500	3100	3600	2800	1200
Building 2	800	1800	2300	1800	
Building 3	1100	1300	1400		
Building 4	2200	600			
Building 5	1900				

Table 5-3 Switch Distance between Parking Facilities

Switch Distance (ft.)	Parking 7	Parking 6	Parking 5	Parking 4	Parking 3	Parking 2
Parking 1	4300	5200	4300	800 0	3000	1700 00
Parking 2	2500	4100	4200	2600	2500	
Parking 3	1600	3000	3100	2800		
Parking 4	3600	4500	3600			
Parking 5	2400	1000				
Parking 6	1600					

5.2.1 Parking Search Process

As described before, although the parking search process is basically a random phenomenon, to some extent it can be formulated using appropriate criteria. For example, suppose an undergraduate student is going to attend her/his first class in building 1 (Figure 5-2). Obviously, the first selection of this student is parking 1 which is the nearest to the target building. If there is no available space there, she/he has to select between other alternatives within the acceptable walking distance. Parking facilities 2 and 4 are both in acceptable walking distance, but the difference in walking distances between building 1 and these two parking facilities is not significant. Therefore, after checking parking 1, the student does not rely on the walking distance criterion to select next desired parking facility. According to the map, due to shorter time needed to switch from parking 1 to 4, the student will check parking 4 as the second selection. Now, suppose that she/he is not able to find any free space in parking 4. From this point, it is not possible to formulate the search procedure based on pre-defined criteria. The student may select parking 2 as the next alternative, or decide to go and check parking 1 to see if any free space has been provided since the previous try.

As another example, suppose a commuter, which her/his target building is building 5. Obviously, the first selected parking for this commuter is parking 7. According to the map, the walking distances between building 5 and parking facilities 3 and 6 are approximately the same. Also, the driving distances between parking 7 and parking facilities 3 and 6 do not differ significantly. Therefore, just the first parking selection of this commuter is predictable, and further selections have to be considered randomly. Defined search patterns for different buildings are shown in Figure 5-3.

It can be clearly seen that for commuters with target buildings 1 and 3, first two parking selections are predictable. This possibility is limited to the first selection for commuters with target buildings 4 and 5. In the case of commuters whose final destination is buildings 2 or 6, no selection is predictable. Thus, the first selection is considered randomly to start the search process between two existing alternatives.

5.2.2 *Simulation Results*

Implementing the proposed optimization model on the designated problem must consider the effect of different class assignments on the parking search time. A computer program has been developed in this research to process different steps of the optimization algorithm. The program has been run for 100,000 non-repetitive candidate solutions.

Figure 5-4 demonstrates an example of different parking utilization patterns for a specific class assignment. Also, the average search time that is the objective value for this class assignment is presented. Only 20 different utilization patterns are listed in this Figure to show the variation. Definitely, investigation of more patterns increases the accuracy of the results.

Figure 5-5 presents the difference between search times, corresponding to the best and the worst class assignments, for different numbers of candidate solutions. According to the graph, increase in the number of candidate solutions results in greater difference in search times, due to consideration of more possible class assignments.

Figure 5-3 Parking search pattern for different buildings

Figure 5-4 Overall parking search time for different parking utilization patterns

Figure 5-5 Effect of class assignment on the parking search time

Figure 5-6 Overall parking search time corresponding to the best answer(s)

Figure 5-6 shows search times for the best answer(s) versus different numbers of candidate solutions. According to the results, increasing the number of trial class assignments, the program is able to find new answers with shorter parking search times. Obviously, the quantitative results are strictly dependent on spatial characteristics of the problem, such as the relative position of buildings and parking facilities, as well as the campus road network.

CHAPTER VI

CASE STUDY

The University of Akron main campus has been selected in a case study to evaluate the feasibility and performance of the proposed model. This selection was primarily due to the availability of class scheduling information. In addition, several parking surveys and data investigation at the University of Akron indicated conflict in parking demand distribution resulting in excessive amount of parking search time and high volume of cars with unnecessary cruising over the traffic network to find a free spot.

The Fall 2013 class schedule on Mondays, provided by the university Registrar Office, has been used in the case study. Table 6-1 presents a summary of input information as well as modeling criteria. In addition, the scaled plan of the campus being considered, including buildings and parking facilities, is demonstrated in Figure 6-1.

6.1 Database Structure

Database structure for every optimization problem depends on the objective function, constraints, and the data processing approach. For the defined problem, the database is composed of different arrays as follows:

- Class:[id, Department, Size, Requirement, Start time, End time]
- Student:[id, Dept., 1st class id, 2nd class id, ..., Last class id, Car ownership]
- Faculty:[id, Dept., 1st class id, 2nd class id, ..., Last class id, Car ownership]

- Staff:[id, Dept., Car ownership]
- Building:[id, Dept., Room]
- Room:[id, Building, Number of seats, Instructional Facility]
- Parking:[id, Capacity, Search time parameters (α , β , and γ)]
- Walking Distance: (Building to Building, Parking to Building)
- Driving Distance: (Parking to Parking)

All the data included in the above arrays are obtainable from enrollment information, departmental databases, campus parking and transportation service database, and direct measurement. During the simulation process, a variety of new arrays, such as arriving commuters, departing commuters, arrival times, and departure times, parking occupancy, etc., are generated dynamically in real time.

6.2 Testing and Results

Implementing the parking search model aims to test the feasibility and effectiveness of the proposed method. Additionally, it tests the sensitivity of the model to changes in classroom assignment, walking and driving distance range, and the level of prior knowledge about the parking facilities. Those variables are all treated as model parameters which can be changed in the simulation process.

A computer program has been developed to process different steps of the described optimization algorithm. The program uses different random seeds to generate vehicle arrivals and departures within discussed time intervals and following Poisson distribution (or uniform distribution for no-class commuters). 1000 non-repetitive candidate solutions were considered.

Table 6-1 Model Specifications

Number of classes	1858
Class size range	5-346
Number of departments	102
Class start times	6:40-21:05
Class end times	7:30-22:40
Campus official hours	7:00 - 17:00
Number of undergraduate students	22619
Number of undergraduate students with class on Monday (car ownership)	14200 (55%)
Number of graduate students	3975
Number of graduate students with class on Monday (car ownership)	1800 (65%)
Number of faculty	1891
Number of faculty with class on Monday (car ownership)	1100 (90%)
Number of staff (car ownership)	1424 (90%)
Total number of buildings	60
Number of buildings facilitated for classes	38
Number of Parking Lots	36
Average Driving Speed	20 mph
Maximum Acceptable search time	15 min
Maximum Acceptable number of Parking trials	5
Maximum Acceptable Walking Distance	1500 ft.

Figure 6-1 The University of Akron main campus

The qualitative properties of the proposed optimization model are examined by investigating the variation in the parking search time due to change in model parameters. Figure 6-2 presents the potential parking search time reduction under different travel demand and parking search parameters.

According to Figure 6-2a, lower parking search time can be achieved for higher percentage of commuters who arrange their arrival and departure only based on the class time schedule (p_0). The reason is that these commuters leave the campus within a short time interval after the last class and provide more free spaces and consequently less search time for the incoming vehicles.

Figure 6-2b shows the relationship between the parking search time and the prior knowledge level (pr). Logically, at the time of parking commuters use their prior knowledge when the occupancy in the aimed facility reaches to a certain level which is inversely related to the parking capacity of the facility. For simplicity, we used a linear trend, from zero to a maximum value to represent the percentage of commuters who will switch to a nearby facility based on their prior knowledge of the aimed facility when it is full. Table 6-2 has listed the different levels of the commuters' prior knowledge used in the modeling.

Figures 6-2c and 6-2d describe the sensitivity of the parking search time to two behavioral parameters, $\Delta(WD)_0$ and $\Delta(DD)_0$. According to Figure 6-2c, a higher value of $\Delta(WD)_0$ (insignificant difference in walking distance by commuters) results in more parking selections and consequently less parking search time. On the other hand, as shown in Figure 6-2d, the parking search time shows a gentle increasing trend with the increase in $\Delta(DD)_0$ (insignificant difference in driving distance by commuters). This can

be attributed to the acceptance of a longer driving distance by commuters during the search process. Although this flexibility may result in more parking options, the increase in the driving distance prolongs the overall search time.

Figures 6-2e and 6-2f present the variation in parking search time due to the change in Poisson process rate, μ . As discussed before, the developed parking search model uses Poisson process to simulate the arrivals and departures for those commuters who come to and leave campus in specific time intervals based on the predefined activity schedule. Table 6-3 shows the range of Poisson process rates as well as the correspondent length of arrival-departure time window. According to results, the lower rate for the Poisson process, the higher amount of parking search time. Since the higher rate of departures is equivalent to the shorter departure time window, parking facilities will lose the occupancy by lower rate and consequently the new arrivals need to search more to find a free spot.

Next, the quantitative improvements resulted from each objective functions (parking search time and number of parking trials) are examined. The model was evaluated for more than 1000 non-repetitive alternatives (search space) and under different combinations of modeling parameters, including the percentage of commuters closely following the class schedule, the prior knowledge level of parking availability, indifferent walking distance, and indifferent driving distance.

Table 6-2 Prior Knowledge Levels

Prior Knowledge Level	Percentage of commuters relying on the prior knowledge when the aimed facility is full
1	70%
2	75%
3	80%
4	85%
5	90%

Table 6-3 Poisson Process Rates Length of Arrival/Departure Time Window

ΔT (min)	μ (percent/min)
20	23
25	18
30	15
35	13
40	12
45	10

As discussed earlier, the optimum class assignment to be determined depends on the parking demand and parking search parameters. Figure 6-3 shows the summary of variation in parking search time under different combinations of model parameters. Although each scenario results in a different optimum class assignment (with the minimum total parking search time), in all cases the parking search time reduction is around 20 percent when the model is applied. It was found that the objective function values associated with assignments 104, 598, 633, 794, and 933 (indicated in red) are all very close to the overall lowest parking search time when different random seeds are used for each assignment; the difference between those optimized values is less than 10 percent. In other words, by arranging classes based on any of those assignments, at least 18 (i.e. 20×0.9) percent reduction in the search time can be achieved regardless of the variation in other model parameters.

Figure 6-4 presents the optimization results based on the number of parking trials. Regardless of the variation in model parameters, class assignments 104, 410, 598, and 632 (indicated in green) are very close to the minimum value (within the 10 percent interval) and the maximum possible reduction in the objective function value is approximately 16 percent. That is, these assignments will result in at least 14.4 (0.9×16) percent decrease in the total number of parking trials under any combination of model parameters.

Figure 6-2 Parking search time vs. model parameters

Figure 6-3 Parking search time minimization

Figure 6-4 Number of parking trials minimization

Finally, assignments 104 and 598 (circled) are selected as the pareto optimal solutions (bi-objective optimums) which result in the minimum levels of the both parking search time and the number of parking trials under any combination of model parameters. At this time, we cannot explain the cause to such connections with those peculiar assignments, but believe that it is campus specific, directly related to the location and capacity of classroom buildings and each parking facility and the parking demand. As a minimum, we found that the proposed optimization model is feasible to implement and the results are meaningful.

CHAPTER VII

SPECIAL EVENT PARKING MANAGEMENT

The application of developed search model is not limited to the campus parking and can be expanded to many other problems. In this chapter, it is shown that how the proposed model can investigate the effect of parking guidance information system on parking search time during special events.

According to the literature, there is no study conducted to consider the effect of PGI system on the special event parking search process. This study introduces a model to simulate the effect of PGI system on the special event parking search process and investigates the sensitivity of the results to different combination of modeling parameters. The main goal is to assess the feasibility of PGI system implementation to reduce the parking search time. Lock 3 park in Akron downtown area is considered as the case study to evaluate proposed model.

7.1 Parking Choice Parameters

Modeling the special event parking search is often a complex process due to the contribution of many factors related to the travel demand, surrounding traffic network, and the existing management strategies. Here, the parameters contributing in the modeling process has been discussed.

7.1.1 Demand to Supply Ratio

Due to higher levels of occupancy in parking lots, the higher demand to supply ratio, the more facilities to be checked by drivers to find a free space and consequently the higher experienced search time. This factor is a key to the feasibility of any parking demand management strategy and is considered as a modeling parameter.

7.1.2 Distribution of Parking Facilities around the Event Venue

Obviously, attendees choose parking facilities within the acceptable walking distance from the event venue. In general, the facilities with shorter walking distance to the event venue are more desirable parking options for drivers. However, making decision among different parking options needs familiarity with the location of parking facilities and the surrounding road network. Therefore, this study takes into account the parking search behavior for both familiar and non-familiar drivers.

Drivers who are familiar with the surrounding network start the search process from the rationally closer parking facilities to the event venue. Here, we use the criteria defined in Chapter 4 to simulate the parking search behavior of this group. For example, suppose a traveler wants to make the first parking selection between alternatives p_i and p_j which are located within the acceptable walking distance from the event venue. The following condition states the condition in which the walking distance does not influence driver's decision:

$$\left| \min WD_{p_i} - \min WD_{p_j} \right| \leq \Delta(WD)_0 \quad (7-1)$$

where, WD_{p_i} and WD_{p_j} are walking distances between the event venue and facilities p_i and p_j , respectively.

Further, assume the traveler has checked the parking facility p_f and found no free space. So, she/he wants to select between two other alternatives p_i and p_j within the acceptable walking distance from the event venue. At this point, drivers will make the decision based on the driving distance from p_f to two potential alternatives. The following inequality states the condition in which drivers will be indifferent to the driving distance criterion in the parking facility selection:

$$\left| \min DD_{p_f p_i} - \min DD_{p_f p_j} \right| \leq \Delta(DD)_0 \quad (7-2)$$

where: $DD_{p_f p_i}$, and $DD_{p_f p_j}$ are minimum driving distances between p_f and facilities p_i and p_j respectively.

Parameters $\Delta(WD)_0$ and $\Delta(DD)_0$ are defined based on the relational location of buildings and parking facilities and can be found by conducting appropriate surveys. Using these parameters, the parking search list of travelers can be processed in the form of some layers with specific priorities. More specifically, $\Delta(WD)_0$ specifies different search layers considered by the traveler and $\Delta(DD)_0$ influences the alternative selection process within each layer.

The parking search for drivers who are not familiar with the area cannot be easily formulated based on pre-defined criteria since they do not have any information about the location of parking facilities. The assumption is that they navigate to the event venue and start searching for parking from there, except when a parking facility from the first search layer is located in the way.

From this point, the parking search is considered as a random route choice process. The surrounding traffic network is simulated as a graph with parking lots, network entrances, intersections and the event venue as major nodes and the connecting

streets as the links. It has to be considered that the random route selection will stop if the driver finds a parking option readily accessible from the approached node. For example the driver will select the parking facility right after the approached node or very close to the previously tried facility. Obviously, the assumption is that all drivers search for parking spaces within the acceptable walking distance from the event venue.

7.1.3 Prior knowledge about Parking Availability

During the peak demand period, some travelers may use their prior knowledge about the free space availability in the parking lots to eliminate some alternatives from the search list. In other words, during specific time intervals, some attendees may not check the nearest facilities to the venue since they know these facilities are possibly full. To consider this influential factor in the search process, in addition to the proportion of travelers with the prior knowledge, this study defines different levels of prior knowledge use based on the different levels of high parking occupancies.

7.2 Parking Search Time

The list and the order of parking facilities to be checked by each driver is specified based on the discussed search criteria. Since a commuter may check different parking facilities to find a free space, this study considers three components for the parking search time:

- Access time to the firstly selected parking facility
- The time needed to check a parking facility to find a free space
- The time needed to switch from one parking facility to another

Thus, the parking search time can be formulated as follows:

$$st = t_a + \sum_{m=1}^{\theta} t_c^m + \sum_{m=2}^{\theta} t_s^m \quad (7-3)$$

$$t_c^m = \alpha_m(1 + \beta_m u_m^{\gamma_m}) \quad (7-4)$$

$$t_s^m = \begin{cases} \frac{(D_m)_{min}}{V}, & \text{driver is familiar with the parking locations} \\ \frac{D_m}{V}, & \text{otherwise} \end{cases} \quad (7-5)$$

where, t_a is the access time to the first parking option, t_c^m is the time needed to check the m^{th} selected facility, u_m is the utilization of the m^{th} selected facility, t_s^m the time needed to switch from the $(m-1)^{th}$ selected facility to the m^{th} one, D_m is the driving distance from the $(m-1)^{th}$ selected facility to the m^{th} one, V is the average driving speed, and α_m , β_m , and γ_m are parameters related to the parking facility and must be calibrated.

To estimate the parking search time, the developed model assigns drivers to the parking facilities indicated in the search list and tracks each vehicle to measure time between arrival (first parking selection) to find a free space.

7.3 Parking Guidance Information System

In this study, the PGI system is based on in-vehicle device that provides drivers by the list of available parking options sorted by the walking distance to the event venue. In addition, the information includes the driving distance to the listed parking facilities. Therefore, drivers will be able to choose the appropriate parking option based on the criteria discussed previously. In other words, regardless of being familiar with the existing road and parking system, drivers who receive and rely on this information can compare different available parking options and navigate to the most desirable one. Since

finding free space in the selected facility must be guaranteed, the parking search time can be expressed as follows:

$$st = t_a + t_c \quad (7-6)$$

where, t_a is the access time to the selected facility, and t_c is the time needed to check the selected facility.

For drivers who do not use and rely on the PGI system, the search time can be estimated based on the procedure discussed in Chapter 4. Thus, the percentage of travelers receive and rely on the real-time parking information is a key factor to estimate the total parking search time during special event.

A challenge to implement discussed PGI system is the time gap between receiving the information and arrival to the recommended facility. The system has to be calibrated to estimate this time gap and update the parking information based on the occupancy increase rate to ensure finding free space in the aimed facility.

7.4 Special Event Parking Search Model

The objective of developed search model is to estimate the total parking search time considering different parameters. In addition to the parking and road network information, major parameters necessary to process the model are as follows:

- Incoming demand from each entrance node, $D_n, n \in \{1, 2, \dots, N\}$
- Percentage of drivers familiar with the parking locations, F
- Percentage of drivers with prior knowledge about parking availability, PR
- Percentage of drivers receiving and relying on the parking information, PG
- The insignificant difference in walking distance, $\Delta(WD)_0$

- The insignificant difference in driving distance, $\Delta(DD)_0$

The first step toward the parking search time estimation is to generate an arrivals list for each entrance node using the random assignment method. Table 7-1 shows different fields of the arrival list for node n . The arrival time and parking search time are considered as dynamic fields and will be updated through the simulation process. The final arrival list will be achieved by attaching processed lists for all nodes and will be used as the major input to the process demonstrated in Figure 7-1.

7.5 Numerical Simulation and Results

The proposed model is numerically simulated for the special event in Lock 3 park, Akron, Ohio. Figure 7-2 shows the study area map including the parking facilities, event venue, road network, and entrance nodes. It is assumed that the demand starts to enter the network one hour before the event start time with the peak on the fifth 10 minutes. Another assumption is that the road network has enough capacity to prevent congestion. In addition, no queue is supposed to be formed in the entrance of parking facilities.

The demand for each entrance node is assigned based on the daily traffic counts obtained from Akron Metropolitan Area Transportation Study (AMATS) website and the total number of event attendees for the considered event. Parking facilities specifications are summarized as well in Table 7-2. The model is evaluated for various combinations of input parameters.

Table 7-1 Arrivals List

Field	Driver id	t_{arr}	f	pr	pg	st
Comment	---	Arrival Time	Familiarity with parking locations	Prior Knowledge about parking availability	Relying on PGI	Parking search time
Range	1 to D_n	< Event	0 or 1	0 or 1	0 or 1	variable
Criteria	---	---	$\sum f = F.D_n$	$\sum pr = PR.D_n$	$\sum pg$	---

Figure 7-2 Lock 3 Park in Akron, OH

Table 7-2 Parking System Specification

Parking lot	Capacity	a	β	γ	O_{PR}^*
1	570	45	3	1.58	550
2	500	45	3	1.58	480
3	2000	60	4	2	1950
4	1000	60	2.5	1.32	970
5	270	20	2.75	1.13	255
6	690	45	3	1.58	670
7	1140	60	2.5	1.32	1100
8	260	20	2.75	1.13	245
9	50	15	2	1	45
10	180	20	2.75	1.13	170

* The occupancy in which drivers start to use prior knowledge

Figure 7-3 demonstrates the sensitivity analysis results under different percentages of drivers receiving and relying on the PGI system, PG . For higher values of PG , travelers' decision-making process is influenced more by the real-time parking information, and the parking search time shows less sensitivity to other model parameters.

According to the results (Figures 7-3a), the parking search time decrease by increase in the value of $\Delta(WD)_0$. As discussed before, this parameter is used to define different search layers considered by drivers. Table 7-3 shows the processed search layers for this case study.

Higher value of $\Delta(WD)_0$ is equivalent to more flexibility in the parking choice that results in more parking alternatives inside search layers and consequently less parking search time. Whereas, as shown in Figure 7-3b, the parking search time fluctuates by increase in $\Delta(WD)_0$. The reason is more flexibility in parking choice inside each search layer on one hand (decrease in search time), and acceptance of parking alternatives with longer driving distance on the other hand (increase in search time).

Figure 7-3c shows the variation in parking search time by increase in the percentage of travelers familiar with parking locations and the surrounding road network, F . As discussed before, the parking search process follows different patterns for familiar and non-familiar drivers. The first group follows a sequential search influenced by defined behavioral parameters. While, the second group search for parking basically through a random route choice trend. Therefore, when one of these groups is in majority, the demand for specific parking options increase and consequently the search time goes higher.

Table 7-3 Search Layers

$\Delta(WD)_0$ (ft)	Parking Facilities									
	P8	P7	P9	P5	P3	P10	P1	P6	P2	P4
	Search Layers									
100	Layer 1	Layer 2			Layer 3			Layer 4		Layer 5
200	Layer 1	Layer 2						Layer 3		
300	Layer 1	Layer 2						Layer 3		
400	Layer 1		Layer 2						Layer 3	
500	Layer 1					Layer 2				

Figure 7-3d shows the relationship between the parking search time and the percentage of drivers with prior knowledge about parking availability, PR . Reasonably, this group of drivers start judging about the availability of free spaces when the occupancy in the aimed facility reaches to a certain level, O_{PR} (Table 7-2). This level is proportional to the parking capacity and must be found by conducting appropriate surveys.

Figure 7-3e illustrates the effect of demand to supply ratio on the total parking search time. More parking demand results in higher utilization of parking facilities and increases the search time due to the restriction in available parking options as well as more time needed to check each parking facilities. Thus, the parking search time shows an exponentially increasing trend when the demand goes higher. In other words, according to the results, the PGI system works more effectively for higher demand to supply ratio.

The percentage of travelers relying on the PGI system, pg , can be considered as a measure of efficiency for the implemented PGI system. It can be clearly seen that regardless of any combination of modeling parameters, using an efficient PGI system ($PG=90\%$), an effective reduction in the parking search time can be expected (at least 33% for the presented ranges of parameters).

(a)

(b)

(c)

(d)

(e)

$\Delta(WD)_0$: Insignificant difference in walking distance
 $\Delta(DD)_0$: Insignificant difference in driving distance
 F: Percentage of drivers familiar with the parking locations
 PR: Percentage of drivers with prior knowledge
 D/S: Demand to supply ratio
 PG: Percentage of drivers relying on the PGI information

Figure 7-3 Numerical Simulation Results

CHAPTER VIII

CONCLUSION & FUTURE WORK

In this study, a new approach for parking demand management on university campuses was developed and explained. This comprehensive activity-based model relies on alternative ways in class assignment, constrained by other model parameters and implementation criteria such as parking demand, walking distance, driving distance, and prior knowledge about the parking availability. The model was tested for various combinations of the input parameters to assess the feasibility of reducing both the parking search time and the number of parking trials under different conditions.

According to the case study conducted at the University of Akron, using the proposed method, the parking demand can be properly balanced over the parking system, and consequently, the parking search time and the number of parking trials can be reduced by approximately 18% and 14.5% respectively. Since this paper is mainly a methodology study, we tried to stay focused on model development based on smart class assignment as a proactive way to manage the campus parking demand. We did not consider roadway congestion nor demand-based pricing since traffic congestion is not a reported problem and the parking pricing strategy is not commonly used on most U.S. university campuses.

The proposed methodology is novel and can be a good reference in the literature for future studies. The proposed method is feasible and can potentially be used as a useful companion tool for campus parking management with no additional cost. Discussion is currently underway with the Office of Registrar and the Office of Parking Services at the University of Akron to test and evaluate the model next year. More details can be reported in the future on the successful stories and lessons learned during the practical applications of the model.

Application of the proposed model is not limited to the campus parking and can be applied to simulate and evaluate variety of parking demand management policies. To show this flexibility, the model was applied to a special event parking problem to investigate the performance of Parking Guidance Information (PGI) system on the search process and the total parking search time. For this purpose, Lock 3 park located in downtown Akron was selected as the case study. A sensitivity analysis was performed to assess the effect of contributing parameters on the parking search time. According to the results, using an efficient PGI system the parking search time can be effectively reduced.

The proposed model can be improved to take into account the congestion, delay, and queue formation over the traffic network. Furthermore, additional features such as parking pricing, parking spot reservation, and park and ride system can be added to the developed search process. In addition, the future work could include developing an algorithm to find the optimum PGI configuration.

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