2017-05-30

Deployment of Autonomous Electric Taxis with Consideration for Charging Stations

Sounthar Manickavasagam

Deployment of Autonomous Electric Taxis with Consideration for Charging Stations

by

Sounthar Manickavasagam

A Thesis

Submitted to the Faculty

of the

WORCESTER POLYTECHNIC INSTITUTE

In partial fulfillment of the requirements for the

Degree of Master of Science

in

Data Science

by

May 2017

APPROVED:

Professor Andrew C. Trapp, Thesis Adviser

Professor Yanhua Li, Thesis Co-Adviser

Professor Jian Zou, Thesis Reader

Abstract

Autonomous electric vehicles are set to replace most conventional vehicles in the near future. Extensive research is being done to improve efficiency at the individual and fleet level. There is much potential benefit in optimizing the deployment and rebalancing of Autonomous Electric Taxi Fleets (AETF) in cities with dynamic demand and limited charging infrastructure. We propose a Fleet Management System with an Online Optimization Model to assign idle taxis to either a region or a charging station considering the current demand and charging station availability. Our system uses real-time information such as demand in regions, taxi locations and state of charge (SoC), and charging station availability to make optimal decisions in satisfying the dynamic demand considering the range-based constraints of electric taxis. We integrate our Fleet Management System with MATSim, an agent-based transport simulator, to simulate taxis serving real on-demand requests extracted from the San Francisco taxi mobility dataset. We found our system to be effective in rebalancing and ensuring efficient taxi operation by assigning them to charging stations when depleted. We evaluate this system using different performance metrics such as passenger waiting time, fleet efficiency (taxi empty driving time) and charging station utilization by varying initial SoC of taxis, frequency of optimization and charging station capacity and power.

Acknowledgment

First and Foremost, I would like to express my sincere gratitude to my adviser and mentor Prof. Andrew C. Trapp for his continuous support and motivation throughout my Masters. His guidance, patience, and knowledge have really inspired me and helped me grow as a researcher. Prof. Trapp inspired me to take up a challenging research topic of my choice and made sure I succeed by providing me valuable feedback in every step of this Thesis journey. I have enjoyed all my interactions with him which will always be one of the best memorable experiences for me in WPI.

I would also like to express my since gratitude to my co-adviser Prof. Yanhua Li for his continuation support and motivation to complete my Thesis. Insights from Prof. Li's immense knowledge and experience in Urban Analytics helped me understand the scope of the problem and validate various solutions. I have also learned how to effectively approach a problem from his vast research experience.

It was a great honor to have Prof. Trapp and Prof. Li as my thesis advisers and I will be always thankful to them.

I am very grateful to Prof. Jian Zou for accepting to be my thesis reader. His continuous encouragement and valuable feedback helped me improve the quality of my work.

I am deeply grateful to all the Faculty and Staff in our Data Science Department for their teachings and support which was instrumental in the successful completion of this research.

I also like to acknowledge the continuous support from my manager Jason B. Fuller and members of CMO team in HERE Technologies for my research throughout my internship.

I would like to dedicate my thesis to my mom and express my special thanks to my Sisters, Dad and Brother-in-law for their selfless support and for always being there for me. I am also thankful to my extended family, cousins, school friends who always wanted me to succeed in my endeavors.

Last but not least, I would like to express my gratitude and thanks to my friend Jegajeeth Kanna for his non-stop support and help from day one I landed in the United States.

Contents

Chapter 1

Introduction

The automobile industry is entering the new era of Autonomous Electric Vehicles (AEVs) which can fundamentally redefine our transportation systems. AEVs can completely automate the way we travel, increase the ease of navigation and safety as well as reduce the impact we have on the environment when combined with renewable electric power sources. While they offer all of these compelling advantages, there is a need to build new technologies and infrastructure to lay the ground for their adoption and efficient utilization.

Electric vehicles have been on the road since 2010 [1]; their adoption is set to be the norm in the coming years with advances in their total distance range per charging cycle and availability of more charging stations [2]. Many countries are providing tax benefits to encourage the adoption of electric vehicles and this coupled with the increasing trend of electricity generation from renewable sources, can make them completely carbon emission-free mode of transport.

Driving any vehicle requires formal training, and despite that, human errors lead to accidents resulting in loss of property and even life. Extensive research is being done to replace the human aspect in operating a vehicle, and they are already delivering promising results in implementing various levels of autonomy in vehicles.

Level 5 autonomous vehicles will be able to drive completely on their own based on inputs from a wide array of sensors, motion planning, and machine learning algorithms, high definition maps and data from nearby vehicles without any human intervention [3]. Aided with all this information in real time, they can increase the safety of the passengers as they can avoid accidents which humans are not capable of foreseeing. Autonomous vehicles will also increase the vehicle utilization as they can perform tasks without a driver and this makes them well suited to act as autonomous taxis which can be on the road all day serving passengers without suffering any fatigue.

So based on this trend, we will most likely see the adoption of Autonomous Electric Vehicles (AEV) that can result in an environmentally friendly mode of transport which also offers better user experience for people traveling. There will be a massive deployment of autonomous electric taxi fleets as both Tesla [4] and Uber [5] are already working towards this goal. As passenger cars spend about 96% percent of the time in parking [6], Tesla wants to provide the option for users to let their cars to join a taxi fleet when not in use and get paid for serving passenger requests. Similarly, Uber plans to have their own fleet of autonomous electric vehicles instead of current driver-operated cars.

Implementing these Autonomous Electric Taxi Fleets (AETF) in urban cities share some of the same problems faced in dispatching, conventional taxis along with limited range and charging based constraints of the electric vehicles. On-demand mobility services require constant rebalancing of these vehicles across regions based on dynamic demand to reduce the waiting time for passenger and idle time for the taxis. Electric taxis require multiple recharging sessions because of their limited range [7]. To reduce their time spent on charging stations, they have to be assigned to charging stations which can offer them the shortest charging sessions. Charging stations play a critical role in operating any electric taxi fleet, maximizing their utilization can improve the fleet efficiency in serving passengers [8]. To address these problems, we have implemented a fleet management system with an online optimization system integrated with various data sources like taxis serving in a region, unmet demand in a region, the location of idle vehicles and availability of charging stations. This fleet management system has full control of all taxis in the fleet, and it will move them based on the decisions from the optimization system to increase the fleet utilization.

1.1 Problem Background

The rise in urban population density has made it challenging for the public transportation systems to handle the demand because of the inherent limitations to the speed at which their infrastructure can expand. At the same time, recent technological advancements have enabled newer modes of transportation. Mobility-on-Demand (MoD) services like Uber and Lyft have taken advantage of the people need for an instant and convenient way of traveling in recent years, and their adoption is considered the future of urban mobility [9].

MoD and Taxi dispatching face similar problems in meeting the user demand efficiently. With limited number of vehicles in their fleet, it is beneficial to find ways to reduce the waiting time for passengers to board a vehicle once they have placed a request. It is important to ensure their vehicles are not idle and serve many requests as possible to increase their overall fleet utilization. These problems are addressed by repositioning vehicles to the regions with high demand, so more vehicles can reach their passengers fast. However, because of the spatial and temporal nature of the user requests in the urban setting, the demand in these regions are dynamic and uncertain resulting in a greater number of vehicles being idle in an area where high demand no longer exists. This imbalance leads to inefficiency in the fleet usage and requires rebalancing strategies that can continuously adapt to the dynamic nature of the user mobility. Rebalancing of vehicles based on demand is a widely studied optimization problem.Studies [10, 11] use a linear optimization program to rebalance the idle vehicles to improve the efficiency of an autonomous ride sharing taxi fleet.

Rebalancing strategies for a fleet of electric vehicles offer more challenges because of the need for extended charging time required by each of these vehicles for their continuous operation. While advances are being made related to the battery capacity and to reduce the time it takes to charge, these vehicles will still be off the road to charge every few hours in a day. With only limited charging infrastructure rolled out in urban cities, distributing the demand across charging stations is important to avoid long queues of depleted vehicles in the charging stations resulting in less number of vehicles on road [12].

Placement of charging stations plays a critical role in solving this problem. Existing studies [13–15] provide linear optimization based strategies to find the optimal locations for charging stations to improve the fleet efficiency and balance the utilization across charging stations.

In recent times, agent-based microscopic simulation models are used to study and evaluate various scenarios and strategies. With the increase in computational power, these systems are now capable of simulating millions of agents like vehicles, passengers, public transport, charging and parking facilities and as well as their interactions with each other. They can be configured to simulate the activity and preferences of each agent, closely mirroring the real-world. This gives us tremendous insights in understanding complex scenarios as well as the ability to test, how new infrastructure and policies can affect the dynamic urban mobility.

Studies [16] and [17] simulate autonomous electric taxi fleets in urban cities like Berlin and study how the fleet size, charging station locations and rebalancing strategies affect the fleet's ability to satisfy user demand.

1.2 Contribution

We have created a fleet management system with an online optimization model that can rebalance idle taxis across regions via repositioning on current demand and assigning charge depleted taxis to charging stations that can provide them with fast charging time. This system helps with both the problem of rebalancing and charging station assignment together improving overall user experience and fleet utilization.

The online optimization conducted in this study is performed using 0–1 integer optimization. For every discrete time t, the model assigns each idle and charge depleted taxi to a distinct region and charging station respectively based on various constraints and parameters like demand in a region, charging station availability and range limitations of idle taxis. The objective of this model is to serve user requests while improving the taxi fleet utilization through reducing total idle time and energy conservation through distance traveled. The Fleet Management system gets real time information of all taxis in the fleet, charging station availability and user requests. It also has complete control over the autonomous taxis and can execute the decisions from the optimization model.

We have used MATSim, an open source multi-agent transport simulation tool integrated with our optimization model, to act as the Fleet management system. It will simulate an urban autonomous taxi fleet deployment scenarios, vehicle interaction with charging stations with real user requests and road networks. This can also be used to realistically evaluate different optimization models for routing and rebalancing [18] and [19]. We have extensively customized MATSim to simulate autonomous electric taxi behavior and its integration with our custom online optimization model. To the best of our knowledge, our approach of simulating an Autonomous Taxi Fleet Management System with an optimization model that can rebalance the fleet based on demand and assign taxis to charging stations is novel.

We have implemented a prototype of this combined system of simulation-optimization and used it to analyze the impact of different parameters based on performance metrics such as passenger waiting time, empty drive ratio and charger occupancy, and found them to be effective. We have also suggested improvements to this system like how integrating a demand prediction model can improve its performance in meeting user demand.

The remainder of this paper is organized in the following manner. In Chapter 2, we introduce the transport simulation tool MATSim and our custom autonomous electric vehicles module. In Chapter 3, we show the formulation of our online optimization model. In Chapter 4, we discuss about the integration between MATSim modules and the online optimization model. In Chapter 5, we provide the details of our experimental setup and detailed analysis of its results. In Chapter 6, we end with the summary of our work and provide our insights for future work.

Chapter 2

Autonomous Electric Taxi Fleet Simulation using MATSim

2.1 Introduction to MATSim

MATSim is a large scale, multi-agent, transport, micro-simulation framework implemented in Java. It is an open source software primarily developed at ETH Zurich [20]. Simulations in MATSim are based on agents and their activities. Agents can be vehicles, passengers, and dispatchers, each performing their operations such as serving a passenger, requesting a vehicle and dispatching vehicles respectively. Given a scenario of vehicles and passenger trip information such as time and location of pickups and drops, MATSim can simulate those activities and evaluate different plans in each iteration and score them based on the cost function defined. With multiple iterations, it can eventually find the best plan in terms of cost quality to complete the defined activities.

We can define a scenario in the MATSim using the following input files:

1. Network: This file provides the road network for the vehicles to traverse. This network is extracted from real-world road networks along with information like free-flow speed and capacity per hour. Based on the network information in this file, MATSim creates a network of nodes with links connecting them in a x−y coordinate system.

2. Vehicles: This file provides information about the vehicles in the scenario. It defines the starting location and time of each vehicle along with their battery capacity and starting State of Charge (SoC) which is the amount of charge in their battery.

3. Population: This file provides the activities of all passengers in the simulation like their time and location of their travel activity. In a static scenario, We have to submit the entire plan for each passenger which requires prior knowledge of all their activities while in dynamic agents scenario, not all this information is needed.

MATSim is widely used to simulate entire transportation activities of various cities to find patterns and evaluate different policies. It is used in study [21] to decrease the passenger traveling time without increase in cost and in study [22] to study the impact of deploying autonomous electric taxi fleet on traffic congestion in Berlin city. For additional information on the MATSim tool, we refer to [20].

2.2 Autonomous Electric Vehicles Module

MATSim is designed to be extensible to add more custom behaviors and scenarios to mimic new and evolving modes of transport. To simulate an always online service like MoD, MATSim should have the ability to handle new requests at any point of simulation and reoptimize its vehicle planning and routing. This functionality is implemented using Dynamic Vehicle Routing Problem (DVRP) module which is described in detail in [23]. Numerous other functionalities can be built over the DVRP module to simulate complex passenger, vehicle and dispatcher behavior in a MoD service.

In this study, we have modeled all vehicles in the fleet to exhibit autonomous and electric vehicle behavior. To achieve this, we have implemented custom functionalities by extending the electric taxi implementation in [24]. The autonomous behavior of these vehicles gives the dispatch system complete control over these vehicle movements and get real-time status information like its location, passenger details, and SoC. To simulate electric vehicles, we have added behaviors like discharging power from their batteries based on the speed they are traveling, the ability to charge their batteries when plugged into a port in the charging station. We also have simulated charging stations in the network with the ability to charge vehicles plugged to its ports, queue for vehicles waiting for their turn to charger. These charging stations is also connected to the Fleet Management System which can access all its status information in real time. We have modeled the characteristics including battery capacity, discharge rate of electric vehicles in the simulation as that of electric vehicle model Nissan Leaf 2012 [25]. Using this custom module, we can simulate deployment of the autonomous electric vehicle fleet in cities with real user trip information data and evaluate various optimization models to rebalance and assign vehicles to charging stations.

In the next chapter, we will discuss about the formulation of our online optimization model in detail.

Chapter 3

Online Optimization Model

The problem of rebalancing idle vehicles across regions and finding optimal charging stations for charge depleted vehicles can be modeled as an online optimization problem. Online optimization is used to make decisions in near real-time with only data available at that point of time [26]. Both rebalancing and charging station assignments predominantly depend on the demand for vehicles and charging stations respectively. Offline optimization requires the knowledge of future demand but predicting future user demand on MoD services is found to be challenging, and error in demand prediction can drastically affect the model performance. Online optimization does not suffer from this drawback and has been proven to perform better than offline optimization models in few scenarios like shown in [19]. Integrating optimization models with MATSim have been proven effective in analyzing and evaluating various strategies as shown in [27, 28].

We have formulated our optimization model using Binary Integer Programming (BIP). BIP is a type of Integer Programming where the variables can be only either 0 or 1. They are known as 0–1 Integer Problems for the same reason. BIP is widely used for assignment based problems where typically 0 denotes no assignment while 1 denotes an assignment. This binary type of decision is well suited for this problem of rebalancing and charging station assignment, where each taxi is assigned either to a distinct region or a charging station.

3.1 Assumptions

We have made assumptions related to various aspects of this problem while coming up with our model formulation.

3.1.1 Related to time

- We consider discrete time intervals.
- We consider appropriate level of discretization for these time intervals in terms of minutes.

3.1.2 Related to taxis

- MATSim will assign taxis to pickup passengers only within their current region.
- Idle taxis are taxis which are not serving any request at time t.
- Idle taxis will be moved to other regions to meet their demand at time t. Once a taxi is assigned to a region, they will move to the center of the region and can start serving passengers inside that region.
- Idle taxis with SoC less than a certain threshold θ at time t will be assigned to a charging station.

3.1.3 Related to Demand

- In online optimization based approach, We consider only the demand at time t and assume we don't have any information on the future demand.
- We try to ensure that all demand at each time interval t are met, but it is not always possible when the demand is more than the taxis available in the fleet and SoC of the taxis can limit their ability to serve requests out of their range.
- In case of demand in a region is less than a certain threshold, MATSim will not consider them as demands. This is to prevent premature balancing.
- If there is demand less than the threshold for successive k time periods, then MATSim will consider them as demands. This is to ensure that those demands are met as they have persisted over multiple time periods.

3.1.4 Related to Regions

- We partition the entire region of the city into smaller square shaped regions of equal size.

3.1.5 Related to Charging Station Locations

- We partition the entire region of the city into square grids of equal size and assume there are charging stations within that region.
- We assume there will be less number charging stations than the number of regions, as its less likely for every region to have a charging station.

3.1.6 Related to Charging Stations

- We assume all charging stations have the same total number of ports available for taxis to get plugged and start the charging session.
- We assume taxis will be added to a queue of infinite size when there is no port available for them to get plugged.
- We assume taxis will continue charging up to their maximum battery capacity and can unplug themselves after a charging session and leave the charging station to start serving requests in that region.

3.1.7 Related to charging station reachability

- MATSim will assign taxis to a request only if they have enough SoC to complete the request and reach at least one charging station from the drop off location of that request. This is to ensure there is enough charge in the taxi to complete its request once started and no taxi is stranded on the road without the ability to reach at least one charging station after dropping a passenger.
- Taxis with low SoC tend to become idle as their ability to reach a charging station after completing a request is limited.

3.2 Problem Formulation

We provide a 0–1 integer programming formulation for the AETF rebalancing and charging station assignment problem. We will start with the sets, parameters and variable definitions, followed by the constraints, equations, objective and complete formulation.

3.3 Set Definition

The different sets used in our model formulation are as follows.

- E: Set of all autonomous electric taxis, indexed by e
- I: Subset of E which denotes autonomous electric taxis that are idle, indexed by i
- R: Set of regions, indexed by r
- S: Set of charging stations, indexed by s
- T: Set of time periods, indexed by t

3.4 Parameter Definition

The different parameters which are part of our model formulation are as follows.

3.4.1 Region Attributes

- n_{rt}: Total number of idle taxis in region r at time t
- d_{rt}: Demand in region r at time t

3.4.2 Taxi Attributes

- c_{it}: Charge in taxi i at time t
- δ_{si}^{t}: Charge required to reach charging station s for taxi i at time t.
- δ_{ri}^{t}: Charge required to reach region r for taxi i at time t

3.4.3 Charging Station Attributes

- p_{st}: Total number of charging ports in charging station s
- u_{st}: Sum of total number of taxis in queue and total number of taxis that are en route to charging station s at time t

3.5 Integer Programming Formulation

The formulation of our online optimization model is as follows.

- Decision Variables:
  1. x_{ist}: Binary variable denotes assignment of taxi i to charging station s at time t

$$x_{ist} = \begin{cases} 1 \text{ if taxi } i \text{ is assigned to charging station } s \text{ at time } t; \\ 0 \text{ Otherwise.} \end{cases} \tag{3.1}$$

  2. x_{irt}: Binary variable denotes assignment of taxi i to region r at time t

$$x_{irt} = \begin{cases} 1 \text{ if taxi } i \text{ is assigned to region } r \text{ at time } t; \\ 0 \text{ Otherwise.} \end{cases} \tag{3.2}$$

- Constraints:
  1. All idle taxis are assigned either to a charging station, or a region, at

time t:

$$\sum_{s \in S} x_{ist} + \sum_{r \in R} x_{irt} = 1, \forall\ i \in I. \tag{3.3}$$

2. All idle taxis can be assigned only to those charging stations that are reachable:

$$x_{ist} \leq \lfloor 1 + c_{it} - \delta^t_{si} \rfloor,\ \forall\ i \in I,\ s \in S,\ t \in T. \tag{3.4}$$

3. All idle taxis can be assigned only to those regions that are reachable:

$$x_{irt} \leq \lfloor 1 + c_{it} - \delta^t_{ri} \rfloor,\ \forall\ i \in I,\ r \in R,\ t \in T. \tag{3.5}$$

4. All idle taxis can be assigned only to a charging station if its charge at time t is less than the threshold θ:

$$x_{irt} \leq c_{it} + (1 - \theta),\ \forall\ i \in I,\ r \in R,\ t \in T. \tag{3.6}$$

- Equations:

1. Sets the values of $\overline{\epsilon}_{rt}$, $\underline{\epsilon}_{rt}$:

$$d_{rt} = n_{rt} + \overline{\epsilon}_{rt} - \underline{\epsilon}_{rt},\ \forall\ r \in R,\ t \in T. \tag{3.7}$$

- Objective Coefficients:

1. a_{st}: User defined objective term to incentivize or disincentivize taxi assignment to charging station s at time t

2. a_{rt}: User defined objective term to incentivize or disincentivize taxi assignment to region r at time t

3. b_{rt}: User defined objective term to incentivize or disincentivize meeting demand in the region r at time t

4. $\overline{\epsilon}_{rt}$, $\underline{\epsilon}_{rt}$: Non negative deviation variables to incentivize or disincentivize demand being met in region r at time t

- Objective Function Components:

1. a_{st} incentivize assignment of idle taxis to charging stations with available ports and disincentivize assignments to charging stations where there are no free ports as that might result in long waiting time in the queue for the taxi:

$$\sum_{t \in T} \sum_{i \in I} \sum_{s \in S} \left((a_{st}) x_{ist} \right). \tag{3.8}$$

2. a_{rt} incentivize assignment to regions which requires the least amount of charge for the taxis to reach:

$$\sum_{t \in T} \sum_{i \in I} \sum_{r \in R} \left((a_{rt}) x_{irt} \right). \tag{3.9}$$

3. $\overline{\epsilon}_{rt}$, $\underline{\epsilon}_{rt}$ with b_{rt} incentivize demand being met by assigning idle taxis to those regions:

$$\sum_{t \in T} \sum_{r \in R} \left(b_{rt} (\overline{\epsilon}_{rt} + \underline{\epsilon}_{rt}) \right). \tag{3.10}$$

- Complete Formulation:

  The complete formulation of our model is as follows.

$$\text{minimize} \quad \sum_{t\in T}\left[\sum_{i\in I}\left(\sum_{s\in S}(a_{st})x_{ist} \ + \sum_{r\in R}(a_{rt})x_{irt}\right)+\sum_{r\in R}\left(b_{rt}(\overline{\epsilon}_{rt}+\underline{\epsilon}_{rt})\right)\right] \tag{3.11}$$

$$\text{subject to} \quad \sum_{s\in S}x_{ist}+\sum_{r\in R}x_{irt}=1, \forall\ i\in I \tag{3.12}$$

$$x_{ist}\leq\lfloor 1+c_{it}-\delta^t_{si}\rfloor,\ \forall\ i\in I,\ s\in S,\ t\in T \tag{3.13}$$

$$x_{irt}\leq\lfloor 1+c_{it}-\delta^t_{ri}\rfloor,\ \forall\ i\in I,\ r\in R,\ t\in T \tag{3.14}$$

$$x_{irt}\leq c_{it}+(1-\theta),\ \forall\ i\in I,\ r\in R,\ t\in T \tag{3.15}$$

$$d_{rt}=n_{rt}+\overline{\epsilon}_{rt}-\underline{\epsilon}_{rt},\ \forall\ r\in R,\ t\in T \tag{3.16}$$

$$x_{irt}\in\{0,1\},\ \forall\ i\in I,\ r\in R,\ t\in T \tag{3.17}$$

$$x_{ist}\in\{0,1\},\ \forall\ i\in I,\ s\in S,\ t\in T \tag{3.18}$$

$$\overline{\epsilon}_{rt},\ \underline{\epsilon}_{rt}\geq 0,\ \forall\ r\in R,\ t\in T \tag{3.19}$$

Chapter 4

Integrating MATSim with Online Optimization Model

To implement and study the Fleet Management System, we have to integrate MATSim with our Online Optimization Model. Once integrated, MATSim can simulate the user requests, AETF and charging stations, and implement the various assignment decisions from the optimization model. Figure 4.1 illustrates how the fleet management system with online optimization model is integrated with simulation in MATSim.

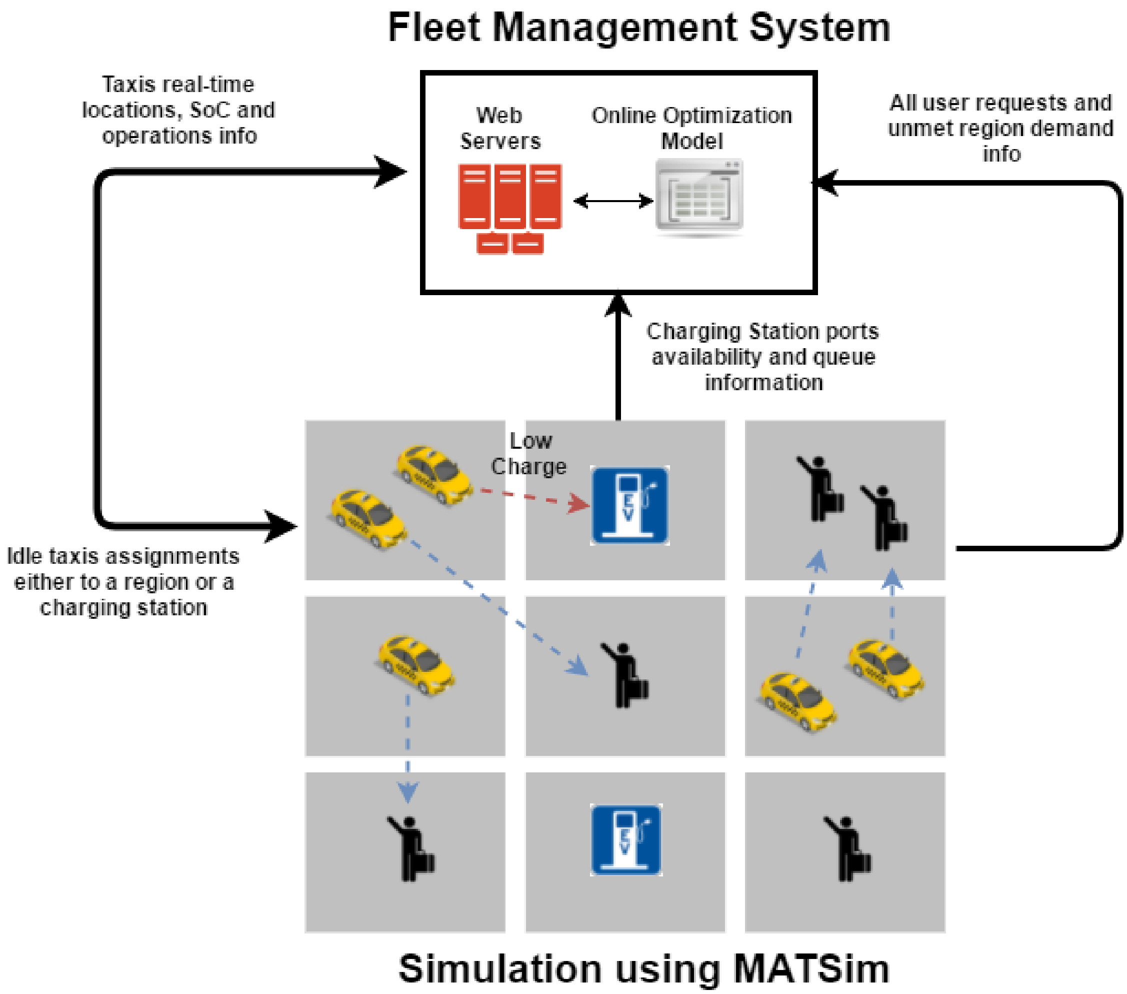


Figure 4.1: Fleet Management System integrated with MATSim

4.1 Parameters from MATSim

We extract parameters from simulation running in MATSim which will be passed to the online optimization model as inputs.

1. Regional Parameters:

   We can define the regions in MATSim by specifying the cell size for each region. MATSim creates square-shaped regions of equal size based on the cell size. Smaller cell size will result in more number of regions. To keep track of regional locations of all taxis in the fleet, MATSim maintains a regional taxi registry. When a taxi enters a region, it will be added to the registry of the new region it entered and will be removed from the region it left. We can identify idle taxis in the registry by checking if they are serving any request. It also maintains a registry for all unplanned requests in each region. Unplanned requests are requests which are not assigned to any taxi signifies the unmet demand in the region. Parameters n_{rt} which is total idle taxis in region r at time t is obtained from regional taxi registry and unplanned requests registry provides the d_{rt} which is total number of demand in region r at t.

2. Taxi Parameters:

   Operational information of all taxis in MATSim are continuously updated when they enter and exit new links in the network. MATSim also updates the SoC of the electric taxis based on the operation they are performing. Discharge rate is proportional to the speed at which the taxi is moving and there will be some discharge even when the taxis are idle. When the taxis are plugged to a port in the charging station, their SoC increases up to their battery capacity. This provides us with the SoC information c_{it} of all taxis in the fleet at any given time t.

   MATSim can retrieve the location coordinates from all taxis in the simulation. Using the current location information, it can calculate the travel path and time it takes for each of this taxi to reach all regions and charging stations. We can estimate the charge required based on the distance to reach each of these locations. Because of events like congestion which can increase the travel time and energy consumption, we can only estimate the energy required.

Underestimating the charge required to reach various locations can result in taxis losing all their charge before reaching their destinations. These estimates provides δ_{si}^{t} which is the charge required to reach charging station s for taxi i at time t and δ_{ri}^{t} which is the charge required to reach region r for taxi i at time t.

3. Charging Station Parameters:

   We can simulate charging stations by defining their location in the network, total number of ports and charging power. We can get various information like number of ports in use, number of taxis in queue and number of taxis that are assigned to each of this charging stations which are en route. This provides us the parameters p_{st} and u_{st}. p_{st} is the total number of ports in the charging station s and u_{st} is the sum of total number of taxis in queue and total number of taxis that are already been assigned and en route to the charging station s at time t.

4. Additional Parameters: We also define the minimum threshold of demand k below which demand in the region is not considered. This is to ensure, premature allocation of taxis to a region whose demand might have been met by other taxis in the region before the assigned taxis reach the region. If the demand below the threshold k is persistent over more than 2 time periods then we consider it as a demand and model might assign idle taxis to the region to meet those demand. Charging power of the charging stations w expressed in kilowatt-hour (KWh) is configured in the simulator to mimic different levels of charging stations [29].

4.2 Integrated Simulation-based Optimization Algorithm

We have implemented the online optimization model in Java using Gurobi Optimizer[30] and integrated with Autonomous Vehicle Module in MATSim. MATSim executes the model at defined time intervals t in T. The algorithm which explains the interaction between MATSim and the optimization model is as follows.

Algorithm 1: Algorithm for rebalancing and assigning charging stations to idle taxis in AETF

Input : Set of Regions R; Set of Charging Stations S; Time intervals t in T to run the model; Minimum charge threshold θ; Minimum demand threshold in regions k.

Output: Regional or Charging station assignments for each idle taxi at time t

. **foreach** t *in* T **do**

  Build optimization model in Gurobi using inputs n_{rt}, d_{rt}, c_{it}, δ^t_{si}, δ^t_{ri}, p_{st}, u_{st}.

  Optimize the resulting model.

  Reassign taxis in MATSim according to optimal taxi assignment decisions.

  MATSim continues to simulate the fleet till next t.

end

4.3 Illustrative Example of Online Optimization Model

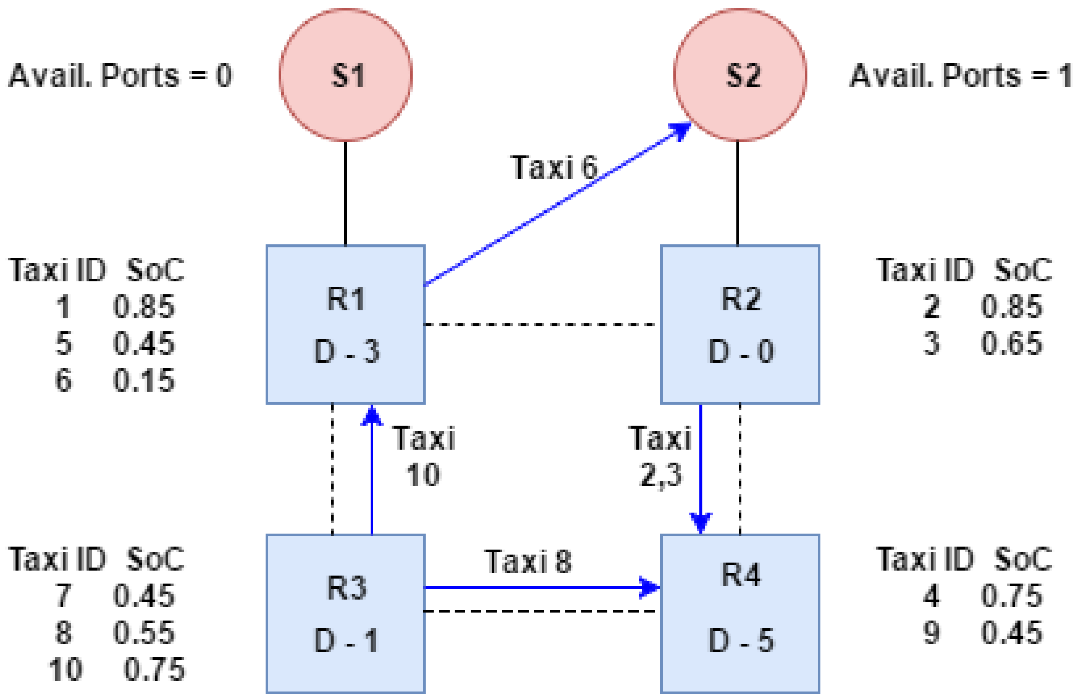


Figure 4.2: Model Decisions Example

Figure 4.2 shows the assignment decisions for a given scenario at time t. The square boxes are the 4 regions named R1, R2, R3 and R4. The dotted lines depict the closest regions to each other. The circles S1 and S2 represent charging stations along with their region R1 and R2 respectively. The demand in the region is denoted by 'D' in each region and IDs of idle taxis with their SoC at time t are shown next to each region. Number of available ports in each charging station are also shown.

The assignment decisions from the model are shown as blue line with arrows along with the IDs of taxis that are being moved. Model's objective is to ensure that the demand is met in each region by moving idle taxis to that region and to assign taxis with low charge to charging stations with available port under given constraints. We can see that Taxi 6 has low SoC and it is being assigned to charging Station S2 instead of S1 as it has a free port available. To meet the demand in Region R4 idle taxis 2 and 3 are moved from region R2 where there is no more demand and idle taxis 8 and 10 are moved to region R4 and R1 respectively from R3 where the demand has reduced. These decisions from the model are optimal and feasible with the given constraints.

This example illustrates how the optimization model makes the decisions based on parameters from MATSim and how MATSim implements those decisions by moving the idle taxis either to a region or a charging station.

Chapter 5

Experiments & Results

We evaluate our Taxi Fleet Management System through various performance metrics by simulating real world scenarios in MATSim. We also analyze how different parameters in the model and the fleet influence the metrics to show how this system can be used to effectively analyze various scenarios. All experiments were run on an Intel Core i7 6th Gen 6700HQ 2.60 GHz processor with 16.0 GB RAM running 64-bit Windows 10.

5.1 Dataset Description

We use the San Francisco Taxi Cabs Mobility dataset which contains over 10 million GPS traces of 500 taxis for a period of 30 days [31]. It also provides occupancy information in each of the taxi along with their time and location using which we can identify the pickup and drop off location of all requests.

To simulate a real-world scenario, we have extracted 1170 taxi requests over a period of 4 hours from 05/23/2008 06:00:00 to 05/23/2008 10:00:00. We have also identified the 310 taxis which were in service during that time period. We have used the same number of requests and taxis from the dataset to mimic the real-world as close as possible.

We used Open Street Map (OSM) to extract the San Francisco road network and convert it into MATSim compatible network.xml file where all the GPS coordinates are mapped to a $x-$y coordinates in EPSG-2227 Spatial Reference System. We created the population.xml and vehicles.xml from the extracted information by mapping the GPS coordinates of pickup and destination to the $x-$y coordinates in the MATSim network.

5.2 Regions and Charging Stations

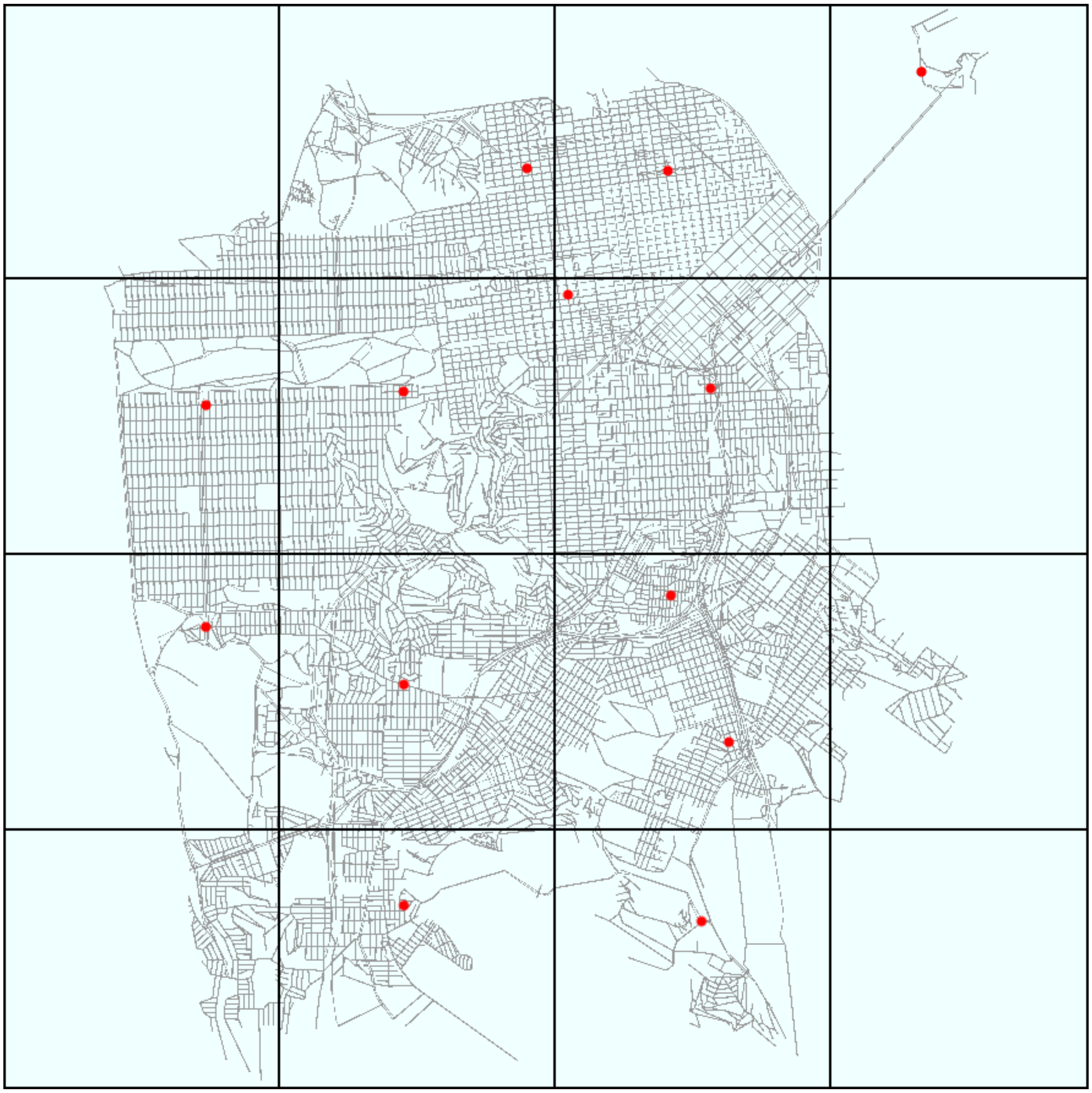


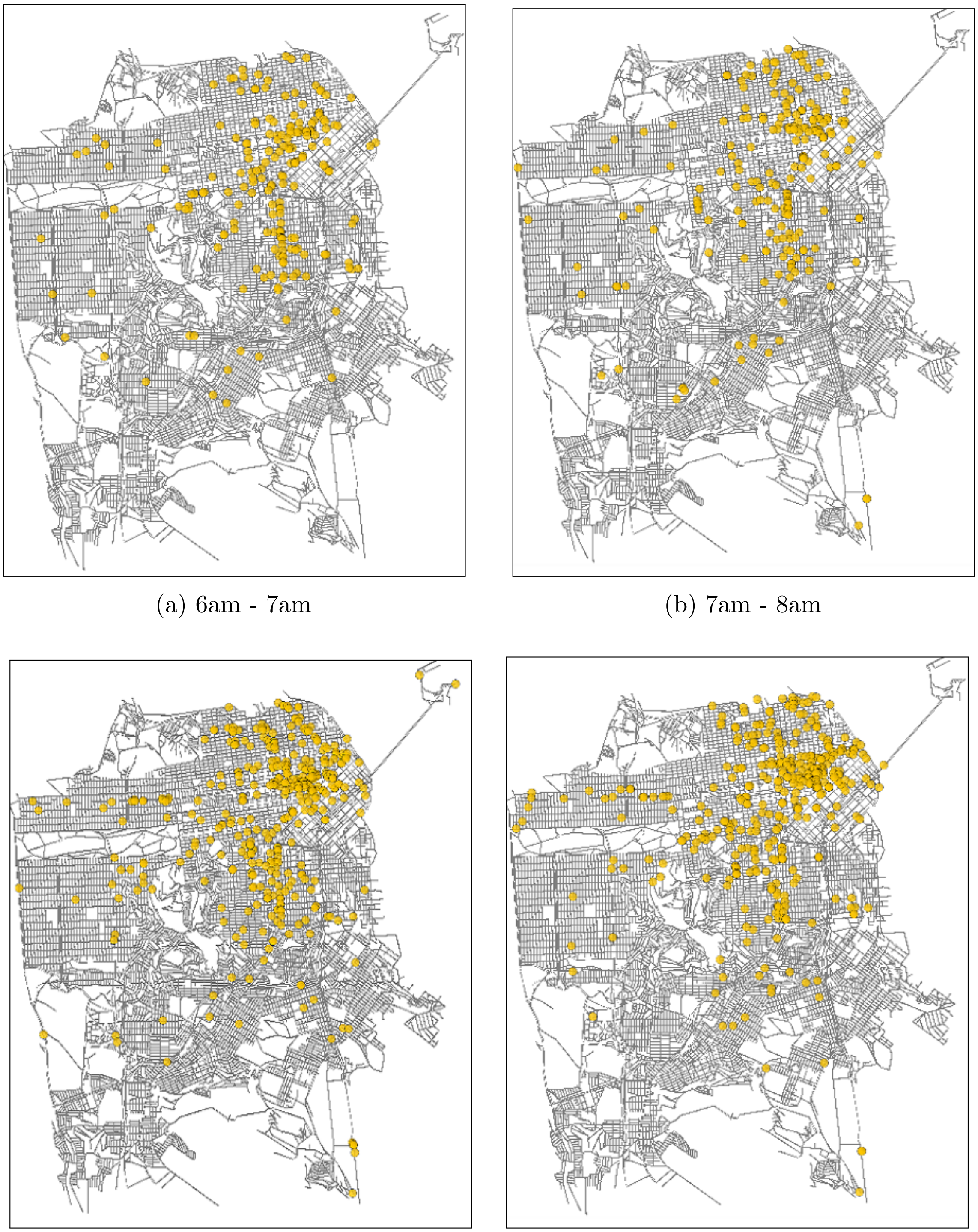
Figure 5.1: Regions and Charging Stations in San Francisco Simulation

Figure 5.1 shows the region partitions and red dots show the charging station locations on the links in the road network. The entire map region is partitioned into 16 square regions of equal size. Higher number of regions up to a level have found to be effective in meeting the demand as the reassignments can be more precise

[32] but they also increase the computational complexity and since we assume that the reassigned taxis will be moved to a parking location close to the center of each region, its not possible to have so many large parking lots inside an urban city.

We have placed 13 charging stations to cover the entire network, so the taxis always have at least one charging station within a certain range when they move across the regions. Few regions have more than one charging station, this is to reduce queue length in charging stations in regions of high demand. All charging stations are assumed to have the same number of ports and charging power in terms of kilowatt-hour (kWh) which determines the time it takes to charge a vehicle to its maximum capacity. We vary the number of ports and charging power in our analyzes to study their impact in detail.

5.3 Demand of User Requests



(a) 6am - 7am

(b) 7am - 8am

(c) 8am - 9am

(d) 9am - 10am

Figure 5.2: Pickup request locations during each hour

Figure 5.2 shows the user pickup requests from the dataset mapped to the MATSim network of San Francisco city. We can see that the number of requests increase with time and most of the pickup requests originate from the top left region which constitutes the Financial District, Nob Hill, Chinatown and Civic Center.

This kind of spatiotemporal distribution of requests requires robust rebalance strategies to improve fleet utilization and provides us a good use case for testing our rebalancing model.

5.4 Taxi Power Consumption and Battery Capacity

We have modeled the power consumption and battery capacity of the taxis in the fleet based on electric vehicle Nissan Leaf 2012. Maximum usable battery capacity is set to be 21 KW. Discharging rate varies based on the vehicle movement which is determined by the speed and acceleration, and auxiliary power consumption like various other electrical components like onboard computer and air conditioning. This has been configured based on the energy consumption in [25].

5.5 MATSim Parameters and Limitations

We run the simulation for 7 hours from 6:00 to 13:00 for serving requests in the period of 4 hours from 6:00 to 10:00. Because of the need for charging the taxis during their operation, not all taxis will be on the road serving, so it takes more time to complete these requests than conventional taxis.

We have set the minimum charge threshold θ to be 20% of the battery capacity. The minimum demand threshold for a region k is set to 5 and persistent demand less than the threshold k for 2 subsequent time intervals will be considered.

We estimate the energy consumption before each taxi is assigned to a request, region or a charging station to ensure they have enough charge to reach a charging station before their charge is depleted. But sometimes because of reasons like traffic congestion, these estimates may not be correct and it can lead to some taxis getting depleted before they can reach a charging station. We can avoid this by over estimating the power consumption and premature charging but it will in turn affect the fleet's ability to serve the user requests effectively. During our experiments, few taxis did get stranded because of the above reason, but the number of taxis affected is less as its around 10% of the fleet and it mostly happens at the end of the simulation.

5.6 Two different scenarios based on initial SoC

The distribution of SoC of all taxis in the fleet is a major factor in determining the number of taxis on road serving requests and number of taxis in charging station at any given point of time. This distribution varies over a period of time-based on the charging cycle of the taxis. To study how these distributions affect the metrics, we experiment with two different scenarios where we randomly assigned the initial SoC to be a percentage of the battery capacity for all taxis as per the percentage distribution shown in the Figure 5.1.

	SoC = 100%	SoC = 50%	SoC = 30%
Scenario 1	50%	40%	10%
Scenario 2	50%	20%	30%

Table 5.1: Scenarios with different percentage distribution of inital SoCs

5.7 Evaluation Metrics

We use 3 metrics from the literature to evaluate the performance of the dispatching system in terms of customer satisfaction and fleet efficiency.

- Passenger Waiting Time: This metric represents how well the demand is being met and it is expressed as average seconds passengers had to wait before they boarded a taxi each hour.

- Empty Drive Ratio: This metric represents the fleet utilization in terms of the average ratio of Unoccupied driving to total driving for all taxis operating in an hour. This ratio tends to be high in electric taxis as they take frequent empty drives to the charging stations.

- Charging Station Occupancy: This metric represents the total number of taxis in the fleet assigned, plugged and queued in all charging stations at a given point of time. This signifies the utilization of charging infrastructure and how long taxis spend in charging stations.

5.8 Varying Time Interval t

The time interval between each rebalancing and charging station assignment decisions is an important parameter in the model. Since its an online optimization model only idle taxis and unmet demand at time t are considered. We experimented with t=10 and t=15 for both the scenarios to analyze how it affects the metrics.

5.8.1 Scenario 1

Average Passenger Waiting Time: From Figure 5.3(a), We can see that average passenger waiting time was low when t=15 than when t=10. This can be because of premature rebalancing of idle taxis when there is upcoming demand in their regions which the model was not aware. Compared to Scenario 2 Figure 5.3(b), waiting time is relatively low in the beginning as number of low charge taxis is less in Scenario 1. The increase in waiting time after hour 8 is because of increase in charge depleted taxis in the fleet as well as because of the increase in user requests.

Empty Drive Ratio: We can see from Figure 5.3(c) that the empty drive ratio is similar when t=15 and t=10 except for few hours in the middle. This can be attributed to premature rebalancing which increases the empty drive ratio as the taxis are moved across regions. The rise in empty drives after hour 9 is because of increased assignment of depleted taxis to the charging stations and rebalancing to meet the high demand.

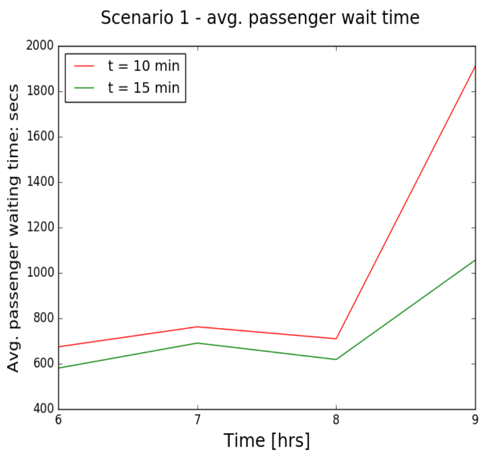
Charging Station Occupancy: From Figure 5.4(a) and Figure 5.4(c), we can see that the charger occupancy is almost same and varying t doesn't influence station assignments in Scenario 1.

5.8.2 Scenario 2

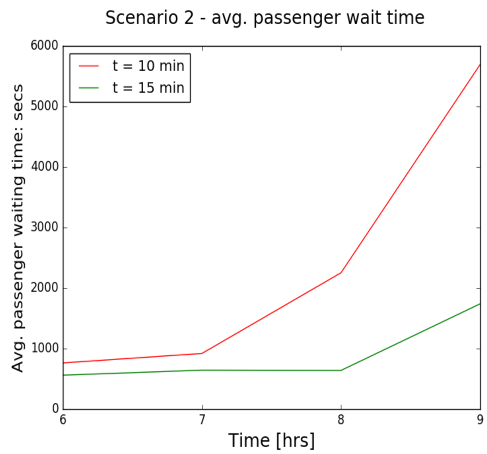
Average Passenger Waiting Time: From Figure 5.3(b), We can see that average passenger waiting time is low when t=15 and overall waiting time is high compared to Scenario 1. This can be because of premature rebalancing along with the high number of low charge taxis in the beginning hours of this scenario which has a cascading effect during the subsequent high demand.

Empty Drive Ratio: From Figure 5.3(d), We can see that empty drive ratio is high when t=10 in the beginning and decreased after hour 9 as the fleet efficiency improved with more taxis joining back the fleet to serve requests after their charging sessions. This also shows how frequent rebalancing can improve the fleet efficiency under right circumstances.

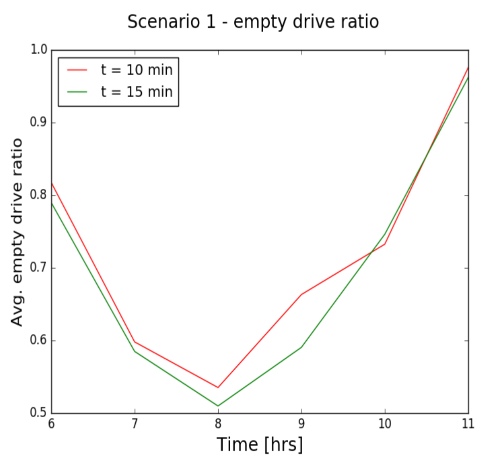
Charging Station Occupancy: Because of high number of low charge taxis in the beginning of Scenario 2, we can see those taxis getting assigned to charging stations in Figure 5.4(b) and Figure 5.4(d). Varying t affects how often the low charge taxis are identified and assigned to a charging station as we can see more initial assignments when t=10 than when t=15, which can provide better turn around time for low charge taxis.



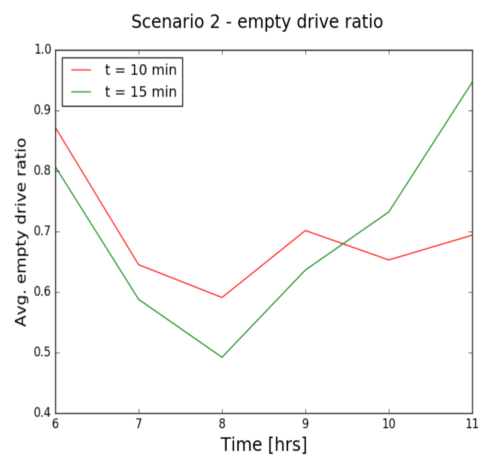
(a)



(b)

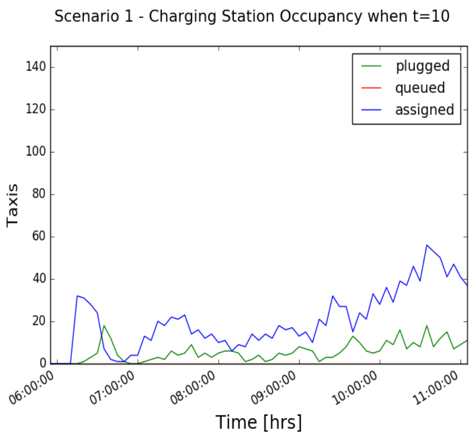


(c)

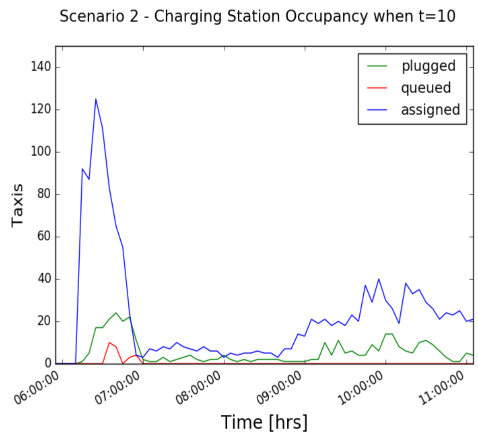


(d)

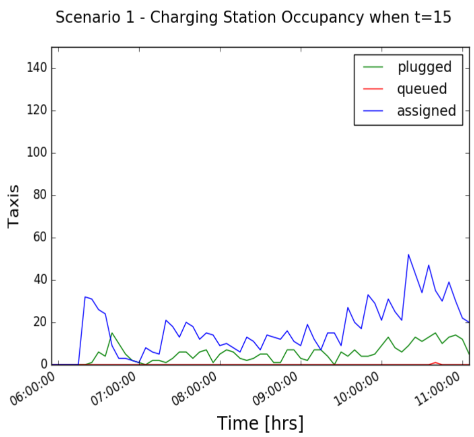
Figure 5.3: Passenger wait time and empty drive ratio with different t



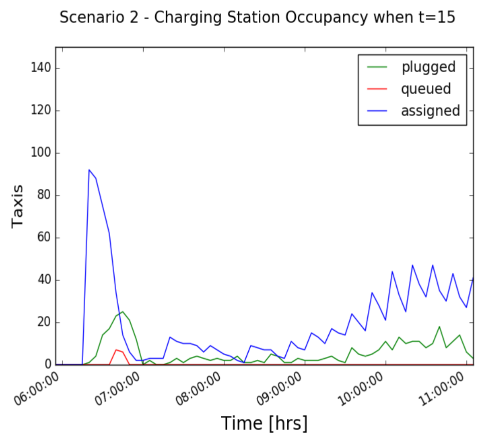
(a)



(b)



(c)



(d)

Figure 5.4: Charger occupancy with different t

5.9 Varying Charging Ports Capacity p

The total number of charging ports in each station is given by p. This defines the maximum number of taxis that can be plugged to a charging station simultaneously. High capacity can reduce the number of taxis in queue waiting for their turn during peak demand.

5.9.1 Scenario 1

Average Passenger Waiting Time: From Figure 5.5(a), We can see that average passenger waiting time is the same when p=15 and p=10. In Scenario 1, number of low charge taxis is less when compared to Scenario 2, so there is no queuing in the charging stations which is influenced by p.

Empty Drive Ratio: We can see from Figure 5.5(c) that the empty drive ratio is also same when p=15 and p=10 because of the same above reason as passenger waiting time.

Charging Station Occupancy: From Figure 5.6(a) and Figure 5.6(c), we can see that the charger occupancy is almost same except for a slight queuing before hour 11 when p=10 which didn't happen when p=15 as the stations had more ports to accommodate all taxis assigned to them.

5.9.2 Scenario 2

Average Passenger Waiting Time: From Figure 5.5(b), We can see that average passenger waiting time is almost similar when p=15 and p=10. The difference of about 5 minutes in the passenger wait time between these charging ports capacity is due to different charging station assignments as p is a parameter in the model based on which the charging stations are assigned.

Empty Drive Ratio: From Figure 5.5(d), We can see that empty drive ratio is almost the same when p=10 and p=15 except in the end where p=15 performed better. This can be because of assignments to farther charging stations because of unavailability of ports in the closest station.

Charging Station Occupancy: Because of high number of low charge taxis in the Scenario 2, resulting in all those taxis getting assigned to charging stations in the beginning hour as shown in Figure 5.6(b) and Figure 5.6(d). We can see that the charger occupancy is almost same except for the significant queuing when p=10.

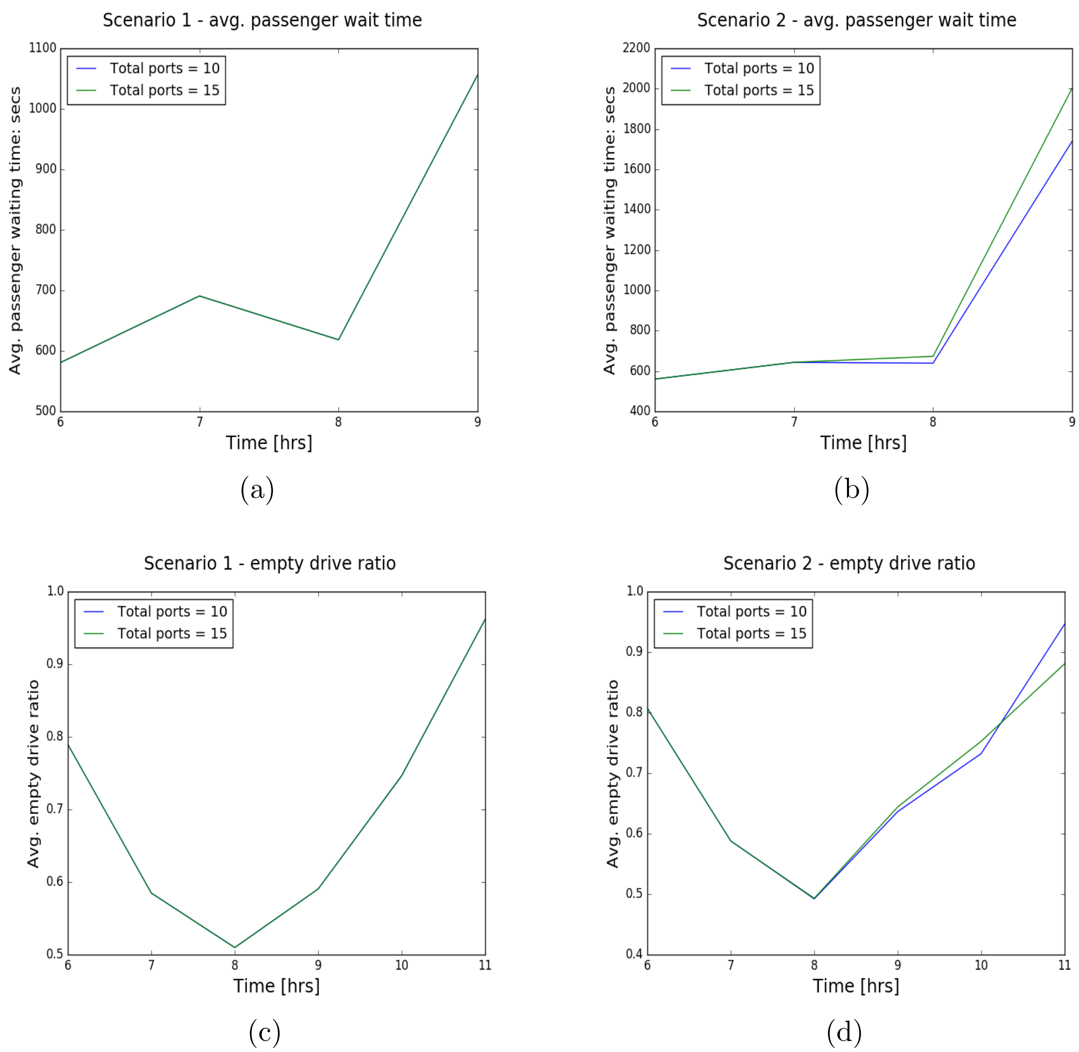
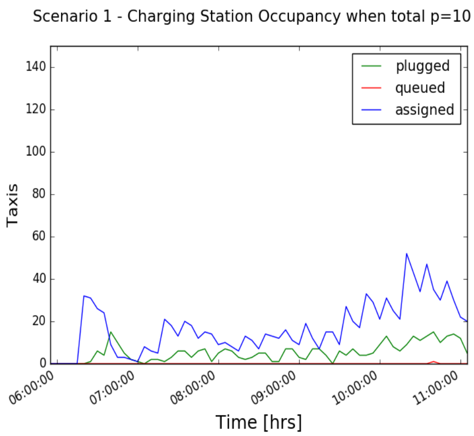
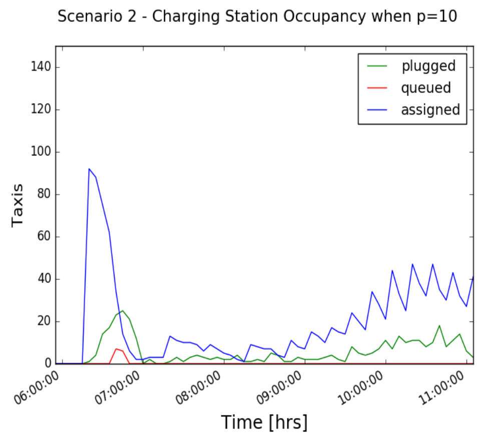


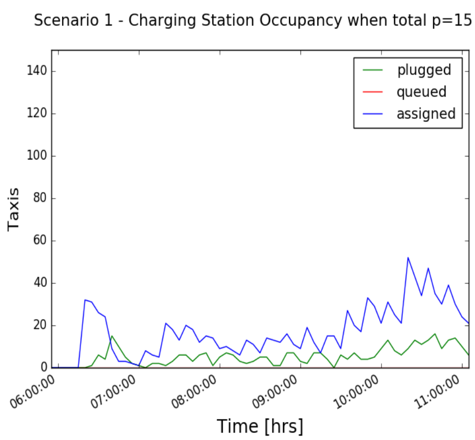
Figure 5.5: Passenger wait time and empty drive ratio with different total number of charging ports per station



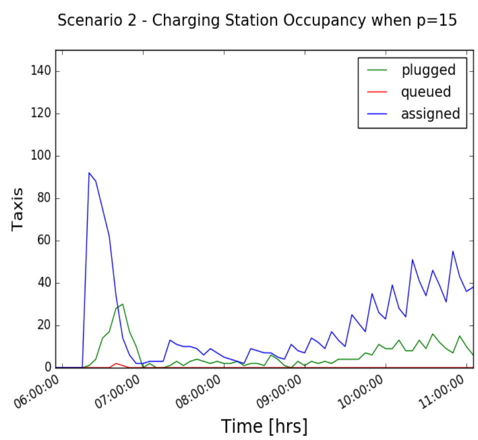
(a)



(b)



(c)



(d)

Figure 5.6: Charger occupancy with different total number of charging ports per station

5.10 Varying Charger Power w

Charging power w denotes the rate at which the taxi connected to it charges. Higher the power lesser the time it takes to charge a taxi to its maximum battery capacity. This can reduce the amount of time each taxi spends on charging during their charging sessions and increase their overall utilization.

5.10.1 Scenario 1

Average Passenger Waiting Time: From Figure 5.7(c), We can see that average passenger waiting time is low when w=135 than when w=50. This can be attributed to less time spent by taxis on charging stations for each charging cycle.

Empty Drive Ratio: We can see from Figure 5.7(c) that the empty drive ratio is slightly lower when w=135 and w=50 because of the same above reason as passenger waiting time.

Charging Station Occupancy: From Figure 5.8(a) and Figure 5.8(c), we can see that the charger occupancy is high when w=50 as expected because of the longer charging cycles which also resulted in queuing after hour 11. Charger occupancy is uniform across hours when w=135 as it facilitates faster charging.

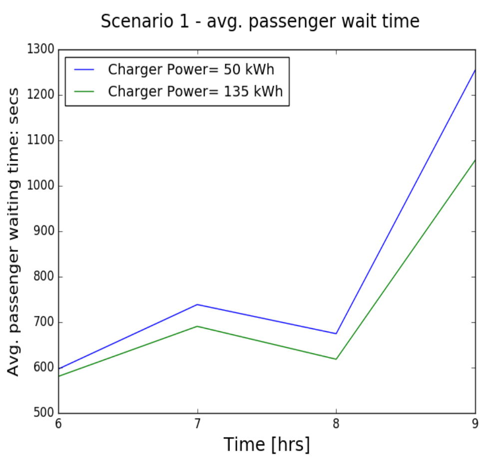
5.10.2 Scenario 2

1. **Average Passenger Waiting Time:** From Figure 5.7(d), We can see that average passenger waiting time is better when w=135 when compared to w=50. In Scenario 2, we have a high number of low charge taxis assigned to the charging stations in the beginning hours, so more taxis are available during the peak hours resulting in less passenger wait time.

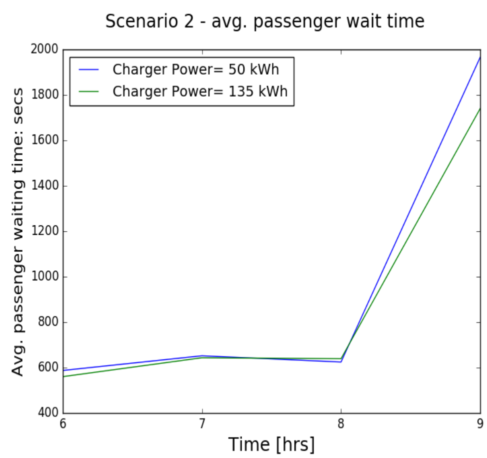
2. **Empty Drive Ratio:** From Figure 5.7(d), We can see that empty drive ratio is almost the same when w=50 and w=135 except for in the beginning hour where w=135 had better empty drive ratio. This is due to less time spent on charging stations by taxis during charging when w=135.

3. **Charging Station Occupancy:** From Figure 5.8(b) and Figure 5.8(d), we can see that the charger occupancy is high from the beginning when w=50

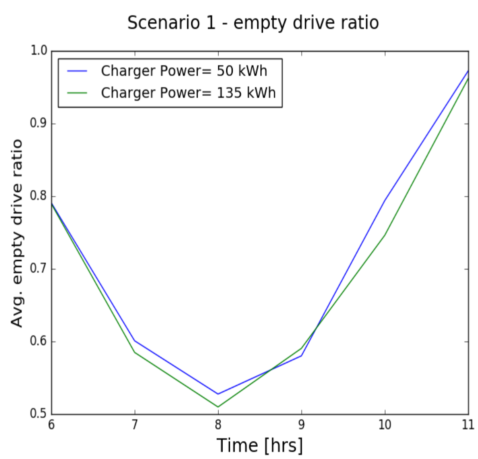
compared to w=135 because of the longer charging cycles which also resulted in significant queuing during hour 7 and 10.



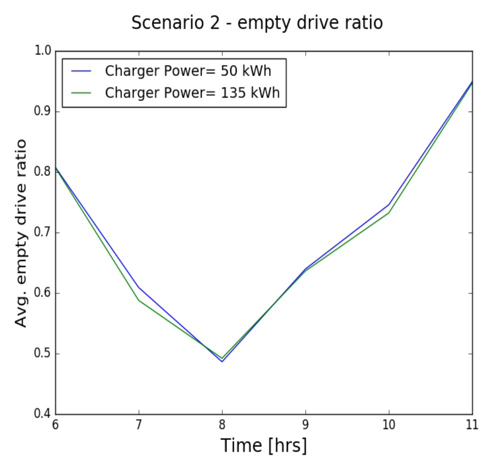
(a)



(b)

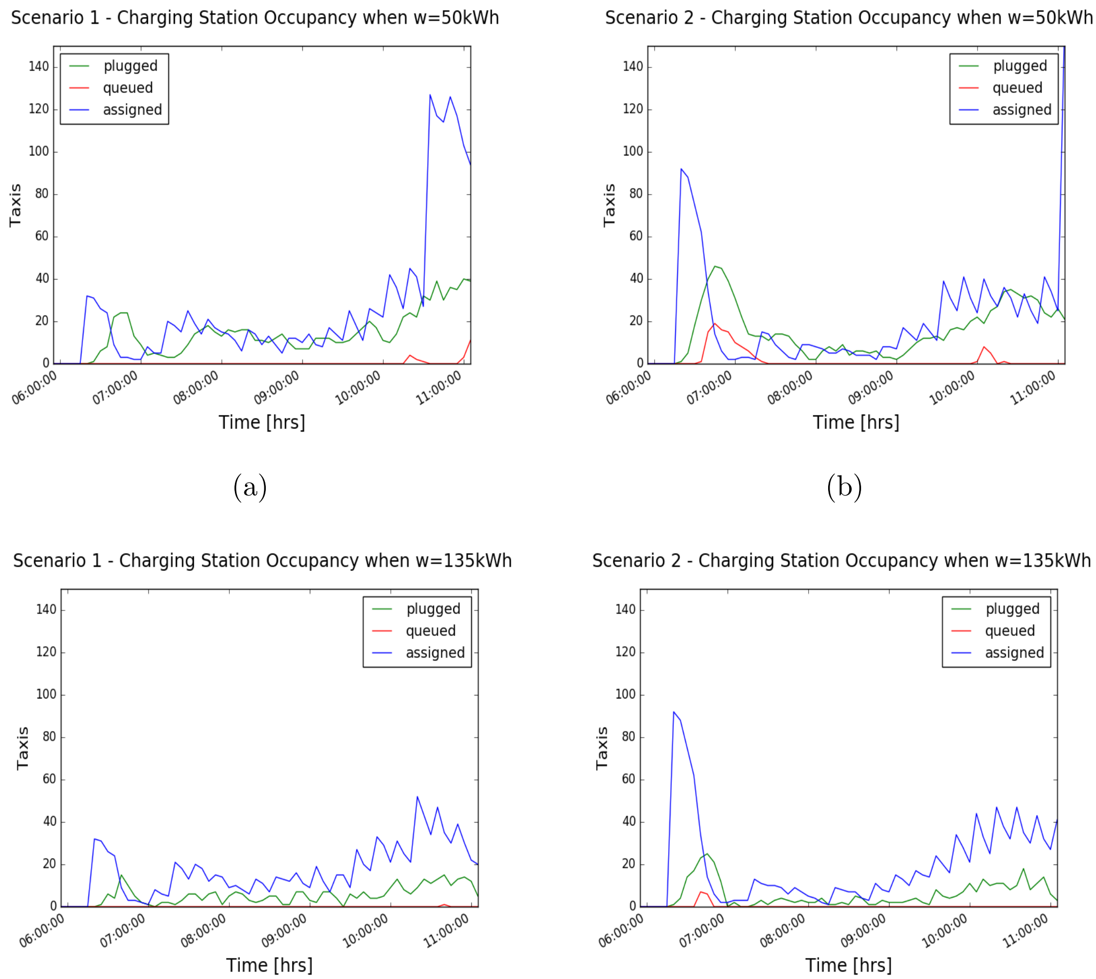


(c)



(d)

Figure 5.7: Passenger wait time and empty drive ratio with different charging power



(a) (b)

(c) (d)

Figure 5.8: Charger occupancy with different charging power

5.11 Comparing Scenario 1 and Scenario 2

By comparing the results from above experiments with Scenario 1 and 2, we can see that the total number of taxis with low charge in the fleet is one of the important factor that affects the performance of the fleet in serving user requests. Charging station infrastructure based parameters such as p and w have a directly proportional effect on the fleet performance. Parameter t which governs the frequency of optimization can be made dynamic based on the need for rebalancing every hour, as its effect on the fleet vary based on the demand and the scenarios.

Chapter 6

Conclusion

6.1 Summary

Autonomous Electric Taxis are going to be the conventional mode of transport in urban cities in the near future. Rebalancing of idle taxis based on demand and assignments of taxis to right charging stations are going to be two important problems in operating these fleets. We have come up with a fleet management system with an online optimization model to continuously solve this problem based on the varying demand and charging station utilization.

We used a simulation-based optimization approach to implement this system building over existing extensions in MATSim. We also evaluated this system using real-world data and analyzed his performance. We also illustrated how this simulation based on approach can be used to analyze different scenarios, parameters, and strategies effectively before rolling them out in the real world.

6.2 Future Work

The inherent limitation of online optimization is not to consider future demand. So the current system cannot make decisions based on future demand which is important for electric taxis as their mobility is bounded by their SoC. This can be addressed by a hybrid approach of online and offline optimization along with predicting demand in real time using Machine Learning.

We need a fleet management system that can anticipate and prepare for future demand by preemptively charging taxis where there are ports available in charging stations and start moving taxis towards regions where there is going to be high demand.

We also have to incorporate more parameters in the simulation like real-time congestion prediction and mitigation to accurately estimate the range of the taxis to improve the overall fleet efficiency.

Model Predictive Control (MPC) based approach can make decisions based on information towards horizon [32, 33]. We can use simulation to realistically simulate the complex fleet behavior to extract various parameters for MPC instead of making statistical assumptions should result in a robust fleet management system.

Bibliography

[1] United States Department of Energy.gov. *The History of the Electric Car*. Sept. 2014. URL: https://www.energy.gov/articles/history-electric-car.

[2] *Federal Highway Administration Unveils National 'Alternative Fuel and Electric Charging' Network*. Nov. 2016. URL: https://www.transportation.gov/briefing-room/fhwa5616.

[3] Kenneth H Goodrich, Jim Nickolaou, and Mark D Moore. "Transformational Autonomy and Personal Transportation: Synergies and Differences between Cars and Planes". In: *16th AIAA Aviation Technology, Integration, and Operations Conference*. 2016, p. 3604.

[4] Kirsten Korosec. *4 Reasons Why Tesla's Autonomous Driving Announcement Matters*. 2016. URL: http://fortune.com/2016/10/20/tesla-self-driving-hardware-matters/.

[5] Mark Harris. *Uber Could Be First to Test Completely Driverless Cars in Public*. 2015. URL: http://spectrum.ieee.org/cars-that-think/transportation/self-driving/uber-could-be-first-to-test-completely-driverless-cars-in-public.

[6] *Seven million front gardens disappear to make way for cars*. URL: `http://www.racfoundation.org/research/mobility/spaced-out-perspectives-on-parking`.

[7] *Global EV Outlook 2016*. URL: `https://www.iea.org/publications/freepublications/publication/global-ev-outlook-2016.html`.

[8] T Donna Chen, Kara M Kockelman, and Moby Khan. "The electric vehicle charging station location problem: a parking-based assignment method for Seattle". In: *Transportation Research Board 92nd Annual Meeting*. Vol. 340. 2013, pp. 13–1254.

[9] William J Mitchell, Chris E Borroni-Bird, and Lawrence D Burns. *Reinventing the automobile: Personal urban mobility for the 21st century*. MIT press, 2010.

[10] Javier Alonso-Mora, Samitha Samaranayake, Alex Wallar, Emilio Frazzoli, and Daniela Rus. "On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment". In: *Proceedings of the National Academy of Sciences* (2017), p. 201611675.

[11] Kevin Spieser, Samitha Samaranayake, Wolfgang Gruel, and E Frazolli. "Shared-vehicle mobility-on-demand systems". In: *Transportation Research Board 96th Annual Meeting*. 2016.

[12] Hua Qin and Wensheng Zhang. "Charging scheduling with minimal waiting in a network of electric vehicles and charging stations". In: *Proceedings of the Eighth ACM international workshop on Vehicular inter-networking*. ACM. 2011, pp. 51–60.

[13] Yanhua Li, Jun Luo, Chi-Yin Chow, Kam-Lam Chan, Ye Ding, and Fan Zhang. "Growing the charging station network for electric vehicles with trajectory

data analytics". In: *Data Engineering (ICDE), 2015 IEEE 31st International Conference on*. IEEE. 2015, pp. 1376–1387.

[14] Georg Brandstätter, Michael Kahr, and Markus Leitner. "Determining optimal locations for charging stations of electric car-sharing systems under stochastic demand". In: (2017).

[15] Georg Brandstätter, Markus Leitner, and Ivana Ljubić. *Location of charging stations in electric car sharing systems*. Tech. rep. Technical report, Department of Statistics and Operations Research, University of Vienna, Vienna, Austria, 2016.

[16] Carlos Lima Azevedo, Katarzyna Marczuk, Sebastián Raveau, Harold Soh, Muhammad Adnan, Kakali Basak, Harish Loganathan, Neeraj Deshmunkh, Der-Horng Lee, Emilio Frazzoli, and Moshe Ben-Akiva. "Microsimulation of Demand and Supply of Autonomous Mobility On Demand". In: *Transportation Research Record: Journal of the Transportation Research Board* 2564 (2016), pp. 21–30.

[17] Joschka Bischoff and Michal Maciejewski. "Simulation of city-wide replacement of private cars with autonomous taxis in Berlin". In: *Procedia Computer Science* 83 (2016), pp. 237–244.

[18] Katarzyna Anna Marczuk, Harold Soh Soon Hong, Carlos Miguel Lima Azevedo, Muhammad Adnan, Scott Drew Pendleton, Emilio Frazzoli, and Der Horng Lee. "Autonomous mobility on demand in SimMobility: Case study of the central business district in Singapore". In: *Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), 2015 IEEE 7th International Conference on*. IEEE. 2015, pp. 167–172.

[19] Katarzyna A Marczuk, Harold SH Soh, Carlos ML Azevedo, Der-Horng Lee, and Emilio Frazzoli. "Simulation Framework for Rebalancing of Autonomous Mobility on Demand Systems". In: *MATEC Web of Conferences*. Vol. 81. EDP Sciences. 2016, p. 01005.

[20] A. Horni, K. Nagel, and K.W. Axhausen. *The Multi-agent Transport Simulation MATSim*. 2016. ISBN: 9781909188785. URL: https://books.google.com/books?id=0Qw9ngAACAAJ.

[21] Zahra Navidi Kashani, Nicole Ronald, and Stephan Winter. "Comparing demand responsive and conventional public transport in a low demand context". In: *Pervasive Computing and Communication Workshops (PerCom Workshops), 2016 IEEE International Conference on*. IEEE. 2016, pp. 1–6.

[22] Michal Maciejewski and Joschka Bischoff. *Congestion effects of autonomous taxi fleets*. 2016.

[23] Michał Maciejewski and Kai Nagel. "Towards multi-agent simulation of the dynamic vehicle routing problem in MATSim". In: *International Conference on Parallel Processing and Applied Mathematics*. Springer. 2011, pp. 551–560.

[24] Maciejewski Michal. *MATSim Electric Vehicle Module*. Apr. 2017. URL: https://github.com/matsim-org/matsim/tree/master/playgrounds/michalm.

[25] Bartłomiej Ohde, Grzegorz Ślaski, and Michał Maciejewski. "Statistical analysis of real-world urban driving cycles for modelling energy consumption of electric vehicles". In: *Journal of Mechanical and Transport Engineering* 68.2 (2016), pp. 25–39.

[26] Patrick Jaillet and Michael R Wagner. "Online Optimization, An Introduction". In: *Risk and Optimization in an Uncertain World*. INFORMS, 2010, pp. 142–152.

[27] Michał Maciejewski. "Benchmarking minimum passenger waiting time in online taxi dispatching with exact offline optimization methods". In: *Archives of Transport* 30 (2014).

[28] Michał Maciejewski. "Online taxi dispatching via exact offline optimization". In: *Logistyka* (2014).

[29] Murat Yilmaz and Philip T Krein. "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles". In: *IEEE Transactions on Power Electronics* 28.5 (2013), pp. 2151–2169.

[30] Inc. Gurobi Optimization. *Gurobi Optimizer 7.0 Reference Manual*. 2017.

[31] Michal Piorkowski, Natasa Sarafijanovic-Djukic, and Matthias Grossglauser. *CRAWDAD dataset epfl/mobility (v. 2009-02-24)*. Downloaded from `http://crawdad.org/epfl/mobility/20090224`. Feb. 2009. DOI: `10.15783/C7J010`.

[32] Fei Miao, Shuo Han, Shan Lin, John A Stankovic, Desheng Zhang, Sirajum Munir, Hua Huang, Tian He, and George J Pappas. "Taxi dispatch with real-time sensing data in metropolitan areas: A receding horizon control approach". In: *IEEE Transactions on Automation Science and Engineering* 13.2 (2016), pp. 463–478.

[33] Rick Zhang, Federico Rossi, and Marco Pavone. "Model predictive control of autonomous mobility-on-demand systems". In: *Robotics and Automation (ICRA), 2016 IEEE International Conference on*. IEEE. 2016, pp. 1382–1389.