Optimizing Charging Station Turnover During Peak Demand

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***Abstract*—This project examines the optimization of turnover during peak demand at EV charging stations through various business models which use elements of game theory, such as Nash equilibrium based negotiations between customers or new pricing concepts. Queuing at charging stations is a growing problem due to the increasing popularity of electric vehicles, so new approaches are needed to minimize waiting times and congestion at charging stations without expanding the infrastructure. This paper examines the extent to which business models can be used to optimize the turnover of a charging station. The application of game theory methods, such as negotiation, to achieve a Nash equilibrium, has yielded encouraging results in terms of optimising turnover. For this purpose, a data-driven modeling approach is used to simulate new business models within an agent-based simulation and to evaluate them against a baseline and against each other.**

***Index Terms*—Multiagent-based Simulation, Game Theory, EV Charging, Turnover optimization, Business Models**

I. Introduction

In recent years, there has been an increase in the number of electric vehicles, which has been promoted as a strategy to mitigate climate change and reduce CO_2 emissions [1] [2]. Electric cars are also being purchased in Switzerland as a way of tackling climate change and reducing CO_2 emissions. This statement is supported by Table I, a survey carried out by the Touring Club Switzerland in collaboration with the GFS Bern to analyse the prevailing reasons and motivations for the purchase of electric vehicles in Switzerland between 2019 and 2023.

TABLE I: Survey on the reasons for buying an electric car in Switzerland 2019 to 2023 [3]

Reasons	2019	2020	2021	2022	2023
Climate/CO_2 emissions	67%	65%	67%	53%	47%
Electric cars are the future	34%	35%	40%	29%	-
Increasing range of the vehicles	-	-	-	26%	25%
Sufficient charging options	13%	14%	17%	16%	20%
Rising oil prices and shortages	-	-	-	18%	20%

The results of the survey show that climate change and the reduction of CO_2 emissions remain the main reasons for purchasing electric vehicles. This is also supported by the fact that respondents see electric vehicles as a key component of future transport solutions. Since 2022, there has been an increase in other reasons for purchase, such as improving the range of electric vehicles or the price of oil and scarcity of resources. In addition, the availability of charging infrastructure is becoming increasingly important. The need and motivation to purchase electric vehicles is supported by Figure 1, which shows the number of new registrations of electric vehicles in Switzerland and Liechtenstein over the years.

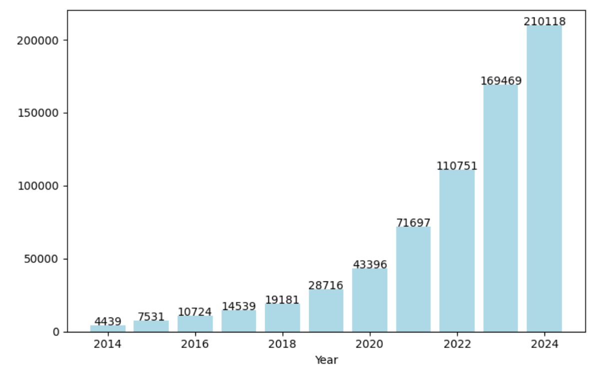

Fig. 1: New EV registrations per year in Switzerland and Liechtenstein conducted by the Federal Statistical Office (BFS) and the Federal Road Traffic Office (ASTRA) [4] [5]

From 2014 to 2024, the number of new registrations increased from 4439 to 206131, which illustrates the importance of electric vehicles in Switzerland [4]. This trend is also clearly supported by a survey conducted by Auto-Schweiz on the choice of drive system when buying a car in Switzerland in 2022: over 60 percentage want to buy a car with at least a partly electric drive system, and just under half would buy a purely electric car[6]. According to existing literature, the number of electric vehicles (EVs) worldwide is expected to reach 50 million by 2030 [7]. The growing demand and number of electric vehicles is likely to lead to longer waiting times and queues at charging stations [8]. This creates the problem of charging station overload and has been documented as a challenge for charging station operators as it hinders electric vehicle users to charge and leads to longer waiting times[9] [10]. Charging stations are not operating at maximum efficiency, and as the battery capacity of electric vehicles increases, the time required to fully charge them also increases [11]. This inefficient utilization of charging space has the potential to result in missed opportunities for charging station operators to generate turnover[12]. To address this issue, it is necessary to implement optimization strategies that enhance the utilization rate of charging stations without the need for additional infrastructure [13].

The objective of this bachelor's project is to optimize usage in during peak demand using game theory methods such as negotiation and balancing the interests of charging station owners as well as electric vehicle users to optimize turnover. To achieve this goal, different business models with different pricing strategies and/or game theory based negotiations between customers are simulated on a dataset of customers generated in a data-driven modeling approach. The simulation encompasses a charging station with high demand, which is simulated across the different business models, which are evaluated in terms of their impact on charging behavior and turnover growth compared to the baseline.

This project is organized as follows. Section II provides the necessary background information and related work to create an understanding of fundamental components. Section III outlines the design and structure of the simulation and explains some of the implementation concepts that are important for simulating and supporting the different business models. Section IV evaluates how well the business models achieve the stated goals. Section V discusses the extent to which the stated goals were achieved, as well as the difficulties, lessons learned, and changes that occurred during the course of the project..

II. Fundamentals

This section provides a foundation of fundamental background concepts, along with a list of related works.

A. Background

The project is based on various external concepts and data sources to model the different subsystems such as the customer data set or the simulation itself. The following paragraphs outline which concepts and collected data were used and incorporated into the project.

1) Data-Driven Modeling: The simulation is based on a data-driven model, where a data-driven and agent-based approach is employed to simulate complex real-life scenarios. The data-driven approach is based on empirical data in the form of observations and literature research [14][15]. For example, to ascertain the peak demands, real-time occupation of charging stations are observed and the values are extracted to normalize them. The data is then interpolated so that probabilities can be determined, which in turn can be used to generate customer arrival times. Additional data points are also collected to create a data set about the customer, including information about the vehicle type and its capacity, as well as the customer's willingness-to-pay (WTP).

The data-driven approach is responsible for controlling the behavior of individual agents whose actions and states are analyzed using the agent-based approach. The behavioral patterns of these agents at the micro level are described, evaluated and combined with the aim of making hypotheses about their behavior based on the data-driven analysis. By evaluating agent aggregation at the micro level and assuming specific distributions of charging behavior and charging station usage, the micro-macro link is ensured. Furthermore, the aggregated turnover can be measured and compared to the baseline, and the interaction tendencies of the agents can be identified.[15]

2) Customer Generation: In order to conduct the simulation, it is necessary to create a customer dataset that is as representative as possible. The following sections will demonstrate, for the various attributes of the customer dataset, what initial data was utilized and how it is represented in the dataset.

a) Arrival Times: The arrival times determine the arrival of an agent for charging, which must be as accurate as possible and based on real-world data. The data is derived from real-world data by observing the live occupancy of charging stations over several days in Switzerland [16]. The data is then extracted and normalized. The normalized data is then interpolated to give us some probabilities that can then be assigned to an agent to give them accurate times.

b) Willingness To Pay: As part of a study conducted in Germany, a choice-based conjoint analysis was conducted to determine the willingness to pay (WTP), i.e., the amount that customers are willing to pay extra per kWh, and then compared to the commercial providers[17]. [18] The Willingness to Pay (WTP) is influenced by various factors, including geographical location, competitive market conditions, and plug and station power. For instance, prices in urban centers tend to be lower compared to suburban areas due to the utilization of stations, because lower utilization means higher costs [18][19]. Due to the limitations and scope of this project, commercial provider rates throughout Switzerland were retrieved. Further research and surveys can be conducted in the future to determine a more accurate WTP. As demonstrated in II, the following prices for direct current (DC) charging, based on various providers, were recorded as of October 2024:

TABLE II: Charging rates for DC charging in Switzerland. Data from: [20][21][22]

Provider	DC Charging per kWh [CHF]
MOVE	0.70
Plug'n Roll	0.83
Evpass	0.98
eCarUp	1.19
Tesla	0.40
Seco	0.65 - 0.70

The prices of the various providers of charging stations within Switzerland [20] were retrieved and used as a reference together with the basic price specified and published by the State Secretariat for Economic Affairs (SECO)[21]. The mean value determined in this way was then implemented as the standard rate within the project. In order to estimate the willingness to pay, the calculated standard rate was compared with the highest rate charged by a providerII, thereby obtaining a range of willingness to pay. Considering that the operating costs of gas vehicles are 50-70 percentage points [23] higher than those of electric vehicles, it can be argued that the willingness to pay could be even higher. The willingness to release is essentially the inverse of the WTP, representing the amount of Swiss francs per kilowatt that a customer would be willing to receive in order to release their spot.

c) Willingness to wait: Waiting time is defined as the duration a customer must wait in line before being able to charge their vehicle. A model-based prediction derived from a survey conducted in Japan among 60,000 EV owners offers a valuable indication of the distribution of allowable waiting times[24]. The survey results indicate that nearly 85 percentage of respondents consider waiting times above 15 minutes to be too high or not allowable. The distribution of acceptable wait times is dependent on the location of the charging station, such as workplace stations or ones next to the highway [24]. Within the simulation, wait times are assumed to be distributed linearly between 0 and 15 minutes, after which customers are likely to leave the station.

d) Battery Capacity: The battery capacity of the customer's vehicle is determined on the basis of the battery capacity of the five most popular electric vehicles (EVs) in Switzerland, as measured by new registrations [25]. These vehicles are then matched with their corresponding battery capacities, which are assigned based on their likelihood as determined by sales figures.

e) Target Battery Level: It is hypothesized that customers who arrive have a SOC between 10 and 40 percentage points and that they charge their vehicle to at least 30 percentage points or to full charge. This is most frequently observed with less than 90 percentage points[26]. However, this assumption could vary in reality and depending on the location and the utilisation of the charging station [19], so further investigation may be worth exploring in the future.

f) Number of Customers: As the simulation is supposed to solve a future problem where EVs have a very high market share, Norway, with the highest EV market shares at the moment [27], is a good reference point for some figures.

Monitoring of a station in Oslo [10] that had 10 charging points from October to December showed that during these months there were on average about 190 charging events per day and that the station had significant queuing, if scaled down to the station in the simulation with 6 charging points this would be about 114 charging events per day, and since the simulated station has a power of 40kW instead of the 50kW of the monitored station, scaling down the charging events per day to an average of 100 should result in a demand slightly above the monitored station in Oslo. Over 30 days this results in a total of 3000 customers trying to charge at the station.

3) Charging Station: The simulated charging station is intended to represent the most popular charging station in Switzerland, the most common charging power is in the 23 to 42 kW range [16], the station in the simulation provides 80 amps at 500 volts, which equals 40 kW. It is also assumed that the station is able to deliver full power to all 6 charging points within the station. The type of connector and the type of charging are not taken into consideration in the simulation.

4) Business Models: In order to develop a business model, it is essential to consider the following components: strategic choices, value creation, value capture, and the value network.[28]

In order to develop a business model, it is essential to identify the target customer base, the value proposition and the service offered, and to ascertain the revenue streams. The focus is on drivers of electric vehicles who require a charging solution. The service provider provides the infrastructure and aims to generate revenue from charging electric vehicles. Revenue mechanisms encompass the income generated from charging vehicles. The objective is to adopt a success-oriented approach to increase turnover [29]. The business models are based on two key principles: the fact that cars with a higher SOC charge more slowly in order not to damage the battery by keeping the OCV below a certain threshold [30], and the fact that customers whose car has a lower SOC have a higher willingness to pay [31].

a) Smart Pricing Model: The Smart Pricing model is a straightforward system designed to regulate customer usage duration and prevent overcharging at charging stations. It employs a dynamic switching strategy, where customers with higher State-of-Charge (SOC) are substituted with those having lower SOC. This approach is implemented through the Constant Current-Constant Voltage (CC-CV) algorithm, a widely adopted technique that prevents overloading of lithium-ion batteries, ensuring their longevity [30] [32] The charging change is regulated by this algorithm. The CC-CV algorithm is composed of two phases. Initially, the battery is charged at a constant current until it reaches approximately 4.2 V, at which point it transitions to the second phase, the constant voltage phase [30]. In this phase, the voltage is maintained at a constant level while the current decreases exponentially until it reaches the minimum threshold value, which is typically 0.1C [30] [33][34]. The algorithm utilises the Open Circuit Voltage (OCV), which is defined as the voltage of the battery. Elevated OCV levels can result in long-term battery damage [32]. Once the OCV attains the 4.2 V threshold, it is crucial to reduce the charge current exponentially to maintain a constant OCV below the threshold. The OCV can be determined by the SOC through interpolation, which involves the retrieval of values from laboratory experiments to establish the OCV-SOC relationship[35][30][34]. This ensures that the battery always has the equivalent OCV next to the SOC. In this context, when the SOC reaches 80 percentage, the charging will switch to CV, which results in higher charging rates. Given the absence of research on a business model similar to this one, which adapts prices based on the SOC and the cc-cv algorithm, questions have been raised regarding the feasibility of charging different amounts for different SOCs and the possibility of someone spoofing their SOC to obtain lower prices.

b) Release and Reward Model: The release and reward model takes advantage of the fact that low SOC/efficient customers or new customers have a higher willingness to pay, and offers arriving customers the opportunity to try to skip the queue and get a spot immediately by having them pay a fee, the customers who are already charging are then asked if they are willing to leave the station for a future discount, should they accept, the arriving customer will swap spots, a portion of the fee is used to fund the discount for the leaving customer. This should not only increase revenue by swapping efficient charging customers with inefficient charging customers, but also increase profits with the skip queue fees collected.

c) Auction Model: This business model is based on the principle of an auction, in which electric vehicle users can place bids independently depending on their willingness to pay. An auction functions so that a seller offers something and at least one buyer can purchase it by placing a bid [36] [37]. In the context of the application of the business model to the simulation, each agent now has the additional option of attending an auction instead of waiting or leaving, whereupon they are included in a pool with other participants. The basis for determining the highest bidder is a 'hidden auction' in which the bids are not visible to others; in this case, it is each agent's willingness to pay [36]. In order to prevent the occurrence of malicious strategies, the individual who is responsible for the charging process is prohibited from putting their spot up for auction. Instead, the individuals who are waiting are permitted to initiate an auction. Following the determination of a winner, a request for negotiation will be directed to the individual who is responsible for the charging process. Following the determination of the highest bidder, the winning party will enter into negotiations for the charging spot. If this arrangement is mutually beneficial, as indicated by a Nash equilibrium, the charging spot will be subject to change. The winner pays the bidded amount based on the wtp and the provider gets a provision for helding the auction. In such a scenario, the provider is able to generate profit, whilst simultaneously increasing the utilisation of the station. For the individual who is charging, receiving a bonus is a more advantageous strategy than fully charging their batteries. For the winning bidder, the outcome is determined by their WTP, and they also benefit from a reduction in waiting time, which is also the most beneficial strategy for them.

B. Related Work

The simulation is built using an agent-based modeling approach[38], which is a popular method for modeling systems consisting of autonomous, interacting agents, these agents are created using a data-driven modeling approach [14] [15]. A key concept of the simulation is how to avoid the effect of charging algorithms [30] that cause changes in charging speed based on SOC [35] by prioritizing customers with low SOC, and replace them using game theory based approaches [39].

Related Work	Applied concepts
Parsons et al. (2002) [39]	Game Theory in agent-based systems
Antelmi et al. (2022)[40]	Agent-based simulations
Macal & North(2009)[38]	Agent-based modeling
Habib et al. (2021).[14]	Data-driven modeling
Sajjad et al. (2016) [15]	Data-driven agent-based modeling
Weixiang Shen et al. (2012)[30]	Charging algorithms
Elmahdi et al. (2021) [35]	Battery state of charge

TABLE III: Summary of related work

III. Design and Implementation

A. Design

For the implementation, the MESA framework for Python [41] is used, namely its model component, which includes classes for the model, which is the core of the simulation, the agent component, on which the different agents such as the customer and the provider are based, and the scheduler, which provides different activation orders for the agents.

As shown in figure **??** the simulation reads the various variables, such as the number of days of the simulation or the price for a kw of electricity, etc. from the config, and then creates environments / mesa models for each business model, these environments are then simulated independently on the same customer data set. 1440 model steps are executed per day of simulation, which is one step per minute. During each step of the simulation, the agents decide what action to take based on their state, which then are saved in a timestamped csv. The output CSV can be analyzed and evaluated with other code, or imported into tools such as Disco [42] to gain a deeper understanding of the process.

B. Implementation

The simulation consists of various entities and agents that are placed within the environment / model. The following sections explain how these agents work and interact, and how some of the key principles are implemented.

1) Environment Model: The Environment Model class, creates the different agents, based on the configured variables and the customer data generated by the Customer Generator, the customer agents are then added to the Mesa Base Scheduler [41] , in order of ascending arrival time, which simplifies some parts of the simulation like the queue, where there is no need to keep track of the order of the customers, since the customer who arrived first is simulated first, he will able to claim the first free spot once a step is executed, before the customers behind him in the queue get a chance.

2) Charging Station: The charging station is an entity that keeps track of which customers are currently charging, and provides methods for occupying, releasing or swapping a spot with another customer, and for charging the car once a customer has occupied a spot, here an imitation of the CC CV algorithm is used, which reduces the amperage after 80% SOC, in reality how fast and at what SOC the amperage decreases would be different for each battery and car, but is not simulated here.

3) Customer Agent: The customer agent is a state machine that, depending on its state, can perform different actions, each for each minute/step of the simulation, it can perform different actions that are then saved in a csv, including some attributes of the customer at that point in time, which are later used in the evaluation. These actions only reflect the changes of the last minute, i.e. a customer who is charging makes a payment for his amount every minute, and not a payment for the whole charging amount in the end, but the total payment can be calculated when looking at the output of the simulation.

4) Provider Agent: There are different providers for different business models, the provider can then be changed in the environment depending on which business model is to be simulated. The providers themselves do not have a step function, since they do not perform actions of their own, but only react to actions / requests of the customers.

5) Agent Interaction: Because the customer needs to be able to interact with different provider agents offering a different business model, the methods used may change from one business model to another because the type of interaction between the agent changes, with the result that if a new business model wants to implement a new type of interaction, such as buying a subscription, it wouldn't be enough to simply add a new provider, the code for the customer agent would also need to be changed to handle that new type of functionality.

Using the skip queue request of the release and reward model as an example, the customer agent code has methods to calculate whether the customer is willing to pay the price offered by the provider. When the customer arrives at the station, and cannot get a spot, he checks to see if the provider has a "request_skip_queue" method (cf. Listing 1).

```
elif hasattr(self.model.provider,'request_skip_queue'):
    if(self.evaluateSkipQueueForExtraPayment()):
        if(self.model.provider.request_skip_queue(self)):
```

Listing 1: Request Skip Queue

If the provider provides this method, the customer will then evaluate if the skip queue price is within his threshold, and only then will he request to skip the queue.

6) Nash Equilibrium Implementation: Achieving a Nash equilibrium between the different parties was one of the main goals, the release & reward and auction model are designed in such a way that the provider can never loose, there might be changes when changing prices or provider cuts, but in the worst case they perform the same as the baseline. For the release and reward model, it is important that the customers who swap spots both benefit from the swap. The simulation aims to replicate how it would work in real life, if the customer finds it worthwhile to skip the queue, he will request the provider to skip the queue, the provider will then ask the customers who are currently charging, starting with the highest SOC / least efficient charger, if they are willing to release their spot for a future bonus. Only if the provider finds a swap partner will the swap be initiated, thus ensuring the Nash equilibrium between the two customers.

7) Willingness to Pay implementation: Since a customer's willingness to pay is not static, but depends on the SOC of the vehicle, the attribute represents an amount the customer is willing to pay extra per kilowatt, which when combined with the standard price of the charging station is essentially a price threshold the customer has; if the actual price is above his threshold, for example because he has reached 80% SOC in the dynamic pricing model, he will stop charging and leave the station.

```
if self.check_price_threshold():
    ...
    charge()
    ...
else:
    if (self.model.charging_station.release_spot(self)):
        self.state = CustomerState.LEFT_STATION
        self.perform_action(CustomerActions.LEFT_BECAUSE_PRICE_IS_TO_HIGH, 0, 0, 0)
```

Listing 2: Check Price Threshold

On the other hand, if a customer has a threshold above the actual price (cf. Listing 2), they may take advantage of some of the offerings provided by the different business models, such as the skip queue option.

While evaluating whether to pay the extra price to skip the queue, the customer divides the skip-queue price by the amount of kWh he plans to charge, if the amount he has to pay extra per kWh is less than his WTP extra per kWh, he considers the offer worthwhile and asks the provider to skip the queue. This logic is implemented in the code section in Listing 3.

```
def evaluateSkipQueueForExtraPayment(self):
    self.extra_per_kwh = (self.model.provider.
        skip_queue_price/(self.
        target_battery_level- self.
        current_battery_level)*1000)
    return (self.extra_per_kwh <= self.
        willingness_to_pay_extra_per_kwh)
```

Listing 3: Check Price Threshold

IV. Results and Evaluation

This Section outlines and compares the performance of the different business models, and also assesses the accuracy of the simulation.

While the distribution of customer arrival times is somewhat noisier than the actual arrival data on which it is based. However, over several different generated datasets, the distribution will approach the one in the collected data.

The baseline was determined following the execution of a 30-day multi-agent simulation involving 3,000 customers. This baseline facilitates the calculation of key metrics, including the number of consumers who paid for charging at the station, the turnover for provider collected from customers, and the aggregate electricity consumption measured in watts. Each business model was then implemented and simulated to facilitate analysis of the differences based on the key metrics, as well as the behavior of each agent.

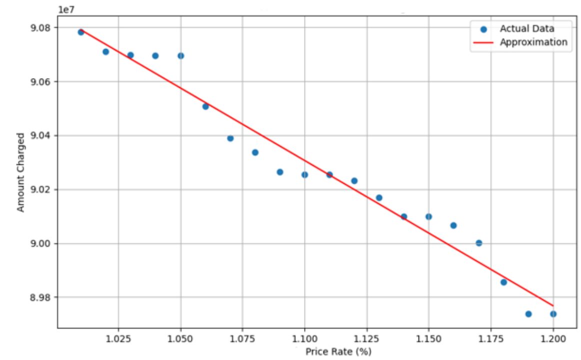

Fig. 2: Price Rate vs KW's Charged

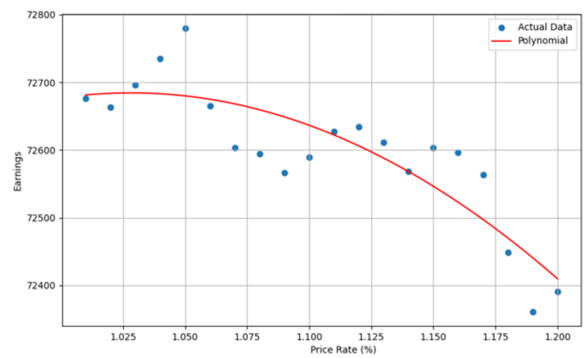

Fig. 3: Price Rate vs Earnings

A. Smart Pricing Model

The smart pricing model has been developed to address the issue of customers charging for extended periods at charging stations. The model's fundamental objectives are threefold: to minimize overcharging, to reduce wait times, and to enhance turnover. Smart pricing is applied as soon as the customer reaches an SOC of 80 percentage, which results in higher charging rates. This method depends on the percentage of increase, which will show different outcomes for different rates. In order to predict the various possible outcomes, a linear regression analysis is conducted to forecast the impact of an increase ranging from 1% to 20% on the outcome.

As shown in Figure 2, the amount of kilowatts charged decreases as the price increases, indicating that the assumption that the higher price would free up space for more efficient chargers and therefore increase the amount of kilowatts that could be charged is at least partially incorrect, while this may be the case during peak demand, the higher price also discourages customers from charging during off-peak times, also indicating that this business model does not actually have a Nash equilibrium, as the supplier profits more if it does not apply the additional charge during off-peak times.

However, as shown in Figure 3, the amount earned remains roughly the same up to a 5% price increase, *i.e.*, the provider earns slightly more with less electricity used, so the business model is successful in improving profitability for the provider, but fails to improve any of the aspects the customer is interested in.

In terms of profitability or money earned per kilowatt sold, a 5% price increase is also ideal for the provider and performs better than the other percentages simulated.

Theoretically, the business model could be improved by removing the price increase when there is no one waiting in the queue, but this would probably make the business model difficult to apply in real life because the price is not transparent at all.

B. Release and Reward Model

In the simulation, the release and reward model had a release fee of CHF 5 that customers had to pay to jump the queue, the provider got CHF 1 as a cut, and the remaining 4 CHF was given as a bonus to the customer who willingly released his spot.

This configuration resulted in 113 swaps over the 30 days (results may vary if the simulation is run with newly generated customer records), as shown in the decision tree in Figure 4. This indicates that at a crowded station like

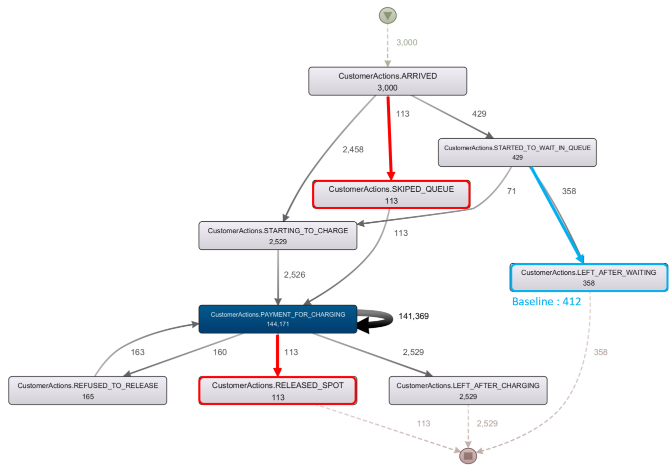

Fig. 4
Release and Reward model - Decision Tree

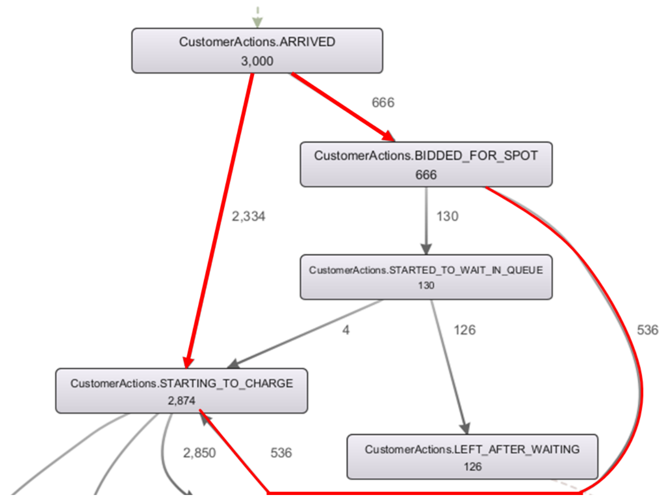

Fig. 5: Auction Model - partial Decision Tree

the one simulated, nearly 4 customers per day will pay a fee to skip the queue, and just as many will accept to give up their seat to receive part of the paid fee as a future discount. The number of customers willing to pay to skip the queue is actually higher than 113, but since no one is willing to give up their spot, these customers simply have to wait normally. Here, the performance of the business model could be greatly improved by simply forcing the paying customers to give up their seats, but this way the business model would lose the Nash equilibrium aspect of the negotiation. Compared to the baseline, the model allowed 54 more customers to load at the station, the reason this is not 113 is probably because the customers who jump the queue cause some other customers to leave the station because they have to wait longer.

C. Auction Model

The results of the auction model indicate that customer behavior at the micro level differs from the baseline. Consequently, a greater number of customers are more likely to engage in this business model, as evidenced by the increase in the number of customers who are able to charge. This business model is the most profitable for the provider in terms of revenue. It allows the provider to generate additional revenue in the form of fees for each auction held.

As illustrated in figure 5, the decision tree of the auction model reveals that all arriving customers have the option to either obtain a charging spot directly or to bid for a charging spot. This model allows any customer to bid as there is no minimum bid amount. This ensures that all customers will try to bid in order to jump the queue. A surprisingly high 80% of bids result in a swap, meaning that 536 of the 666 customers who placed a bid bid high enough for someone to accept their bid. This increase in swaps compared to the release and reward model can be explained by the fact that there is no limit to the swap price, and bidders who might not be willing to pay the fee in the release and reward model are still able to swap in the auction model because someone has been found who is willing to release their spot for a lower fee. On the other hand, there are also bidders who pay a higher price and are able to get someone with a lower willingness to release to swap. Overall, this business model increases customer engagement, which allows for more negotiations and swaps, which in turn leads to an 11.05 percent increase in the number of customers able to charge. The provider receives a fee for each auction held, which also increases the payment to the provider by 5.99 percentage points.

D. Discussion

As illustrated in Table IV, there are certain relative differences in the percentage of each business model in comparison to the baseline. An analysis of the various

TABLE IV: Relative differences to the baseline [%] (1) Num. customers able to charge at the station; (2) payment by customer to provider [CHF]; (3) total amount of charged power [Watts]

	Baseline	Smart Pricing Model		Release and Reward Model		Auction Model	
Customers	2588	2602	+ 0.54%	2642	+ 2.09%	2874	+ 11.05%
Payment	72645.88	72779.75	+ 0.18%	74037.38	+ 1.92%	76995.40	+ 5.99%
Watts	90807344.33	90694942.71	- 0.12 %	92405482.36	+ 1.76%	95273788.44	+ 4.92%

business models reveals a consistent trend of an increase in customers, suggesting that more customers are able to charge at the charging stations within a given time period. The Smart Pricing Model indicates that while the number of customers has increased, they are charging less, suggesting that customers are not overcharging or spending excessive time at the station. This is beneficial in terms of maximizing the utilization of charging stations and reducing peak demand. However, from a financial perspective, this approach is the least profitable. Both the release and reward model as well as the auction model shows some significant increases in all key metrics. The Release and Reward model demonstrates that the utilization of a negotiation method enables providers to generate additional revenue and increase the number of customers able to charge at the station. The auction model, based on auction theory and negotiation techniques, exhibits the most prominent increase in customer ability to charge at the charging station. Furthermore, the generated payment to the provider increases by 5.99 percentage points compared to the baseline, which is the most profitable business model. In order to determine the statistical significance of the outcomes, it is necessary to conduct additional tests. Consequently, the mean value of the payment to the provider is referenced, and its distribution is analyzed. In order to determine the statistical significance of the outcomes. it is necessary to conduct additional tests. The mean of the payment to the provider is therefore taken and its distribution is analysed. The Shapiro-Wilk test is used to compare the w-value of the business model to ascertain whether it is normally distributed.In all cases, the result was a non-normal distribution. Consequently, it can be concluded that the bootstrapping method is a suitable technique for determining the statistical significance of the values and for identifying uncertainties.

TABLE V: Comparison to baseline, with a mean 24.50

	Smart Pricing Model	R&R Model	Auction Model
mean	24.13	25.05	25.66
p-value	0.2478	0.0576	0.0002
Significance	False	False	True

As shown in Table V, only the auction model shows a statistically significant change in the payment to the provider, i.e. it is the only model that generates a significant amount of additional revenue compared to the baseline.

1) Limitations: This project was an approach to identify the extent to which business models can be used to optimize the turnover of an electric charging station. Using data-driven modeling, a real customer data set and simulation environment were generated. The implementation of game theory elements, such as negotiation, showed some valuable results that could be an approach to solve this optimization problem in the near future. However, the project encountered two primary limitations: Firstly, the definition of agents within the project was based on specific parameters, allowing for autonomous behavior and decision-making in line with their interests. However, in a real-world setting, numerous additional factors may influence customer behavior, making it impossible to account for all of these variables. This obstacle may be partially overcome in the future with a study on the behavior and preferences of electric car owners. Secondly, the placement and configuration of charging stations can affect the results. For instance, a charging station situated in a city center will differ from one located in a suburban area. Consequently, the heterogeneity of data sources and geographic locations can compromise the accuracy of the results. Given the simulation's objective of addressing future scenarios, it is essential to overcome this obstacle by adjusting certain parameters and conducting experiments with multiple charging stations to enhance the representativeness and make assumptions about the population.

V. Final Considerations

A. Summary

A data-driven modeling approach was employed to create and model a dataset of customers. This approach utilized a combination of observation data and literature research. The customer data set was then evaluated using different business models that were expected to increase revenue during peak demand periods. The results were then analyzed using various tools such as Disco to gain insight into how well the models performed, then their performance was analyzed against each other and it was explained why the models performed well or not.

B. Conclusions

The goal of the bachelor's project was to find business models that optimize the turnover of a charging station during peak demand by simulating the different business models, comparing them with each other and evaluating which models work. Furthermore, the simulation should be as realistic as possible and allow others to evaluate the business models using their own data.

The success of the project can be attributed to the creation of optimization approaches in the form of business models. The use of business models facilitates the comparison of results with the baseline, allowing the identification of differences in key metrics and agent behavior.The use of business models in the simulation allowed conclusions to be drawn about the effectiveness and ineffectiveness of turnover optimization. These conclusions show that the use of a business model can have some impact on turnover optimization. The analysis revealed that each business model has a positive impact on the utilization of charging stations, thereby allowing more customers to charge. In contrast, the smart pricing model addresses the utilization of charging stations by preventing customers from overcharging or remaining for extended periods, a benefit that is especially valuable during peak demand periods, but can have negative effects during of peak hours. Furthermore, the practical implementation of this model may not be feasible due to the potential unwillingness of customers to accept a higher charging rate. Consequently, it is essential to carefully adjust the charging rate to ensure optimal turnover. The approaches that involve negotiation and the achieving of a Nash equilibrium have demonstrated significant benefits, such as an increase in the number of customers able to charge, an increase in turnover, and an increase in the sale of electricity, measured in watts.

The effectiveness of the business model is largely due to its negotiation feature, which facilitates the exchange of charging spots between customers when it is mutually beneficial for both parties. The provider benefits financially from these exchanges by collecting skip-queue fees or auction commissions. However, the effectiveness of the pricing model, which uses a pricing strategy to solve this optimization problem, depends on the configuration of the charging rates, as misconfigured rates can potentially reduce turnover.

C. Future Work

As future work, customers could be surveyed about their willingness to pay extra when given the option to skip the queue, their willingness to share, and other attributes. At best, these surveys and the data collection of other attributes would be done at the same station to get accurate results. Furthermore, the feasibility of implementing a smart pricing model could be evaluated by employing diverse methodologies, such as machine learning, and leveraging customer historical datasets. The implementation of the Release and Reward model and the Auction Model in a real-life scenario, taking into account routing options, could be a viable option in a city with multiple charging stations, as well as in the context of geographical factors and differences in customer behaviors.

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APPENDIX

Contribution Statement

Both authors contributed equally to the research, design, execution, and writing of this research.

Code Implementation

Especially since the simulation may not be completely accurate and cannot be applied to all charging stations, it is important to provide the possibility to test the models with improved or different data; this is possible by using the code provided in the GitHub repository https://github.com/JanisEnzler/Charging-Station-Optimization.

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Aid	**Usage**	**Affected Part**
DeepL Write	Translations and rewording	Throughout the work
Elicit	Support with research work	Throughout the work
Disco	Process map and decision tree	For the evaluation
Gtihub Copilot	Full Line Code Completion	Code
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