

Electricity Trading Agent for EV-enabled Parking Lots

Jurica Babic¹(✉), Arthur Carvalho², Wolfgang Ketter³, and Vedran Podobnik¹

¹ Faculty of Electrical Engineering and Computing,
University of Zagreb, Zagreb, Croatia
{jurica.babic,vedran.podobnik}@fer.hr

² Farmer School of Business, Miami University, Oxford, OH, USA
arthur.carvalho@miamioh.edu

³ Rotterdam School of Management,
Erasmus University Rotterdam, Rotterdam, Netherlands
wketter@rsm.nl

Abstract. The reduction of greenhouse gas emissions is seen as an important step towards environmental sustainability. Perhaps not surprising, many governments all around the world are providing incentives for consumers to buy electric vehicles (EVs). A positive response from consumers means that the demand for the charging infrastructure increases as well. We investigate how an existing traditional parking lot, upgraded with chargers, can suit the present demand for charging stations. In particular, a resulting *EV-enabled parking lot* is an electricity trading agent (i.e., broker) which acts as an energy retailer and as a player on a target electricity market. In this paper, we use agent-based simulation to present the EV-enabled parking lot ecosystem in order to model the underlying dynamics and uncertainties regarding parking lots with electricity trading agent functionalities. We instantiate our agent-based simulations using real-life data in order to perform the what-if analysis. Several key performance indicators (KPIs), including parking utilization, charging utilization and electricity utilization, are proposed. We also illustrate how those KPIs can be used to choose the effective investment strategy with respect to the number and speed of chargers.

Keywords: Trading agents · Agent-based simulation · EV-enabled parking lot · Electric vehicles

1 Introduction

Recent years have seen a steady growth in the sales of electric vehicles (EV). For example, a recent report by McKinsey & Company [14] estimates that the

This paper extends the paper “Extending Parking Lots with Electricity Trading Agent Functionalities” presented at the “Workshop on Agent-Mediated Electronic Commerce and Trading Agent Design and Analysis (AMEC/TADA 2015) @ AAMAS 2015”.

share of EVs in new sales reached 12% in Norway, 4% in the Netherlands, and growth rates of 50% in France, Germany, and the UK. As a consequence of the increasing number of EVs on the road, there is a growing need for charging stations [19] as well.

A potential solution to address the need for charging stations is to transform traditional parking lots into EV-enabled parking lots, in a sense that EV-enabled parking lots provide not only *parking services*, but also the possibility for EV owners to charge and discharge their cars for a price [3], *i.e.*, to take advantage of the *electricity service* [2, 7, 18]. Within this perspective, the parking lot’s smartness comes from the possibility to act as an electricity retailer and a player on a target electricity market.

A single EV is, to a certain degree, a prosumer, in a sense that it can procure electricity from its battery (discharge) as well as consume electricity (charge) [9]. A single EV, however, is not able to actively participate in an electricity market on its own due to the fact that it only has a modest amount of electricity available to buy or sell. Our proposed model tackles this issue by putting the parking lot owner in the role of an electricity broker [17] which trades electricity between EVs and the target electricity market, thus behaving as an “aggregator” [12].

Due to the inherently complex and dynamic environment, a potential obstacle, from a business perspective, to the process of transforming parking lots into EV-enabled parking lots is the complexity of estimating the utilization of the electricity service and its profit [1]. The information about electricity service utilization is valuable to the EV-enabled parking lot’s owner because it provides guidelines on how many traditional parking spots need to be upgraded with electricity chargers, while the information about profits enables one to calculate the amount of time required to recover the cost of the initial investment.

In this paper, we suggest an agent-based simulation approach [5, 11, 13] for studying the economic benefits of EV-enabled parking lots. In particular, our main contribution is a computational technique that allows one to estimate the parking lot’s electricity service utilization and profitability given a period of time. We illustrate the application of our approach using data derived from a real-world parking lot and electricity market. To the best of our knowledge, our work is the first to suggest a computational tool to study the economic feasibility of EV-enabled parking lots.

The paper is organized as follows. Section 2 presents the EV-enabled parking lot ecosystem through the definition of entities and relationships among them. The agent-based simulation set-up, as well as simulation scenarios, are presented in Sect. 3. Section 4 elaborates upon simulation results. Section 5 concludes the paper and presents ideas for future work.

2 EV-enabled Parking Lot Ecosystem

Figure 1 presents the EV-enabled parking lot ecosystem, which consists of 3 *entities*, namely the *EV-enabled Parking Lot*, the *Electric Vehicles*, and the *Electricity Market*, and 2 *relationships*, namely the “EV-enabled Parking Lot - Electric

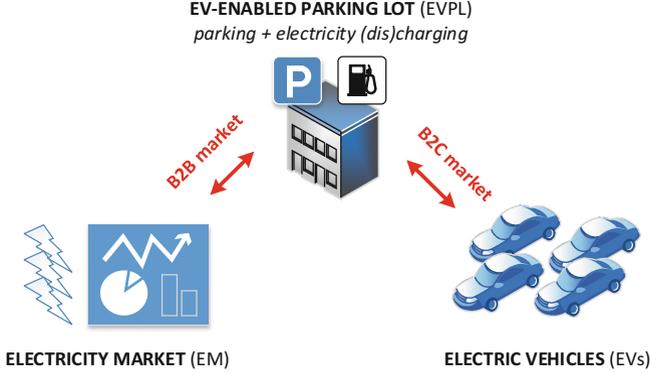


Fig. 1. Entities and relationships in an EV-enabled parking lot ecosystem

Vehicles” relationship and the “EV-enabled Parking Lot - Electricity Market” relationship. We model entities and relationships through, respectively, *agents* and *markets*. The EV-enabled Parking Lot acts as a broker connecting both markets, as we detail later. Table 1 describes all the parameters and values in the EV-enabled Parking Lot ecosystem.

2.1 EV-enabled Parking Lot Agent

As shown in Table 1, the EV-enabled Parking Lot agent (EVPL) is defined according to the tuple:

$$EVPL = (EVPL^{spots}, EVPL^{qs}, EVPL^{mrg}, EVPL^{pp}, EVPL^{(d)cr}, EVPL^{cuc}, EVPL^{ic}) \quad (1)$$

The EVPL agent model is shown in Fig. 2. Furthermore, the EVPL agent implements 3 activities, which we describe next.

Calculation of free parking spots and queue size. This activity is *event-based* and triggered after an Electric Vehicle agent (EV) wants to either enter or leave the EVPL. If the EV wants to enter the EVPL, the EVPL will provide the EV with a free parking spot from its pool of free parking spots (if the pool is not empty) or the EV will be put in the EVPL queue (if there is space, i.e., if the current number of EVs in the queue $EVPL^q$ is smaller than a queue size $EVPL^{qs}$).

Calculation of electricity price. This activity is *time-based* and regularly occurs with an hourly frequency. In the beginning of every time-slot (hour), the EVPL fetches the current electricity price (ep^{EM}) from the Electricity Market agent (EM) and uses its profit margin ($EVPL^{mrg}$) to calculate its selling ($EVPL_{ep}^{sell}$) and buying ($EVPL_{ep}^{buy}$) electricity prices as follows:

Table 1. EV-enabled parking lot ecosystem model parameters.

Parameter (unit)	Description	Notation	Value
EVPL parking spots	Number of parking spots	$EVPL^{spots}$	30, 60, 90
EVPL queue size	Number of spaces in a queue	$EVPL^{qs}$	0
EVPL margin	EVPL profit margin relative to the electricity market price	$EVPL^{mrg}$	0.1
EVPL parking price (€/h)	Price EV pays for each parking hour	$EVPL^{pp}$	3
EVPL (dis)charge rate (kW)	Maximum rate at which electricity is charged or discharged	$EVPL^{(d)cr}$	5, 10, 20
EVPL charger unit cost (€/charger)	Cost for one charger	$EVPL^{cuc}$	2,000, 10,000, 30,000
EVPL investment cost (€)	Investment cost for chargers	$EVPL^{ic}$	$EVPL^{ps} \cdot EVPL^{cuc}$
EV home supplier margin	Home supplier profit margin relative to electricity market price	EV^{mrg}	$N\{\mu = 0.2, \sigma = 0.1, a=0, b=1\}$
EV (dis)charge quantity (kWh)	Amount of electricity an EV is willing to charge or discharge	$EV^{(d)cq}$	$N\{\mu = 15, \sigma = 10, a=-30, b=30\}$
EV charge sensitivity	Probability an EV will be subjected to a price matching mechanism for a charging service	EV^{cs}	0.8
EV discharge sensitivity	Probability an EV will be subjected to a price matching mechanism for a discharging service	EV^{dcs}	1
EV stay longer	Probability an EV will stay parked longer to fully complete the electricity service	EV^{sl}	0.2
EV parked home time (h)	Amount of hours potentially spent by an EV (dis)charging at home	EV^{pht}	$U\{a=1, b=12\}$
EV arrival rate (EV/h)	Hourly arrival rates. Derived from the work by Ferreira <i>et al.</i> [6]	EV^{ar}	2, 1, 2, 1, 1, 1, 1, 2, 2, 24, 43, 18, 7, 15, 14, 22, 18, 14, 8, 10, 7, 6, 3, 1, 3
EV service rate (EV/h)	Hourly service rates. The mean number of hours an EV will stay parked is given by $1/EV^{pr}$. Derived from the work by Ferreira <i>et al.</i> [6]	EV^{pr}	0.15, 0.85, 3.85, 0.35, 0.35, 0.35, 0.07, 0.18, 0.16, 0.16, 0.28, 0.30, 0.33, 0.36, 0.38, 0.45, 0.66, 0.44, 0.62, 0.45, 0.51, 4.76, 4.35, 3.85
Simulation steps (h)	Simulation duration in time slots	t	8,760
Electricity market prices (€/kWh)	Real-world electricity prices from the day-ahead Nord Pool Elspot market (2014)	ep^{EM}	Hourly electricity prices during one year period

$$EVPL_{ep}^{sell} = ep^{EM} \cdot (1 + EVPL^{pm}) \quad (2)$$

$$EVPL_{ep}^{buy} = ep^{EM} \cdot \frac{1}{(1 + EVPL^{pm})} \quad (3)$$

Thereafter, EVs charge energy at the EVPL at a price $EVPL_{ep}^{sell}$ and they discharge energy at a price $EVPL_{ep}^{buy}$.

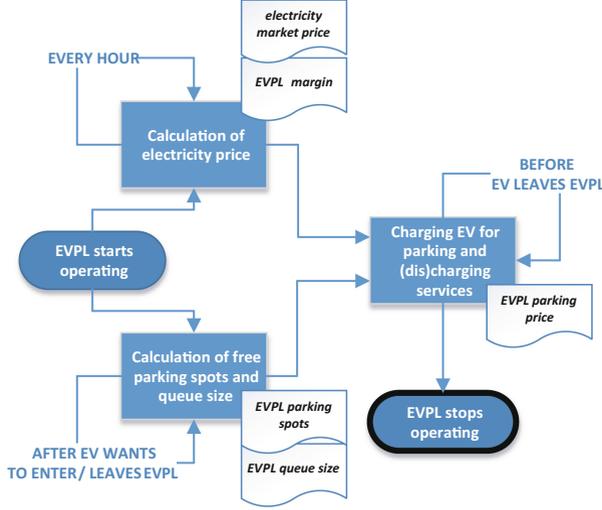


Fig. 2. The model of a EV-enabled parking lot agent

Payment for parking and (dis)charging services. This activity is *event-based* and triggered before an EV leaves the EVPL. The EV needs to pay to the EVPL agent for both parking and the electricity service provided. Therefore, the EVPL revenue from an electric vehicle EV is calculated as follows:

$$EVPL^{rev} = EVPL^{ps} + EVPL^{ets} \quad (4)$$

where $EVPL^{ps} = [timeParked(EV)] \cdot EVPL^{pp}$ is the revenue from parking service, and $EVPL^{ets} = EV^{(d)cq} \cdot EVPL_{ep}^{trade}$ is the revenue from electricity service, where:

$$EVPL_{ep}^{trade} = \begin{cases} EVPL_{ep}^{sell} & \text{if } EV^{(d)cq} \geq 0 \\ EVPL_{ep}^{buy} & \text{if } EV^{(d)cq} < 0 \end{cases} \quad (5)$$

The $timeParked(EV)$ is the parking duration of the electric vehicle agent EV . We note that the EVPL rounds up $timeParked(EV)$ to the nearest larger integer to mimic real-world practices regarding parking service payment. We also note that EV 's (dis)charge quantity, $EV^{(d)cq}$, is a positive value in case EV is charging its battery at the EVPL, and a negative value in case EV is discharging its battery.

2.2 Electric Vehicle Agent

As shown in Table 1, the Electric Vehicle agent (EV) is defined according to the tuple:

$$EV = (EV^{mrg}, EV^{(d)cq}, EV^{cs}, EV^{dcs}, EV^{sl}, EV^{pht}, EV^{ar}, EV^{pr}) \quad (6)$$

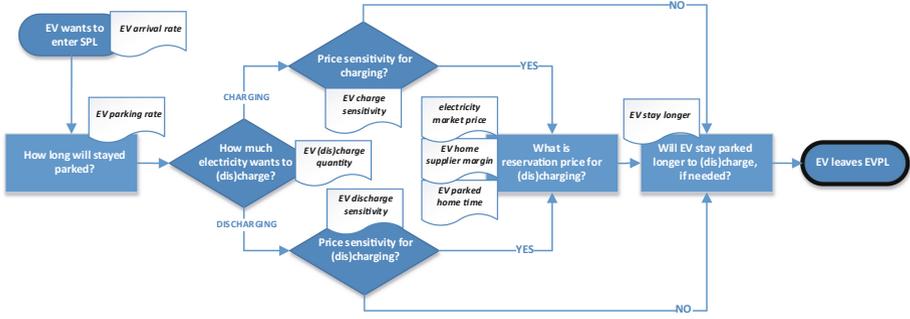


Fig. 3. The model of electric vehicle agent

The EV life cycle is described with a flowchart in Fig. 3. In particular, the EV agent implements 5 activities, which we describe next.

Calculation of parking duration. We model arrivals and staying at the parking lot using a M/M/c/0 queue with time varying parameters, allowing different timeslots (hours) to have different arrival rates (EV^{ar}) and service rates (EV^{pr}). This activity is *event-based* and triggered after an EV enters the EVPL, which is defined by the arrival rate EV^{ar} . The calculation of parking duration for a specific EV (EV^{ipd}) is based on the service rate EV^{pr} .

Calculation of the amount of electricity an EV is willing to (dis)charge. This activity is *event-based* and triggered after an EV enters the EVPL. We assume that the amount of electricity an EV is willing to (dis)charge, $EV^{(d)eq}$, follows a normal distribution with mean equal to 15 kWh, truncated at ± 30 kWh, the standard deviation being equal to 10. A positive value of the EV's (dis)charge quantity means that EV is willing to charge its battery at the EVPL, whereas a negative value means that it is willing to discharge, *i.e.*, sell electricity. By setting the mean value to 15 kWh, we mimic the real-world situation where more cars want to charge their batteries rather than discharge. The truncation is set to mimic the maximum capacity of today's mid-size EVs (*e.g.*, Nissan Leaf).

Determining whether the EV is willing to (dis)charge regardless of price. This activity is *event-based* and triggered after an EV enters the EVPL and wants to charge or discharge a certain amount of electricity. This activity decides whether EV will take into account the electricity price when deciding whether to engage in (dis)charging. The electric vehicle EV will engage in charging, regardless of the current electricity price $EVPL_{ep}^{sell}$, with the probability $1 - EV^{cs}$. On the other hand, EV will engage in discharging, regardless of the current electricity price ($EVPL_{ep}^{buy}$), with the probability $1 - EV^{dcs}$.

Through the probabilities EV^{cs} and EV^{dcs} , we mimic the real-world situation where a car arrives at a charging station and needs to charge its battery regardless of the price, *e.g.*, because the battery is almost empty or because there is no other charging station nearby. In our simulation, EV^{dcs} is always set to 1

because it would be irrational for *EV* to discharge at a price lower than what was previously paid for charging.

Calculation of the reserve price for (dis)charging. This activity is *event-based* and triggered after an EV enters the EVPL, and the same wants to (dis)charge a certain amount of electricity while taking into account the profitability aspect of such a transaction. In case of charging, the electric vehicle *EV* decides to proceed with the transaction only if the *EV*'s reserve price, $EV^{buy(res)}$, is higher than the current electricity price offered by the EVPL, $EVPL_{ep}^{sell}$. In case of discharging, the *EV* decides to proceed with the transaction only if the *EV*'s reserve price, $EV^{sell(res)}$, is lower than the current electricity price offered by the EVPL, $EVPL_{ep}^{buy}$.

For the calculation of *EV*'s reservation prices, we assume that *EV* has the alternative choice of (dis)charging at home, where its home supplier forms an electricity price analogously to the EVPL, but with different profit margin EV^{mrg} . We assume that EV^{mrg} follows a normal distribution with mean equal to 0.2, standard deviation equal to 0.1, and truncated at $[0, 1]$. Further, we assume that *EV* was parked at home for EV^{phd} hours before entering the EVPL in case of discharging or, in case of charging, that *EV* will be parked at home for EV^{phd} hours after leaving the EVPL. The value EV^{phd} follows a uniform distribution with range $[1, 12]$.

Determining whether the EV will stay parked longer to fully complete the electricity service. This activity is *event-based* and triggered after an EV enters the EVPL and decides to (dis)charge a certain amount of electricity. The EVPL's (dis)charging rate is defined by parameter $EVPL^{(d)cr}$, and the *EV*'s initial parking duration, EV^{ipd} , is defined according to the hourly service rate EV^{pr} .

A priori, the maximum amount of electricity an EV is able to (dis)charge is $EVPL^{(d)cr} \cdot EV^{ipd}$. If the amount of electricity demanded/offered by *EV* is less than or equal to $EVPL^{(d)cr} \cdot EV^{ipd}$, *i.e.*, $EV^{(d)cq} \leq EVPL^{(d)cr} \cdot EV^{ipd}$, then there is enough time for the *EV* to fully (dis)charge its battery during its parking time. On the other hand, if $EV^{(d)cq} > EVPL^{(d)cr} \cdot EV^{ipd}$, then it means that there is not enough time for the *EV* to fully (dis)charge its battery during its initial parking period. In the latter situation, the *EV* has two options: (i) to partially (dis)charge $EVPL^{(d)cr} \cdot EV^{ipd}$; or (ii) to prolong its parking time until the full (dis)charging is complete, which means that the *EV* will stay parked longer, *i.e.*, for a total of $EV^{(d)cq}/EVPL^{(d)cr}$ hours. We assume that the *EV* will go for option (iii) with probability EV^{sl} .

2.3 Electricity Market Agent

The role of the Electricity Market agent (EM) is to provide electricity for the EVPL agent. The underlying electricity price, ep^{EM} , is available with an hourly granularity for the whole calendar year. In our simulations, we use real-world

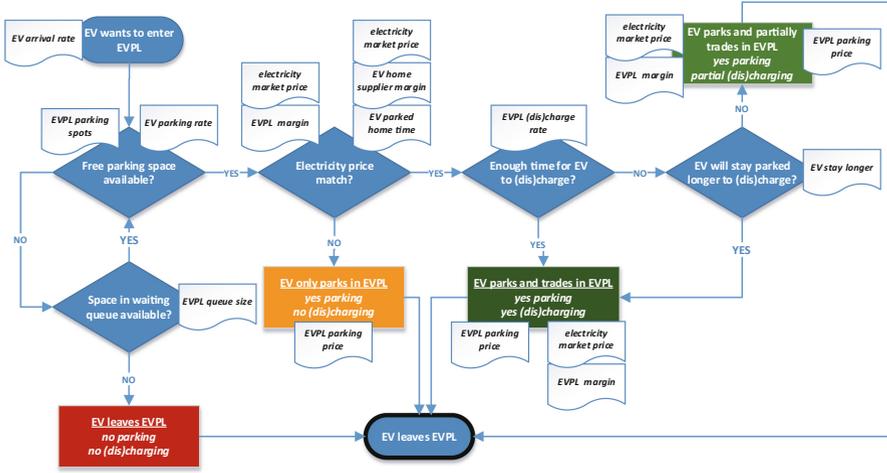


Fig. 4. EV-enabled parking lot transaction model

electricity prices from the day-ahead Nord Pool Elspot market¹, where the price volatility is not as high as in real-world intra-day markets. Consequently, the EM agent provides conservative, stable electricity prices.

2.4 EV-enabled Parking Lot B2C Market

The EV-enabled Parking Lot B2C (Business-to-Consumer) market models the “EV-enabled Parking Lot - Electric Vehicles” relationship. Activities in this market are defined through the EVPL transaction model shown in Fig. 4, which has 4 major steps as we detail next.

Entering the EVPL by the EV. Every EVPL transaction begins with an *EV* entering the EVPL. The occurrence of this event is modeled with the arrival rate EV^{ar} .

Determining whether there is a free parking space available at the EVPL. The *EV* can enter the EVPL only if there is an available parking spot. If there is no parking space available at the time of the *EV*’s arrival, the *EV* will be put in the EVPL queue in case there is space, i.e., current number of *EV*’s in the queue $EVPL^q$ is smaller than a queue size $EVPL^qs$. If there is no space available in the queue as well, the *EV* leaves the EVPL without parking and without (dis)charging. Consequently, the *EV* does not pay any money to the EVPL.

Matching EVPL electricity price with EV’s reserve price. In case of charging, the *EV* will proceed with the electricity transaction only if the *EV*’s

¹ Available at: www.nordpoolspot.com/historical-market-data.

reserve price, $EV^{buy(res)}$, is higher than the current electricity price at the EVPL, $EVPL_{ep}^{sell}$. In case of discharging, the EV will proceed with the electricity transaction only if the EV 's reserve price, $EV^{sell(res)}$, is lower than the current electricity price at the EVPL, $EVPL_{ep}^{buy}$. Nevertheless, even if the electricity price matchmaking fails, the EV will still park at the EVPL for EV^{ipd} hours, and leave the EVPL after paying $EVPL^{ps} = \lceil timeParked(EV) \rceil \cdot EVPL^{pp}$ for using EVPL's parking service.

Determining whether there is enough time for the EV to fully complete (dis)charge service. After the EV decides to (dis)charge a certain amount of electricity, some calculation should be made regarding whether there is enough time for the EV to fully (dis)charge. Such a calculation must take into account the EVPL charging rate, $EVPL^{(d)cr}$, and the EV 's initial parking duration EV^{ipd} .

If there is enough time for the EV to fully (dis)charge, then the EV will park at the EVPL for EV^{ipd} hours, (dis)charge $EV^{(d)cq}$ amount of electricity, and leave the EVPL after paying $EVPL^{rev}$ (see Eq. (4)) for using both the EVPL's parking and electricity services. If there is not enough time for the EV to fully (dis)charge, *i.e.*, $EV^{(d)cq} > EVPL^{(d)cr} \cdot EV^{ipd}$, then, as mentioned before, the EV has two options, which are determined according to the probability EV^{sl} :

- (i) to partially (dis)charge $EVPL^{(d)cr} \cdot EV^{ipd}$ of electricity; or
- (ii) to prolong its parking time until the full (dis)charging is complete, *i.e.*, the EV will stay parked for a total of $EV^{(d)cq}/EVPL^{(d)cr}$ hours.

When option (i) is activated, then the EV will park at the EVPL for EV^{ipd} hours, (dis)charge $EVPL^{(d)cr} \cdot EV^{ipd}$ amount of electricity, and leave the EVPL after paying $EVPL^{rev}$ for using both the EVPL's parking and electricity services. If option (ii) is activated, the EV will park at the EVPL for a total of $EV^{(d)cq}/EVPL^{(d)cr}$ hours, (dis)charge $EV^{(d)cq}$ of electricity, and leave the EVPL after paying $EVPL^{rev}$ for using both EVPL's parking and electricity services. Clearly, the EVPL's profit is higher when option (ii) is activated.

2.5 EV-enabled Parking Lot B2B Market

The EV-enabled Parking Lot B2B (Business-to-Business) market models the "EV-enabled Parking Lot - Electricity Market" relationship. This relationship is an important prerequisite for the EVPL ecosystem because it procures the necessary amount of electricity for charging services as well as it liquidates discharged electricity from parked EVs to the EM. It is important to note that our present model assumes perfect information about prices from both EVs and EVPL's point-of-view. Also, a transaction between the EVPL and the EM is presumed to have perfect liquidity.

3 EV-enabled Parking Lot Simulation Set-Up

Due to the high stakes and complexity of the interactions within the EVPL ecosystem, the real-life applicability of our proposed model needs to be first

considered in a risk-free and feature-packed simulation environment. Such an environment allows one to determine whether EVPLs can deal with uncertainties imposed by EV owners in a profitable way.

At the core of our model is a M/M/c/0 queue with time varying arrival and service rates. In such settings, traditional closed-form equations offered by queueing theory are often invalid [8, 16]. Hence, we opted to represent our model as an agent-based simulation², which allows for a rich analysis under dynamic and highly volatile settings [10]. Table 2 shows the values of the simulation parameters. These values reflect three different sizes of EVPLs (*small*, *medium*, and *large*) and three different types of chargers: (i) *slow* and *cheap*, (ii) *moderately fast* and *reasonably priced*, and (iii) *fast* and *expensive*. Consequently, different parking lot sizes and charger infrastructures equates to the total of nine possible scenarios that might happen in the real-world and are therefore incorporated in our analysis.

Table 2. Scenario-dependent parameter values and results.

Scenario (<i>(dis)charge rate-parking size</i>)	EVPL (dis)charge rate (kW)	Charger unit cost (€/charger)	EVPL parking spots	Profits from electricity trading (€)	Profits from extended parking (€)	Aggregate profits $EVPL_{agg}^{profit}$ (€)	Mean parking util. (%)	Mean charger util. (%)	Mean electricity util. (%)
SLOW-SMALL	5	2,000	30	1,769.09	47,332.42	49,101.51	61.4	36.5	21.3
SLOW-MEDIUM	5	2,000	60	2,785.62	69,738.83	72,524.45	50.7	33.3	16.7
SLOW-LARGE	5	2,000	90	3,172.07	80,304.99	83,477.06	37.7	33.8	12.7
STEADY-SMALL	10	10,000	30	1,810.53	16,778.21	18,588.74	58.5	21.9	12.4
STEADY-MEDIUM	10	10,000	60	2,825.14	23,359.06	26,184.2	48.2	19.3	9.4
STEADY-LARGE	10	10,000	90	3,104.85	25,252.31	28,357.16	35.0	19.2	6.9
FAST-SMALL	20	30,000	30	1,907.26	5,548.62	7,455.88	58.2	12.1	6.8
FAST-MEDIUM	20	30,000	60	2,920.72	7,204.47	10,125.19	48.1	10.5	5.1
FAST-LARGE	20	30,000	90	3,216.65	8,123.31	11,339.96	34.5	10.6	3.8

4 Results and Discussion

Our analysis of the EVPL ecosystem identifies potential consequences for the EVPL business by considering different investment pathways. In particular, under the model assumptions and parameter values, we scrutinize the 9 different EVPLs from the perspectives of both *electricity trading* and *extended parking* due to the provision of electricity service. Furthermore, we discuss the EVPL utilization, which is an important key performance indicator (KPI) that provides insights on the usage of the parking and electricity services.

² Our simulation is implemented using *R*, a free software environment for statistical computing and graphics. It takes around three minutes to simulate one year scenario on a system with 4-core CPU and 8 GB RAM. Please note *R* does not utilize multi-threading and therefore a computer with less CPU cores will produce similar running times.

4.1 Benefits from Electricity Trading

The fifth column (i.e., *profits from electricity trading*) in Table 2 presents how much money the EVPL earned under different scenarios. It can be noticed that profits from electricity trading increase with parking size and charger speed. Although this outcome is intuitive and somewhat expected, the low absolute values, including low profit discrepancies between the nine scenarios, might make one question about the profitability of the EVPL business. For example, given that in the best case scenario the EVPL makes a profit of just over 3,200 € per year, it would take decades for the parking lot’s owner to obtain the invested money back. However, the overall benefit from the energy service is not only measured in terms of electricity trading profits, but also from the extra time an EV was parked in order to fully complete the (dis)charging operation, a point that we discuss next.

4.2 Benefits from Extended Parking

The sixth column (i.e., *profits from extended parking*) in Table 2 presents how much money the EVPL earned due to the prolonged parking in each scenario. Recall that prolonged parking may occur when the (dis)charging operation cannot be fully completed during the EV’s initial parking period. In that case, there is the probability EV^{sl} that an EV will prolong its parking duration to fully (dis)charge. Otherwise, the EV will settle for the amount of electricity that is feasible during the initial parking duration. The probability EV^{sl} encodes real-world examples of behavioral patterns of EV owners. For instance, an EV owner that frequently travels to distant locations might suffer from *range anxiety* [15]. Also, an EV owner may not be able to charge at home due to a lack of the required infrastructure, thus the same has to resort to a EVPL.

Interestingly, the results show that the most profitable investment option is to buy the slowest type of charger. The rationale behind this result is that, in comparison to other charger types, the slowest charger increases the chance that the requested amount of electricity $EV^{(d)ca}$ cannot be transferred between the EV and the EVPL within the initial parking duration. Another interesting point is that the results in Table 2 show that the EVPL’s main source of income is due to the extended parking service. In our simulations, the parking service has a fixed price $EVPL^{pp}$ set at 3 €/h. As for the electricity service, assuming the discharge rate $EVPL^{(d)cr}$ of 5 kW, the ep^{EM} price set at reasonable 0.035 €/kWh, and the EVPL’s profit margin $EVPL^{mrg}$ to be 10%, then the EVPL can expect the maximum profit of 0.0175 € for a single parking space in one hour. Hence, the parking service can bring as much as 170 times more profit than the electricity service alone.

4.3 EV-enabled Parking Lot Utilization

We introduce three types of KPIs that explain how well a particular EVPL is utilized:

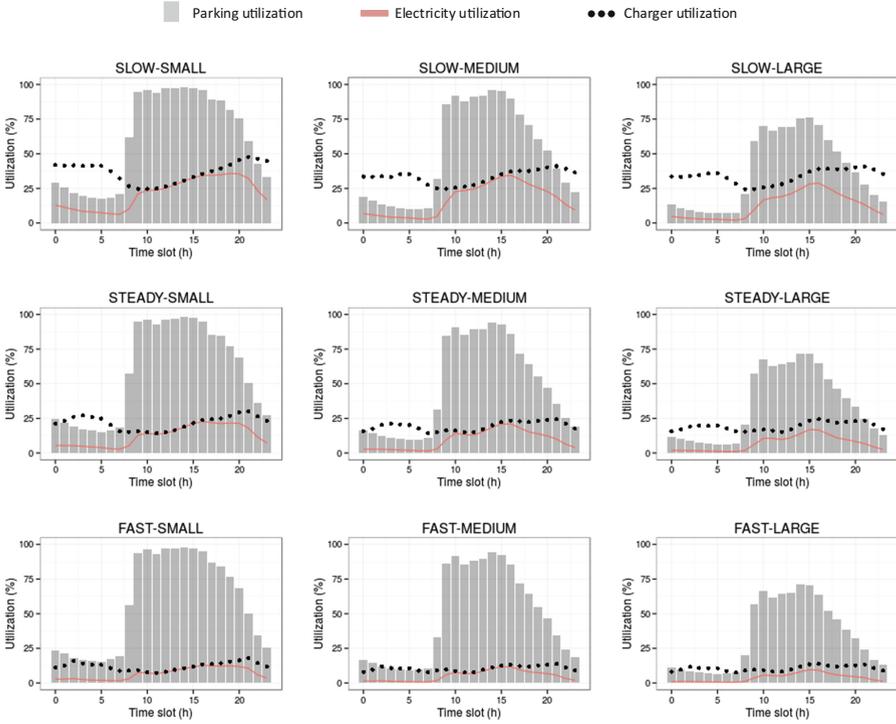


Fig. 5. Parking, charger, and electricity utilizations

- parking utilization;
- charger utilization; and
- electricity utilization.

Parking utilization measures how many EVs were parked at the EVPL. *Charger utilization* is defined as the ratio between the amount of electricity EVs (dis)charged and the maximum amount of electricity that could be (dis)charged in case chargers from occupied parking spots ran at 100% rate while EVs were parked. *Electricity utilization* is defined as the ratio between the amount of electricity EVs (dis)charged and the potential amount of electricity that could be (dis)charged in case all chargers ran at 100% rate all the time. Figure 5 shows the hourly mean values for the three KPIs in each scenario.

Figure 5 shows that the peak hours are between 9 AM and 5 PM, which is in accordance with the arrival rates EV^{ar} and service rates EV^{pr} . Small EVPLs have higher parking utilizations than medium and high EVPLs. Also, large EVPLs have the lowest levels of parking utilization throughout the whole day, which implies that the number of parking spots in large EVPLs in our simulation is indeed too high. Although the arrival rates are lower during night hours (at most three cars per hour), the corresponding parking utilization values

from Fig. 5 shows that the amount of time an EV stays parked is prolonged due to the introduction of electricity service.

The KPI charger utilization explains how efficient the chargers of occupied parking spots operate and, thus, it effectively minimizes the impact of the EVPL's size on our analysis. Notably, the results in Fig. 5 show that the charger utilization is higher during off-peak hours than during on-peak hours. The reason for this lies in the fact that parking durations, defined by EV^{pr} , are significantly lower during off-peak hours than during on-peak hours, thus promoting the overall mean charger utilization for off-peak hours.

In contrast to the charger utilization, the electricity utilization KPI indicates the overall performance regarding the EVPL's electricity trading. Figure 5 shows that the electricity utilization correlates with the parking utilization. It also shows that the difference between electricity and charger utilization is lower during on-peak hours and higher during off-peak hours.

The mean values of electricity utilizations are 16.92%, 9.59% and 5.25% for slow, steady and fast charger scenarios, respectively. Furthermore, the maximum values of electricity utilizations are 35.86%, 22.77%, and 12.89% for, respectively, slow, steady, and fast chargers. These numbers can be very helpful for the EVPL when deciding how many traditional parking spots need to be upgraded with electricity chargers. First, from Table 2, one can conclude that the most profitable scenarios are those with slow chargers, due to increased profits from extended parking. Furthermore, from Table 1, one can see that the price of such a charger is $EVPL_{slow}^{cuc} = 2,000\text{€}$ ³. The payback period (PB) for transforming traditional parking lots into EV-enabled parking lots, assuming that the transformation is implemented by upgrading all parking spots with slow chargers, are:

$$PB_{small}^{full(slow)} = \frac{EVPL_{small}^{ps} \cdot EVPL_{slow}^{cuc}}{EVPL_{agg}^{prof}} = 1.22 \quad (7)$$

$$PB_{medium}^{full(slow)} = \frac{EVPL_{medium}^{ps} \cdot EVPL_{medium}^{cuc}}{EVPL_{agg}^{prof}} = 1.65 \quad (8)$$

$$PB_{large}^{full(slow)} = \frac{EVPL_{large}^{ps} \cdot EVPL_{medium}^{cuc}}{EVPL_{agg}^{prof}} = 2.15 \quad (9)$$

It is noteworthy that the above calculation is conservative due to fact that the EVPL investment costs could be smaller in practice due to economy of scale. Nevertheless, the payback numbers are even more impressive if the EVPL owner decides, based on the data on electricity utilizations shown in Fig. 5, to optimize the number of traditional parking spaces which will be upgraded with chargers. From Fig. 5, one can conclude that only around 36% of parking spots need to be upgraded with electricity chargers in order to maintain the EVPL electricity service. Therefore, the PB in the case of optimal charger installation is the following:

$$PB_{small}^{optimal(slow)} = 36\% \cdot PB_{small}^{full(slow)} \approx 0.44 \quad (10)$$

³ Available at: <http://www.greenbiz.com/blog/2014/05/07/rmi-whats-true-cost-ev-charging-stations>.

Similar calculations show that $PB_{medium}^{optimal(slow)} \approx 0.59$ and $PB_{large}^{optimal(slow)} \approx 0.77$. In words, it would take less than one year for an investor to get the invested money back, thus showing that the economic benefits of investing in EV-enabled parking lots are quite significant.

5 Conclusion and Future Work

EV-enabled parking lots provide a natural solution to address the current need for charging stations due to the increased number of electric vehicles on the road. From a business perspective, two potential obstacles to the process of transforming parking lots into EV-enabled parking lots are the complexity of estimating the utilization of the electricity service and the profitability of the resulting EV-enabled parking lot. In this paper, we proposed an agent-based simulation approach that tackles the above problems. Using real-life data, we showed how one can use our approach to study the economic benefits of EV-enabled parking lots. In particular, we illustrated how to estimate the EV-enabled parking lot's profit due to the trade of electricity and extended parking service, how to estimate the number of needed chargers using the electricity utilization KPI, and how to estimate the payback period concerning the invested money.

When using our approach, one must tailor the parameter values in Table 1 to the underlying parking lot setting. One exciting research direction is to perform a case study where one estimates *a priori* the metrics previously discussed using our approach and, then, measures *a posteriori* the accuracy of such estimations. Another research direction relevant to the computational sustainability community is on how to integrate our simulation approach with broader, energy-related simulators, such as Power TAC [4, 10]. This would allow one to use competitive benchmarking in order to study the impact of more elaborate trading strategies by the EVPL.

Acknowledgements. The authors acknowledge the support of the research project “Managing Trust and Coordinating Interactions in Smart Networks of People, Machines and Organizations”, funded by the Croatian Science Foundation under the project UIP-11-2013-8813 and COST Action IC1404 on Multi-Paradigm Modelling for Cyber-Physical Systems, funded by European Union.

References

1. Babic, J., Carvalho, A., Ketter, W., Podobnik, V.: Economic benefits of smart parking lots. In: Proceedings of the Erasmus Energy Forum 2015 Science Day: Energy Informatics & Management (EIM 2015), pp. 1–8 (2015)
2. Babic, J., Carvalho, A., Ketter, W., Podobnik, V.: Extending parking lots with electricity trading agent functionalities. In: Workshop on Agent-Mediated Electronic Commerce and Trading Agent Design and Analysis (AMEC/TADA 2015)@AAMAS 2015 (2015)

3. Babic, J., Carvalho, A., Ketter, W., Podobnik, V.: Modelling electric vehicle owners' willingness to pay for a charging service. In: Proceedings of the Erasmus Energy Forum 2016 Science Day: Energy Informatics & Management (EIM 2016), pp. 1–8 (2016)
4. Babic, J., Podobnik, V.: An analysis of power trading agent competition 2014. In: Ceppi, S., David, E., Podobnik, V., Robu, V., Shehory, O., Stein, S., Vetsikas, I.A. (eds.) AMEC/TADA 2013-2014. LNBIP, vol. 187, pp. 1–15. Springer, Cham (2014). doi:[10.1007/978-3-319-13218-1_1](https://doi.org/10.1007/978-3-319-13218-1_1)
5. Babic, J., Podobnik, V.: A review of agent-based modelling of electricity markets in future energy eco-systems. In: International Multidisciplinary Conference on Computer and Energy Science (SpliTech), pp. 1–9. University of Split, FESB (2016)
6. Ferreira, M., Damas, L., Conceicao, H., D'Orey, P.M., Fernandes, R., Steenkiste, P., Gomes, P.: Self-automated parking lots for autonomous vehicles based on vehicular ad hoc networking. In 2014 IEEE Intelligent Vehicles Symposium Proceedings, pp. 472–479. IEEE, June 2014
7. Gerding, E., Stein, S., Robu, V., Zhao, D., Jennings, N.R.: Two-sided online markets for electric vehicle charging. In: Proceedings of 12th International Conference on Autonomous Agents and Multi-Agent Systems, pp. 989–996 (2013)
8. Hasofer, A.: On the single-server queue with non-homogeneous poisson input and general service time. *J. Appl. Probab.* **1**(2), 369–384 (1964)
9. Hosseini, S.S., Badri, A., Parvania, M.: A survey on mobile energy storage systems (MESS): applications, challenges and solutions. *Renew. Sustain. Energy Rev.* **40**, 161–170 (2014)
10. Ketter, W., Collins, J., Reddy, P.: Power TAC: a competitive economic simulation of the smart grid. *Energy Econ.* **39**, 262–270 (2013)
11. Ketter, W., Peters, M., Collins, J., Gupta, A.: A multiagent competitive gaming platform to address societal challenges. *Mis Q.* **40**(2), 447–460 (2016)
12. Khalen, M., Ketter, W., van Dalen, J.: Balancing with electric vehicles: a profitable business model. In: Proceedings of European Conference on Information Systems 2014, Tel Aviv, Israel, pp. 1–15 (2014)
13. Macal, C.M., North, M.J.: Tutorial on agent-based modelling and simulation. *J. Simul.* **4**(3), 151–162 (2010)
14. McKinsey & Company. Electric vehicles in Europe: Gearing up for a new phase? (2015)
15. Neubauer, J., Wood, E.: The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. *J. Power Sources* **257**, 12–20 (2014)
16. Rothkopf, M.H., Oren, S.S.: A closure approximation for the nonstationary M/M/s queue. *Manage. Sci.* **25**(6), 522–534 (1979)
17. Urieli, D., Stone, P.: Tactex'13: a champion adaptive power trading agent. In: Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence (2014)
18. Valogianni, K., Ketter, W., Collins, J., Zhdanov, D.: Effective management of electric vehicle storage using smart charging. In: Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence (2014)
19. Zhang, L., Brown, T., Samuelsen, S.: Evaluation of charging infrastructure requirements and operating costs for plug-in electric vehicles. *J. Power Sources* **240**, 515–524 (2013)