DC/Wireless Hybrid Charging Slot Design for Electric Vehicle Park Areas to Maximize Customer Satisfaction

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Abstract

Electric vehicles are becoming more and more popular due to their environmental friendliness and sustainability. The increasing prevalence of electric vehicles brings the problem of charging for the company that provide this infrastructure. In this research, in order to evaluate DC and wireless charging methods, we create two mathematical models in order to offer an electric vehicle charging enabled parking lot design. The first model, Offline Parking Installation Model, aims to determine the minimum number of charging slots to be installed in the parking lot while the second model, Online Energy Operations Model, aims maximizing customer satisfaction by satisfying customer's energy demand. The ultimate goal of both models is to maximize customer satisfaction as well as maximizing the net profit of an operating company and number of vehicles charged. In the end, we will calculate how many and what type of charging stations should be installed and energy income. Throughout our calculations, Python 3.11 was used with the PyCharm environment and CPLEX 22.1 was used for modeling.

Keywords: Electrical vehicles, charge slot design, energy scheduling, customer satisfaction

1. Introduction

The decline in fossil resources, the issues that countries have with each other in this regard, as well as the detrimental effects of emissions caused by vehicles on global warming have been the major factors of the preference of using electric vehicles (EVs)(**13** & **14**). Even if the number of electric vehicles is still lower than the number of Internal Combustion Engine Vehicles (ICEVs), the rate of EVs keeps increasing with the developed technology along with beneficial reasons such as having zero emissions, being environment friendly, and energy and cost-efficient day by day. Increase in electric vehicle sales can be shown in Figure 1, which presents the global electric car sales.

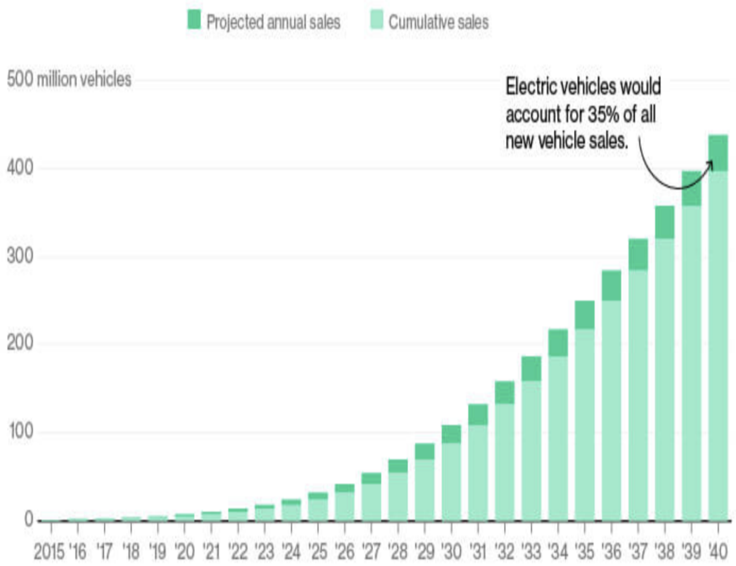


Figure 1: Global Electric Car Sales (**34**)

Although the increase rate in the usage of EVs has been accelerating nowadays, it has always been much slower than the increase rate of ICs because of fuel-charging issues. This issue can simply be explained with the egg and chicken theory as Delacrétaz and Van Dijk stated (**3**). People who consider buying an EV want charging infrastructure to become widespread, while people who consider making investments in charging infrastructure would want to see more EVs on roads.

Due to the fact that fossil resources are decreasing, both the increase in fossil fuel prices and incentives for EVs expedited the investments in EVs and related technology resulting in more electric vehicles on the road, and more charging stations in service.

2. Literature Review

Electric vehicles are getting widespread with the developed technology and increased demand. But for the sustainability of electric vehicle usage, charging infrastructure should be widespread as well. Vehicles should be able to reach a charging station whenever needed. That's why, issues such as locating and allocating charging stations and modifying parking lots so that EVs can be charged at the same time, have become one of the important research topics. Since location approaches of stations are still developing and new charging methods are slowly getting adopted, not many studies have been done. But there are some research and articles that somehow cover our focused topic: DC and wireless charging.

2.1. Wired Charging

Zeb and Imran discussed an optimized combination of 3 different types of EV chargers, Level 1,2 and 3 to achieve a proper placement with one of the objective functions as minimizing installation costs. For this research, authors considered the EV load, derived from the number of EVs, arrival and departure times, charging features, as a stochastic process and used Particle Swarm Optimization (PSO). Then, verified their model on a real distribution system of the National University of Sciences and Technology Pakistan. As a result, they obtained that the combined system reduced costs from $3.55 million to $1.99 million (**18**).

Babic and Carvalho studied the transformation of parking lots into electric vehicle-enabled parking lots by adding charging systems as well as willingness–to-pay model based on historical data and electricity prices. The authors offered a new frame based on discrete-event simulations and queueing theory, then decided the number of EV chargers and charging prices should be implemented to maximize the profit. In the article, how an EV-enabled parking lots' profit calculation is shown with several assumptions. Then, the authors applied their study at a parking lot in Melbourne, Australia, and ended up with a result of %9 to %13 of the parking spots, which corresponds to 47 to 68 out of 524 spots should be EV enabled. This study is also applicable in different parking lot scenarios because there are no such constraints on the parking lot location (**19**).

In one research, Zeng and Niu present a review of the literature in terms of technical needs, scheduling approaches, and solver algorithms for the integration of Electric Vehicles into grids through the vehicle-to-grid (V2G) technology. The authors emphasize that, thanks to the V2H, which is a smaller version of V2G technology, plug-in electric vehicles (PEV). can meet the electricity supply for homes when they are parked. According to the authors, there are two different mainstream scheduling methods, centralized and decentralized, for V2G implementation. In the centralized method, the charging behaviors of PEV are focused on a specific target, while in the decentralized method, the PEV strategies vary according to electricity prices. The authors acknowledge that there is a more important criterion in determining the strategies needed for V2G implementation than the centralized or decentralized method, which is mathematical optimization. The authors review different types of algorithms in the literature for optimal V2G strategies. The authors state that the PSO and Genetic Algorithm (GA) models stand out for the most optimal V2G strategy. The authors compare different algorithm models according to how effective they are and what constraints they have. The authors' findings show that the Linear Programming (LP) mathematical optimization model is more prominent in terms of effective solutions than the Non-Linear Programming (NP) and Mixed Integer Programming (MIP) models (**20**).

According to Bayram, the most suitable charging station design for the facilities based on two different assumptions. In their first assumption, they consider workplace parking lots (i.e., long-term parking during working hours), while in their other assumptions, they consider public parking lots (i.e., shorter-term parking). The purpose of the first model is to calculate the energy required for service. The second model's objective is to calculate the optimal arrival rate while maximizing revenue, and the effects of using multiple charging methods in this model are also examined. Linear cost functions are adopted for service and waiting for costs. A high arrival rate is assigned for fast charging methods, while a low arrival rate is assigned for long-term charging, thus finding optimum arrival rates for different charging types. Performance improvements with optimum load allocation have been made and tested in simulation. The discrete event simulation was repeated 30 times, and according to the results obtained, the average waiting time was reduced by 60%, and the station waiting queue was reduced by 42% (**25**).

Mirzaei and Kazemi present planning for the most appropriate capacity, location, and time for electric vehicle parking lot installation. First, it presents a method to predict the power exchange that will take place between the parking lot and electric vehicles. Thus, the network cost will be minimized in unnecessary moments. In addition, he proposed a criterion for arriving at the car park under time and energy constraints; according to these criteria, it would minimize the time and energy to reach the car park. Then, the uncertain budget required for establishing and developing the car park is modeled to maximize profit. In addition, the effects of the budget on parking lot planning and the growth rate of electric vehicles were examined by defining different scenarios. It was concluded that the budget allocation in different years was utterly dependent on EV growth. It is also stated that as the budget uncertainty increases, parking lot planning and investment returns are negatively affected. It is expected that the profit of the parking lot will increase thanks to the photovoltaic sources planned to be placed on the roof. Finally, when the voltage profile is examined, it is found that the suggested model can keep the voltage in the system within the proper limits even when the maximum load is reached

(**24**).

A smart EV parking model with bidirectional power flow is demonstrated by He and Zhu, and they suggest the best charge/discharge strategy to maximize revenue for the parking lot owner and cut down on costs for electric vehicle users. The simulation is carried out in Matlab using real-world parking data gathered from University of Technology Sydney(UTS) underground parking lot, and comparisons are made between the proposed and unregulated charge/discharge techniques. The simulation findings suggest that the benefit to the car park owner may be raised by almost 300% when compared to the outcomes of the conventional charging algorithm. Additionally, the average related cost reduction for EV users is 47% (**26**).

2.2. Wireless Charging

Many wireless charging system topologies that can be used in electric vehicle applications have been compiled by Mohamed and Aymen. This article mentions some statistics on the use of wireless charging systems, and also this paper touches on alternative coil designs, mathematical models, and WPT (Wireless Power Transfer) topologies for both dynamic and static charging techniques. A list of all the key parameters and variables that go into creating a mathematical model for the wireless charging system is shown in the article. By focusing on the associated mathematical models that are utilized to determine the provided electrical power as a function of the EV's location on streets and its speed, this study provides a thorough examination of wireless charging systems. Additionally, the authors of this paper suggest a brand-new generic mathematical model that may be used for both dynamic and static charging techniques (**21**).

Jang analyzed the initial costs associated with installing wireless charging stations for electric vehicles in public transit networks (EVs). The initial installation cost for static wireless charging (SWC), quasi-dynamic wireless charging (QWC), and dynamic wireless charging (DWC) are compared in this article. This research is particularly concerned with the cost of energy logistics in transportation, which is the price of transferring and storing the energy required to run the transportation system. Real data gathered from the OLEV (On-Line Electric Vehicle) systems now in use on the KAIST (Korea Advanced Institute of Science and Technology) campus and in Gumi City are used. Analysis of the initial costs is done using mathematical optimization models for each type of EV and infrastructure system. A cost-sensitivity study is carried out to address the variable cost estimates for batteries and infrastructure equipment in the present market. It was concluded that a DWC system where battery costs are high but infrastructure costs for charging are cheap is more beneficial. However, SWC is more advantageous if the cost structure is the reverse. A QWC system's cost-benefit analysis falls in the middle of the

DWC and SWC systems' results (**22**).

Ahmad describes the obstacles to the national adoption of electric car charging infrastructure as well as some possible solutions in the article. The main obstacles that are discussed in this paper are power handling challenges, deployment of optimal charging infrastructure, efficiency management, and maintenance issues. A comprehensive examination of the Inductive (Wireless) charging system for EVs in the Indian context, along with a mathematical model and simulation results are demonstrated in this article. To determine if the installation of wireless charging infrastructure in India is economically feasible in the current environment, a study in this area has been conducted. The economic study was conducted with several public utility parking areas such as airports, hospitals, hotels, and metro stations. The cost of charging the electric vehicle was calculated using the annual cost of commercial electricity and a payback period of five years for the wireless charging system. The total cost of implementing a single wireless charging system is estimated to be 25,840 rupees. The findings demonstrate that wirelessly charged electric vehicles (EVs) not only offer convenience to the user but additionally aid in the conservation of fossil fuels, resulting in a far less polluted environment at reduced operating costs (**23**).

Csonka focuses on how the transition to the electric bus in the decarbonization process will be optimal in terms of charging power and electricity costs. In his review, the author investigates the optimization of the use of static and dynamic charging technologies in the infrastructures of cities through a mathematical model. This mathematical model, which focuses on the daytime charger characteristics, analyzes how much electrical power should be taken from which charger and analyzes to reach the optimum cost and charging power. The model focuses on the cost of charging infrastructure, maximum achievable charging power, and coefficient capacity. There is also a case study for the application of this mathematical model. Infrastructure technologies in the region of Kobanya in the city of Budapest were used to exemplify this mathematical model. The study proposes two different plans for the optimal system in the Kobanya region, where there are 26 bus lines. Furthermore, thanks to this model, the author concluded that dynamic chargers might be preferred where a single static charger can cover the cost of a dynamic charger line longer than 1600 meters. As a result of the study, the author concludes that this advanced model helps to determine the charging characteristics of electric bus lines (**28**).

And about the economical comparison of wired and wireless charging systems, Longo and Zaninelli focused on an economic analysis of adapting wired and wireless charging systems in the article, and they did their research considering parking places. 2 different scenarios were applied in this study, first is a parking place with 50 spots, and the second is a parking place with 200 spots. All the comparisons of energy losses, annual recharge energies, average electricity prices, annual costs, and net present values were done based on these two different scenarios and additionally based on the Italian and European Markets with the classical economical indexes. The authors also thought of the possibility of hiring employees to help customers; 1 for 50 spot parking and 3 for 200 spot parking, which brings extra costs. In the end, it is obtained that wireless systems should only be used if they guarantee an efficiency value of 86% for 50 spots parking places and 96% for 200 spots parking places, where energy losses are higher. Also, when labor costs are included, wired systems should be advised (**27**).

Table 1: List of Literature

Article Title	**Author**	**Objective**	**Solution Approach**	**Software Used**
1.Optimal Placement of Electric Vehicle Charging Stations in the Active Distribution Network	Muhammad Zulqarnain Zeb et al.	Reach an optimized combination of chargers with minimized costs.	Particle Swarm Optimization (PSO)	MATLAB and OpenDSS
2.Economic Analysis On The Use Of Wired and Wireless Recharging Systems	M. Longo et al.	Comparing wireless and wired charging by economic analysis.		
3.A Data-Driven Approach To Managing Electric Vehicle Charging Infrastructure In Parking Lots	Jurica Babic et al.	Maximizing management's profit while transforming parking lots to EV-enabled parking lots.	Discrete-Event Simulations	
4.An Optimal Charging/Discharging Strategy for Smart Electrical Car Parks	Tingting He et al.	To create a model combining V2G and G2V technology that maximizes profit while minimizing cost.	Charging / discharging algorithm	MATLAB
5.A Comprehensive Analysis of Wireless Charging Systems for Electric Vehicles	Naoui Mohamed et al.	Analyzing existing WPT systems and related technologies used and presenting possible coil shapes for EVs.		
6.Initial Energy Logistics Cost Analysis for Stationary, Quasi-Dynamic, and Dynamic Wireless Charging Public Transportation Systems	Young Jae Jang et al.	Comparing the three wireless charging systems in order to minimize energy logistic cost.	The Particle Swarm Optimization (PSO) algorithm	

Table 2: List of Literature (cont'd)

Article Title	**Author**	**Objective**	**Solution Approach**	**Software Used**
7.Optimal Design of Electric Vehicle Charging Stations for Commercial Premises	Islam Safak Bayram et al.	Creating a closed-form expression for the capacity of a PEV charging station.	Markovian queues, Linear cost function, Lagrange multipliers	Simulation program
8.A Dynamic Approach to Optimal Planning of Electric Vehicle Parking Lots	M.J. Mirzaei and A.Kazemi.	Maximizing the distribution system operator's profit.	Genetic algorithm, Chromosome structure and Probabilistic modeling	Simulation program
9.Integrating plug-in electric vehicles into power grids: A comprehensive review on power interaction mode, scheduling methodology and mathematical foundation	Yanchong Zheng et al.	Optimizing the scheduling strategy of EVs.	GA, PSO, meta-heuristic algorithms, simulated annealing	
10.Challenges and Potential Solutions for the Deployment of Wireless Charging Infrastructure for xEVs in India	Y. Varshney and A. Ahmed.	Potential solutions for the challenges to set up wireless charging stations in India.		Ansys maxwell
11.Optimization of Static and Dynamic Charging Infrastructure for Electric Buses	Bálint Csonka	Optimizing the charging of electric buses by minimizing the cost of charging infrastructure.	Interior Point Algorithm	MATLAB
12.Optimal siting and sizing of distribution system operator owned EV parking lot.	Mohammad Amin Kazemi et al.	Deciding on the number, location and capacity of Ev parking lots in order to max profit	Genetic algorithm	

3. Preliminaries

3.1. Electric Vehicles Charging Technologies

Electric vehicles do not have an internal combustion engine that directly contributes to motion and driving. They contain one or more electric motors that convert the electrical energy into motion energy in order to provide motion. Also, to start the electric motors, the energy stored in the vehicle's battery is used.

The biggest issue to be considered in electric vehicles is undoubtedly about refueling. In electric vehicles, refueling means charging the vehicle and the most important distinction in charging is being wired or wireless. Electric vehicles have two charging methods as Wired and Wireless charging which are divided into AC and DC methods for wired, static and dynamic methods for wireless as can be seen in Figure 2. Further descriptions and details about charging methods will be given in the following sections (**4**).

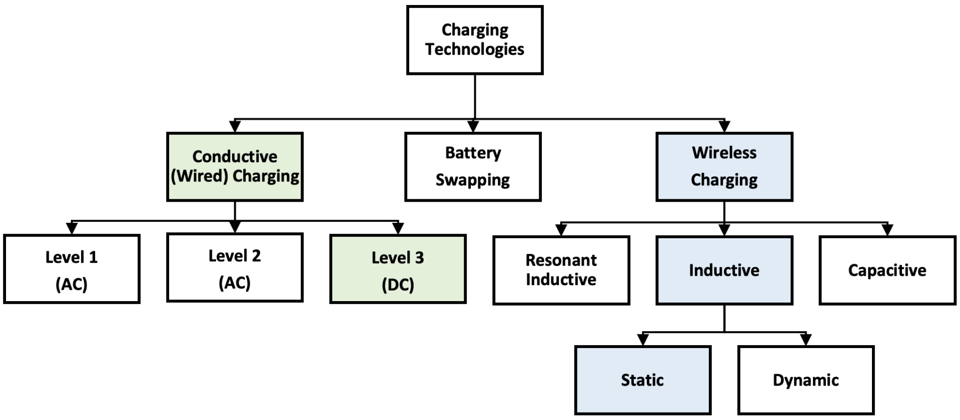


Figure 2: EV Charging Methods

3.1.1. Wired (Conductive) Charging

Wired (conductive) charging is a method that allows to transmit power directly from a generator to the vehicle's charging port. Alternating current (AC) is always used to transport the power coming from the networks. However, a power converter, known as On-Board Charger (OBC) which is located on the vehicle in AC method and in the charging station in DC method, is required for conversion to Direct Current (DC) to charge batteries, because electric vehicles cannot be charged directly via AC, since electric energy can only be stored as DC and electric vehicles' batteries want to be charged with DC.

Wired charging is employed in fully electric or plug-in hybrid electric vehicles and is divided into two as AC charging and DC fast charging (**6**). Figure 3 describes how wired charging is applied schematically. As can be seen in Figure 2, wired charging methods are divided based on three charging levels. Level 1 and Level 2 are applied for AC, Level 3 is applied for DC charging methods. Higher levels produce more electricity and charge the electric vehicle more quickly.

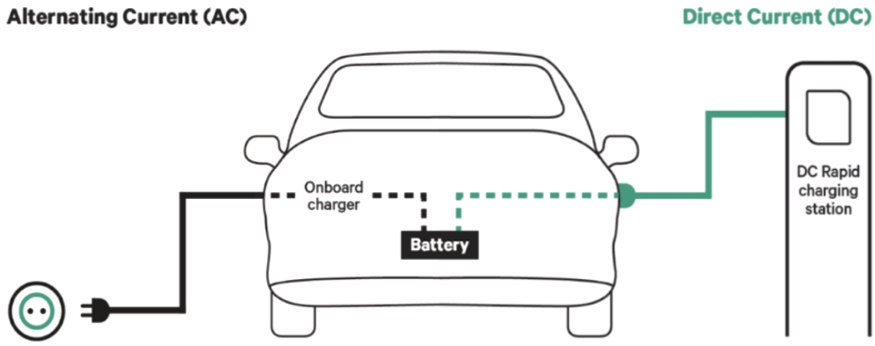


Figure 3: Working Principle of Conductive Charging

AC Charging

EV batteries are not charged directly by AC charging systems; rather, batteries are charged by On-Board Charger (OBC) that supplies the battery. This technology adds weight to the entire system since the power converter, OBC, is located inside the vehicle (**1**). The OBC is not only responsible for the AC/DC conversion. It also enhances the quality of the regulated current by reducing electromagnetic interference (EMI), switching loss, and ripples (**8** & **9**).

Level 1 AC charging is the slowest way to charge an electric vehicle. Level 1 charges are primarily utilized for residential charging (**11**). Level 1 charger charges using a 120-volt (V), alternating current (AC) socket (**2**), which can deliver power between 1.3 kW to 2.4 kW. An empty EV battery might need more than 24 hours to fully charge. The installation cost of the Level 1 charging station has an average cost of $800 (**6**). When it comes to the cost of charging, it usually varies between $1.20 and $13.00 depending on the EV battery's capacity, and the cost of energy (**10**).

When it comes to Level 2 because they charge more quickly than Level 1 charging, they are the most often utilized at public charging stations. Level 2 chargers are faster since they charge using a 240-volt (V), alternating current (AC) socket, which can deliver power between 3 kW to 19 kW. Such power output corresponds to a range of 18 to 28 miles per hour. Moreover, the average installation cost of level 2 charging stations is $3,000 (**6**).

DC Charging

DC chargers, also referred to as Level 3 chargers, are the fastest type of charge available for EVs. The power level of the DC charge ranges between 48 kW to 450 kW and could offer between 80–100 miles of travel also their installation cost varies between $40,000 and $80,000 (**13**).

It is already explained that electric vehicle batteries run on Direct current, and batteries can be directly charged when employing Direct current charging systems. This method uses the inverter at the fast-charging station to convert the alternating current from the grid to DC, allowing it to be supplied straight to the battery pack of the vehicle without first passing through a rectifier (without using OBC)(**4**).

While DC fast chargers give consumers faster charging options, they also have the possibility of suddenly placing a heavy load on the electrical system because of the charging station's high-power requirements. Because of this, the cost of maintenance, repair, and servicing for DC fast charging stations can increase by several thousand dollars every year. Therefore, placing charging stations in strategic locations in public spaces might aid in lowering potential yearly additional expenditures (**11**).

Battery Swapping

With this technique, a used or completely discharged battery is swapped out with a fresh, fully charged battery (**2**). Due to the lengthy payback period, this technology was not taken into account.

3.1.2. Wireless Charging

Wireless and fast charging are possible for many electronic devices like mobile phones in today's world. Big EV producers have created a variety of charging options for electric vehicle users, including wireless charging pads embedded in roadways, charging stations, and charging points. The wired charger techniques demand EVs to stop and use physical connection cables to charge for a few minutes or hours. Also, the maximum amount of cables a charging station can have, which is currently two cables, restricts the amount of vehicles can be charged at a time. In order to improve EV users' contentment and lessen their tension while waiting for their vehicles to be charged and charge more vehicles at the same time, switching to wireless charging methods can be considered as an applicable, and a convenient option (**21**).

It is possible to charge electric vehicles with no need for cable or any physical contact which eliminates the need for On-Board Charger resulting in lower mass, price and energy connection even on the roadside, while at the same time, a widespread charging station network can be established with stations that can be used by using wireless charging (**5**),(**33**).

Wireless Charging Systems are divided into three primary technologies: Inductive, Resonant Inductive, and Capacitive wireless charging. Figure 4 represents the schematic representation of inductive charging. The Inductive wireless charging is integrated with an AC/DC converter that converts the AC power from the electrical grid to DC. It is then transformed once more into AC power and delivered to the transmitting (or primary) coil at a high frequency. These parts are all located below the roadway. The receiving (secondary) coil in the electric vehicle gets electricity from the transmitting coil through the air gap using electromagnetic induction (**5**). While the primary coils convert the electrical power to magnetic power, the secondary coils collect the generated electromagnetic field energy and convert it into electrical energy (**33**). The battery is then charged once the AC power has been converted to DC via an AC/DC converter.

Inductive wireless charging can be categorized as either static or dynamic inductive charging. Electric Vehicles remain stationary while being charged using static inductive technology, while in dynamic wireless charging it is possible to charge the electric vehicle in motion (**5**).

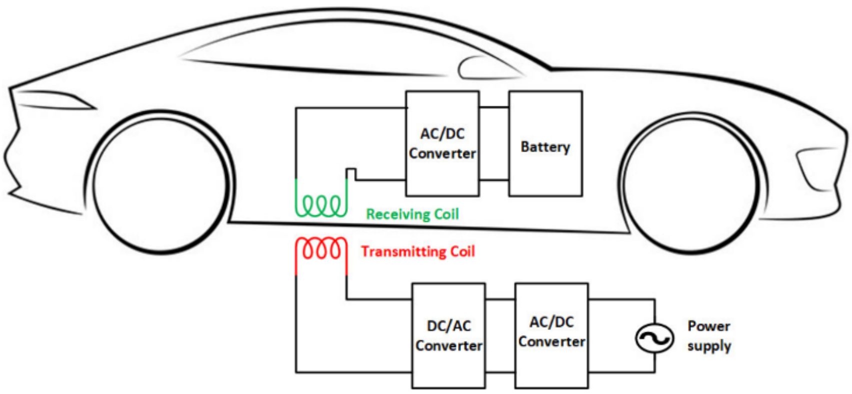


Figure 4: A Simplified Diagram of Inductive Charging (**5**)

Static Wireless Charging System

In the static charging system, the receiver coil (secondary coil) is placed in the middle, front, or rear of the receiver for power transfer to the vehicle. The converter converts the AC power from the transmitter (primary coil) to DC power so that the power is stored in the batteries. During the charging process, the battery control system actively monitors the system to prevent safety problems. Static wireless system can supply up to 22 kW and their installation cost varies between $2700 and $13000. Figure 5 represents the working principle of wireless charging.

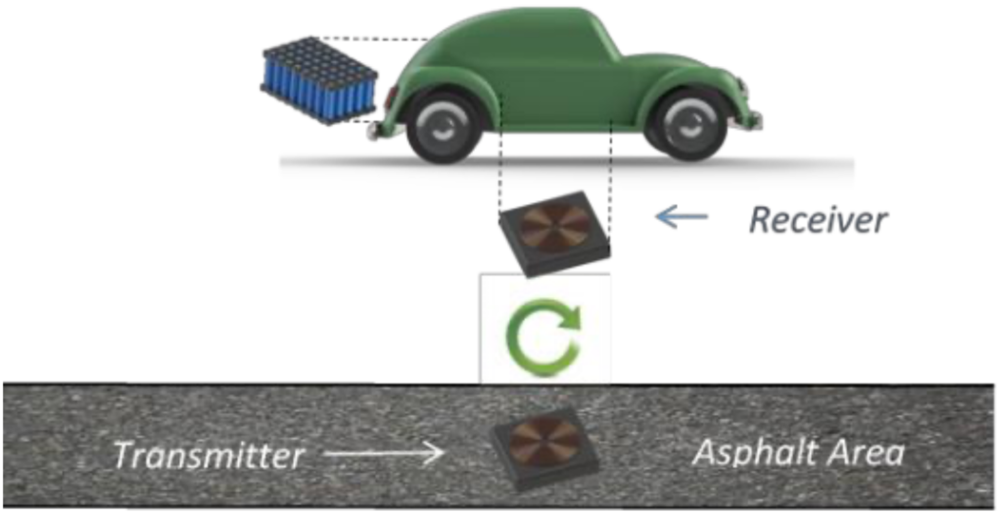


Figure 5: Working Principle of Static Wireless Charging (**6**)

The air gap distance between the pads on the ground and the vehicle is one of the factors affecting the charging time, and the efficiency in power transmission decreases as the gap increases (**15**). The air distance between the pads (receiver and transmitter) should be between 20 cm and 100 cm for a more efficient transferring power (**16**). Many researchers are working on how to increase this distance without losing productivity. Also, the correct alignment of coils to increase efficiency increases connection strength. There are examples of misalignment in Figure 6 (**15**).

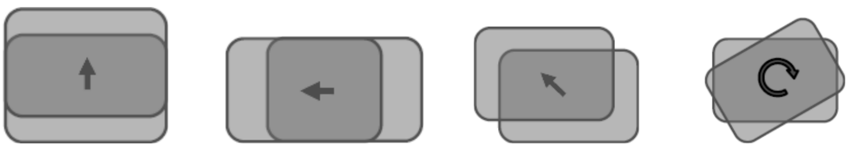


Figure 6: Misalignment Positions

For this wireless technology, many universities, research laboratories and companies are continuing their research studies. Research is ongoing on the safety of this technology for living beings, and positive results are published every day, even stating that it is safer than the radiation emitted by the phones we always carry with us (**15**).

3.2. Charging Connectors

The component that establishes the connection between the EV and the charging station is known as the socket or charging connector. EV sockets need to be designed to match the outlet on the car and the outlet on the EV charging station. The model of the electric vehicle as well as the power rating of the charging inlet determines the type of socket. Electric car sockets frequently change depending on standards and location (**11**). The market offers two types of EV sockets: AC EV and DC EV charging sockets. In Figure 7, charging sockets of various shapes are shown (**13**).

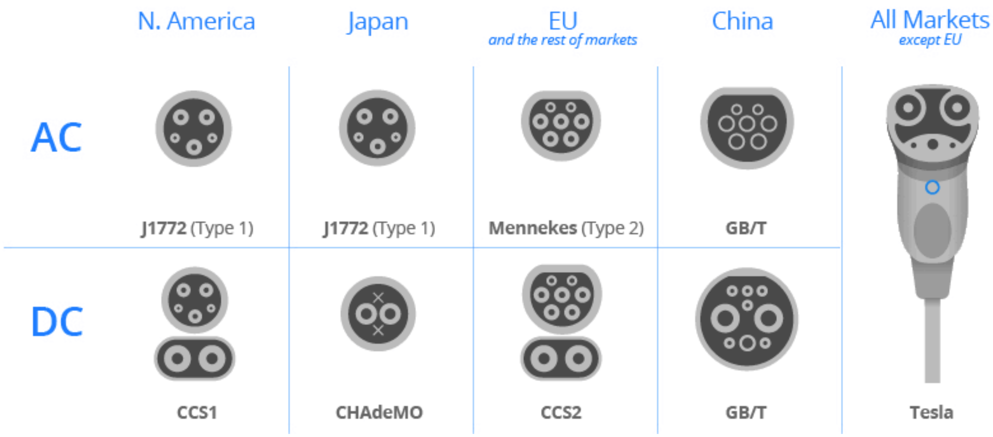


Figure 7: Charging Sockets

3.2.1. AC Connectors

Two different types of AC EV Sockets are available. Type 1 is the SAE J1772 standard, which is used in countries such as Japan and North America. It has a 7.4 kW maximum charging capacity. Some of the EVs that use the Type 1 charging connectors are the Peugeot iON, Mitsubishi, Nissan Leaf, and ENV200.

The second type of AC EV sockets is the IEC 62196-2 standard, which is used in Europe. It is utilized for public charging and has a 43-kW charging capacity. Some of the EVs that use these Type 2 charging connectors are the BMWi3, Tesla Model S, i8, Renault Zoe, and Volvo V60 (**13**).

3.2.2. DC Connectors

DC EV plugs allow EVs to get charged up to 350 kW. Faster direct current is provided and is mostly utilized in public charging stations (**13**). There are three different types of DC charging sockets. The first type is the CCS (Combined Charging System). The SAE has certified and recognized the CCS Socket for use in North America (**11**). A Type 2 AC socket and DC socket are combined to form the Combined Charging System. Its range reaches a capacity of 350 kW. This charging connection is employed by a large number of manufacturers of electric vehicles. They are BMW, Mercedes, Porsche, Kia, Hyundai, Jeep, Volkswagen, Land Rover, Ford, Jaguar, Bentley, Rolls Royce, and more automakers (**13**).

The second type is CHAdeMO charging connector. Everywhere DC fast charging is accessible, CHAdeMO socket is utilized since it has been established a standard in Japan (**11**). This type of charging socket has a 100-kW charging capacity. Among the businesses that make use of CHAdeMO sockets are Mitsubishi, and Nissan (**13**).

The last type is the Tesla supercharger. This charging connector was introduced by Tesla for its latest electrical cars. Tesla supercharger is identical for both Level 1 and Level 2 charging. The vehicle battery may be fully charged in this instance using 480 V rapid charging technology (**13**).

3.3. Battery Types

3.3.1. Lead Acid

It is among the oldest kind of batteries ever produced. Lead acid batteries are inexpensive and widely available (**29**). However, due to their low specific energy, these batteries are quite heavy. These batteries may release gases both when they're running and charging, chemical gases that need to be evacuated (**30**).

3.3.2. Nickel Cadmium

The specific energy of nickel-cadmium batteries is lower than Li-ion batteries but higher than lead acid batteries (**31**). Unlike other battery types, it can survive deep discharge and is regarded as suited for usage in challenging circumstances. NiCad batteries also have a long life cycle (**29**). High temperatures, however, may cause these batteries to have charging issues. NiCad batteries should also be disposed of carefully since they contain the dangerous heavy chemical cadmium (**30**).

3.3.3. Nickel Metal Hydride

NiMH batteries last a long time and offer high specific energy. Even when the SoC is weak, these batteries deliver voltage that is practically consistent (**29**). They are regarded as environmentally beneficial as well. However, when charged and discharged, they operate inefficiently. Furthermore, rapidly charging these batteries could raise their temperature. They function poorly in cold temperatures and have a high rate of self-discharge (**30**).

3.3.4. Lithium Ion

When compared to other battery types, Li-on batteries have more specific energy, energy density, and faster charging ability (**29**). Their lifespan is good, and their discharge rate is low (**32**). But, temperature affects the performance of Li-on batteries. Also, capacity can be reduced after some charge-discharge cycles (**30**).

4. Problem Definition

İstanbul Airport currently has 18,000 vehicles capacity car park and is in service for all types of cars. Even though İGA provides EV charging service for its fleet at the apron, the company is unable to satisfy the demand for EV charging service to commercial EVs at its car park due to a lack of an electrical charging system. Given this reason, İGA wants to allocate 10% of its capacity for EV charging. Also, the company is considering the DC charging method but also wants to consider the wireless charging option.

In this regard, our Senior Design Project aims to develop mathematical optimization models in order to design a DC/Wireless Hybrid Charging Slots for park areas. The ultimate goal of these models is to maximize customer satisfaction along with the objectives of maximizing company's net profit and the number of vehicles charged. As we stated with highlighted colors in Figure 2, we will focus on DC and Static Wireless charging methods while developing mathematical models.

Wired DC Charging

As it is explained in Section 3.1.1, DC charging is one of the wired charging methods that transfer the power from a generator to the vehicle's battery with the help of a power converter. As shown in Figure 3, the DC charging method has the power converter inside the charging station, and it only requires plugging in with a wire.

For one of the models, we will only consider DC charging stations and develop the model accordingly. The sample car park layout for the DC charging option prepared by a design program AutoCAD can be seen in Figure 8. As demonstrated in the sample layout, one DC charging station has two cables and can charge maximum of two vehicles at the same time due to this cable restriction.

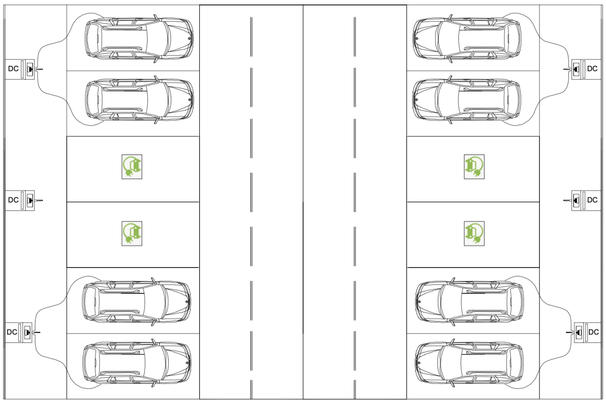


Figure 8: DC Infrastructure Model

Static Wireless Charging

As we have explained in Section 3.1.2, static wireless charging is one of the wireless charging methods that eliminate the need for plugging in and provides charging without a physical connection. As shown in Figure 4 and Figure 5 charging occurs with the transmitter (primary coil) located underground and the receiver (secondary coil) located on the vehicle. The other model that we will develop, will be based on wireless charging stations. The sample car park layout for the Wireless charging option prepared by a design program AutoCAD can be seen in Figure 9.

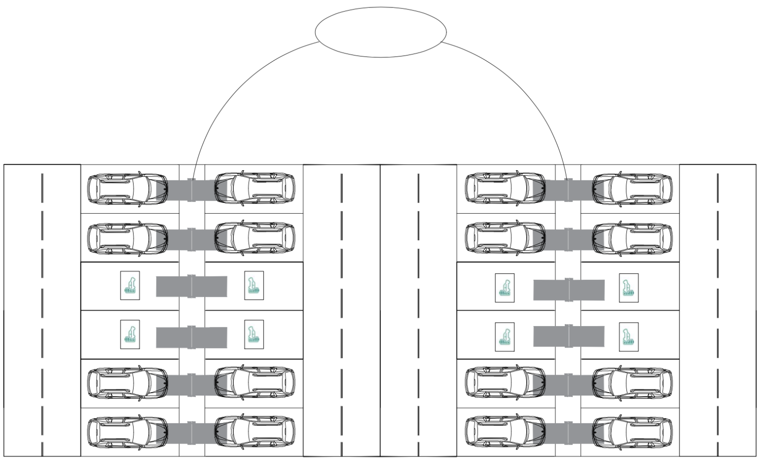


Figure 9: Wireless Infrastructure Model

5. Solution Methods

5.1. Data Gathering

To be able to continue with the project and prepare mentioned models, data such as power levels, average battery sizes, charging times, and selling prices per kWh are needed. Charging times vary depending on the vehicle model, battery type, and incoming current. According to the data gathered from Barlingen, a table for average electric car charging times is prepared as Table 3 (**12**).

Table 3: Average Electric Car Charging Times

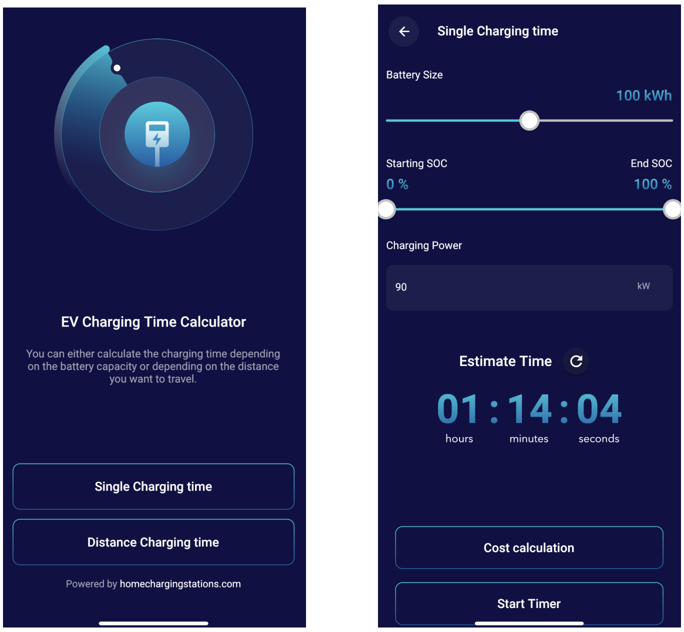
Type of EV	Small EV	Medium EV	Large EV	Light Commercial
Average Battery Size (Right) **Power Output (Below)**	25 kWh	50 kWh	75 kWh	100 kWh
Level 1 (AC) 2.3 kW	10h30m	24h30m	32h45m	43h30m
Level 2 (AC) 7.4 kW	3h45m	7h45m	10h00m	13h30m
Level 2 (AC) 11 kW	2h00m	5h15m	6h45m	9h00m
Level 2 (AC) 22 kW	1h00m	3h00m	4h30m	6h00m
Level 3 (DC) 50 kW	36 min	53 min	1h20m	1h48m
Level 3 (DC) 120 kW	11 min	22 min	33 min	44 min
Level 3 (DC) 150 kW	10 min	18 min	27 min	36 min
Level 3 (DC) 240 kW	6 min	12 min	17 min	22 min

Besides the charging time data from charging companies and websites, charging time calculators can also be used to have an insight into average charging times. EV Charging Time Calculator, shown in Figure 10, is a reliable example of a calculator given the fact that the time information it provides is consistent with the information gathered from written sources.

Figure 10: EV Charging Time Calculator App

In the following chapters and calculations on this project, to ease the work and be able to work with power levels that are not indicated in previous tables, charging time data is calculated via the EV Charging Time Calculator app. Calculation steps are shown in Figure 11. In Step 1; the Single Charging Time option is selected because the aim is to calculate the time depending on the battery capacity. Once Step 1 is completed, in Step 2; Battery Size, Starting and End SOC(State of Charge) which represents the remaining charge level, and Charging Power are selected by the user. Then estimated charging time is calculated.

As an example calculation, the charging time of an EV with a battery size of 100 kW, which has Starting SOC as 0% and End SOC as 100%, assuming the EV's battery is empty and wants to be fully charged, by 90 kW charging power is calculated as 1 hour 14 minutes, which can also be seen in Figure 11.



(a) Step 1 (b) Step 2

Figure 11: Charging Time Calculation Steps on the App

Selling prices data is collected from various electric vehicle charger companies such as ZES, E-şarj and Sharz.net that serve in Turkey. Selling prices as Turkish Lira per kW can be seen in Table 4. From this point on, ZES's selling price data will be taken into account and the selling price parameter value will be determined based on ZES for the calculations.

Table 4: EV Charging Selling Prices per kWh

Power Level	ZES	Eşarj	Sharz.net
AC 7,4 kW	7,8 ₺/kWh	6,5 ₺/kWh	6,5 ₺/kWh
AC 7,4-11 kW	7,8 ₺/kWh	6,5 ₺/kWh	6,5 ₺/kWh
AC 22 kW	7,8 ₺/kWh	6,5 ₺/kWh	6,5 ₺/kWh
DC 50 kW	9,8 ₺/kWh	7,7 ₺/kWh	8,25 ₺/kWh
DC 60-90 kW	9,8 ₺/kWh	8,2 ₺/kWh	8,25 ₺/kWh
DC 90+ kW	9,8 ₺/kWh	8,2 ₺/kWh	9,0 ₺/kWh

Combined data table of DC and Wireless charging options is prepared as Table 5. In every calculation that will take place in this paper, data in Table 5 will be taken as a reference and used when needed unless new further data is provided.

Table 5: DC and Wireless Charging Data

		Charging Method	DC			Wireless		
		Installation Cost	40,000 - 70,000 $			2700 – 13,000 $		
		kWh Unit Fee	9,8 ₺			7,8 ₺		
		Capacity per kWh	50	90	180	7,4	11	22
Type of EV	**Average Battery Size**							
Small EV	25 kWh	**Charging Cost (₺)**	245	245	245	195	195	195
		Time	33 m	18 m	9 m	3h 45m	2h 30m	1h 45m
Medium EV	50 kWh	**Charging Cost (₺)**	490	490	490	390	390	390
		Time	1h 5 m	37m	18m	7h 39m	5h 3m	2h 30 m
Large EV	75 kWh	**Charging Cost (₺)**	735	735	735	585	585	585
		Time	1h 40m	55m	27m	11h 15m	7h 35m	3h 47m
Light Commercial EV	100 kWh	**Charging Cost (₺)**	980	980	980	780	780	780
		Time	2h 13m	1h 14m	37m	15h	10h 6m	5h 3m

While preparing the table, charging time information is derived from the previously addressed calculation app Figure 10 as explained in Figure 11. Selling price per kW value, kWh Unit Fee as the way written in this table, assumed to be ZES's selling price data as highlighted in Table 4. Charging Costs are calculated by multiplying Capacity per kWh by kWh Unit Fee.

The total energy demand for EVs in the parking lot is shown in Table 6. The total energy is calculated by multiplying the energy capacity of the station with the number of customers which are generated randomly, demanding this type of station per day. For example, a DC station with an energy capacity of 50 kW is demanded by 100 customers per day to charge their electric vehicle, which means that 5000 kW is required per day from this type of station. To determine the total amount of energy demand from all the stations, the total energy demands in summed for each type of station as shown in Table 6.

Table 6: Demand for energy

Station capacity/kWh	**Number of customers/day**	**Total energy demand**
DC (50 kW)	100	5000
DC (90 kW)	120	10800
DC (180 kW)	50	9000
Wireless (7.4 kW)	35	259
Wireless (11 kW)	20	220
Wireless (22 kW)	15	330
Total		25609 kW/day

5.2. Parking and Charging Process System Flowchart

To understand how the parking and charging system works, what the mobile application we planned to develop is for better, and develop mathematical models, we designed a process flowchart for our system as shown in Figure (12).

First, the customer enters the car park and goes to a parking slot depending on their membership and reservation status. Like other existing parking lot systems and EV charging systems, we also decided to plan our system with memberships and reservations. If the customer is a member, first reservation status is checked according to flowchart. Customers with reservations reach to slot directly. Customers with no reservations first provide data such as current and target charge level, and estimated duration, then get method and slot recommendation. If the arriving customer is not a member, they receive a subscription warning to be able to connect to station and get recommendations once they reach to a slot. The connection between the vehicle and stations and charging initiation are done by the mobile application. Once the recommendations are offered by the app, customers can act either on advice or on their own will and start charging. During charging, we plan to notify customers about increasing driving range before reaching the desired charge level. Then, two conditions could occur: Customer can decide to leave early or wait until charging is completed. When the customer decides to leave early, state of charge information and range recommendation will be given. If the customer still wants to leave, next steps are payment and leaving the car park. If the customer

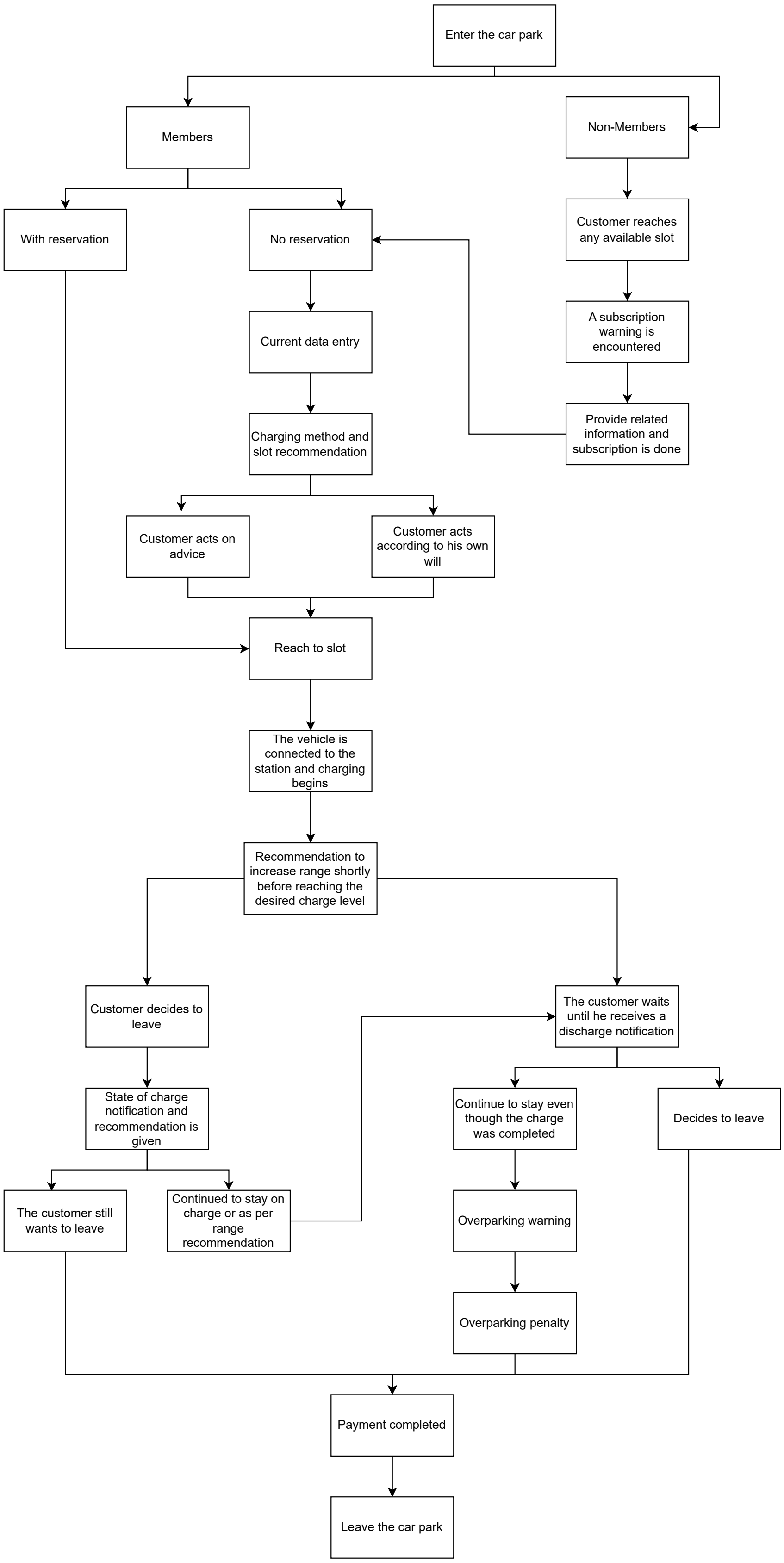


Figure 12: Parking and Charging System Flow Chart

takes the recommendation, they wait until the discharge notification. When the customer waits until charge completion, they receive a discharge notification and mobile gives a warning about overparking penalties. If the customer take the vehicle, next steps are payment and leaving the car park. If the customer continue to stay even though the charging is completed, overparking warning is done and overparking penalty is applied.

5.3. Mathematical Model

Since the fixed installation is constant and the energy selling prices are dynamic and changes based on the parking lot's current situation, we decided to evaluate these two situations in two different models. The first model is the Offline Parking Installation Model and with this model we will determine the installation cost based on the optimal number of stations that will be installed in the parking lot. The second model is the Online Energy Operations Model where the overall selling profit will be determined.

$$Z(t) = -F + \sum_{\bar{t}=1}^{t} (E(t) + O(t)) \tag{1}$$

As can be seen from figure (13) the inputs for the OPIM model are S_W and S_{DC} these are number wireless and DC charging slots respectively. After solving the OPIM model E_W and E_{DC} which are the installed Wireless and DC capacity in the system will be calculated and used as an input for the OEOM$_t$ model. Finally, after solving the OEOM$_t$ model the amount of energy needed to satisfy the demand will be determined.

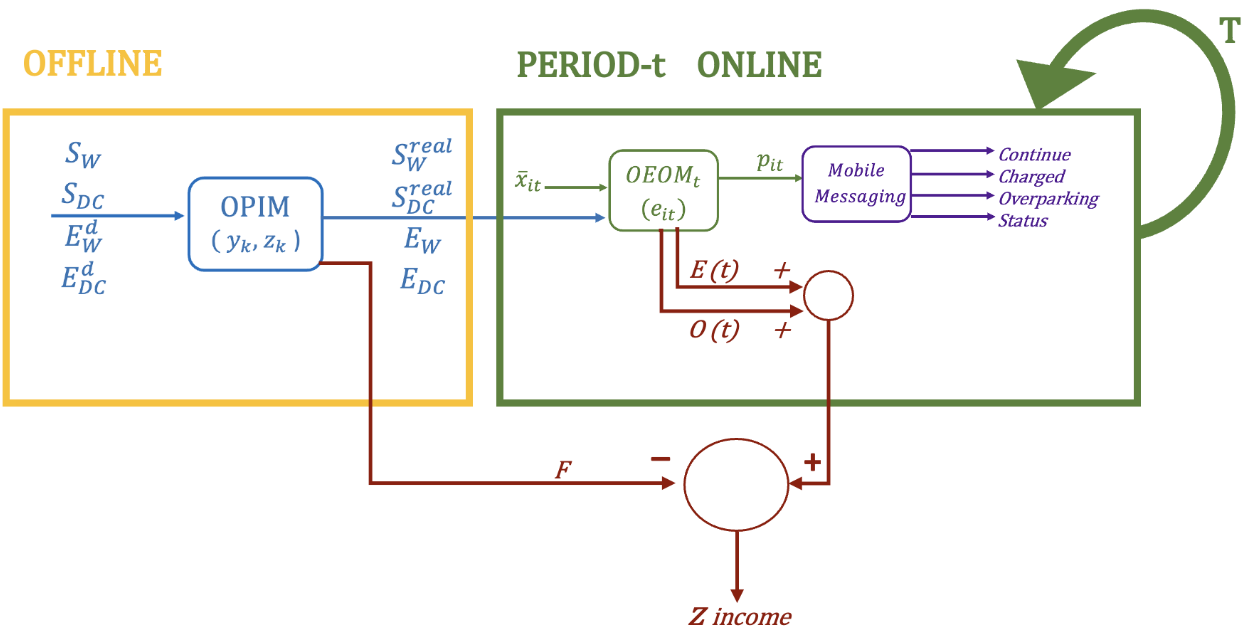


Figure 13: Mathematical Model Flow Chart

5.3.1. Offline Parking Installation Model (`OPIM`)

The aim of the offline parking installation model is to determine the minimum number of slots that can be installed in the parking lot. In this section the index set, parameters, objective function and constraints of the model is demonstrated. Figure (14) represents the flowchart of `OPIM` model.

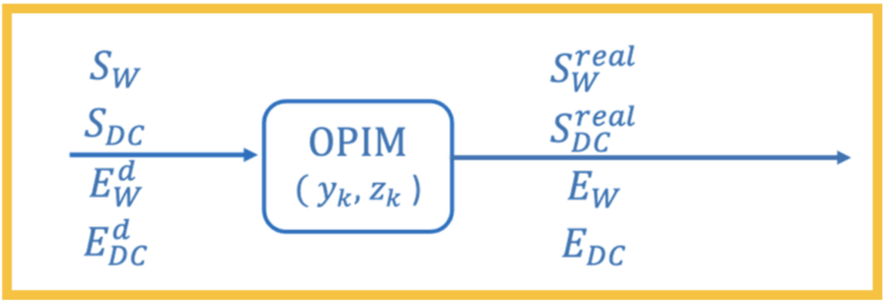


Figure 14: OPIM Model Flow Chart

As shown in figure, the inputs for the `OPIM` model are the estimated number of wireless and DC slots which is represented by S_W and S_{DC}, and the estimated wireless and DC energy demand represented by E_W^d and E_{DC}^d. The outputs of the `OPIM` model after solving it will be the real number of wireless and DC slots required which is represented by S_W^{real} and S_{DC}^{real}, and the actual total installed energy represented by E_W and E_{DC}. Also, if charging station of type-k is installed or not with the number of type-k charging stations installed and they are represented by y_k and z_k.

5.3.1.1. Index Sets

Table 7 represents the list of index sets that we will be using in our `OPIM` model. $\mathbf{K_W} = \{1, ..., K_W\}$ is the index set of Wireless charging stations (CS) and $\mathbf{K_{DC}} = \{K_{W+1}, ..., K_W + K_{DC}\}$ is the index set of DC charging stations where $k \in \mathbf{K}$ and $k = \{1, 2, 3\}$ for wireless and $k = \{4, 5\}$ for DC. Each index represents charging stations with different capacities, which are defined as 7.4 kW, 11 kW , 22 kW for wireless charging and 90 kW and 180 kW for DC charging respectively. The set of all charging stations is represented by $\mathbf{K}$ which is the combination of wireless and DC charging station sets, also can be formulized as $\mathbf{K} = \mathbf{K_W} \cup \mathbf{K_{DC}}$.

We assume there will be 4 types of EVs for this project which will be represented by l, and all indices are collected in the set of $\mathbf{V} = \{1, ..., V\}$ where $l = \{1, 2, 3, 4\}$. l stands for Small EV with battery capacity 25 kW, Medium EV with battery capacity 50 kW, Large EV with battery capacity 75 kW and Light Commercial EV with battery capacity

100 kW respectively.

$\mathbf{S_W} = \{1, ..., S_W\}$ is the set of wireless charging slots and $\mathbf{S_{DC}} = \{1, ..., S_{DC}\}$ is the set of DC charging slots at the car park. The set of all slots, reserved for both wireless and DC charging, is represented by $\mathbf{S}$ and formulized as $\mathbf{S} = \mathbf{S_W} \cup \mathbf{S_{DC}}$.

Table 7: List of Index Sets of Offline Parking Installation Model

Index Sets	
$\mathbf{K_W}$	set of wireless charging station types
$\mathbf{K_{DC}}$	set of DC charging station types
$\mathbf{K}$	set of all charging station types, $\mathbf{K} = \mathbf{K_W} \cup \mathbf{K_{DC}}$
$\mathbf{S_W}$	set of wireless charging slots
$\mathbf{S_{DC}}$	set of DC charging slots

5.3.1.2. Parameters

Table 8 represents the parameters for the `OPIM` model. f_k shows the fixed installation cost of type-k charging station, where $k \in \mathbf{K}$. w_k is the supply capacity of type-k charging station in kW, where $k \in \mathbf{K}$ and $i = \{1, 2\}$, 1 representing wireless and 2 representing DC slots. τ represents the length of a period which is assumed as 1 hour in this project. e_i^d represents the customer's energy demand at slot-i. The customer's energy demand is equivalent to either EV's battery capacity in case of full charging or battery capacity corresponding to desired charge level in case of customer specifies the requested level. t_i represents the customer parking duration at slot-i. t_i^I is the customer-i's claimed entrance time and t_i^F is the customer-i's claimed leaving time. They are both based on the estimated length of stay information that the customer will provide before starting charging in order to receive charging method recommendations. E_W^d and E_{DC}^d represent the estimated 1-period (τ) for Wireless and DC energy demand respectively.

Table 8: List of Parameters of Offline Parking Installation Model

Parameters	
K_W	number of wireless charging station types
K_{DC}	number of DC charging station types
K	number of all charging station types
S_W	number of wireless charging slots
S_{DC}	number of DC charging slots
f_k	fixed installation cost of type-k charging station, $k \in \mathbf{K}$
w_k	supply capacity of type-k charging station, kW, $k \in \mathbf{K}$
τ	length of a period,
e_i^d	customer energy demand at slot-i, kWh
t_i	customer parking duration at slot-i
t_i^I	customer-i's claimed entrance time
t_i^F	customer-i's claimed leaving time
E_W^d	estimated 1-period (τ) wireless energy demand, kW
E_{DC}^d	estimated 1-period (τ) DC energy demand, kW

Estimation of S_W and S_{DC}

In order to determine the total number of slots required in the parking lot, we first decided to estimate by generating random data over seven days and analyzing. This is done to ensure that there are sufficient number of slots from each type in the parking lot in order to be able to satisfy all customer demand and minimize the number of lost customers before getting the actual number of slots.

We created a seven-day, 1-week data. First, we determined the number of customers logging into the system in each period in an hour. Since there are 24 hours in a day and we need seven days of data, we created data for a total of 7*24=168 periods. We generated random numbers between 0 and 3 to determine how many customers came in the relevant period, and we repeated this for 168 periods.

For example, in the Table 9, we found how many customers came in which period on the first day. Then, after determining 38 customers, we created separate data for each customer.

Table 9: Period and Incoming Customer Information of the Day 1

	Period	Number of incoming customers:
DAY 1	1	1
	2	1
	3	2
	4	2
	5	1
	6	1
	7	1
	8	1
	9	2
	10	2
	11	2
	12	2
	13	0
	14	0
	15	3
	16	2
	17	1
	18	3
	19	2
	20	0
	21	3
	22	1
	23	2
	24	3
	SUM	**38**

The data we have created for customers on Day 1 is shown in the Table 10. The customer IDs are seen in the first column when we examine the table in detail. Since 38 customers came on Day 1, they were listed from 1 to 38. In the second column, the period numbers of these customers are given. In the third column, the number of periods the customer stays in the system is determined by generating a random number. It is assumed that the customers will stay in the system for a minimum of 1 hour and a maximum of 8 hours. In the fourth column, we collected the input period and the number of periods to determine when the customer will leave the system. In the fifth column, how much kW of energy the customer wants during their stay in the system is determined by generating a random number; it is assumed that the customers will demand a minimum of 29 kW and a maximum of 120 kW of energy. In the sixth column, the energy the customer is supposed to receive in a period is written; we found this by calculating (the total demanded energy / how many periods they stay in the system). Using this data, we determined which charger would be suitable for them. In the last column, the information about which charger the customer uses is stated; if the energy demand in a period is more than 22 kW, they are assumed to use a "DC" charger if not "Wireless". Thus, we have created synthetic data containing the input-output information of a customer and how many kW of energy they receive from which charger. We did this for every customer who came in for seven days. We have a dataset of 244 customers over 168 periods.

Table 10: Data of Customers Arriving on Day 1

ID	Entry period	Duration of stay	Exit period	Energy demanded	Demanded energy in 1 period	Suitable charger
1	1	2	3	74	37	DC
2	2	5	7	32	6,4	Wireless
3	3	4	7	73	18,25	Wireless
4	3	2	5	105	52,5	DC
5	4	4	8	87	21,75	Wireless
6	4	6	10	52	8,666666667	Wireless
7	5	2	7	111	55,5	DC
8	6	3	9	95	31,66666667	DC
9	7	1	8	56	56	DC
10	8	8	16	70	8,75	Wireless
11	9	4	13	57	14,25	Wireless
12	9	3	12	55	18,33333333	Wireless
13	10	8	18	61	7,625	Wireless
14	10	6	16	90	15	Wireless
15	11	7	18	109	15,57142857	Wireless
16	11	5	16	39	7,8	Wireless
17	12	2	14	92	46	DC
18	12	5	17	88	17,6	Wireless
19	15	5	20	66	13,2	Wireless
20	15	6	21	91	15,16666667	Wireless
21	15	4	19	92	23	DC
22	16	5	21	97	19,4	Wireless
23	16	2	18	83	41,5	DC
24	17	7	24	30	4,285714286	Wireless
25	18	4	22	86	21,5	Wireless
26	18	8	26	52	6,5	Wireless
27	18	6	24	114	19	Wireless
28	19	4	23	85	21,25	Wireless
29	19	3	22	39	13	Wireless
30	21	4	25	97	24,25	DC
31	21	5	26	71	14,2	Wireless
32	21	6	27	35	5,833333333	Wireless
33	22	6	28	65	10,83333333	Wireless
34	23	2	25	81	40,5	DC
35	23	6	29	91	15,16666667	Wireless
36	24	4	28	54	13,5	Wireless
37	24	5	29	111	22,2	DC
38	24	1	25	42	42	DC

Using all this data, we created a chart as shown in Table 11. Our aim here is to determine how many customers there are instantaneously in each period and how many chargers should be in this direction. To explain, we placed each customer in the relevant periods on the first day. In contrast, the stay periods of the customers using DC chargers are painted in green, while those of customers using wireless chargers are painted in blue. When we examine it in detail, we can see how many customers are instantaneously in which period and which charger they use. For example, there are eight customers in the system in the seventeenth period, six of them are Wireless chargers, and two are DC chargers.

Table 11: Instant Status Table of Slots on Day 1

	DAY 1																								DAY 2				
Customer ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1	1	1																											
2		1	1	1	1	1																							
3			1	1	1	1																							
4			1	1																									
5				1	1	1	1																						
6				1	1	1	1	1	1																				
7					1	1																							
8						1	1	1																					
9							1																						
10								1	1	1	1	1	1	1	1														
11									1	1	1	1																	
12									1	1	1																		
13										1	1	1	1	1	1	1	1												
14										1	1	1	1	1	1														
15											1	1	1	1	1	1	1												
16											1	1	1	1	1														
17												1	1																
18												1	1	1	1	1													
19															1	1	1	1	1										
20															1	1	1	1	1	1									
21															1	1	1	1											
22																1	1	1	1	1									
23																1	1												
24																	1	1	1	1	1	1	1						
25																		1	1	1	1								
26																		1	1	1	1	1	1	1	1				
27																		1	1	1	1	1	1						
28																			1	1	1	1							
29																			1	1	1								
30																					1	1	1	1					
31																					1	1	1	1	1				
32																					1	1	1	1	1	1			
33																						1	1	1	1	1	1		
34																							1	1					
35																							1	1	1	1	1	1	
36																								1	1	1	1		
37																								1	1	1	1	1	
38																								1					

	DAY 1																								DAY 2				
Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	1	2	3	4	5
# of All customer	1	2	3	5	5	6	4	3	4	5	7	8	7	6	9	8	8	8	9	8	9	8	9	10	10	8	7	4	2
# of Wireless customer	0	1	2	4	4	4	3	2	4	5	7	7	6	6	8	6	6	7	9	8	8	7	7	6	7	5	5	3	2
# of DC customer	1	1	1	1	1	2	1	1	0	0	0	1	1	0	1	2	2	1	0	0	1	1	2	4	3	3	2	1	0

Proceeding in this way, we created the Table 12 with seven days of data. Then, to interpret this table numerically, we combined all the data we obtained into the Table 13 containing the whole week, as one week occupancy chart of slots. In this table, it is possible to see how many customers are instantaneously on which day and in which period, as well as access to information such as how many customers were in the system on average during the whole week in that relevant period or how many people were found in the system during that period.

We wanted to prepare the same table separately for both DC and Wireless customers and make comments based on chargers with Table 14 and Table 15 .

Table 12: One Week Customer Schedule

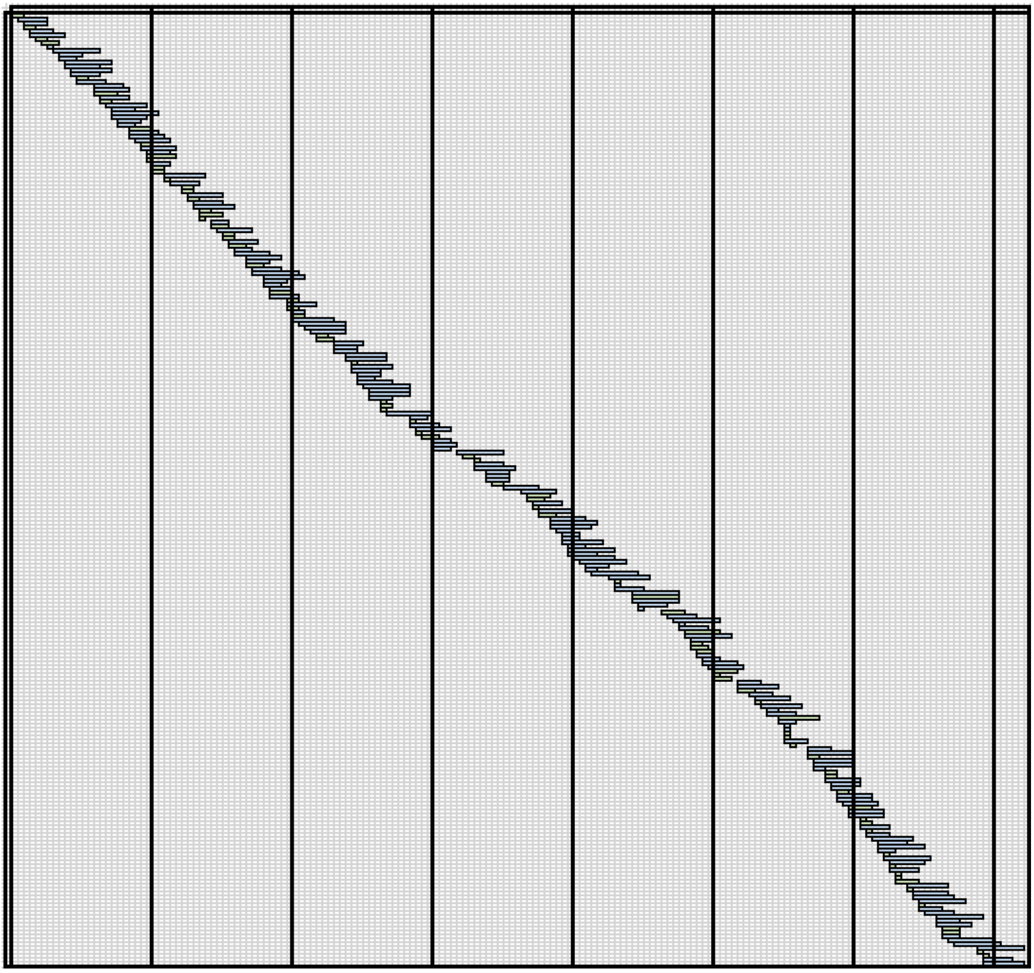


Table 13: One Week Occupancy Chart of Slots

ALL	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
day 1	1	2	3	5	5	6	4	3	4	5	7	8	7	6	9	8	8	8	9	8	9	8	9	10		
day 2	10	8	7	4	2	4	6	6	7	5	6	7	6	6	5	5	7	7	6	8	9	9	6	8		
day 3	9	6	4	5	6	6	5	6	6	5	8	8	8	11	10	11	8	4	4	4	4	5	5	4		
day 4	6	4	4	1	1	2	2	4	3	6	7	7	5	2	1	2	4	6	6	5	7	6	8	11		
day 5	10	9	9	9	6	5	5	6	4	3	6	7	5	4	4	5	5	6	5	5	8	9	10	9		
day 6	9	5	5	3	4	3	4	5	4	6	5	5	10	6	3	2	4	7	5	7	8	9	10	12		
day 7	8	9	10	6	8	8	8	9	7	8	8	9	7	6	9	11	10	9	5	4	3	5	6	5		
AVG	8	6	6	5	5	5	5	6	5	5	7	7	7	6	6	6	7	7	6	6	7	7	8	8	→	8,43
max	10	9	10	9	8	8	8	9	7	8	8	9	10	11	10	11	10	9	9	8	9	9	10	12	→	12,00

Table 14: One Week Occupancy Chart of DC Slots

DC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
day 1	1	1	1	1	1	2	1	1	0	0	0	1	1	0	1	2	2	1	0	0	1	1	2	4		
day 2	3	3	2	1	0	2	3	1	3	2	2	2	3	3	1	1	1	1	1	0	1	1	1	3		
day 3	3	1	0	0	2	2	1	0	0	0	1	0	0	0	0	3	1	0	0	0	1	1	1	1		
day 4	1	0	0	0	0	1	1	1	0	0	1	1	0	0	0	0	2	3	3	2	1	0	0	0		
day 5	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	2	2	2	1	1	3	4	3	2		
day 6	4	2	2	1	1	1	1	1	0	0	0	1	3	2	1	1	2	2	0	2	2	1	1	1		
day 7	1	3	3	0	0	1	1	3	1	2	1	1	0	0	0	2	2	2	0	0	0	1	1	0		
AVG	2	1	1	0	1	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	1	1	1	2	→	1,86
max	4	3	3	1	2	2	3	3	3	2	2	2	3	3	1	3	2	3	3	2	3	4	3	4	→	4,00

Table 15: One week occupancy chart of Wireless slots

Wireless	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
day 1	0	1	2	4	4	4	3	2	4	5	7	7	6	6	8	6	6	7	9	8	8	7	7	6		
day 2	7	5	5	3	2	2	3	5	4	3	4	5	3	3	4	4	6	6	5	8	8	8	5	5		
day 3	6	5	4	5	4	4	4	6	6	5	7	8	8	11	10	8	7	4	4	4	3	4	4	3		
day 4	5	4	4	1	1	1	1	3	3	6	6	6	5	2	1	2	2	3	3	3	6	6	8	11		
day 5	10	9	9	9	6	5	5	5	4	3	5	6	4	3	3	3	3	4	4	4	5	5	7	7		
day 6	5	3	3	2	3	2	3	4	4	6	5	4	7	4	2	1	2	5	5	5	6	8	9	11		
day 7	7	6	7	6	8	7	7	6	6	6	7	8	7	6	9	9	8	7	5	4	3	4	5	5		
AVG	6	5	5	4	4	4	4	4	4	5	6	6	6	5	5	5	5	5	5	5	6	6	6	7	$\longrightarrow$	6,86
max	10	9	9	9	8	7	7	6	6	6	7	8	8	11	10	9	8	7	9	8	8	8	9	11	$\longrightarrow$	11,00

Finally, the estimation of S_W and S_{DC} is calculated by taking the maximum of the maximum number of slots at each period, can also be referred as Max-Max approach. We observed that the estimated number of DC slot, $S_{DC} = 4$, whereas the estimated number of Wireless slot, $S_W = 11$. On the other hand, the average number of slots is taken as an alternative solution referred as Average Approach, where $S_{DC} = 1,86$ and $S_W = 6,86$.

Estimation of E^d_W and E^d_{DC}

In order to determine the estimated 1-period wireless and energy demand to be used in our mathematical models, we decided to use the random data we generated above. We took the 'Entry period', 'Demanded energy in 1 period' and 'Suitable Charger' information from Table 10, then find the estimated wireless and DC energy demands in 1 period separately based on only Day 1.

For estimated 1-period wireless energy demand, E^d_W , we first summed the total demanded energies in 1 period for each period that a wireless charger is suitable and created Table 16.

Then, we turned this table into a histogram as seen in Figure 15.

To determine E^d_W and decide on its value, we used two approach strategies. First approach is Max Approach where the value of E^d_W is the maximum value of demanded energies. According to this approach and as can be seen in Table (16), $E^d_W = 47$. Normal curve approach suggests to take the mean and the standard deviation of values and determine the estimated 1-period wireless energy demand by $E^d_W = \mu + 2\sigma$. According to the normal curve approach $E^d_W = 43.086$.

For estimated 1-period DC energy demand, E^d_{DC} , again we summed the total demanded energies in 1 period for each period that a DC charger is suitable and created Table (16).

Table 16: Demanded Wireless Energy in Periods on Day 1

Period	Demanded energy in period
2	6.4
3	18.25
4	30.41666667
8	8.75
9	32.58333333
10	22.625
11	23.37142857
12	17.6
15	28.36666667
16	19.4
17	4.285714286
18	47
19	34.25
21	20.03333333
22	10.83333333
23	15.16666667
24	13.5
Max	47
Mean	20.75483193
Standart Deviation	11.16569986

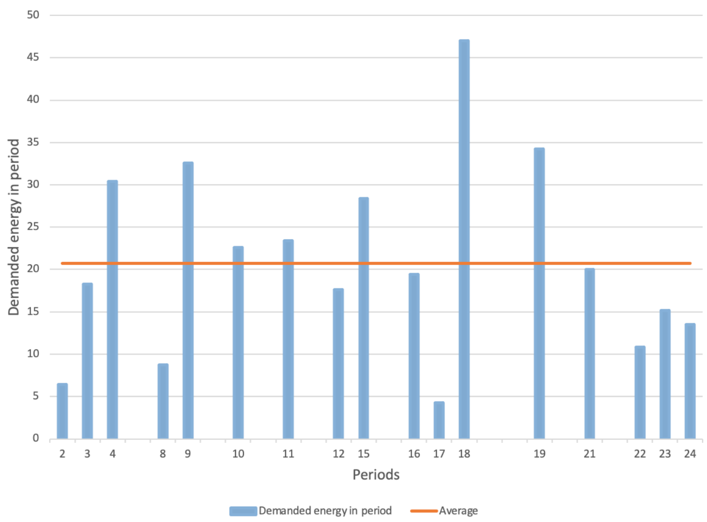


Figure 15: Total Demanded Wireless Energies for Periods on Day 1

Table 17: Total Demanded DC Energies in Periods on Day 1

Period	Demanded energy in period
1	37
3	52.5
5	55.5
6	31.66666667
7	56
12	46
15	23
16	41.5
21	24.25
23	40.5
24	64.2
Max	64.2
Mean	42.91969697
Standard Deviation	13.41035425

Then, we turned this table into a histogram as seen in Figure 16 .

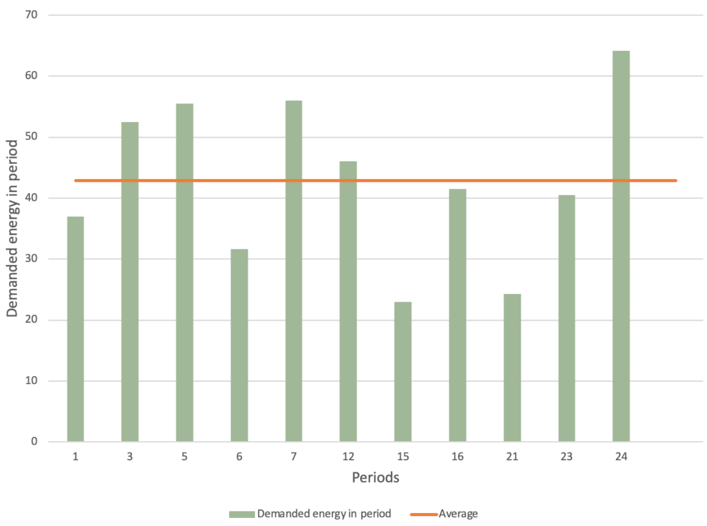


Figure 16: Total Demanded DC Energies for Periods on Day 1

To determine E^d_{DC} and decide its value, we again used the same two approaches that we mentioned above. According to the first approach, Max approach, $E^d_{DC} = 64.2$. According to the normal curve approach, the estimated 1-period DC energy demand is determined by $E^d_{DC} = \mu + 2\sigma$ and by taking the mean and the standard deviation value as seen in Table 17, which results in $E^d_{DC} = 69.738$.

5.3.1.3. Decision Variables

Decision variable y_k, where $k \in \mathbf{K}$, is introduced to determine if charging station-k is installed or not. It is a binary decision variable and it takes value 1 if charging station-k is installed, 0 otherwise. z_k is introduced to determine the number of type-k charging.

Table 18: List of Decision Variables of Offline Parking Installation Model

Decision Variables	
y_k	1 if charging station-k is installed, 0 otherwise $k \in \mathbf{K}$
z_k	number of type-k charging stations installed $k \in \mathbf{K}$

Objective Function

The aim of the objective function for the Offline Parking Installation Model is to minimize the total number of slots installed in the parking lot.

$$\min \sum_{k \in \mathbf{K}} f_k z_k \tag{2}$$

Constraints

Constraints (3) and (4) exist to ensure that Wireless and DC type of charging stations are installed in the parking lot. Since we need a uniform charger type, these constraints make sure selecting a unique type, i.e., 22 kW for wireless and 90 kW for DC, by setting the sum equal to 1.

$$\sum_{k \in \mathbf{K}_W} y_k = 1 \tag{3}$$

$$\sum_{k \in \mathbf{K}_{DC}} y_k = 1 \tag{4}$$

Constraints (5) and (6) are introduced to show that number of type-k charging station installed must be less than or equal to the product of number of charging slots and type-k charging stations installed with control value (binary 0 or 1) for wireless and DC respectively. As mentioned in Section 5.3.1.2 the estimation of S_W and S_{DC} is calculated by taking the maximum of the maximum number of slots at each period and it is observed that the estimated number of DC slot is 4, $S_{DC} = 4$, whereas the estimated number of Wireless slot is 11, $S_W = 11$.

$$z_k \leq S_W \; y_k, \qquad k \in \mathbf{K}_W \tag{5}$$

$$z_k \leq S_{DC}\ y_k, \qquad k \in \mathbf{K}_{DC} \tag{6}$$

Constraints (21) and (22) show the sum of supply capacity of type-k wireless and DC charging stations multiplied is greater than the estimated wireless and DC energy demand. These constraints make sure that the total installed energy capacity is enough for estimated customer demands.

$$\sum_{k \in \mathbf{K_W}} w_k z_k \geq E_W^d, \tag{7}$$

$$\sum_{k \in \mathbf{K_{DC}}} w_k z_k \geq E_{DC}^d, \tag{8}$$

Constraint (9) is the binary constraint of y_k and it takes values 0 or 1 only.

$$y_k \in \{0, 1\}, \qquad \forall k \in \mathbf{K} \tag{9}$$

Constraint (10) make sure z_k takes only zero or non-negative integer.

$$z_k \in \ \mathbb{Z}^+ \cup \{0\} \tag{10}$$

Overall Offline Parking Installation Model

$$\min \sum_{k \in \mathbf{K}} f_k z_k \tag{11}$$

s.t

$$\sum_{k \in \mathbf{K}_W} y_k = 1 \tag{12}$$

$$\sum_{k \in \mathbf{K}_{DC}} y_k = 1 \tag{13}$$

$$z_k \leq S_W.y_k \qquad k \in \mathbf{K}_W \tag{14}$$

$$z_k \leq S_{DC}.y_k \qquad k \in \mathbf{K}_{DC} \tag{15}$$

$$\sum_{k \in \mathbf{K_W}} w_k z_k \geq E_W^d \tag{16}$$

$$\sum_{k \in \mathbf{K_{DC}}} w_k z_k \geq E_{DC}^d \tag{17}$$

$$y_k \in \{0, 1\}, \qquad z_k \in \ \mathbb{Z}^+ \cup \{0\} \tag{18}$$

Output

After solving the `OPIM` model, the real number of slots S_W^{real} and S_{DC}^{real} will be determined using Equations (19) and (20).

$$S_W^{real} = \sum_{k \in \mathbf{K_W}} z_k \tag{19}$$

$$S_{DC}^{real} = \sum_{k \in \mathbf{K_{DC}}} z_k \tag{20}$$

Also after solving the `OPIM` model, using equations (21) and (22), we will be able to calculate E_W and E_{DC} which represent the total installed energy for wireless and DC capacities respectively. They will be used as inputs for the Online Energy Operations Model.

$$E_W = \sum_{k \in \mathbf{K_W}} w_k z_k \tag{21}$$

$$E_{DC} = \sum_{k \in \mathbf{K_{DC}}} w_k z_k \tag{22}$$

Numerical Example

To understand how E_W and E_{DC} are calculated a numerical example is represented as shown below. As can be seen for E_W charging station type 3 is chosen which is equivalent to 22 kW and 3 of this type is installed in the parking lot which is represented by $z_3 = 3$.

$$\begin{array}{lll} y_1 = 0 & w_1 = 7.4 \text{ kW} & z_1 = 0 \\ y_2 = 0 & w_2 = 11 \text{ kW} & z_2 = 0 \\ y_3 = 1 & w_3 = 22 \text{ kW} & z_3 = 3 \end{array}$$

$$E_W = (22).3 = 66 \text{ kW}$$

For E_{DC} charging station type 1 is chosen which is equivalent to 90 kW and 2 of this type is installed in the parking lot which is represented by $z_1 = 2$.

$$y_1 = 1 \qquad w_1 = 90 \text{ kW} \qquad z_1 = 2$$

$$y_2 = 0 \qquad w_2 = 180 \text{ kW} \qquad z_2 = 0$$

$$E_{DC} = (90).2 = 180 \text{ kW}$$

5.3.2. Online Energy Operations Model ($\texttt{OEOM}_t$)

The **aim** of the $\texttt{OEOM}_t$ is to determine the maximum number of satisfied customers before leaving the system. By doing this, we will assure maximum energy selling and income. In this section the index set, parameters, objective function and constraints of the $\texttt{OEOM}_t$ model is demonstrated. Figure 17 represents the flow chart of $\texttt{OEOM}_t$ model.

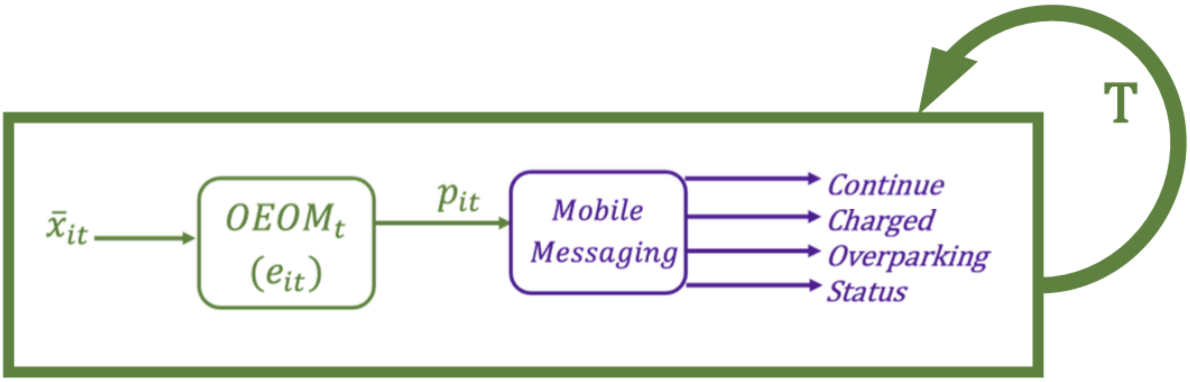


Figure 17: $\texttt{OEOM}_t$ Model Flow Chart

As shown in the figure, the inputs for the $\texttt{OEOM}_t$ model are E_W and E_{DC} they are the outputs of the $\texttt{OPIM}$ model and they represent the installed Wireless and DC capacity in the system. The output of the model will be the amount of energy in kW transferred to each slot at period-t and it is represented by e_{it}.

Index Sets

Table 19 represents the list of index sets that we will be using in our $\texttt{OEOM}_t$ model. $\mathbf{S_W} = \{1, ..., S_W^{real}\}$ is the set of wireless charging slots and $\mathbf{S_{DC}} = \{1, ..., S_{DC}^{real}\}$ is the set of DC charging slots at the car park.

Table 19: List of Index Sets of Online Energy Operations Model

Index Sets	
$\mathbf{S_W}$	set of wireless charging slots
$\mathbf{S_{DC}}$	set of DC charging slots

5.3.2.1. Parameters

Table 20 represents the list of parameters of the $\texttt{OEOM}_t$ model.

Table 20: List of Parameters of Online Energy Operations Model

Parameters	
τ	length of a period, hr
e_i^d	customer energy demand at slot-i, kWh
w_k	supply capacity of charging station-k, kW
t_i	customer parking duration at slot-i
t_i^I	customer-i's claimed entrance time
t_i^F	customer-i's actual leaving time
t_i^J	customer-i's claimed leaving time
$\bar{x}_{it}$	1 if park slot-i is occupied at period-t, 0 otherwise , $i \in \mathbf{S}$
x_{it}^+	1 is customer$-i$ is overparking, 0 otherwise
p_{it}	unsatisfied energy demand percentage of customer at slot$-i$
E_W	installed wireless capacity, kW
E_{DC}	installed DC capacity, kW
c_W^e	wireless charging selling price, $TL/period$
c_{DC}^e	DC charging selling price, $TL/period$
c_W^o	wireless overparking price, $TL/period$
c_{DC}^o	DC overparking price, $TL/period$

To investigate the system with this model for each period and decide further actions such as energy distribution, keeping track of the slots and their status to see if they are occupied at period-t or not is essential. That's why $\bar{x}_{it}$ is introduced to control the parking slot status. As can be seen in equation (23), $\bar{x}_{it}$ is checking if the slot-i is occupied at period-t. It takes value 1 if the parking slot is occupied at period-t and 0 otherwise.

$$\bar{x}_{it} = \begin{cases} 1, & \text{if slot-i in occupied at period-t} \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

x_{it}^+ represents the overparking case. It is a binary parameter where it is 1 if the customer is overparking, 0 otherwise as shown in (24). In addition, overparking incurs when the current time t is sometime after customer's claimed leaving time t_i^F as explained in (25).

$$x_{it}^+ = \begin{cases} 1, & \text{if customer}-i \text{ is overparking}, \qquad i \in \mathbf{S} = \mathbf{S_W} \cup \mathbf{S_{DC}} \\ 0, & \text{otherwise} \end{cases} \tag{24}$$

$$x_{it}^+ = \bar{x}_{it} 1_{t_i^F}[t], \quad \text{where } 1_{t_i^F}[t] = \begin{cases} 1, & \text{if } t > t_i^F \\ 0, & \text{otherwise} \end{cases} \tag{25}$$

p_{it} is introduced to show the unsatisfaction demand of slot-i (customer-i) and it's calculated using Equation (26). It takes value between 0 and 1. If the value is 1 demand is not satisfied, and if $p_{it} = 0$ then demand is fully satisfied.

$$p_{it} = \frac{e_i^d - \sum_{t':t_i^I}^{t-1} e_{it'}\tau}{e_i^d} \qquad \in [0, 1] \tag{26}$$

c_W^o and c_{DC}^o are the overparking prices in TL per period for wireless and DC charging slots respectively, which are introduced as penalty costs to minimize occupied charging station slots for long hours. The parameters that are not explained in this section has already been explained in Table (8).

5.3.2.2. Decision Variables

In this section the decision variable that will be used in $\mathtt{OEOM}_t$ is explained in Table 21.

Table 21: List of Decision Variable of Online Energy Operations Model

Decision Variables	
e_{it}	amount of energy in kW transferred to slot-i at period-t

Decision variable e_{it} indicates the amount of energy in kW that is transferred to slot-i at period t.

Objective Function

The aim of the objective function for the Online Energy Operations Model is to maximize the satisfied demand of the customers before leaving the system.

$$\max \sum_{i \in \mathbf{S}} p_{it} e_{it} \tag{27}$$

Constraints

Constraints (28) and (29) is introduced to ensure that the installed energy is sufficient for all wireless and DC slots. This is achieved by ensuring that the sum of energy transferred to all wireless and DC slots is less than or equal to the total installed energy capacity for wireless and DC.

$$\sum_{i \in \mathbf{S}_W} e_{it} \leq E_W, \tag{28}$$

$$\sum_{i \in \mathbf{S}_{DC}} e_{it} \leq E_{DC}, \tag{29}$$

Constraints (30) and (31) are introduced to the model as energy control constraints. Constraint (30) demonstrates the upper-bound of the energy that could be transferred from a wireless slot-i. The amount of energy transferred to a wireless slot-i should be less than or equal to the total capacity of installed wireless stations in the system.

Since DC charging option does not allow energy control, it can provide only 90 or 180 kW, there is no need for an energy control constraint for DC option but Equation (31) ensures that the transferred energy is 90 kW if there is a customer in the slot-i.

$$e_{it} \leq (\sum_{k \in \mathbf{K}_W} w_k y_k)\bar{x}_{it}, \qquad i \in \mathbf{S}_W \tag{30}$$

$$e_{it} = (\sum_{k \in \mathbf{K}_{DC}} w_k y_k)\bar{x}_{it}, \qquad i \in \mathbf{S}_{DC} \tag{31}$$

Since the energy can not have negative values, in order for e_{it}, which represents the amount of energy in kW/hr transferred to slot-i at period-t, not to take a negative value, we introduced Constraint (32) to the mathematical model as non-negativity constraint.

$$e_{it} \geq 0, \qquad i \in \mathbf{S} \tag{32}$$

Online Energy Operations Model at Period-t ($\mathtt{OEOM}_t$)

$$\max \sum_{i \in \mathbf{S}} p_{it} e_{it} \tag{33}$$

s.t

$$\sum_{i \in \mathbf{S}_W} e_{it} \leq E_W \tag{34}$$

$$\sum_{i \in \mathbf{S}_{DC}} e_{it} \leq E_{DC} \tag{35}$$

$$e_{it} \leq (\sum_{k \in \mathbf{K}_W} w_k y_k)\bar{x}_{it} \qquad i \in \mathbf{S}_W \tag{36}$$

$$e_{it} = (\sum_{k \in \mathbf{K}_{DC}} w_k y_k)\bar{x}_{it} \qquad i \in \mathbf{S}_{DC} \tag{37}$$

$$e_{it} \geq 0, \quad i \in \mathbf{S} \tag{38}$$

Income Equation

After solving the $\texttt{OEOM}_t$ model, the income equation will be updated. The income equation is formed using the fixed installation cost, energy profit and overparking profit. Each part of the income equation will be explained in this section.

Optimized Fixed Installation Cost

The optimized fixed installation cost is determined using the $\texttt{OPIM}$ model which is the offline parking installation model. It is represented by (39) and it takes a negative sign since it represents the installation cost.

$$F = \min \sum_{k \in \mathbf{K}} f_k z_k \tag{39}$$

Optimized Energy Income

The optimized energy profit is determined using the $\texttt{OEOM}_t$ model which is the online energy operations model. It is represented by (40), where e_{it} is the amount of energy in kW transferred to slot-i at period-t determined for the OEOM_t model and c^e_W and c^e_{DC} are introduced to represent the energy selling prices for wireless and DC charging in TL/kW respectively.

$$E(t) = \sum_{i \in \mathbf{S_W}} c^e_W e_{it} + \sum_{i \in \mathbf{S_{DC}}} c^e_{DC} e_{it} \tag{40}$$

Overparking Income

The Overparking Income is determined using Equation (41) where x^+_{it} is introduced to represent overparking. Overparking incurs when the slot is occupied at period-t and period-t is longer than the claimed leaving time. c^o_W and c^o_{DC} are the overparking prices in TL per period for wireless and DC charging slots respectively, which are introduced as penalty costs to minimize occupied charging station slots for long hours. Overparking prices are constant and overparking parameter is determined based on slot status. So, the overparking income $O(t)$ will be determined and calculated deterministically.

$$O(t) = \sum_{i \in \mathbf{S_W}} c^o_W x^+_{it} + \sum_{i \in \mathbf{S_{DC}}} c^o_{DC} x^+_{it} \tag{41}$$

Overall Optimized Income Equation

$$Z(t) = -F + \sum_{\bar{t}=1}^{t} (E(t) + O(t)) \tag{42}$$

6. Mobile Application

As a part of this senior design project, we decided to develop an EV mobile application that customers will use. As we stated earlier, charge initiation, charging process control, customer notifications such as charging completion,range advice and overparking, charging duration and fee information and payment will be on this app.

General Outline of the Application

Firstly, "Welcome" page appears in the application as shown in Figure 18. Here, the user is redirected to two different pages depending on whether he is a member or not. If there is not a membership, user will be directed to the membership creation page by clicking the "Sign Up" button. If there is a subscription, "Already Have An Account?" button will direct user to the login screen.

We want some information from the user to become a member; these are, respectively as shown in Figure 18, username, email, phone number, address, and gender(optional). In this section, we get general information about the user.
For login security, we request users to create a password and information about the tool to be used in calculations. This information; Car name (optional), car model (optional), battery capacity, and car type. When they enter this information, users are registered to the system.

Customers who already have a membership login by entering their "username" and "password" information on the "Login" screen.

After logging in, the "Home" screen appears. On this page, the user encounters eight different options.

- On the "Personal Information" page, general information entered by the user during registration is listed.
- "Billing Information" page includes one-time payments and registered credit card information.
- The customer's past and future reservation information is listed on the "Transactions and Reservation" page, and a new reservation can be created on this page.
- On the "My Cars" page, the information entered by the user about the vehicle during registration is listed. In addition, there are options such as adding new vehicles or updating vehicle information.
- The "Pricing" page provides information about the price tariffs of the chargers.
- On the "Support Contact Us" page, there is contact information to be used in case of a problem.
- "Log-Out" button, on the other hand, logs out of the system and redirects to the "Welcome" page.
- "Start Charging" page has been created by us to match the customer with the most suitable charger. With the choices made here, the customer is informed about the process.

Of these buttons, only "Start Charging" and "Log-Out" work. Others remained under construction due to time constraints.

Charge Calculation and Slot Recommendation

Figure 19 is the charge calculation and slot recommendation page in our application. The aim of this page is to give DC and Wireless charging information to customers based on the data they provided. As can be seen in the Figure, we enumerated each part from 1 to 13 to make it easier to follow and have an example calculation to explain in detail.

Part 1 represents the vehicle information. Car model, the battery capacity of the vehicle and the type of the vehicle are in this part. We receive these vehicle information from the user at the time of the registration, sign up, and save it in a CSV document for this project. Thus, we can perform our calculations by extracting the values directly from the CSV document without asking the user for this information again on calculation page.

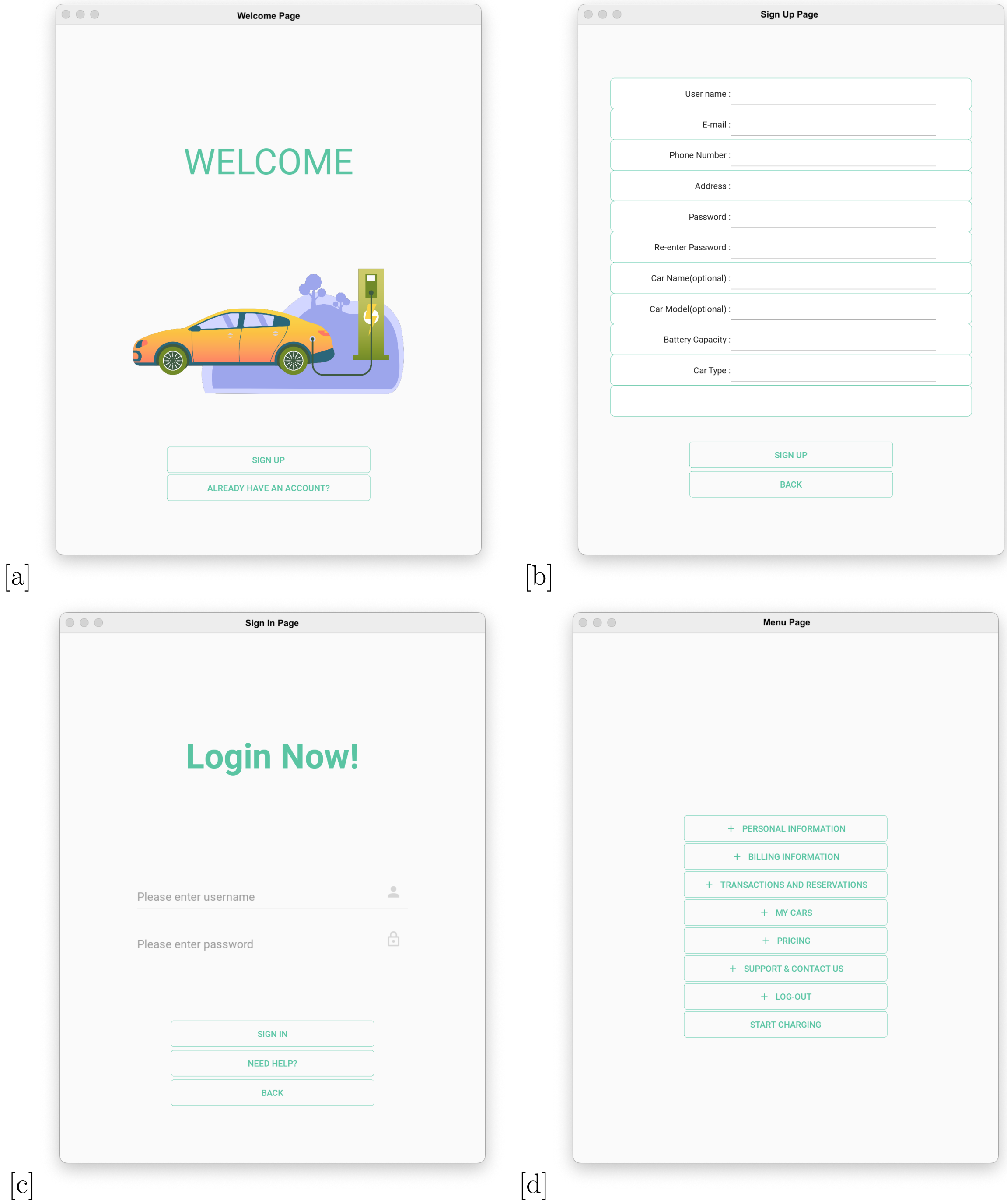


Figure 18: (a) Welcome Page (b) Sign-Up Page (c) Login Page (d) Home Page

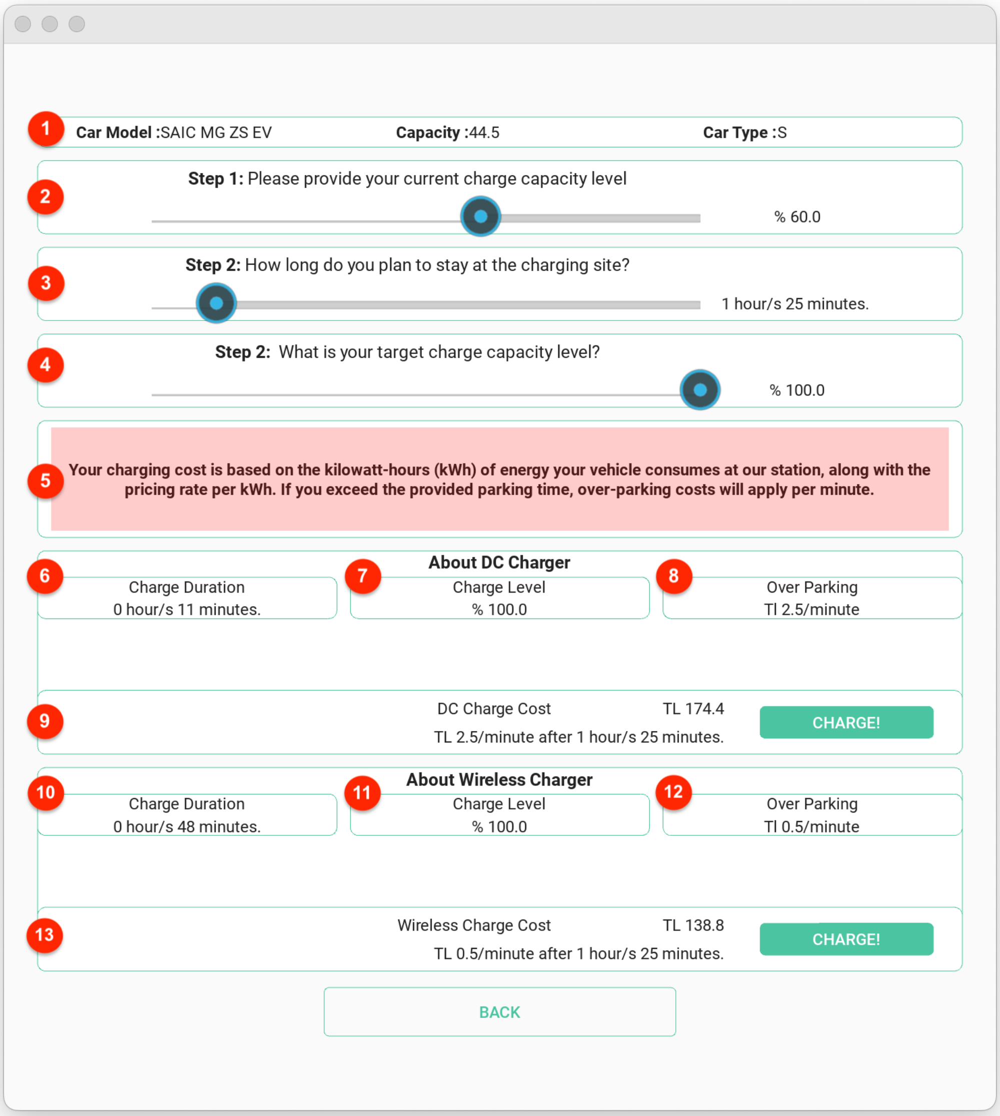


Figure 19: Calculation Screen

There are 3 different data that the customer will provide in order to get charging and slot information. The current battery level, estimated length of stay and desired battery level. In Part 2, customer provides the current charge level of the vehicle's battery. It is referred as Step 1 and In Figure 19 it's provided as 60%. We used UISlider in the design of this part, so we direct the customer to select a single value in the 0-100 value range. In Part 3 which is referred as Step 2 for customers, customer enters the estimated length of stay, in figure 1 hour 25 minutes is given as an example, which tells us how long the customer will occupy the slot and starting time of the overparking penalty if occurs. In Part 4, customer provides the desired charge level, the target charge level needed to be reached at the end of the charging process. This part is referred as Step 3 for customers and in the figure it's set to 100% as an example.

Part 5 provides charging and overparking information. We give information about the calculation of charge duration and when the overparking penalty will be applied.

Parts 6 and 10 are the calculated charge durations of DC and Wireless charge methods respectively, based on customer's data provided. Calculation of charge duration is explained in detail with the example data given in Figure (19) as following: First, the difference between the current and target charge level is calculated. This is the required charge level percentage needed to be satisfied. It is $100\% - 60\% = 40\%$ in the example. Then, corresponding battery capacity in terms of kW is calculated by multiplying the total battery capacity of the vehicle by the required charge percentage. In the example it's calculated as $44.5 * 40\% = 17.8kW$. After finding the corresponding required battery capacity, in order to calculate the charge duration, calculated desired battery capacity is divided by the station capacity, 90 kW and 22 kW for DC and Wireless respectively. Part 6 for DC is found as $17.8/90 = 0.20$ hour then turned into minutes by multiplying with 60 $0.20 * 60 = 12$ minutes while Part 10 for Wireless is found as $17.8/22 = 0.81$ hour which is equal to $0.80 * 60 = 48$ minutes.

Parts 7 and 11 are the reached charged level at the end of charging for DC and Wireless methods. It is calculated using the formula; final charge = min(target charge input, (current charge input + possible charge)). The reason why we do such a process here is that the time the customer is in is sometimes may not be enough for the charge to reach its target charge level. For example, if a vehicle with a battery capacity of 90 kW stays for 30 minutes and requires a full charge from 5% to 100%, it is not possible to meet this with existing chargers. Wireless 11 kW DC can provide 45kW energy to a customer who will stay for 30 minutes and demand ((100%-5%)*90)=85.5 kW energy. In this case, at the end of the transaction, the battery level of the customer becomes 17.2% DC 55% in wireless, that is, he cannot reach the desired 100% level. In this case, the system automatically displays the possible result. However, if the targeted charge level can be met during the stay, the targeted charge level is displayed directly.

Parts 8 and 12 are the overparking penalty information for DC and Wireless chargers. They inform customers the overparking penalty costs per minutes, for DC in Part 8 it's 2.5 TL per minute while for Wireless in Part 12 it's 0.5 TL per minute. And as informed in Part 5, penalty will be applied after the time provided by the customer.
Parts 9 and 13 show the charging costs for DC and Wireless methods respectively. Charging cost is based on the energy (kWh) provided to customers during charging. It is calculated by multiplying the energy capacity with the charging cost per kW which is 9.8 TL for DC and 7.8 TL for wireless respectively. In the example given in Figure (19), Part 9 for DC charger is calculated as $17.8 * 9.8 = 174.4$ TL and Part 13 for wireless charger is calculated as $17.8 * 7.8 = 138.8$ TL.
Once these calculation are done by the application, customer can change either DC or Wireless charger whichever they find more convenient and start charging.

Figure 20 is the charge status control page in our application. Again, parts of this page is enumerated from 1 to 8 to explain easily.
Part 1, 2 and 3 are the start, over and current time respectively. Over time is the time charging will complete. Part 4 represents the total duration of parking including both charging and overparking durations. It starts with the start time and ends when the customer discharges the vehicle. Part 5 is the charge level. Part 6 and Part 7 represent duration of charging and duration of overparking. Part 7 starts when the time passes the stated length of stay by the customer. Lastly, Part 8 shows the cost information. Charge cost is calculated based on charge duration information while overparking cost is calculated based on overparking duration information. Total cost is the summation of these two costs.

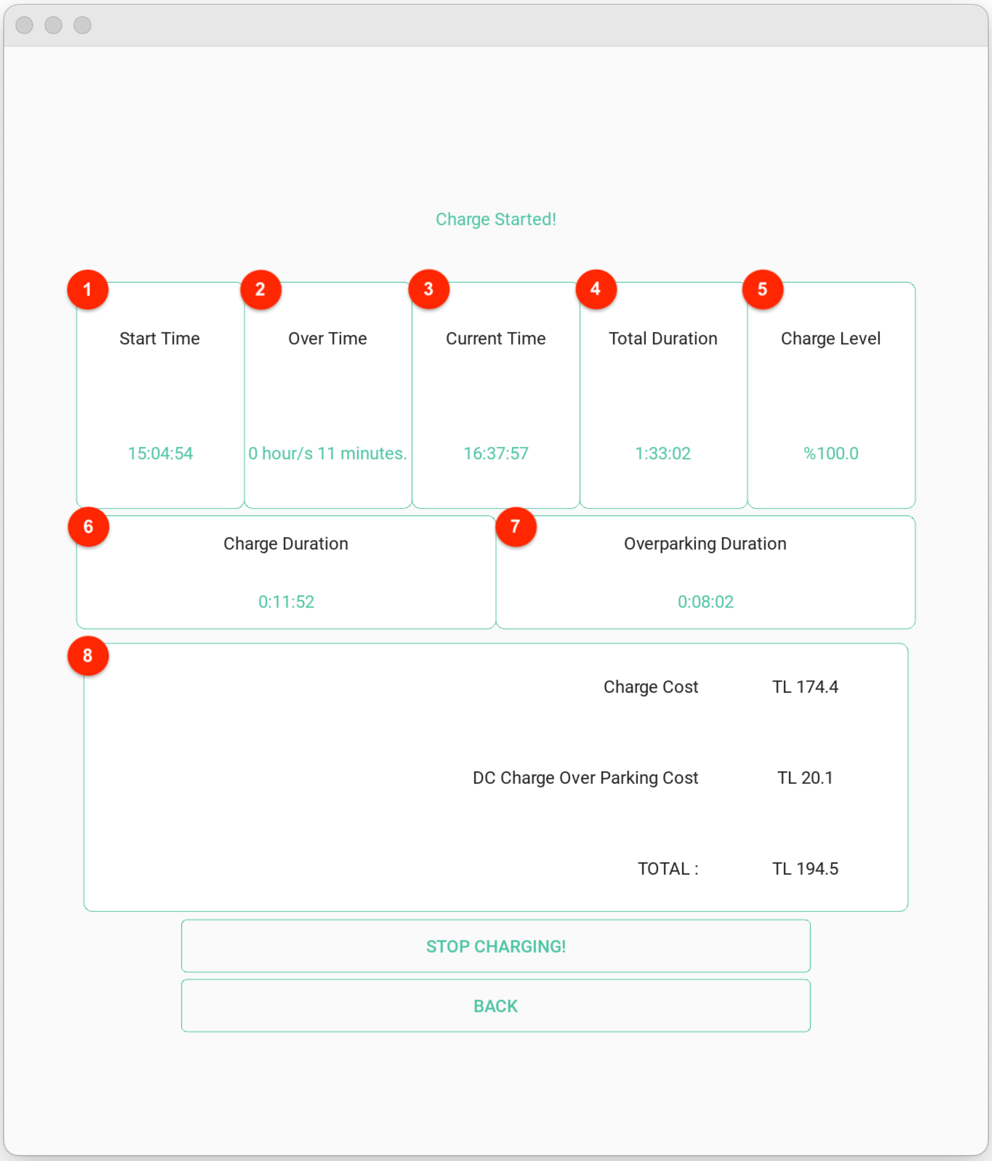


Figure 20: Calculation Screen

Customer Notifications

There will be 3 types of notifications that will be sent to customers. And those notifications will be referred as cases throughout this section and when customers will receive those notifications are shown in the flowchart in Figure (21).

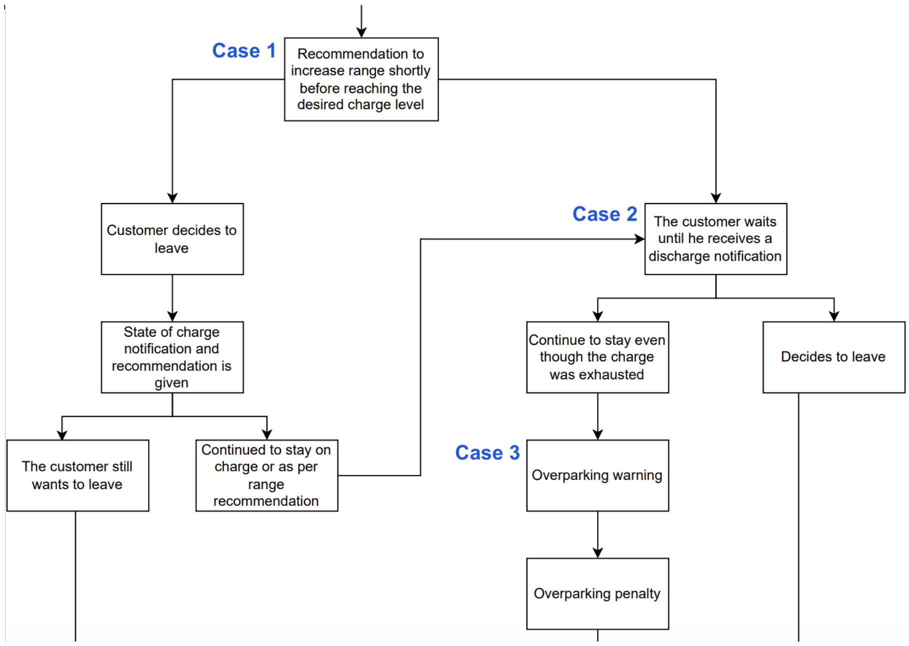


Figure 21: Application Notification Cases on Flow Chart

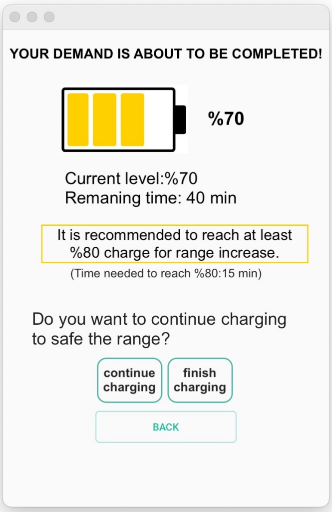


Figure 22: Continue Case Notification

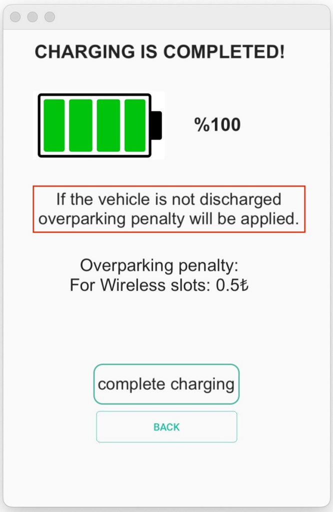


Figure 23: Charged Case Notification

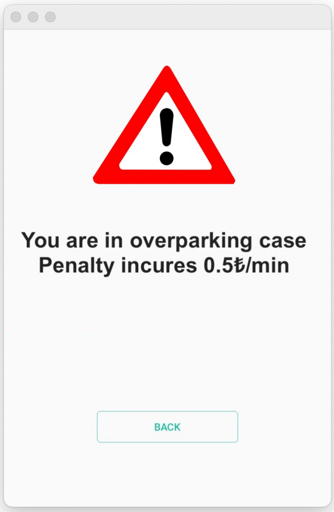


Figure 24: Overparking Case Notification

Case 1 - Continue : First will be sent in case of early leaving and shown in the flowchart on Figure (21) as Case 1. Customers will be reminded that the charging is not completed along with current charge information and range advice will be given if needed as shown in Figure (22). This situation is formulized as :

$$p_i \leq (1 - p_d + g)$$

$$p_i > 0$$

$$t < t_i^F$$

p_d represents the charging rate of the vehicle battery. We calculate the unsatisfied demand p_i, by subtracting p_d from 1. Customers are notified at least $+g$ units of time in advance to receive range advice. Since EV's driving ranges increase after reaching 80%, it is usually recommended to achieve at least 80% battery level. If the customer has a target battery level value more than 80% but decides to leave before reaching it, to be able to increase vehicle's driving range that will affect the customer satisfaction in long term, app will inform customers about range safety and provide needed time information to reach 80%. It is planned that the customer will be notified when 70% of the battery level the vehicle wants to reach is completed. For example, if the customer wants the charging process to end when the battery reaches 75% charge level, the advisory message will go when the battery level reaches 52.5% (70% of 75%). The time that the range advice message is sent for each vehicle varies, but on average, if it charges in DC Charger 15 minutes before, if it charges in Wireless Charger, we send notification 1 hour before. It will ask customers if they want to continue charging as recommended or finish charging. If the customer wishes to continue charging, they can choose to do so through the app.

Case 2 - Charged : The second notification as shown in Figure (23) and labeled as Case 2 on flowchart in Figure (21) is charging completion notification. This situation occurs if $p_i = 0$, in other words, when the unsatisfied energy demand is zero which means the customer received all of their demand. In this case, customers will be notified when the charging is done, so that they can discharge their vehicle and leave. This notification will contain warning about overparking case and its penalty cost. Customers will be informed that if they don't discharge their vehicle an overparking penalty will be applied. But overparking doesn't incur until $t > t_i^F$, not until current period passes the customer's claimed leaving time.

Case 3 - Overparking : The last notification is the overparking warning as can be seen in Figure (24) and showed as Case 3 on flowchart in Figure (21). This case occurs if the unsatisfied demand is less than or equal to satisfied demand and when the current period is after the customer's claimed leaving time and the slot is still occupied as formulated as:

$$p_i \leq (1 - p_d)$$

$$t > t_i^F$$

$$\bar{x}_{it} = 1$$

With this message, customers will be informed that the overparking case is started and penalty is being applied.

Case 4 - Status Notification : Once the charging starts, customers should be able to check the status of the charging anytime. For this purpose we prepared alternative app design for status notifications in several different scenarios as can be seen in Figures (25), (26) and (27). The percentage represents the instantaneous battery level at the time the customer checks. Remaining time to reach the target charge level or stated duration time is also shown. Underneath, there is a bar which represents the timeline of the charging process. 'Start' is the starting time of the charging while 'Finish' is the stated length of stay by the customer. The area between Start and Finish points on the bar is green because no overparking penalty will be applied in this time interval even if the charging is completed. After the Finish point, bar is red since overparking penalty will be applied after stated length of stay. Lastly, 'Now' represent the current time.

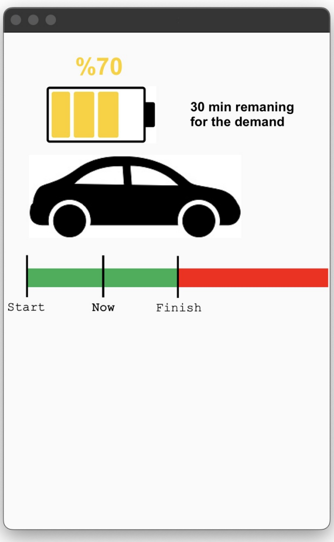


Figure 25: Continue Status Screen

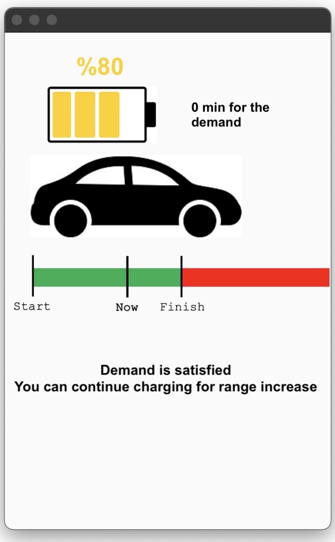


Figure 26: Charged Status Screen

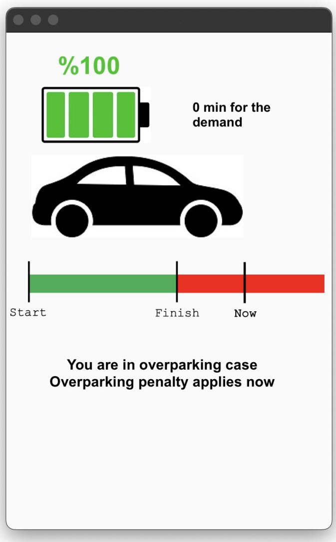


Figure 27: Overparking Status Screen

Figure 25 shows the status of a Continue case, where the charging is not completed.

Figure 26 represents the scenario where the charging is completed since the remaining time is declared as 0 minutes, but no overparking penalty will be applied due to the reason that 'Now' time is in between green zone. Finaly, Figure 27 represents the overparking scenario where the charging is completed and overparking penalty will be applied since 'Now' time is in red zone which means the customer had already passed the stated length of stay and hadn't discharged.

7. Computational Results

Since the OPIM model is a simple model it can be solved using Python or Excel to get exact solution or the numerical example in section (7.1) can be used as an alternative solution. On the other hand, the OEOM$_t$ model is an LP-model and can be solved to optimally with a solver such as Excel solver, Python or Cplex. However, in this senior design project both of the mathematical models are designed in **Python** using **PyCharm** environment. Since the models in this problem are optimization models **IBM CPLEX**, an optimization software package, will be used in Python to find the optimum results for the objectives.

7.1. Numerical Example

In order to explain and simplify the OPIM solution approach and the results a numerical example for the wireless stations installation is presented in this section. Lets assume that the wireless energy demand is 100 kW ($E_W^d = 100$) and the number of wireless stations needed from type-k in the parking lot ($\hat{z_k}$) is calculated using equation (43). Lets also assume that $\hat{z_k}$ should be less than S_w the number of wireless slots in the parking lot if not it will be zero as shown in (44). The number of wireless slots in the parking lot is considered 11 in this example ($S_w = 11$) and the fixed installation cost for stations type 1, 2 and 3 is 2700\$, 7850\$ and 13000\$ respectively.

$$\hat{z_k} = \frac{E_W^d}{w_k} \tag{43}$$

$$\hat{z_k} = \begin{cases} 1, & \text{if } \hat{z_k} \leq s_w \\ 0, & \text{otherwise} \end{cases} \tag{44}$$

Using the above information the following example is demonstrated. As can be seen from the example station type-1 is not considered since the number of stations required is bigger than the number of stations available in the parking lot. Type-2 and type-3 can be installed but since this is an minimization problem the station type with the lower cost will be selected. In this Case Type-3 station is selected and 5 stations will be installed.

Type-1

$$\hat{z_1} = \frac{100}{7.4} = 13.33 = 14 \ , \qquad \hat{z_1} = 14 > S_w = 11 \ , \qquad \text{Then } y_1 = 0 \ , \hat{z_1} = 0$$

Type-2

$$\hat{z_2} = \frac{100}{11} = 9.09 = 10 \ , \qquad \hat{z_2} = 10 < S_w = 11 \ ,$$
$$\text{Cost} = f_2.\hat{z_2} = 7850\$ \ . \ 10 = 78500\$$$

Type-3

$$\hat{z_3} = \frac{100}{22} = 4.54 = 5 \ , \qquad \hat{z_3} = 5 < S_w = 11 \ ,$$
$$\text{Cost} = f_3.\hat{z_3} = 13000\$ \ . \ 5 = 65000\$$$

Solution

$$k^* = Min[78500\$, 65000\$]$$
$$k^* = 3 \ , \text{Install 5 slots of type-3 Wireless stations.}$$

7.2. Solution using Python

7.2.1. OPIM Model

The OPIM model specified in section 5.3.1 is coded in Python and solved using Cplex in the scope of this project. As can be seen in Appendix A.3, firstly inputs values such as S_W , S_{DC} , E^d_W , E^d_{DC} , k_W, k_{DC} are specified based on the estimations made. In addition to that, fixed cost and supply capacity for each station type is identified in the code. After these decision variables, the objective function and then the constraints were coded according to the written mathematical model. After the mathematical model is coded, equations for E_W , E_{DC} specified in section 5.3.1.3 are also coded in order to be used as an inputs for the OEOM$_t$ model.

After implementing the OPIM model in Python the model was run and the output solution is demonstrated in Figure 28. As can be seen from the figure the optimal solution suggests implementing six of type- 1 wireless station ($z_1 = 6$) and one type- 4 DC station ($z_4 = 1$). This means that six wireless stations with supply capacity of 7.4 kW will be implemented and one DC station with supply capacity of 90 kW will be implemented in the parking lot. Finally, the overall optimal solution value for the OPIM model is 56200$ which is equivalent to 1,327,311.37.

```
Solution status: JobSolveStatus.OPTIMAL_SOLUTION
Solution value:  56200.0
y_1  =  1.0
y_2  =  0
y_3  =  0
y_4  =  1.0
y_5  =  0
z_1  =  6.0
z_2  =  0
z_3  =  0
z_4  =  1.0
z_5  =  0
Ew= 44.400000000000006
Edc= 90.0
```

Figure 28: OPIM Model Optimal Solution

7.2.2. OEOM Model$_t$

The OEOM$_t$ model specified in section 5.3.2 is coded and solved in Python and solved in the scope of this project. As can be seen in Appendix A.3, firstly inputs values such as c_W^o , c_{DC}^o , c_W^e, c_{DC}^e, S_W^{real} , S_{DC}^{real} ,c_{DC}^e are specified based on the outputs of the OPIM model. In addition to those inputs, the generated random data used in 5.3.1.2 is used as an input for the model. The model is solved based on this random generated data which contains information such as customerID, arrival time, duration of stay, leaving time, real leaving time, energy demand, energy demand per period and the suitable charging method for each customer. An array for each of the specified data is introduced and loops are created to calculated the energy Income and over-parking income at each period and the model is run until all customers leave the system.

After implementing the OEOM$_t$ model in Python the model was run and the output solution is obtained. The OEOM$_t$ model generates the energy income and the over-parking income as an output at each period. After all the customers leave the system the total energy income and total over-parking income is calculated over all the periods. An example of the output at t=0, t=1 and t=2 is shown in Figure 29.

```
Time period:0
Optimized Energy Income:0
Overparking Income: 0.0
Time period:1
Optimized Energy Income:362.6
Overparking Income: 0.0
Time period:2
Optimized Energy Income:412.52000000000004
Overparking Income: 0.0
```

Figure 29: $\texttt{OEOM}_t$ Model Optimal Solution

The overall, optimal solution is demonstrated in Figure 30. As can be seen from the figure After all the customers leave the system the optimal energy income is **16552.74 TL**, the over-parking income is **1380 TL** and the Total Income is **17932.85 TL** in the first day only. Based on this if the customer demand is approximately in the same range over the months the installation cost will be covered in 74 day and the company will start generating profit as shown in Figure 31.

```
Total Optimized Energy Income: 16552.85 TL
Total Overparking Income: 1380.00 TL
Total Income: 17932.85
```

Figure 30: $\texttt{OEOM}_t$ Model Optimal Solution

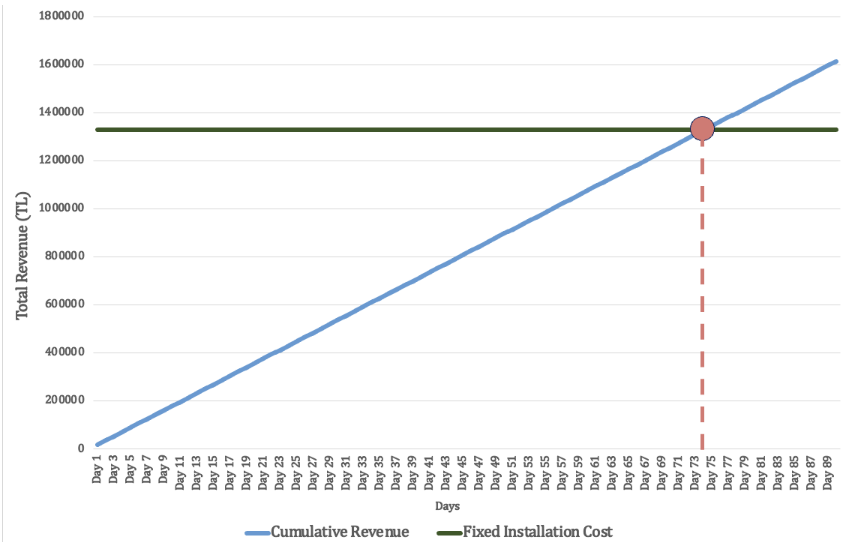


Figure 31: The breakeven point graph for total revenues

Simulation

As a part of our solution approach, we did a simulation. All related work can be seen in Appendix A. Then, we randomly determined the length of stay, and the vehicle battery capacity according to Turkey's ten best-selling electric vehicles. We visualized each period according to the information in the tables (A.1). At every t period, you can follow the customer and slot status, our revenues and lost customer information. The energy distribution is calculated based on the customer's energy demand and for how many periods will they stay. At the t-1, there is only customer-1 in the system his energy demand is 74 kW and the customer will stay for 2 periods. That's why 37 kW will be given to the customer at each period until his demand is satisfied and our earning in the first period is three hundred-sixty-three TL. We multiplied the energy given in each period by the unit energy service fee; while it is 7.8 TL in the wireless model, it is 9.8 TL in DC as we stated in Table 4. We applied a specific over-parking penalty to vehicles that remain on the slot despite the completion of the charging process. The penalty fee for wireless system is 0.5 TL/min and for DC 2.5 TL/min.

YouTube presentation: https://youtu.be/e2TyPczNszc

Python Code Repository: https://drive.google.com/drive/folders/1ba0OUWF16yQ9hHMsG5hC8g 8Su?usp=share_link

8. Conclusion

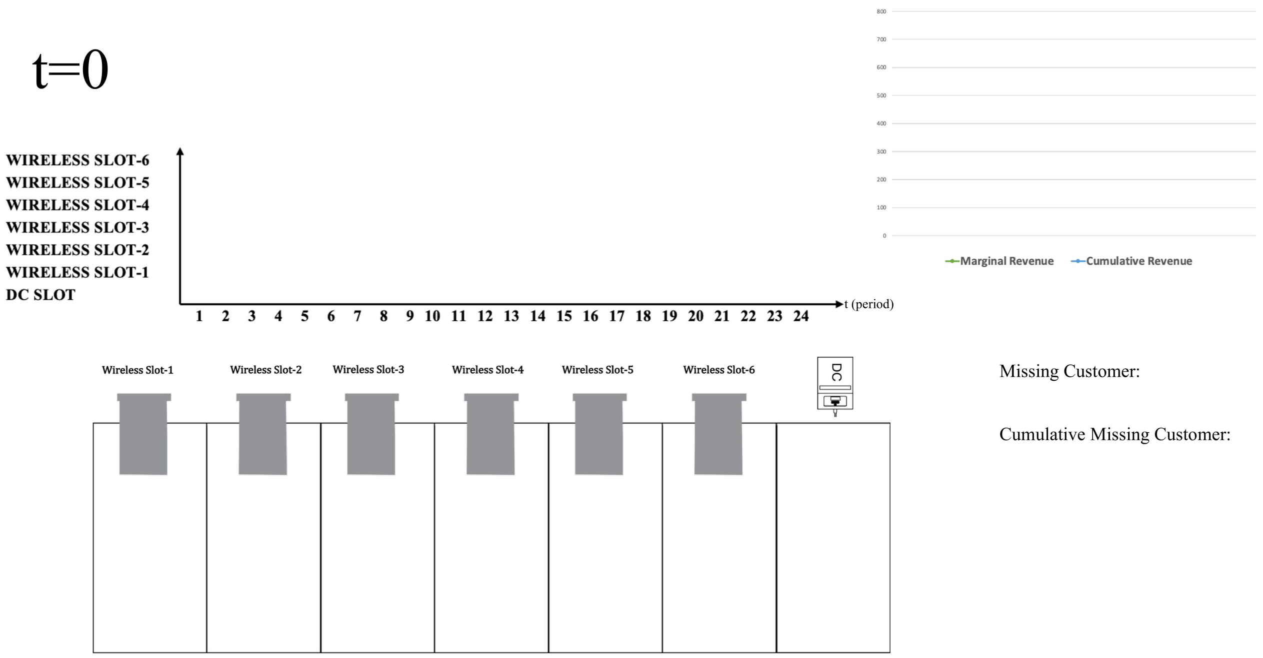
The main purpose of this project is to increase the net profit of the company, increase the number of charged vehicles and ensure customer satisfaction along with designing DC/Wireless Hybrid charging slots in the commercial parking lot of İGA. Considering these objectives, since the fixed installation cost is fixed and the energy sales prices are dynamic and dependent on the parking situation both of these circumstances have been evaluated developing two different models in this project. The Offline Parking Installation Model (OPIM) is the first model and was developed to be used to figure out the installation costs according to the optimal number of stations to be placed in the parking lot. The second model, known as the Online Energy Operations Model (OEOM$_t$), was developed to calculate the total profit generated from selling profit. Following the development of two distinct mathematical models, both mathematical models were created in Python using the PyCharm environment. The exact solution was obtained using IBM CPLEX since the OPIM is a straightforward model. On the other hand, OEOM$_t$ is an LP model that was best solved with Python. The OPIM model optimal solution was implementing six of type- 1 wireless station with capacity of 7.4 kW ($z_1 = 6$) and one type- 4 DC station with capacity of 90 kW ($z_4 = 1$). The overall optimal solution value for the seven stations is 56200$. For the OEOM$_t$ model the data used as input is the same data that was used for the estimation of some of the parameters for the OPIM model. After all the customers leave the system the optimal energy income was **16552.74 TL**, the over-parking income was **1380 TL** and the Total Income was **17932.85 TL** in the first day only. Based on this if the customer demand is approximately in the same range over the months the installation cost will be covered in 2.5 months and the company will start generating profit.

A. Appendix

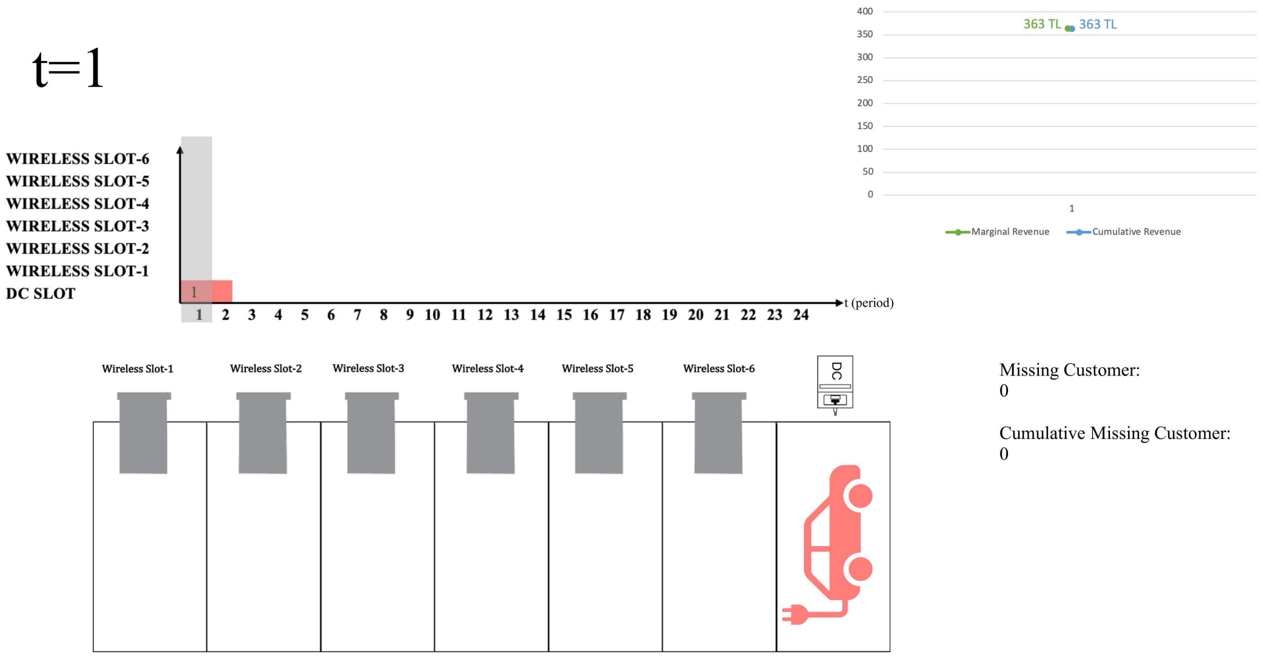
A.1. Illustration Figures

Customer ID	Entry period	Duration of stay	Exit period	Energy demanded	Demanded energy in 1 period	Suitable charger
1	1	2	3	74	37	DC
2	2	5	7	32	6	Wireless
3	3	4	7	73	18	Wireless
4	3	2	5	105	53	DC
5	4	4	8	87	22	Wireless
6	4	6	10	52	9	Wireless
7	5	2	7	111	56	DC
8	6	3	9	95	32	DC
9	7	1	8	22	22	Wireless
10	8	8	16	70	9	Wireless
11	9	4	13	57	14	Wireless
12	9	3	12	55	18	Wireless
13	10	8	18	61	8	Wireless
14	10	6	16	90	15	Wireless
15	11	7	18	109	16	Wireless
16	11	5	16	39	8	Wireless
17	12	2	14	92	46	DC
18	12	5	17	88	18	Wireless
19	15	5	20	66	13	Wireless
20	15	6	21	91	15	Wireless
21	15	4	19	92	23	DC
22	16	5	21	97	19	Wireless
23	16	2	18	83	42	DC
24	17	7	24	30	4	Wireless
25	18	4	22	86	22	Wireless
26	18	8	26	52	7	Wireless
27	18	6	24	114	19	Wireless
28	19	4	23	85	21	Wireless
29	19	3	22	39	13	Wireless
30	21	4	25	97	24	DC
31	21	5	26	71	14	Wireless
32	21	6	27	35	6	Wireless
33	22	6	28	65	11	Wireless
34	23	2	25	81	41	DC
35	23	6	29	91	15	Wireless
36	24	4	28	54	14	Wireless
37	24	5	29	111	22	DC
38	24	1	25	42	42	DC

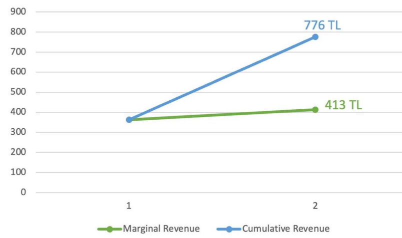
t=0

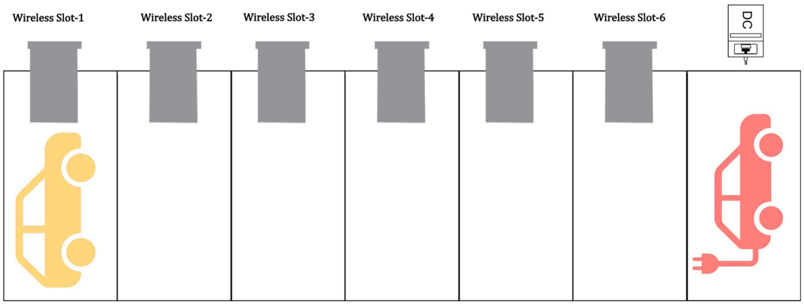

800
700
600
500
400
300
200
100
0
Marginal Revenue
Cumulative Revenue
WIRELESS SLOT-6
WIRELESS SLOT-5
WIRELESS SLOT-4
WIRELESS SLOT-3
WIRELESS SLOT-2
WIRELESS SLOT-1
DC SLOT
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
t (period)
Wireless Slot-1
Wireless Slot-2
Wireless Slot-3
Wireless Slot-4
Wireless Slot-5
Wireless Slot-6
DC
Missing Customer:
Cumulative Missing Customer:

t=1


400
350
300
250
200
150
100
50
0
363 TL
363 TL
1
Marginal Revenue
Cumulative Revenue
WIRELESS SLOT-6
WIRELESS SLOT-5
WIRELESS SLOT-4
WIRELESS SLOT-3
WIRELESS SLOT-2
WIRELESS SLOT-1
DC SLOT
1
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
t (period)
Wireless Slot-1
Wireless Slot-2
Wireless Slot-3
Wireless Slot-4
Wireless Slot-5
Wireless Slot-6
DC
Missing Customer:
0
Cumulative Missing Customer:
0

t=2

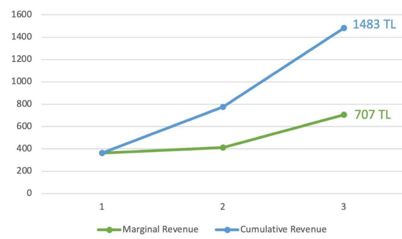


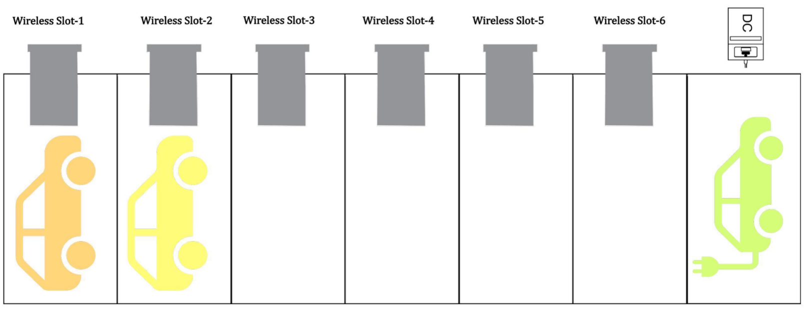


Missing Customer:
0

Cumulative Missing Customer:
0

t=3

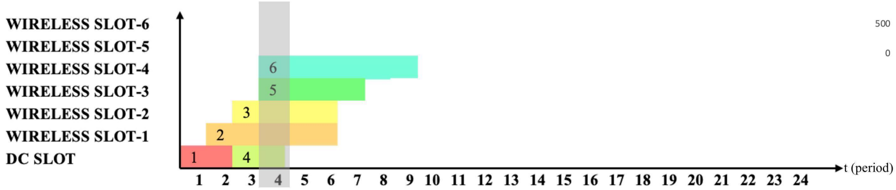


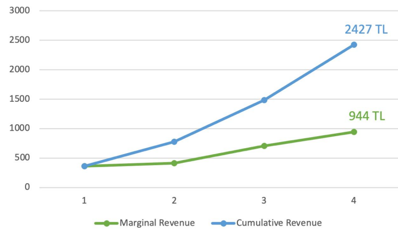


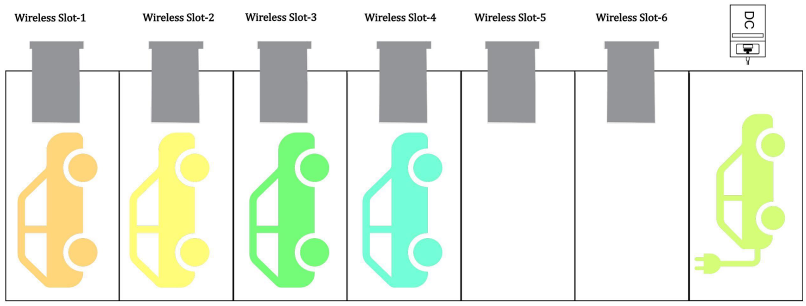
Missing Customer:
0

Cumulative Missing Customer:
0

t=4



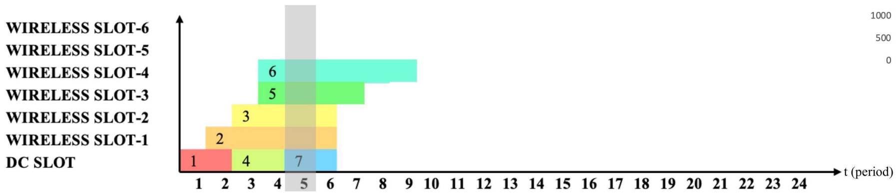


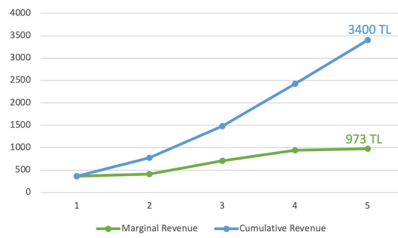


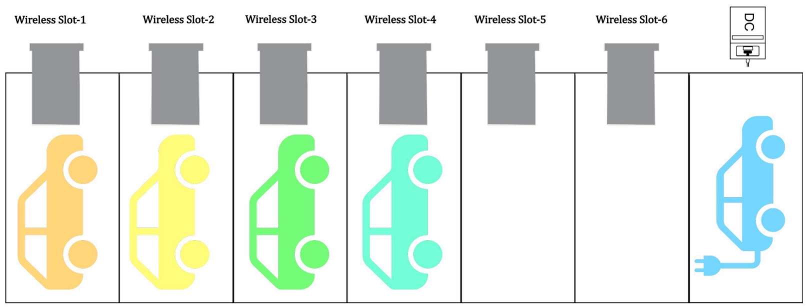
Missing Customer:
0

Cumulative Missing Customer:
0

t=5



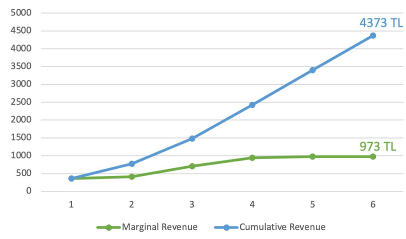


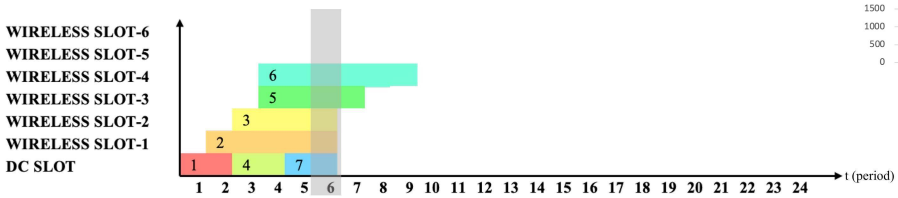


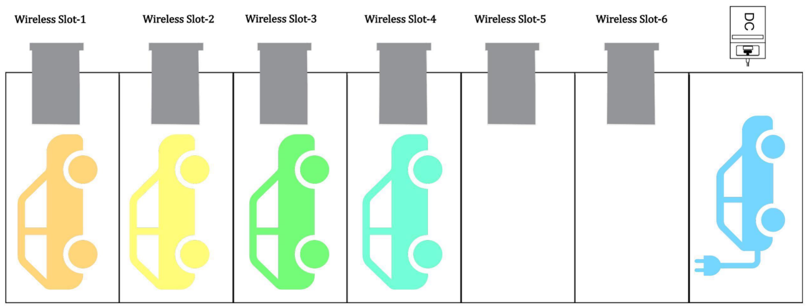
Missing Customer:
0

Cumulative Missing Customer:
0

t=6



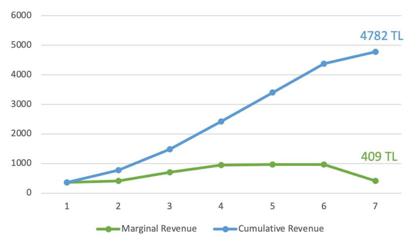


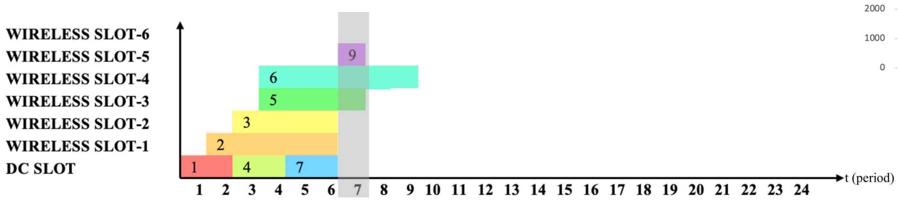


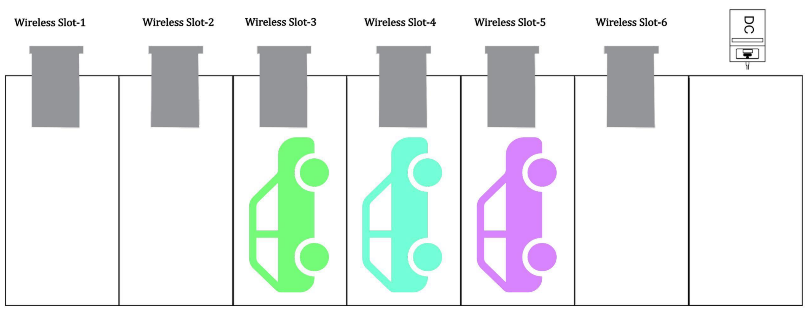
Missing Customer:
1 (C8)

Cumulative Missing Customer:
1

t=7



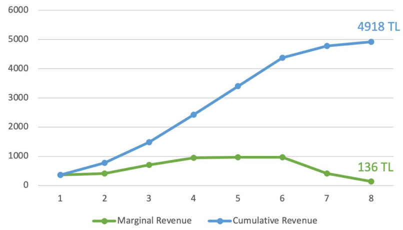


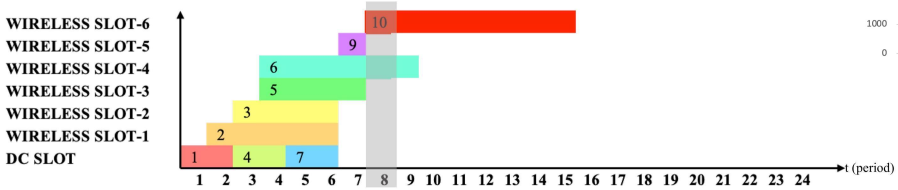


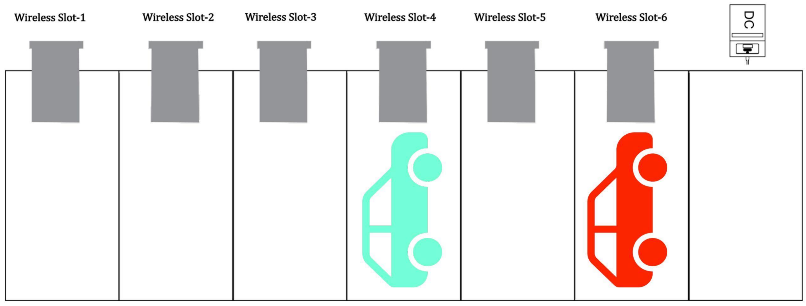
Missing Customer:
0

Cumulative Missing Customer:
1

t=8



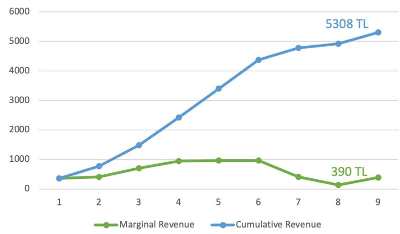


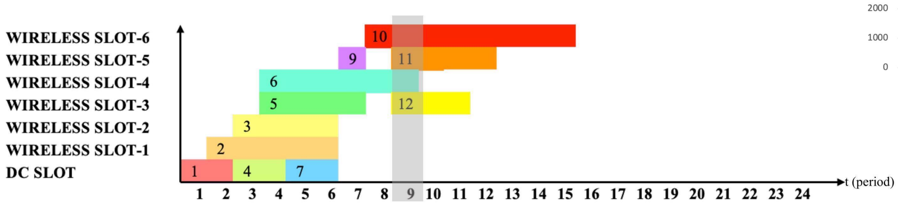


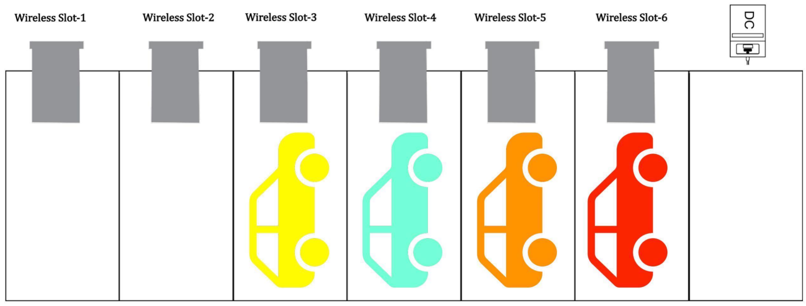
Missing Customer:
0

Cumulative Missing Customer:
1

t=9



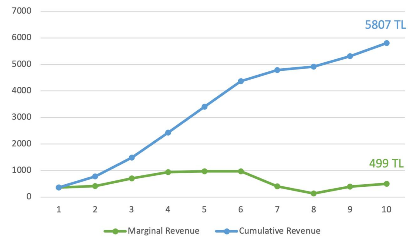


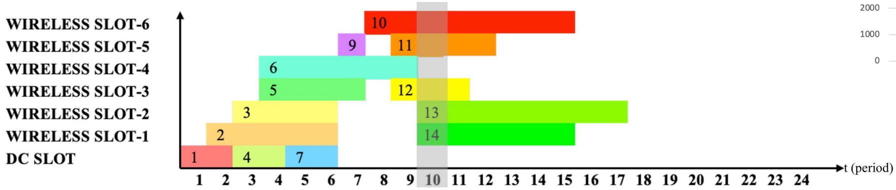


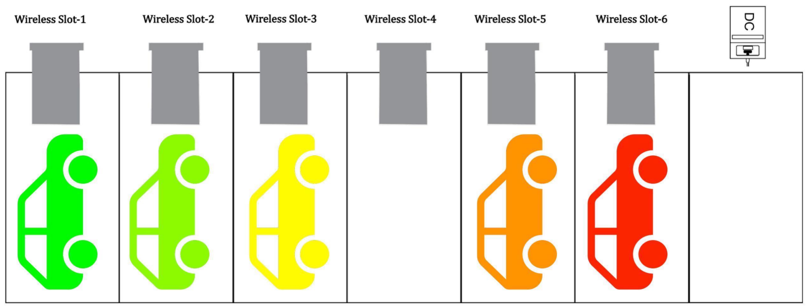
Missing Customer:
0

Cumulative Missing Customer:
1

t=10



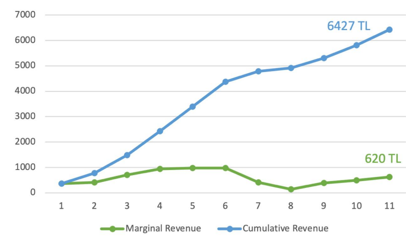


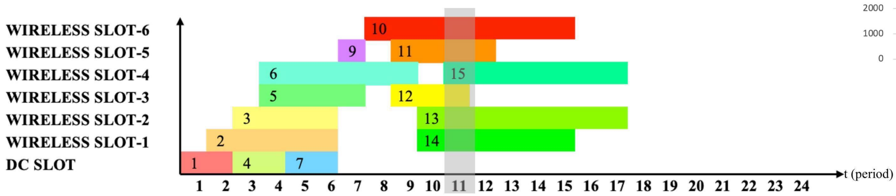


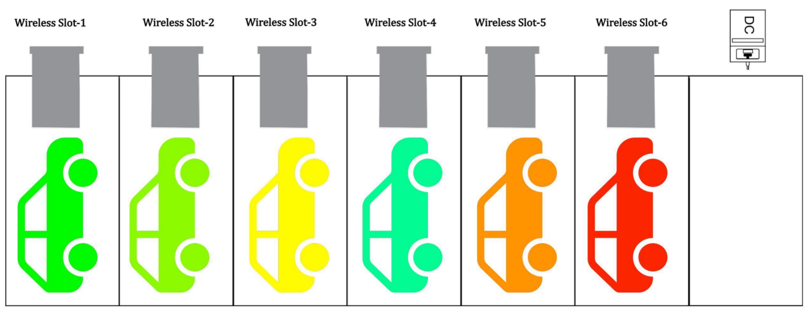
Missing Customer:
0

Cumulative Missing Customer:
1

t=11



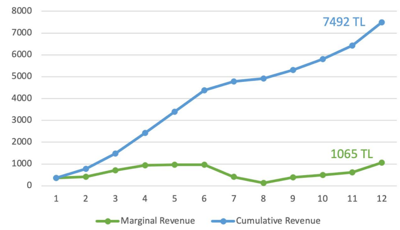


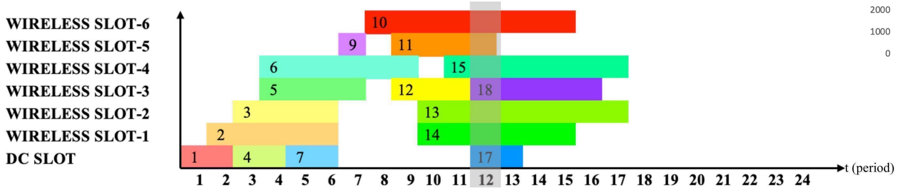


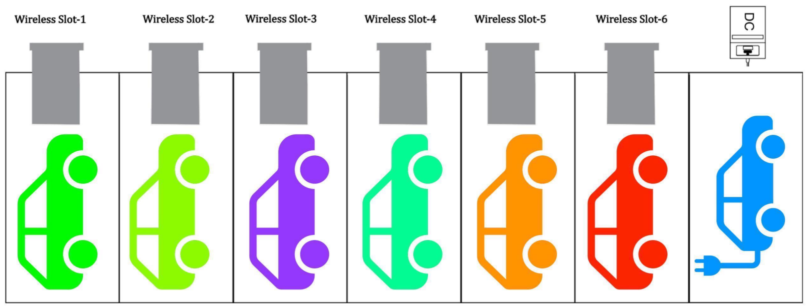
Missing Customer:
1 (C16)

Cumulative Missing Customer:
2

t=12



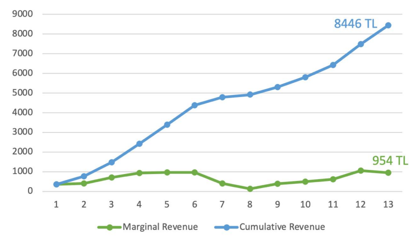


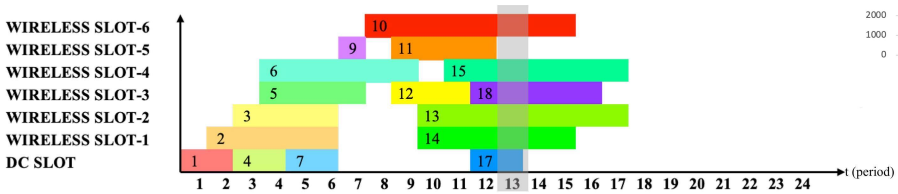


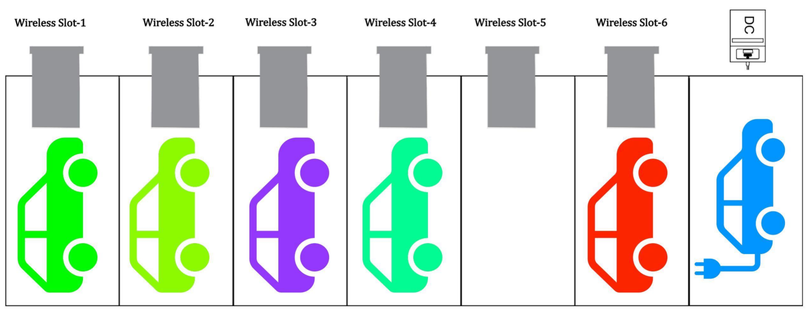
Missing Customer:
0

Cumulative Missing Customer:
2

t=13



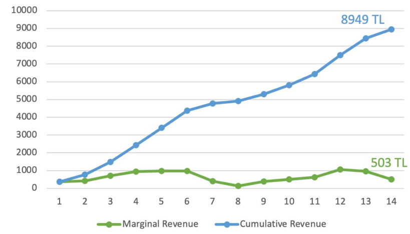


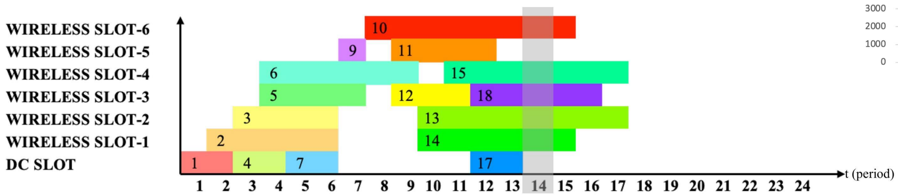


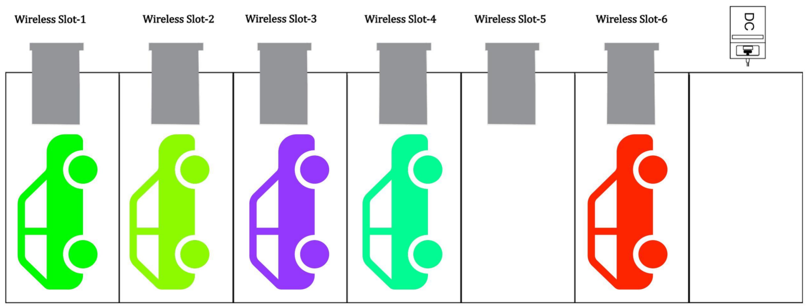
Missing Customer:
0

Cumulative Missing Customer:
2

t=14



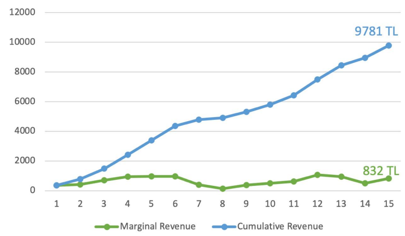


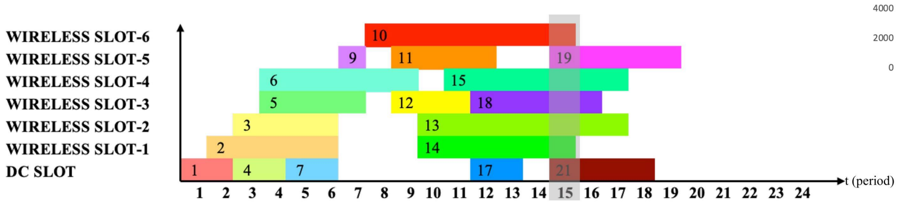


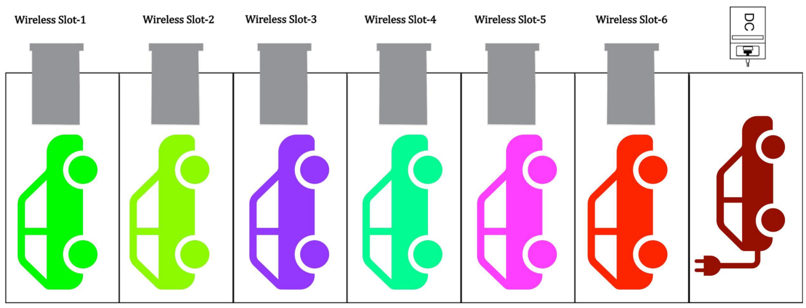
Missing Customer:
0

Cumulative Missing Customer:
2

t=15



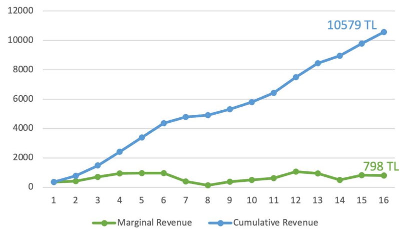


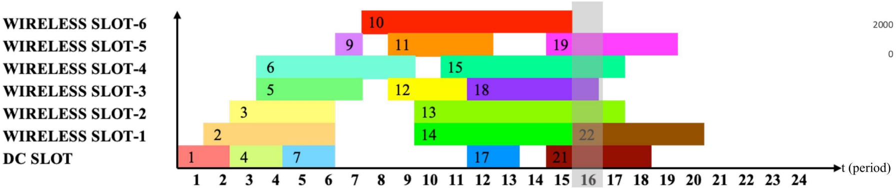


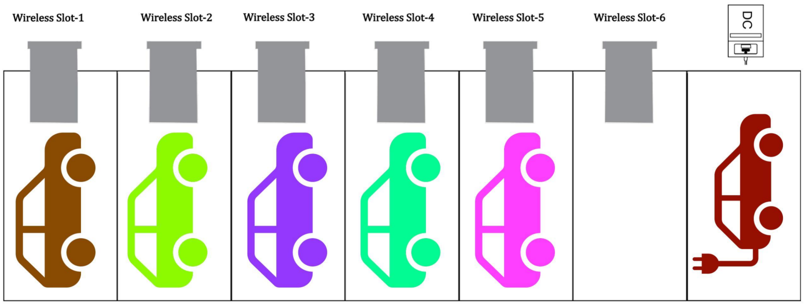
Missing Customer:
1 (C20)

Cumulative Missing Customer:
3

t=16



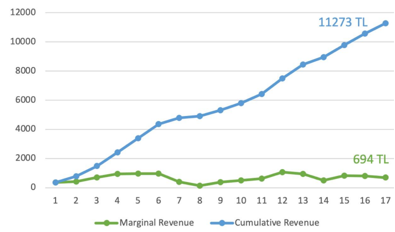


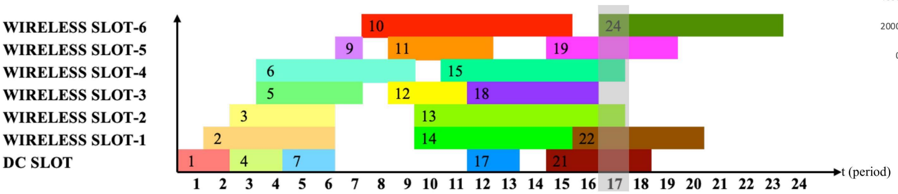


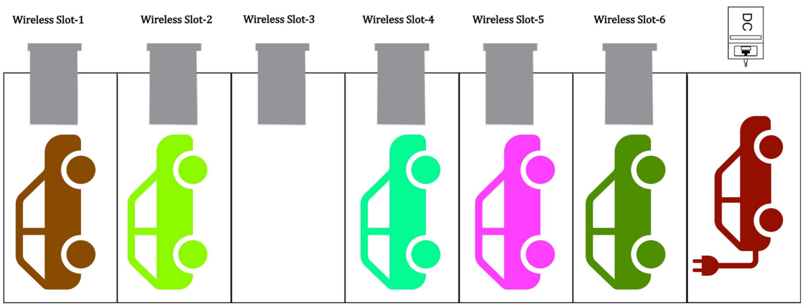
Missing Customer:
1 (C23)

Cumulative Missing Customer:
4

t=17



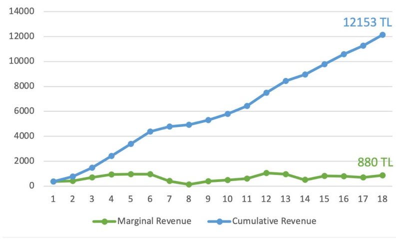


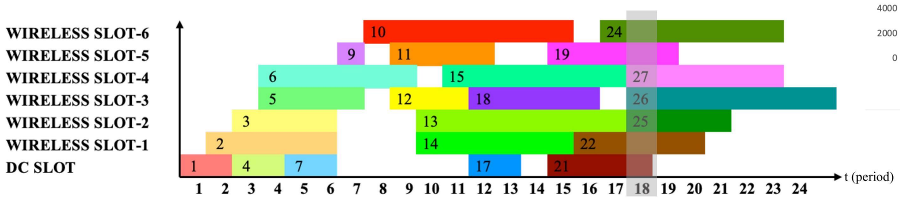


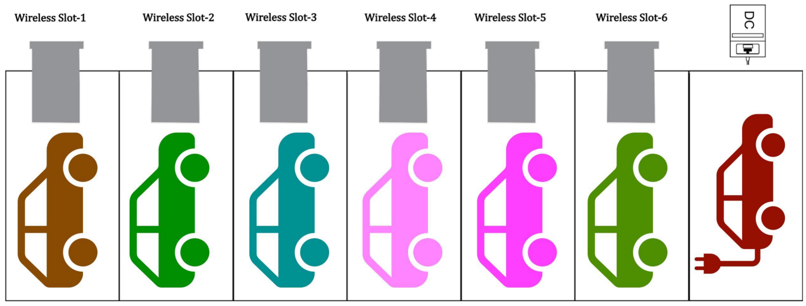
Missing Customer:
0

Cumulative Missing Customer:
4

t=18



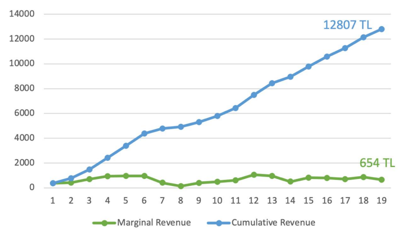


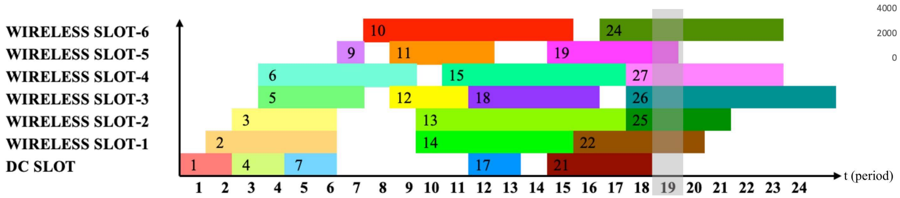


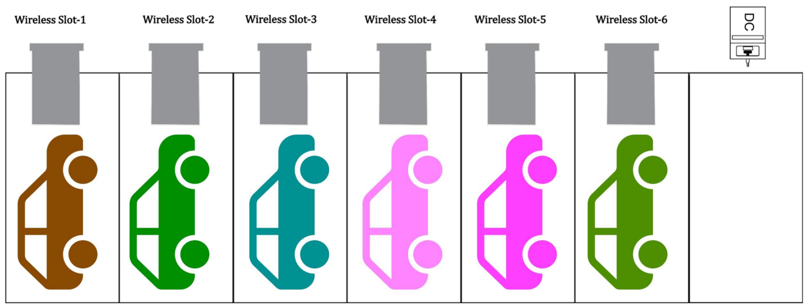
Missing Customer:
0

Cumulative Missing Customer:
4

t=19



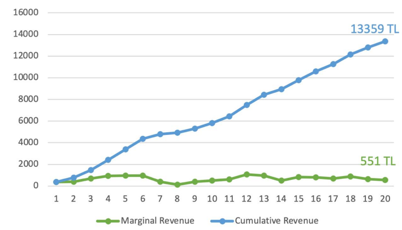


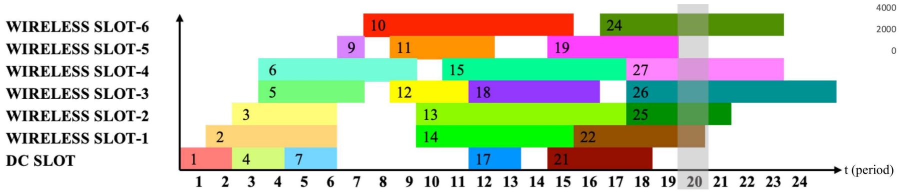


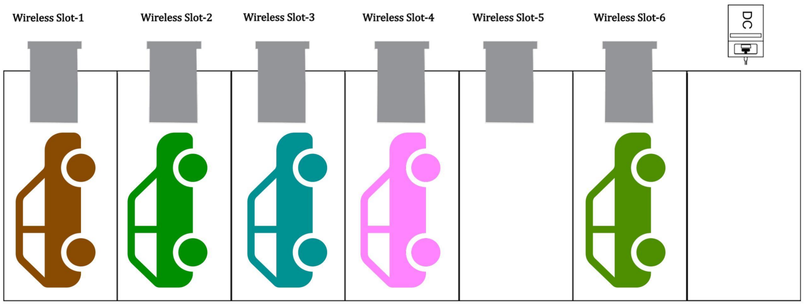
Missing Customer:
2 (C28 & C29)

Cumulative Missing Customer:
6

t=20



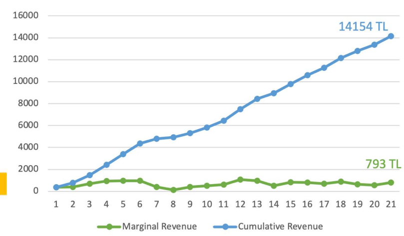


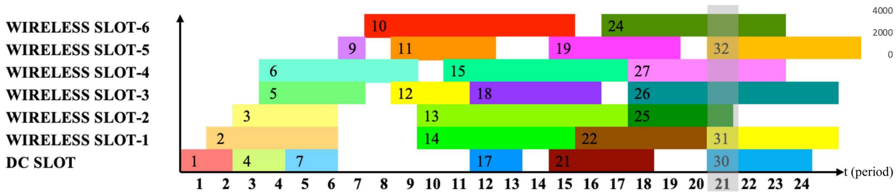


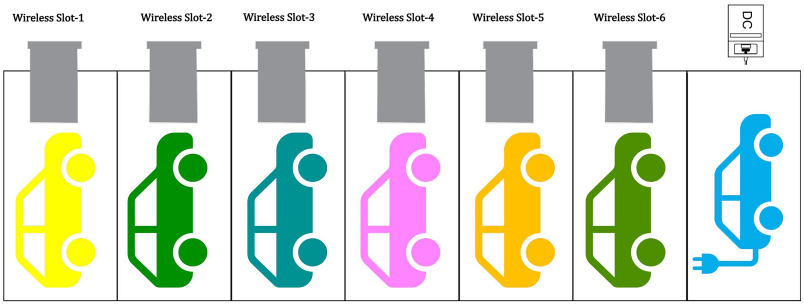
Missing Customer:
0

Cumulative Missing Customer:
6

t=21



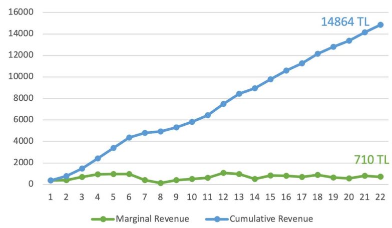


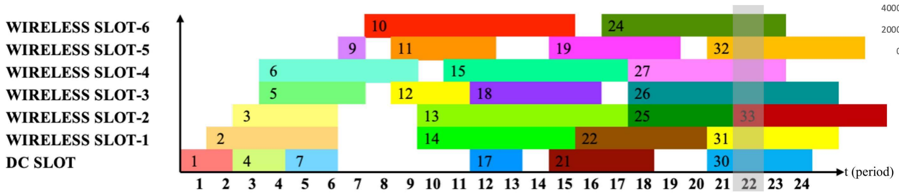


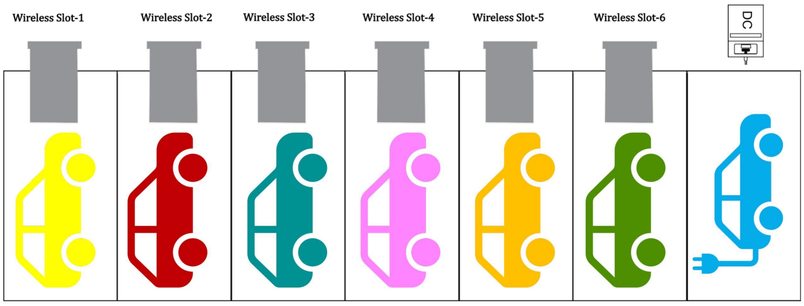
Missing Customer:
0

Cumulative Missing Customer:
6

t=22



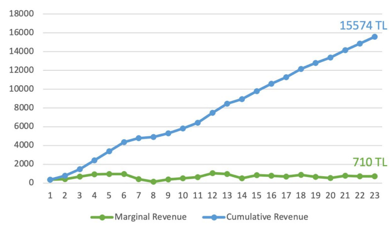


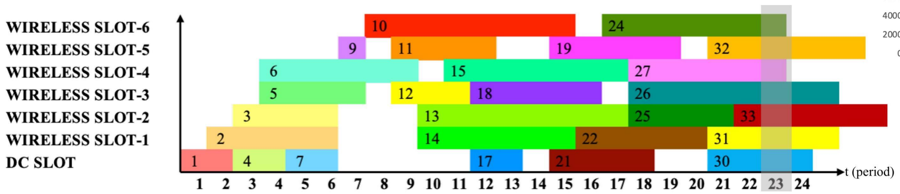


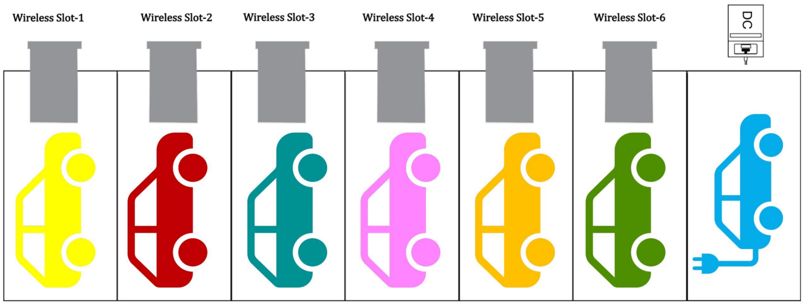
Missing Customer:
0

Cumulative Missing Customer:
6

t=23

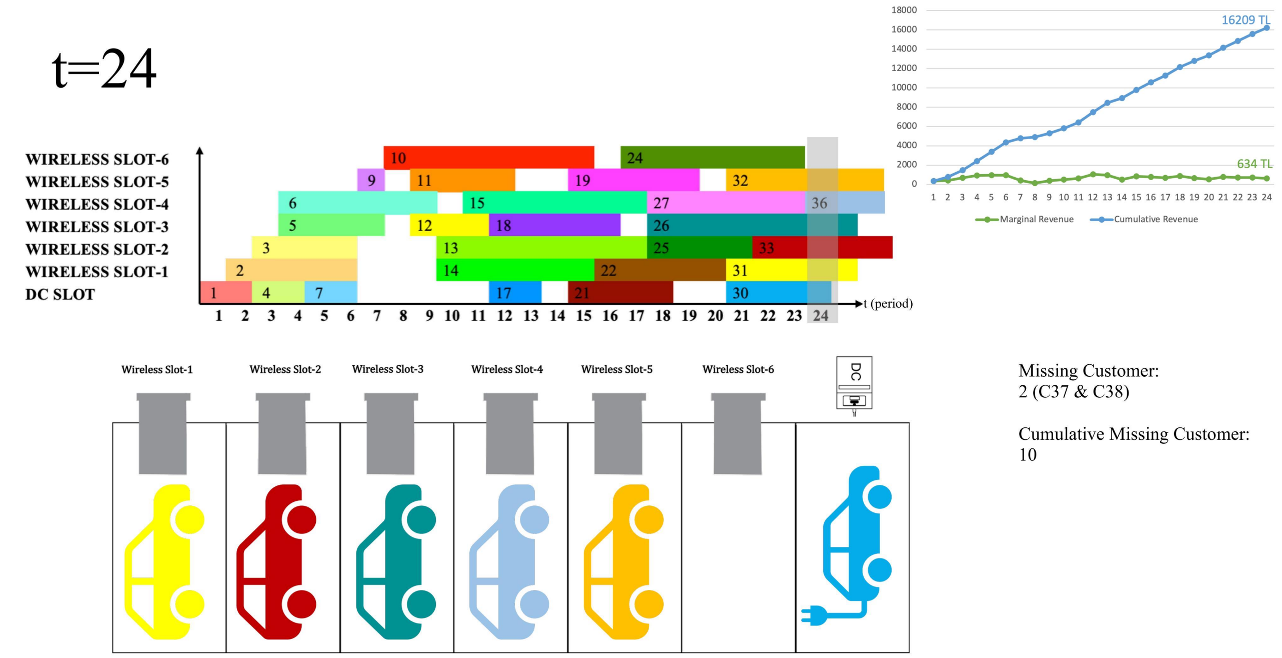






Missing Customer:
2 (C34 & C35)

Cumulative Missing Customer:
8



A.2. OPIM Model Python Code

```
import docplex.mp.model as cpx

Sw = 11
Sdc = 4
Ew_d = 43.086
Edc_d = 69.738
K = [1,2,3,4,5]
Kw = [1,2,3]
Kdc = [4,5]

# Since the index k starts from 1, the first elements of the f and w variables
#are taken as dummy in order to equalize the indices

f = [0,2700,7850,13000, 40000,70000]
w = [0,7.4, 11,22,90,180]


model = cpx.Model(name="MIP Model")

# Decision variables are defined
y = {k: model.binary_var(name="y_{0}".format(k)) for k in K}
```

```
z = {k: model.integer_var(name="z_{0}".format(k)) for k in K}

# Objective function
objective = model.sum(f[k] * z[k] for k in K)

#  Constraints are added
#1. Constraint
model.add_constraint(model.sum(y[k] for k in Kw) == 1, ctname="Constraint_1")

# 2. Constraint
model.add_constraint(model.sum(y[k] for k in Kdc) == 1, ctname="Constraint_2")

# 3. Constraint
for k in Kw:
    model.add_constraint(z[k] <= Sw * y[k], ctname="Constraint_3_{0}".format(k))

# 4. Constraint
for k in Kdc:
    model.add_constraint(z[k] <= Sdc * y[k], ctname="Constraint_4_{0}".format(k))

# 5. Constraint
model.add_constraint(model.sum(w[k] * z[k] for k in Kw) >= Ew_d,
ctname="Constraint_5")

# 6. Constraint
model.add_constraint(model.sum(w[k] * z[k] for k in Kdc) >= Edc_d,
ctname="Constraint_6")

# Model solving
model.minimize(objective)
model.solve()

# Results are printed
print("Solution status:", model.solution.solve_status)
print("Solution value: ", model.solution.get_objective_value())

for v in model.iter_variables():
    print(v," = ",v.solution_value)
```

```
# Ew and Edc values Equi. Calculating from 21 and 22 in the report

toplam = 0
for k in Kw:
    toplam += w[k] * model.get_var_by_name("z_" + str(k)).solution_value
print("Ew= " + str(toplam))

toplam = 0
for k in Kdc:
    toplam += w[k] * model.get_var_by_name("z_" + str(k)).solution_value
print("Edc= " + str(toplam))
```

A.3. OEOM Model$_t$ Python Code

```
import numpy as np
import pandas as pd

# Excel dosyasından verileri alalım
veri = pd.read_excel("C:\\Users\\salma\\Desktop\\Year 4\\Sem 2\\IE 492\\p\\random.
cust. (1).xlsx", sheet_name="Sayfa1").dropna()

veri.head()

OVERPARKING_PRICE_WIRELESS = 30
OVERPARKING_PRICE_DC = 150
INCOME_WIRELESS = 7.8
INCOME_DC = 9.8
NUM_OF_WIRELESS = 6
NUM_OF_DC = 1
NUM_OF_SLOTS = NUM_OF_WIRELESS + NUM_OF_DC
NUM_OF_PLAN_PERIOD = int(np.max(veri["Real çıkış zamanı"]))

Customer_number = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
entry_periods = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
parking_duration = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
energy_demands_per_period = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
real_exits = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
overparkingcus = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
```

```
for customerNo in range(len(veri)):
    station_type = veri.loc[customerNo, "uygun olan charger"]
    t_initial = int(veri.loc[customerNo, "giriş periyodu"])
    t_duration = veri.loc[customerNo, "kaç periyot kalıcak"]
    energy_demand_t = veri.loc[customerNo, "1 periyotta talep ettiği"]
    reel_cikis = veri.loc[customerNo, "Real çıkış zamanı"]
    overparking = 0
    # Boş uygun slot bakalım
    if station_type == "Wireless":
        slot_startingno = 0
        slot_endingno = NUM_OF_WIRELESS
    else:
        slot_startingno = NUM_OF_WIRELESS
        slot_endingno = NUM_OF_SLOTS

    for slotNo in range(slot_startingno, slot_endingno):
        if Customer_number[t_initial, slotNo] == 0:
            # Boş slot bulundu
            # Kalış süresi kadar bu slota atama yapalım
            for t in range(int(reel_cikis-t_initial)):
                Customer_number[t_initial+t, slotNo] = np.copy(customerNo+1)
                entry_periods [t_initial+t,
                                    slotNo] = np.copy(t_initial)
                parking_duration[t_initial+t,
                                slotNo] = np.copy(t_duration)
                energy_demands_per_period[t_initial+t,
                                            slotNo] = np.copy(energy_demand_t)
                real_exits[t_initial+t, slotNo] = np.copy(reel_cikis)
                overparkingcus[t_initial+t, slotNo] = (t>=t_duration)
            break

TotalOptimizedEnergyIncome = 0
TotalOverparkingIncome = 0

for t in range(NUM_OF_PLAN_PERIOD):
    print("Time period:" + str(t))
    income_energy = 0
    for n in range(NUM_OF_WIRELESS):
```

```
        if parking_duration[t][n] >0:
            income_energy += energy_demands_per_period[t][n] * INCOME_WIRELESS
    for n in range(NUM_OF_WIRELESS,NUM_OF_SLOTS):
        if parking_duration[t][n] >0:
            income_energy += energy_demands_per_period[t][n]  * INCOME_DC
    print("Optimized Energy Income:" + str(income_energy))

    cost_overparking = 0
    for n in range(NUM_OF_WIRELESS):
        cost_overparking += overparkingcus[t][n] * OVERPARKING_PRICE_WIRELESS
    for n in range(NUM_OF_WIRELESS,NUM_OF_SLOTS):
        cost_overparking += overparkingcus[t][n] * OVERPARKING_PRICE_DC
    print("Overparking Income: " + str(cost_overparking))
    TotalOptimizedEnergyIncome +=income_energy
    TotalOverparkingIncome +=cost_overparking

TotalIncome = TotalOptimizedEnergyIncome+TotalOverparkingIncome

print("Total Optimized Energy Income: {:.2f} TL".format(TotalOptimizedEnergyIncome))
print("Total Overparking Income: {:.2f} TL".format(TotalOverparkingIncome))
print("Total Income: {:.2f}".format(TotalOptimizedEnergyIncome +
TotalOverparkingIncome))
```

A.4. OPIM Model Code

```python
import docplex.mp.model as cpx

Sw = 11
Sdc = 4
Ew_d = 43.086
Edc_d = 69.738
K = [1,2,3,4,5]
Kw = [1,2,3]
Kdc = [4,5]

# Since the index k starts from 1, the first elements of the f and w variables
#are taken as dummy in order to equalize the indices

f = [0,2700,7850,13000, 40000,70000]
w = [0,7.4, 11,22,90,180]


model = cpx.Model(name="MIP Model")

# Decision variables are defined
y = {k: model.binary_var(name="y_{0}".format(k)) for k in K}

z = {k: model.integer_var(name="z_{0}".format(k)) for k in K}

# Objective function
objective = model.sum(f[k] * z[k] for k in K)

#  Constraints are added
#1. Constraint
model.add_constraint(model.sum(y[k] for k in Kw) == 1, ctname="Constraint_1")

# 2. Constraint
model.add_constraint(model.sum(y[k] for k in Kdc) == 1, ctname="Constraint_2")

# 3. Constraint
for k in Kw:
    model.add_constraint(z[k] <= Sw * y[k], ctname="Constraint_3_{0}".format(k))

# 4. Constraint
for k in Kdc:
    model.add_constraint(z[k] <= Sdc * y[k], ctname="Constraint_4_{0}".format(k))

# 5. Constraint
model.add_constraint(model.sum(w[k] * z[k] for k in Kw) >= Ew_d, ctname="Constraint_5")

# 6. Constraint
model.add_constraint(model.sum(w[k] * z[k] for k in Kdc) >= Edc_d, ctname="Constraint_6")

# Model solving
model.minimize(objective)
model.solve()

# Results are printed
print("Solution status:", model.solution.solve_status)
print("Solution value: ", model.solution.get_objective_value())

for v in model.iter_variables():
    print(v," = ",v.solution_value)

# Ew and Edc values Equi. Calculating from 21 and 22 in the report

toplam = 0
for k in Kw:
    toplam += w[k] * model.get_var_by_name("z_" + str(k)).solution_value
print("Ew= " + str(toplam))

toplam = 0
for k in Kdc:
    toplam += w[k] * model.get_var_by_name("z_" + str(k)).solution_value
print("Edc= " + str(toplam))
```

A.5. OEOM Model$_t$ Code

```python
import numpy as np
import pandas as pd

# Get data from excel file
veri = pd.read_excel("C:\\Users\\salma\\Desktop\\Year 4\\Sem 2\\IE 492\\p\\random.cust. (1).xlsx", sheet_name="Sayfa1").dropna()



veri.head()

OVERPARKING_PRICE_WIRELESS = 30
OVERPARKING_PRICE_DC = 150
INCOME_WIRELESS = 7.8
INCOME_DC = 9.8
NUM_OF_WIRELESS = 6
NUM_OF_DC = 1
NUM_OF_SLOTS = NUM_OF_WIRELESS + NUM_OF_DC
NUM_OF_PLAN_PERIOD = int(np.max(veri["Real çıkış zamanı"]))

Customer_number = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
entry_periods = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
parking_duration = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
energy_demands_per_period = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
real_exits = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))
overparkingcus = np.zeros((NUM_OF_PLAN_PERIOD, NUM_OF_SLOTS))


for customerNo in range(len(veri)):
    station_type = veri.loc[customerNo, "uygun olan charger"]
    t_initial = int(veri.loc[customerNo, "giriş periyodu"])
    t_duration = veri.loc[customerNo, "kaç periyot kalıcak"]
    energy_demand_t = veri.loc[customerNo, "1 periyotta talep ettiği"]
    reel_cikis = veri.loc[customerNo, "Real çıkış zamanı"]
    overparking = 0
    # Boş uygun slot bakalım
    if station_type == "Wireless":
        slot_startingno = 0
        slot_endingno = NUM_OF_WIRELESS
    else:
        slot_startingno = NUM_OF_WIRELESS
        slot_endingno = NUM_OF_SLOTS

    for slotNo in range(slot_startingno, slot_endingno):
        if Customer_number[t_initial, slotNo] == 0:
            # Boş slot bulundu
            # Kalış süresi kadar bu slota atama yapalım
            for t in range(int(reel_cikis-t_initial)):
                Customer_number[t_initial+t, slotNo] = np.copy(customerNo+1)
                entry_periods [t_initial+t,
                               slotNo] = np.copy(t_initial)
                parking_duration[t_initial+t,
                            slotNo] = np.copy(t_duration)
                energy_demands_per_period[t_initial+t,
                                         slotNo] = np.copy(energy_demand_t)
                real_exits[t_initial+t, slotNo] = np.copy(reel_cikis)
                overparkingcus[t_initial+t, slotNo] = (t>=t_duration)
            break

TotalOptimizedEnergyIncome = 0
TotalOverparkingIncome = 0

for t in range(NUM_OF_PLAN_PERIOD):
    print("Time period:" + str(t))
    income_energy = 0
    for n in range(NUM_OF_WIRELESS):
        if parking_duration[t][n] >0:
            income_energy += energy_demands_per_period[t][n] * INCOME_WIRELESS
    for n in range(NUM_OF_WIRELESS,NUM_OF_SLOTS):
        if parking_duration[t][n] >0:
            income_energy += energy_demands_per_period[t][n]  * INCOME_DC
    print("Optimized Energy Income:" + str(income_energy))

    cost_overparking = 0
    for n in range(NUM_OF_WIRELESS):
        cost_overparking += overparkingcus[t][n] * OVERPARKING_PRICE_WIRELESS
    for n in range(NUM_OF_WIRELESS,NUM_OF_SLOTS):
        cost_overparking += overparkingcus[t][n] * OVERPARKING_PRICE_DC
    print("Overparking Income: " + str(cost_overparking))
    TotalOptimizedEnergyIncome +=income_energy
    TotalOverparkingIncome +=cost_overparking

TotalIncome = TotalOptimizedEnergyIncome+TotalOverparkingIncome

print("Total Optimized Energy Income: {:.2f} TL".format(TotalOptimizedEnergyIncome))
print("Total Overparking Income: {:.2f} TL".format(TotalOverparkingIncome))
print("Total Income: {:.2f}".format(TotalOptimizedEnergyIncome + TotalOverparkingIncome))
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