Comparing Business Models for Optimizing Turnover in Electric Vehicle Charging Stations

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***Abstract*—This paper addresses the central question on how to optimize turnover of electric vehicle charging stations (EVCS) during peak demand. We evaluate and compare different business models (BMs), including smart pricing, release & reward, and auction-based mechanisms, that introduce dynamic pricing and negotiation strategies to reduce congestion and increase station utilization. Queuing at charging stations is a growing problem due to the increasing popularity of EVs, thus, new approaches are needed to minimize waiting times and congestion at charging stations without expanding the infrastructure.**

To assess the impact of different BMs, we use a data-driven agent-based simulation, modeling realistic customer behavior and charging dynamics. Our results show that negotiation-based approaches leveraging game theory and Nash equilibrium can significantly enhance station efficiency. The auction-based model increased turnover by nearly 6% compared to the baseline, demonstrating its potential as a practical solution for peak-demand management. These findings suggest that tailored BMs can play a crucial role in optimizing EVCS operations, striking a balance between provider revenue and customer incentives.

***Index Terms*—Multiagent-based simulation, Game theory, EV charging, Turnover optimization, Business models**

I. Introduction

In recent years, the adoption of electric vehicles (EVs) has surged globally as a strategy to combat climate change and reduce CO_2 emissions [1] [2]. This trend is mirrored in Switzerland, where the motivation to purchase electric vehicles predominantly stems from environmental concerns, as evidenced by a survey conducted by the Touring Club Switzerland in collaboration with GFS Bern. The survey, detailed in Table I, highlights that between 2019 and 2023, tackling climate change and reducing emissions consistently ranked as primary factors driving EV purchases. Additionally, improvements in EV range, fluctuations in oil prices, and resource scarcity have recently emerged as significant motivators.

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.

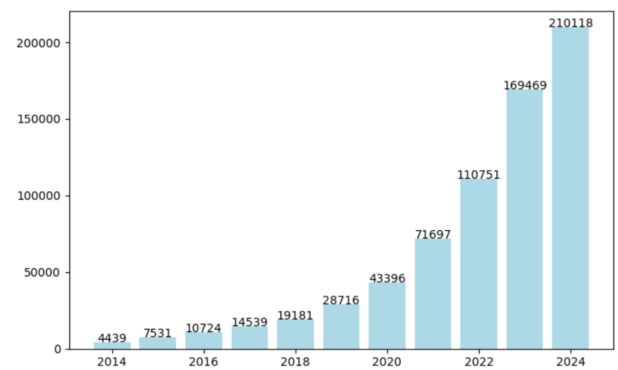

Fig. 1: New EV registrations per year in Switzerland and Liechtenstein conducted by the Federal Statistical Office (BFS) and the Federal Road Traffic Office (ASTRA) [4] [5]

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% 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]. While some EV owners have the option to charge their vehicles at home, a significant portion of users rely on public charging infrastructure. This growing dependency on shared charging stations has been identified as a major challenge for charging network operators, as it not only leads to station overload but also hinders accessibility for EV users, ultimately resulting in extended 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].

This paper proposes and evaluates optimization strategies to enhance the utilization rate of charging stations during peak demand periods without requiring additional infrastructure. Leveraging game theory approaches, such as negotiation and interest balancing between charging station operators and EV users, we explore how these strategies can optimize turnover while ensuring equitable access. Our methodology involves simulating various business models, incorporating dynamic pricing and customer negotiation mechanisms, using a data-driven approach to model high-demand scenarios. These models are evaluated in terms of their impact on charging behavior and revenue generation, providing actionable insights for improving charging station efficiency. All collected data, models, and code is also made available [14].

This paper 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 presents a summary and future work.

II. Fundamentals

This paper builds on various concepts and data sources to model subsystems like customer datasets and simulations.

A. Data-Driven Modeling

The simulation employs a data-driven, agent-based approach to replicate real-life scenarios based on empirical data from observations and literature [15], [16]. Real-time station occupancy data informs peak demand normalization and interpolation, enabling the generation of customer arrival times. Datasets include vehicle types, capacities, and willingness-to-pay (WTP).

Behavioral patterns are analyzed at the micro level, while aggregated data ensures macro-level insights. The analysis evaluates charging behavior, station usage, and interaction tendencies, linking micro-level agent behavior to macro-level outcomes like turnover and station efficiency [16].

B. Customer Generation

The simulation relies on customer attributes derived from real-world data:

- **Arrival times**: based on live station occupancy in Switzerland, data is normalized and interpolated to assign probabilities for agent arrival times [17].
- **Willingness to pay (WTP)**: derived from conjoint analysis in Germany, WTP reflects factors such as geography, market competition, and station utilization [18], [19]. Commercial rates in Switzerland are used as a baseline, and comparisons identify a WTP range [20], [21], [22].
- **Waiting time**: modeled on surveys indicating acceptable wait durations of up to 15 minutes [23].
- **Battery capacity**: inferred from the capacities of the most popular EVs in Switzerland [24].
- **Target SOC level**: customers typically charge between 10% and 90%, depending on location and station utilization [25], [26].
- **Customer volume**: based on Norwegian data, the station is scaled to simulate 100 daily charging events, accounting for differences in station capacity and power [27], [10].

C. Charging Station

The simulated charging station (CS) is intended to represent the most popular CS in Switzerland, where the most common charging power is in the 23 to 42 kW range [17]. 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.

D. Business Models

It is essential to consider the following components in a business model (BM): strategic choices, value creation, value capture, and the value network [28]. To develop a BM, 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 EVs who require a charging solution. The service provider provides the infrastructure and aims to generate revenue from charging EVs. Revenue mechanisms encompass the income generated from charging vehicles. The objective is to adopt a success-oriented approach to increase turnover [29].

- **Smart pricing**: prices are set dynamically based on the state-of-charge (SOC) using the Constant Current-Constant Voltage (CC-CV) algorithm. This approach balances charging efficiency and battery health by adapting the current and voltage during the charging process [30], [31].

- **Release and reward**: customers are offered the option to skip queues by paying a fee, while those vacating their spots receive discounts. This enhances revenue and station utilization by prioritizing efficient customers.
- **Auction**: agents participate in auctions to bid for charging spots, where the highest bidder secures the spot. This approach optimizes profitability and customer satisfaction through dynamic allocation [32], [33].

E. Related Work

The simulation is built using an agent-based modeling approach (ABM) [34], which is widely used to simulate autonomous, interacting agents. Data-driven ABM has been applied to EV charging stations to analyze demand and optimize station placement [15], [16]. However, these studies focus on static optimization rather than real-time interactions between consumers and providers.

TABLE II: Summary of related work

Related Work	Applied concepts
Parsons et al. (2002) [35]	Game Theory in agent-based systems
Antelmi et al. (2022)[36]	Agent-based simulations
Macal & North(2009)[34]	Agent-based modeling
Habib et al. (2021).[15]	Data-driven modeling
Sajjad et al. (2016) [16]	Data-driven agent-based modeling
Weixiang Shen et al. (2012)[30]	Charging algorithms
Elmahdi et al. (2021) [37]	Battery state of charge

Alternative approaches, such as Distributed Constraint Optimization (DCOP) [38] and Multi-Agent Reinforcement Learning (MARL) [39], address scheduling and grid-aware pricing but do not incorporate direct consumer-provider negotiations. Pricing strategies like smart pricing and auction-based mechanisms have been studied independently [30], [35], yet a comparative evaluation of different business models has been not explored.

This paper fills this gap by assessing negotiation-driven business models, where sellers (charging stations) and consumers (EV users) interact dynamically. By integrating game theory principles, including Nash equilibrium, our approach optimizes turnover while balancing station revenue and customer incentives, providing a novel framework for managing peak demand efficiently.

III. Design and Implementation of Business Models

This section elaborates on the design and implementation of the simulation environment for evaluating different business models in electric vehicle charging station (EVCS). The design emphasizes modularity and scalability, ensuring adaptability to various configurations and business scenarios.

A. Design

The design of the simulation environment revolves around three primary components: the *model*, *agents*, and the *scheduler*. Together, they facilitate a flexible and reusable framework for representing the interactions within the EVCS ecosystem.

1) Model: The **model** serves as the foundation of the simulation, encapsulating all global states, variables, and simulation parameters. Key parameters include:

- **Simulation duration**: number of days the simulation runs, divided into minute-level steps.
- **Electricity pricing**: configurable models, such as flat-rate pricing or time-of-use tariffs.
- **Customer data**: predefined attributes such as arrival times, charging needs, and price sensitivity.

The model initializes the simulation environment and manages the creation and state updates of agents. Additionally, it ensures the seamless interaction between agents and provides mechanisms to log simulation data for post-analysis.

2) Agents: Agents in the simulation represent key stakeholders in the EVCS ecosystem. Each agent follows a **state-action framework**, defined as follows:

- **State (S)**: represents the agent's current context (*e.g.*, battery level for customers, grid load for providers).
- **Actions (A)**: a set of possible actions an agent may decide to take (*e.g.*, initiate charging, adjust pricing).
- **Reward (R)**: quantifies the benefit or cost associated with state-action pairs (*e.g.*, revenue for providers or cost savings for customers).

Two main agent types are defined:

- **Customer agents**: simulate EV users with diverse behaviors, including charging preferences, sensitivity to dynamic pricing, and decision-making thresholds.
- **Provider agents**: represent charging station operators implementing different business strategies, such as auction-based pricing or subscription models.

The interaction between agents follows well-defined protocols, enabling a realistic representation of the EVCS operations.

3) Scheduler: As illustrated in Figure 2, the simulation reads configurations from an input file, initializes environments for each business model, and executes minute-level simulation steps. Each step involves agents deciding on actions based on their states, and the outcomes are logged for subsequent analysis.

The **scheduler** determines the activation sequence of agents. A fixed sequential activation, based on the SOC-level, which is a common approach in real-world queue-based operations. This creates a scheduling approach that is closer to a real-world patterns.

B. Implementation

The simulation environment (available in [14]) 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.

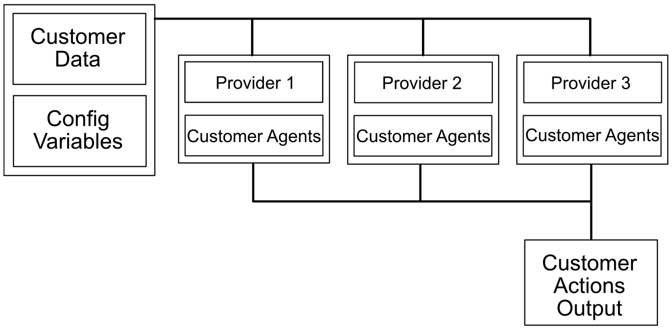

Fig. 2: Simulation Architecture Overview

1) Environment Model: The Environment Model class creates the different agents based on predefined variables and customer data generated by the Customer Generator. These customer agents are then added to the Mesa Base Scheduler [40] in ascending order of arrival time, which simplifies queue management. Since customers are processed according to their arrival order, there is no need for an explicit queue tracking each customer automatically claims the first available charging spot before later arrivals get a chance.

2) Charging Station: The CS 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. Also for charging the vehicle once a customer has occupied a spot. We use an imitation of the CC-CV algorithm, 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 vehicle, but this is not simulated here.

3) Customer Agent: The customer agent is a state machine which, depending on its state, perform different actions for each minute/step of the simulation. It can perform different actions that are then saved in a *.csv*, including attributes of the customer at a point in time, which are later used in the evaluation. These actions only reflect the changes of the last minute. For example, a charging customer makes incremental payments per minute rather than a single payment for the entire session. The total payment can then be derived from the simulation output.

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: Once 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 would not 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 Nash equilibrium between the different parties was one of the main goals. The release & reward and auction model is designed in such a way that the provider can never lose. While adjustments to prices or provider cuts may impact earnings, the worst-case scenario ensures performance remains at least equal to the baseline.

For the release & reward model, it is important that the customers who swap spots both benefit from the swap. The simulation mirrors real-life decision-making: when a customer wants to skip the queue, they request it from the provider. 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 (WTP) 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. When combined with the station's standard price, this forms a price threshold. If the actual charging price exceeds this threshold—such as when the customer reaches 80% SOC under the dynamic pricing model—they will stop charging and leave the station.

Otherwise, if a customer has a threshold above the actual price, 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 2.

```
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 2: Queue Skipping Threshold

IV. Results and Evaluation

This section outlines and compares the performance of the different business models (BM), and also assesses the accuracy of the simulation. Customer arrival times are generated using a data-driven approach, which is done based on real-world data (as described in Section II-B) of CS occupation over several days. Then, data is normalized and interpolated to determine probability distributions for customer arrivals.

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.

A. Smart Pricing Model

The smart pricing model has been developed to address the issue of customers charging for extended periods at CSs. 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%, 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 3, 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.

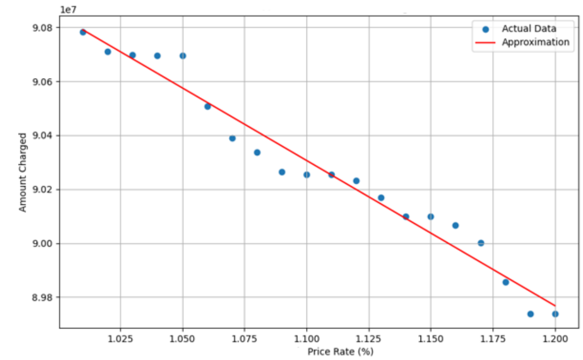

Fig. 3: Price Rate vs KW's Charged

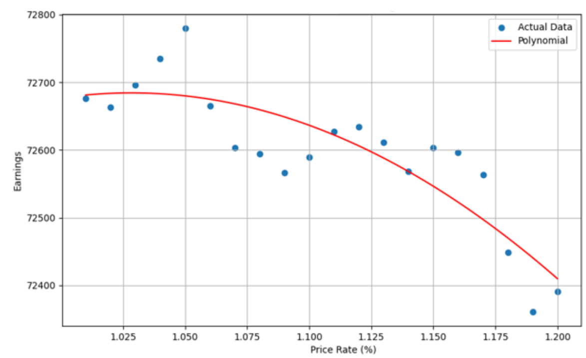

Fig. 4: Price Rate vs Earnings

However, as shown in Figure 4, 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 CHF 4 was given as a bonus to the customer who willingly released his spot.

Over a 30-day period, this configuration resulted in 113 successful spot swaps (results may vary if the simulation is run with newly generated customer records), as shown in the decision tree in Figure 5. This indicates that at a

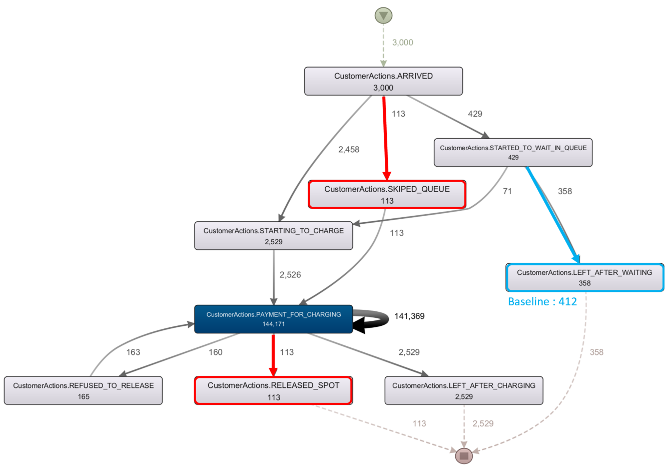

Fig. 5: Release and Reward model - Decision Tree

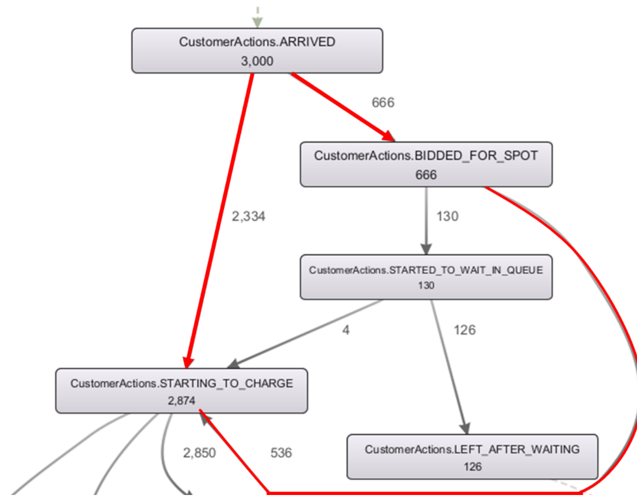

Fig. 6: Auction Model - partial Decision Tree

crowded station like 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 effectiveness of the business model could, in theory, be improved by enforcing mandatory spot releases for paying customers, ensuring that every queue-skipping request is fulfilled, but this would undermine the Nash equilibrium principle by removing the voluntary nature of the exchange and potentially discouraging customer participation. When compared to the baseline, this model enabled 54 additional customers to charge their EVs within the same period. This increase is attributed to the queue-skipping mechanism, which indirectly caused some customers to leave the station when their expected wait time became too long.

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 6, 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 are bidding 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% 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 %.

D. Discussion

As illustrated in Table III, there are certain relative differences in the percentage of each business model in comparison to the baseline. An analysis of the various BMs reveals a consistent trend of an increase in customers, suggesting that more customers are able to charge at the CSs 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 CSs 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

TABLE III: 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%

most prominent increase in customer ability to charge at the CS. Furthermore, the generated payment to the provider increases by 5.99% compared to the baseline, which is the **most profitable** business model.

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 Table IV. 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 IV: 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 IV, 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.

However, we encountered **two primary limitations**: Firstly, the definition of agents was based on specific parameters, allowing for autonomous behavior and decision-making in line with their interests. In a real-world setting, numerous additional factors may influence customer behavior, making it impossible to account for all of these variables. For example, although the auction model resulted in a significant increase in turnover in contrast to other BM models, it does not take into account the additional hardware and software costs involved in making this model operational.

Secondly, the placement and configuration of charging stations can affect the results. For instance, a CS 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 CSs to enhance the representativeness and make assumptions about the population.

V. Final Considerations

A. Summary

This paper investigated the question of which BM can be used to optimize the turnover of an electric CS. Using a data-driven modeling, a real customer data set and simulation environment were created. The integration of game theory elements, such as negotiation, yielded promising results such as the increase of almost 6% in turnover by the auction model, suggesting that these mechanisms could provide effective solutions to the optimization problem in the future.

A data-driven modeling approach was used 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. All data and models are open-source and made available [14].

B. Conclusions

We evaluated business models for optimizing charging station turnover during peak demand. The results revealed that adopting business models enhances utilization (turnover) and revenue by addressing critical factors such as customer behavior and charging station capacity. Notably, the smart pricing and auction models demonstrated tangible benefits, such as increased customer throughput and electricity sales.

While the smart pricing model mitigates overcharging and prolonged station use during peak times, its implementation requires a more careful rate adjustments to balance turnover and customer acceptance. Negotiation-based approaches leveraging Nash equilibrium were effective, yielding increased customer satisfaction and financial gains from skip-queue fees or auction commissions. However, the performance of each model depends significantly on the configuration and customer adaptability. In addition, adopting these models also involve in additional costs related hardware and software to make these systems operational.

C. Future Work

Future work will consider surveys to evaluate customer willingness to adopt features such as skip-the-queue options, sharing preferences, and related behaviors. Collecting and analyzing this data, particularly from specific charging station contexts, would improve simulation accuracy. Additionally, the feasibility of smart pricing models can be enhanced by employing machine learning to analyze historical customer datasets. Implementing models such as Release and Reward or Auction in real-world scenarios, considering routing options, city-wide station networks, and geographical factors, would provide valuable insights into their broader applicability and effectiveness.

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