IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 27, 2017, accepted November 19, 2017, date of publication November 24, 2017,
date of current version February 14, 2018.

Digital Object Identifier 10.1109/ACCESS.2017.2777098

Evaluating Policies for Parking Lots Handling Electric Vehicles

JURICA BABIC[1], (Graduate Student Member, IEEE), ARTHUR CARVALHO[2], WOLFGANG KETTER[3,4], AND VEDRAN PODOBNIK[1], (Senior Member, IEEE)
[1]Faculty of Electrical Engineering and Computing, University of Zagreb, 10000 Zagreb, Croatia
[2]Farmer School of Business, Miami University, Oxford, OH 45056 USA
[3]Rotterdam School of Management, Erasmus University, 3062 Rotterdam, The Netherlands
[4]Faculty of Management, Economics, and Social Sciences, University of Cologne, 50923 Cologne, Germany

Corresponding author: Jurica Babic (jurica.babic@fer.hr)

This work was supported in part by the research project Managing Trust and Coordinating Interactions in Smart Networks of People, Machines and Organizations through the Croatian Science Foundation under Grant UIP-11-2013-8813 and in part by the Croatian Centre of Research Excellence for Data Science and Advanced Cooperative Systems.

ABSTRACT The recent advent of electric vehicles (EVs) marks the beginning of a new positive era in the transportation sector. Although the environmental benefits of EVs are well-known today, planning and managing EV charging infrastructure are activities that are still not well-understood. In this paper, we are investigating how the so-called EV-enabled parking lot, a parking lot that is equipped with a certain number of chargers, can define an appropriate parking policy in such a way that satisfies two challenges: EV owners' needs for recharging as well as the parking lot operator's goal of profit maximization. Concretely, we present three parking policies that are able to simultaneously deal with both EVs and internal combustion engine vehicles. Detailed sensitivity analysis, based on real-world data and simulations, evaluates the proposed parking policies in a case study concerning parking lots in Melbourne, Australia. This paper produces results that are highly prescriptive in nature because they inform a decision maker under which circumstances a certain parking policy operates optimally. Most notably, we find that the dynamic parking policy, which takes the advantage of advanced information technology (IT) and charging infrastructure by dynamically changing the role of parking spots with chargers, often outperforms the other two parking policies, because it maximizes the profit and minimizes the chance of cars being rejected by the parking lot. We also discuss how making a few parking spots EV-exclusive might be a good policy when the number of available chargers is small and/or the required IT infrastructure is not in place for using the dynamic policy. We conclude this paper proposing a technology roadmap for transforming parking lots into smart EV-enabled parking lots based on the three studied parking policies.

INDEX TERMS Electric vehicles, parking lot, parking policy, decision making, simulation, data analysis.

I. INTRODUCTION

Electric vehicles (EVs) are becoming an increasingly popular transportation choice, and this is greatly affecting society as a whole regardless of whether or not one is still driving a conventional vehicle with an internal combustion engine (ICV). For example, on the negative side, the "refueling" with electricity at charging stations rather than with gasoline/diesel at gas stations might cause the electricity grid to overload. On the other hand, EVs are less harmful to the environment in a sense that they produce much less noise and harmful gases when compared to ICVs.

This paradigm shift introduced by EVs results not only in changes in vehicle owners' behavior, but it also causes a redefinition of governmental and business policies. For example, the last few years have witnessed a number of local and/or national governmental policies aimed at subsidizing purchases of EVs [1]–[4]. This led to a substantial increase in EV market penetration in certain regions of the world such as Norway and the Netherlands [5]. Furthermore, governments and businesses (*e.g.*, parking lots and car makers) consistently promote EVs by offering subsidized (free) charging.

With more than a million EVs on the roads worldwide in 2016 [6], one can safely say that the problem of technology acceptance regarding EVs is becoming less of an issue. That said, the key motivation behind this work is the fact that a rapidly growing number of EVs fundamentally changes not only the way people commute to work, but also business models surrounding the transportation sector. In particular, in this work, we are focusing on parking lots that have a potential to offer a parking service to ICVs and EVs alongside a charging service to EVs.

Even though one can argue that a parking lot operator may invest in a few charging stations offering free charging services in the early EV adoption stages, it is obvious that such an approach is not sustainable in a long-term. It is now clear that the EV charging infrastructure development and management has to be approached in a systematic manner, as opposed to a previous common practice where governments and businesses installed charging stations at semi-random places aiming at maximizing EV marketing and popularization. Furthermore, charging cannot remain free for EV owners since somebody has to pay for the electricity cost.

As EV charging is a time-consuming process that can take from many minutes to several hours, the car parking aspect becomes a critical point to consider in this process. In spirit, a charging station can be seen as a parking lot equipped with chargers and, likewise, a parking lot with chargers can be seen as a charging station. That said, we propose a solution on how to redesign parking policies in parking lots with EV chargers in a way that satisfies EV owners' needs for recharging as well as the parking lot operator's goal of profit maximization. Our solution systematically tackles the problems of how to manage parking lots and charging stations.

Within the scope of this work, it is important to explain our definition of *parking policies*. Following the definitions by Young and Miles [7] and Ison and Rye [8], we use the term parking policy to refer to a policy that determines the price, supply, duration, and location of a parking event. Our primary focus in this paper when looking for the optimal parking policies is on the financial aspect of a parking lot, meaning that the *profit* of a parking lot operator is the key metric to determine whether a certain parking policy is performing better than others.

The main contribution of this paper is twofold:

- a *technology roadmap* for transforming parking lots into smart EV-enabled parking lots, including the proposal of three novel parking policies for parking lots handling EVs, which can be used by parking lot operators to cope not only with ICVs, but with EVs as well;
- an *evaluation method*, based on real-world data and simulations, for assessing the efficiency of parking policies in different contexts with respect to EV owners' needs for recharging and the parking lot operator's goal of profit maximization.

We operationalize our contributions and showcase the proposed technology roadmap via a case study concerning parking lots in Melbourne, Australia. Specifically, we provide a detailed sensitivity analysis of the proposed parking policies as well as set recommendations for short-, mid- and long-term transformations of current Melbourne parking lots into smart EV-enabled parking lots. In our simulations, we found that the charging-exclusive parking policy (CHARG-EXCL), which only allows EVs that actually use the charging service to park on the spots equipped with chargers, is optimal for parking lots that have less chargers than what is required to satisfy EV owners' charging demand. On the other hand, the EV-exclusive parking policy (EV-EXCL), which extends CHARG-EXCL by allowing EVs to be parked in a parking spot with a charger without actually using the charging service, is better suited for parking lots that have a bit of redundancy in the number of chargers since, under that policy, the profit of a parking lot operator increases and the number of cars being rejected decreases. The dynamic parking policy, which under certain conditions may allow ICVs to park on parking spots with chargers, outperforms the previous two parking policies when the number of chargers increases substantially because it maximizes profit and minimizes rejection rate.

Besides this introductory section, the rest of this paper is organized as follows. Section II positions our work against the relevant literature. Section III describes the need for redesigning parking policies that are used in parking lots containing EV chargers as well as it presents the methodology we used to evaluate the parking policies. We note that all the variables mentioned throughout the rest of the paper are defined in Section III-B. Section IV formalizes algorithmically the three EV-aware parking policies that we consider in this work. Section V presents a case study based upon real-world data from a parking lot in Melbourne, Australia. Section VI reveals the key insights from performed sensitivity analysis. Finally, Section VII concludes the paper and provides an outlook on future work.

II. RELATED WORK

Broadly speaking, the scientific literature related to parking was relatively scarce until the mid-nineties [9]. Thereafter, several research papers have elaborated upon theoretical aspects of parking. For example, Arnott [10] analyzed the parking garage problem where spatial competition between parking garages exists. From an economic-theory perspective, the author looked into the impact of adding on-street parking as well as mass transit on a central business district's parking policy. Following the importance of the theoretical work, Arnott also emphasized the need for *parking simulation models* [11], [12] to forecast the effects of different parking policies with the aim of finding an efficient downtown parking policy. A more comprehensive theoretical work on parking are offered by Bartner [13], who focused on North American parking planning, and by Mingardo *et al.* [9], who conceptualized parking for European territories.

However, what seems to be noticeable in the current literature is the fact that the vast majority of the studies related to parking policies do not take into account peculiarities of EVs. This is perhaps not surprising as trends in the automotive industry have been traditionally aligned with conventional vehicles with internal combustion engines.

For example, Tsai and Chu [14] proposed a reservation parking policy in which a vehicle owner is able to reserve a parking spot prior to her/his arrival at the parking lot. With two different parking lots used as case studies, their numerical simulation results showed the benefits of having occupancy-dependent reservation prices. The benefits are not only reflected through the parking lot operator's revenue, but also with the reduced amount of pollutant generated from driving a car while searching for a parking spot.

In another work, van Ommeren *et al.* [15] focused on a parking policy that includes on-street parking permits. The focus of the research was in determining users' willingness-to-pay for an on-street parking permit by incorporating cruising costs and house price information, which in turn was used as a proxy for the value of a private parking space.

Kotb *et al.* [16] proposed a parking system based on mathematical modeling using mixed-integer linear programming with the aim of improving the management of current parking systems. Notably, the model proposes parking reservations and pricing policies with the lowest cost and search time for drivers and the highest revenue and resource management for parking operators.

From a methodological point of view, Benenson *et al.* [17] showed how an agent-based model can be used to simulate parking in a city. In particular, the model is able to simulate the behavior of each driver situated in a spacial context. Even though the model scenarios are prone to many assumptions, *e.g.*, parking demand distributions are arbitrary and decision rules of agents are artificial, the simulation-based approach led the authors to interesting conclusions regarding the emergent behavior from a set of interacting agents. In particular, the authors found out that adding several small parking lots in dense areas of central Tel Aviv (Isreal) leads to a decrease in the parking duration for the average car-owning resident.

All things considered, even with the recent advent of EVs, it seems there is limited research on parking policies that take into account EVs as crucial entities in modern parking systems. On the other hand, there seems to be a considerable interest in highly-relevant EV topics such as the impact of EVs on the electric power system [18], [19], EV charging scheduling [20]–[23], and the forecast of EV sales [24]–[26]. For example, Mozafar *et al.* [27] investigated the impact of electric vehicles on the power system by proposing a comprehensive model that is able to provide insights on the effects of power exchange between the grid and EVs on the power system's demand profile as well as on the stability and reliability of the distribution network. Furthermore, Amini *et al.* [28] showcased how important role EV parking lots can play in the power systems by proposing a framework for simultaneous allocation of EV parking lots and distributed renewable resources considering the economic benefits of parking lot investors as well as the technical constraints of the distribution network operator.

Coming back to parking policies, in order to show the importance of designing parking policies with EVs in mind, Bonges and Lusk [29] found out that EV-only parking policy is beneficial for increasing EV sales and lowering the range anxiety of EV owners. These conclusions are consistent with the insights found by Faria *et al.* [30]. In particular, these authors used the net present value model to illustrate economic and environmental benefits of electric vehicle parking.

In contrast to the existing work, which focus on quantifying the impact of parking policies that are designed with conventional vehicles in mind, our work is novel in a sense that it proposes three parking policies for EV-enabled parking lots that are compatible with mixed scenarios, where both EVs and non-EVs co-exist. Furthermore, we evaluate the proposed policies by using a simulation-based approach based on a real-world setting in Melbourne, Australia.

III. TRANSFORMING A PARKING LOT INTO A SMART ELECTRIC VEHICLE ENABLED PARKING LOT

Among the several preceding work on parking policies [10], [13], Mingardo *et al.* [9] discussed the development of parking policies in the most systematic way. Most notably, Mingardo *et al*. identified three crucial phases of the parking policy development in Europe.

In the first phase, parking policies addressed the absence of parking measures by introducing the basic parking regulations. For example, the parking spots in this phase are clearly marked and there also may be rules that restrict vehicles to park during a certain period of time. Such information were communicated in an old-fashioned, non-digital way (*e.g.*, parking signs).

The second phase marked the introduction of parking pricing aiming at controlling car usage and traffic. From the perspective of information and communication technologies, the first parking-related information system emerged through digital displays that indicate the number of available parking spots in a certain facility (*e.g.*, parking garage or parking lot).

Finally, the third phase describes the future trends in the parking policy development. The focal point in this phase is placed on managing parking demand through elements such as advanced pricing schemes, multiple use of parking facilities and extensive reliance on information technology (IT), *e.g.*, guiding vehicle owners to an available spot.

Although the scope of Mingardo *et al*. research is limited to Europe and the term parking policy is used in a broader, urban-level context, we argue that the emergent theory of parking policy development is general to other contexts as well, *i.e.*, it is location-agnostic and applicable to the setting we explain later.

From the described evolution of parking policies, one can notice that advancements in parking policy design is driven by societal needs (*e.g.*, undersupply of parking spots) and technological progress (*e.g.*, introduction of IT systems). As we are currently witnessing one of the most disruptive technological changes in the history of personal mobility, namely the introduction of EVs on a mass scale, it is rather expected that a further redesign of parking policies is needed. The major difference introduced by EVs is the fact that they need to be charged while parked since the charging process

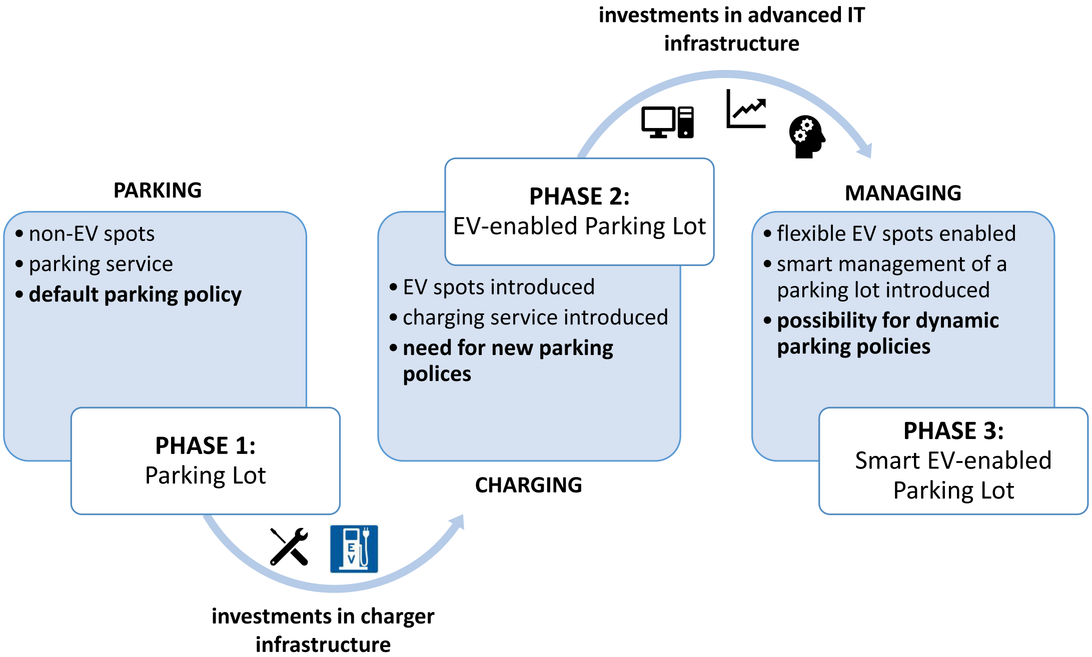


FIGURE 1. Proposed parking lot transformation phases.

is time consuming. Clearly, the underlying assumption is that the parking spot is equipped with a charger.

In this work, we propose a possible solution for an upgrade of current parking policies where a substantial part of users are EV owners. In other words, we are proposing novel parking policies for parking lots upgraded with EV chargers on a certain number of parking spots. Following Mingardo *et al.* [9], we introduce these policies as potential phases a traditional parking lot should go through.

A. TRANSFORMATION PHASES

Fig. 1 presents the parking lot transformation phases, each of which is associated with a certain parking policy. Furthermore, note that each transition between phases is associated with necessary *investments* in either charging infrastructure (*Phase 2*) or advanced IT infrastructure (*Phase 3*).

The *first phase* is characterized by a *parking lot* in a form that is most often available today. Trivially, the parking lot is equipped with parking spots, which have the sole purpose of providing the *parking service* for a certain price per hour. Historically speaking, those parking spots have been most often occupied by internal combustion vehicles (ICVs). It is important to mention that, for the remainder of this work, we refer to ICVs as non-EVs so as to avoid ambiguity related to types of vehicles. Consequently, we refer to such parking spots as *non-EV spots*. The parking lot operates by the *default parking policy* (DEFAULT) presented in Fig. 2, and briefly described and formalized in Section IV.

In the *second phase*, the parking lot, now called the EV-enabled parking lot (EVPL), introduces parking spots

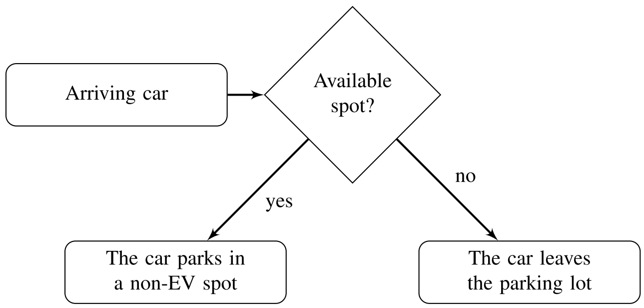


FIGURE 2. Flowchart of the default parking policy.

with installed chargers, *i.e.*, *EV spots*. Such parking spots are transformed from non-EV spots by *investments in charging infrastructure*. As such, EV spots are used to offer the *charging service* for a certain premium price per hour where an EV can be charged. It is obvious that the DEFAULT policy is no longer appropriate since, for example, EVs should have the highest priority for parking in EV spots. This leads to the conclusion that new parking policies need to be developed.

Finally, the *third phase* marks the successful transition of the EVPL into the smart EV-enabled parking lot (S-EVPL). The emphasis in this phase is placed on the smart management of parking spots thanks to the introduction of advanced IT infrastructure. Following the ideas of a proactive planning of parking facilities by Mingardo *et al.* [9], the S-EVPL has EV spots that are flexible, *i.e.*, the role of EV spots may be changed in real-time given the circumstances the S-EVPL is currently in. Naturally, to support such smart management, further innovation in parking policies is needed.

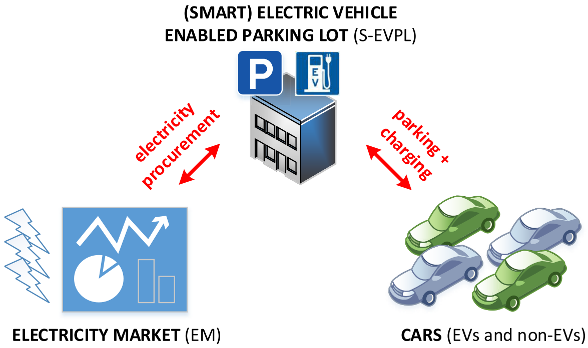


FIGURE 3. Electric vehicle enabled parking lot ecosystem, adapted from [31].

B. (SMART) ELECTRIC VEHICLE ENABLED PARKING LOT ECOSYSTEM

Fig. 3 shows the (S-)EVPL ecosystem comprising of three types of entities: 1) the (smart) electric vehicle enabled parking lot; 2) cars (EVs and non-EVs); and 3) an electricity market (EM).

Recall that the key aspect behind the EVPL is its ability not only to provide the parking service to cars, but also to offer the charging service to EVs as well. The S-EVPL offers the same services as the EVPL, while also enhancing the management of the parking spots. That being said, the S-EVPL is defined in terms of the following variables:

- n_{EV} is the number of parking spots with installed chargers, *i.e.*, EV spots;
- n_{EVCurr} is the number of EV spots that are currently occupied;
- n_{nonEV} is the number of regular parking spots, *i.e.*, non-EV spots;
- $n_{nonEVCurr}$ is the number of non-EV spots that are currently occupied;
- n_{total} is the total number of parking spots in the S-EVPL, *i.e.*, $n_{EV} + n_{nonEV}$;
- p_{park} is the price per hour a car pays for consuming the parking service;
- p_{EV} is the premium price per hour an EV pays for consuming the charging service while being parked in an EV spot.

Within the scope of this work, we define a car through the following two variables:

- *carType* is the type of the car entering the S-EVPL, *i.e.*, EV or non-EV;
- $p_{reservation}$ is the maximum reservation price per hour a car owner is willing to pay for the charging service. Obviously, $p_{reservation} = 0$ money units per hour for non-EVs.

Regarding the parking service, it is important to mention that a car owner does not have a reservation price for parking. Hence, car owners implicitly accepts the underlying p_{park}. That modeling choice is aligned with our data-driven approach in that non-parking events, which could be used as a proxy for calculating willingness to pay for the parking service, are often non-existent in parking data sets.

Finally, the electricity market provides electricity for the (S-)EVPL for the sake of charging parked EVs. The electricity market can have time-varying prices per MWh and it is assumed that the (S-)EVPL can procure the necessary amount of electricity for such a price.

C. METHODOLOGICAL CONSIDERATIONS

Given the above setting, our goal is to find suitable parking policies given different scenarios. One potential approach to find the best policies in a scenario could be by defining an optimization program. However, this would be challenging given that, apart from primarily focusing on profit, we also consider other objectives in our work, including charging utilization as well as rejection rate (see Section V-B). Moreover, our results are highly dependent on several variables that can be extremely stochastic, such as the rates at which cars arrive at the underlying parking lot, parking durations, and electricity prices. That said, we rely on simulations to find optimal parking policies, which are known to be particularly suitable for studying emergent properties of highly dynamic and complex systems [32], [33]. This statement is consistent with the work by Davis *et al.* [34] who explain that simulation models are able to shed light on complex theoretical relationships among entities, even when the relevant empirical data might be missing.

In theory, there can be an infinite number of parking policies. In Section IV, we describe the policies we focus on in this paper, which are realistic in a sense that they draw inspiration from the way the charging service is currently offered (*e.g.*, dedicated parking spots with chargers where non-EVs cannot park).

We now explain our approach by describing the key steps in the simulation process. First, we define the entities and their behavior in our simulation model via algorithms. Next, we configure the experiments by instantiating the simulation model with real-life data. The next step is to run many different scenarios given the experimental configuration, *e.g.*, run distinct scenarios having different EV shares. Importantly, due to the stochastic nature of the simulation model (*i.e.*, each simulation run can produce different results), each scenario is replicated a number of times, and the analysis is performed based on average values resulting from each scenario. We use these average values to evaluate the parking policies under different scenarios.

To run our simulations and assess the performance of the parking policies, we use the *Electric Vehicle-enabled Parking Lot simulator* (EVPL simulator) developed by Babic *et al.* [35]. Most notably, the EVPL simulator allows one to configure, instantiate, run and reason upon a simulation model that captures the underlying dynamics among entities from the (S-)EVPL ecosystem. Recall from Fig. 3 that such entities include the (S-)EVPL, cars that can be EVs and non-EVs as well as the electricity market.

Fig. 4 shows the simulation model from the EVPL simulator, which was designed following the principles of agent-

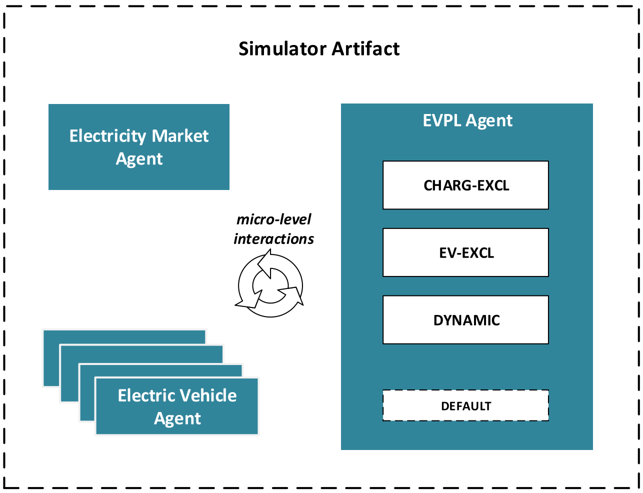


FIGURE 4. Simulator artifact used for evaluation of different parking policies.

based modeling and discrete-event simulations. One can immediately notice that each of the entities from the EVPL ecosystem is represented as an agent in the simulation model. The focus of this study, *i.e.*, the parking policies, are implemented as modules within the EVPL agent in the simulator.

In short, the simulator works as follows. First, it estimates arrival and departure rates per hour from historical parking data concerning a particular parking lot. Based on a queuing theory model, the simulator then simulates the arrival and departure of cars to/from the parking lot. A fraction of these cars are EVs, which is determined by a free-parameter in the simulations. Once an EV arrives at the parking lot, it must obey the parking lot's parking policy. Each EV owner has a reservation price that is derived based on the EV's battery capacity, battery status, and a reference electricity price. That reservation price determines how much the EV owner is willing to pay for the charging service. Specifically, if the reservation price is higher than the charging service fee, then the EV owner will be willing to pay for the charging service. When that happens and an EV spot is available, the parking lot must then provide electricity to charge the EV battery, and the cost of that electricity to the parking lot is determined according to the prices in a suitable electricity market. Since our simulations are based on parking lots located in Melbourne, Australia, the electricity cost is then determined according to the prices in the Australian Energy Market Operator (AEMO) at the time the charging happens. For the sake of brevity, we refer the interested reader to the paper in [35] for more specific details on the EVPL simulator.

IV. PARKING POLICIES FOR (SMART) ELECTRIC VEHICLE ENABLED PARKING LOTS

In the following subsections, we describe three parking policies that take into account the diversity of parking spots (*i.e.*, EV and non-EV spots), as well as cars (*i.e.*, EVs and non-EVs), as presented in Table 1. Note that some of the parking policies are natural extensions of the *default parking*

Algorithm 1 DEFAULT - Default Parking Policy

Input: n_{nonEV}, $n_{nonEVCurr}$, p_{park}
Output: *decision*
1: **if** $n_{nonEVCurr} < n_{nonEV}$ **then**
2: $\quad$ *decision* $\leftarrow$ *car parks for* p_{park} *in a non-EV spot*
3: $\quad$ $n_{nonEVCurr} \leftarrow n_{nonEVCurr} + 1$
4: **else**
5: $\quad$ *decision* $\leftarrow$ *car leaves*
6: **end if**
7: **return** *decision*

Algorithm 2 CHARG-EXCL - Charging-exclusive Parking Policy

Input: n_{total}, n_{EV}, n_{EVCurr}, n_{nonEV}, $n_{nonEVCurr}$, p_{park}, p_{EV}, $p_{reservation}$, *carType*
Output: *decision*
1: **if** $n_{total} > n_{EVCurr} + n_{nonEVCurr}$ **then**
2: $\quad$ **if** *carType* is EV **then**
3: $\quad\quad$ **if** $n_{EVCurr} < n_{EV}$ **then**
4: $\quad\quad\quad$ **if** $p_{EV} \leq p_{reservation}$ **then**
5: $\quad\quad\quad\quad$ *decision* $\leftarrow$ *car parks for* p_{park} *and charges for* p_{EV} *in an EV spot*
6: $\quad\quad\quad\quad$ $n_{EVCurr} \leftarrow n_{EVCurr} + 1$
7: $\quad\quad\quad$ **else**
8: $\quad\quad\quad\quad$ *decision* $\leftarrow$ *DEFAULT*$(n_{nonEV}, n_{nonEVCurr})$
9: $\quad\quad\quad$ **end if**
10: $\quad\quad$ **else**
11: $\quad\quad\quad$ *decision* $\leftarrow$ *car parks for* p_{park} *in a non-EV spot*
12: $\quad\quad\quad$ $n_{nonEVCurr} \leftarrow n_{nonEVCurr} + 1$
13: $\quad\quad$ **end if**
14: $\quad$ **else**
15: $\quad\quad$ *decision* $\leftarrow$ *DEFAULT*$(n_{nonEV}, n_{nonEVCurr})$
16: $\quad$ **end if**
17: **else**
18: $\quad$ *decision* $\leftarrow$ *car leaves*
19: **end if**
20: **return** *decision*

policy (DEFAULT), formalized in Algorithm 1, which is compatible with a parking lot that offers only the parking service. The reason why we introduce and formalize the DEFAULT policy is to illustrate how the (S-)EVPL operates in a so-called *benchmark scenario*, which corresponds to a scenario where all the parking spots are non-EV spots. Simply put, under the DEFAULT policy, the parking decision is based only on whether there is an available spot for a car to be parked. Clearly, the car will either occupy a free spot or it will depart from the parking lot, a behavior which closely resembles the Erlang-B queuing system [36].

A. CHARGING-EXCLUSIVE PARKING POLICY

Algorithm 2 and Fig. 5 describe the *charging-exclusive parking policy* (CHARG-EXCL). Most notably, lines 3-12 in Algorithm 2 handle arriving EVs. In this policy, EV spots can

Algorithm 3 EV-EXCL - Electric Vehicle Exclusive Parking Policy

Input: n_{total}, n_{EV}, n_{EVCurr}, n_{nonEV}, $n_{nonEVCurr}$, p_{park}, p_{EV}, $p_{reservation}$, $carType$
Output: $decision$
1: **if** $n_{total} > n_{EVCurr} + n_{nonEVCurr}$ **then**
2: **if** $carType$ is EV **then**
3: **if** $n_{EVCurr} < n_{EV}$ **then**
4: **if** $p_{EV} \leq p_{reservation}$ **then**
5: $decision \leftarrow$ *car parks for* p_{park} *and charges for* p_{EV} *in an EV spot*
6: **else**
7: $decision \leftarrow$ *car parks for* p_{park} *in an EV spot*
8: **end if**
9: $n_{EVCurr} \leftarrow n_{EVCurr} + 1$
10: **else**
11: $decision \leftarrow$ *car parks for* p_{park} *in a non-EV spot*
12: $n_{nonEVCurr} \leftarrow n_{nonEVCurr} + 1$
13: **end if**
14: **else**
15: $decision \leftarrow DEFAULT(n_{nonEV}, n_{nonEVCurr})$
16: **end if**
17: **else**
18: $decision \leftarrow$ *car leaves*
19: **end if**
20: **return** $decision$

TABLE 1. Summary table indicating under which circumstances a specific type of a car may occupy a specific parking spot under a given parking policy.

Parking policy	non-EV car		EV car	
DEFAULT	+	-	+	-
CHARG-EXCL	+	-	+	-/+
EV-EXCL	+	-	+	+
DYNAMIC	+	-/+	+	+
	non-EV spot	EV spot	non-EV spot	EV spot

only be used by EVs that will consume the charging service. The charging service will only be available to an EV if there is an available EV spot and the EV owner is willing to pay an extra p_{EV} on top of the standard p_{park} for each hour the car occupies the EV spot. Otherwise, EVs are treated as non-EVs. Line 15 in Algorithm 2 reveals that CHARG-EXCL is largely an extended version of DEFAULT.

CHARG-EXCL is consistent with the current business practices used by charging service providers where the EV spots are used for charging only [37].

B. ELECTRIC VEHICLE EXCLUSIVE PARKING POLICY

Algorithm 3 describes the electric vehicle exclusive (EV-EXCL) parking policy. In contrast to CHARG-EXCL, EV-EXCL relaxes the constraint regarding the usage of EV spots for charging only. The green elements in Fig. 6 and Line 7 in Algorithm 3 demonstrate the aforementioned change introduced by the EV-EXCL policy. In particular, the arriving EV is now allowed to park in an EV spot regardless of whether the EV owner wants to charge or not.

Algorithm 4 DYNAMIC - Dynamic Parking Policy

Input: n_{total}, n_{EV}, n_{EVCurr}, n_{nonEV}, $n_{nonEVCurr}$, p_{park}, p_{EV}, $p_{reservation}$, $carType$
Output: $decision$
1: **if** $n_{total} > n_{EVCurr} + n_{nonEVCurr}$ **then**
2: **if** $carType$ is EV **then**
3: **if** $n_{EVCurr} < n_{EV}$ **then**
4: **if** $p_{EV} \leq p_{reservation}$ **then**
5: $decision \leftarrow$ *car parks for* p_{park} *and charges for* p_{EV} *in an EV spot*
6: **else**
7: $decision \leftarrow$ *car parks for* p_{park} *in an EV spot*
8: **end if**
9: $n_{EVCurr} \leftarrow n_{EVCurr} + 1$
10: **else**
11: $decision \leftarrow$ *car parks for* p_{park} *in a non-EV spot*
12: $n_{nonEVCurr} \leftarrow n_{nonEVCurr} + 1$
13: **end if**
14: **else**
15: $decision \leftarrow DEFAULT(n_{nonEV}, n_{nonEVCurr})$
16: **if** $decision$ is *car leaves* **then**
17: *// try to dynamically assign EV spot to non-EV car:*
18: **if** $n_{EVCurr} < n_{EV}$ **then**
19: $decision \leftarrow$ *car parks for* p_{park} *in an EV spot*
20: $n_{EVCurr} \leftarrow n_{EVCurr} + 1$
21: **end if**
22: **end if**
23: **end if**
24: **else**
25: $decision \leftarrow$ *car leaves*
26: **end if**
27: **return** $decision$

C. DYNAMIC PARKING POLICY

Algorithm 4 shows the steps associated with the *dynamic parking policy* (DYNAMIC). By design, it is an extension of the EV-EXCL policy, as evident by the green dotted arrow in Fig. 7. Similar to EV-EXCL, DYNAMIC allows EVs to park on EV spots if there is at least one unoccupied EV spot available or, otherwise, an EV will try to park on a non-EV spot. The crucial change relates to the way non-EVs are treated. That is, in the case when there is an available non-EV spot to a non-EV, DYNAMIC behaves similar to all previous policies: a non-EV will park on a non-EV spot. However, if all non-EV spots are occupied, the S-EVPL will attempt to dynamically assign an EV spot to a non-EV, as evident from lines 16 to 22 in Algorithm 4. It is important to point out that this will only be possible if there is at least one EV spot available for parking, otherwise the car will leave the S-EVPL. We use the term *dynamic* to emphasize the fact

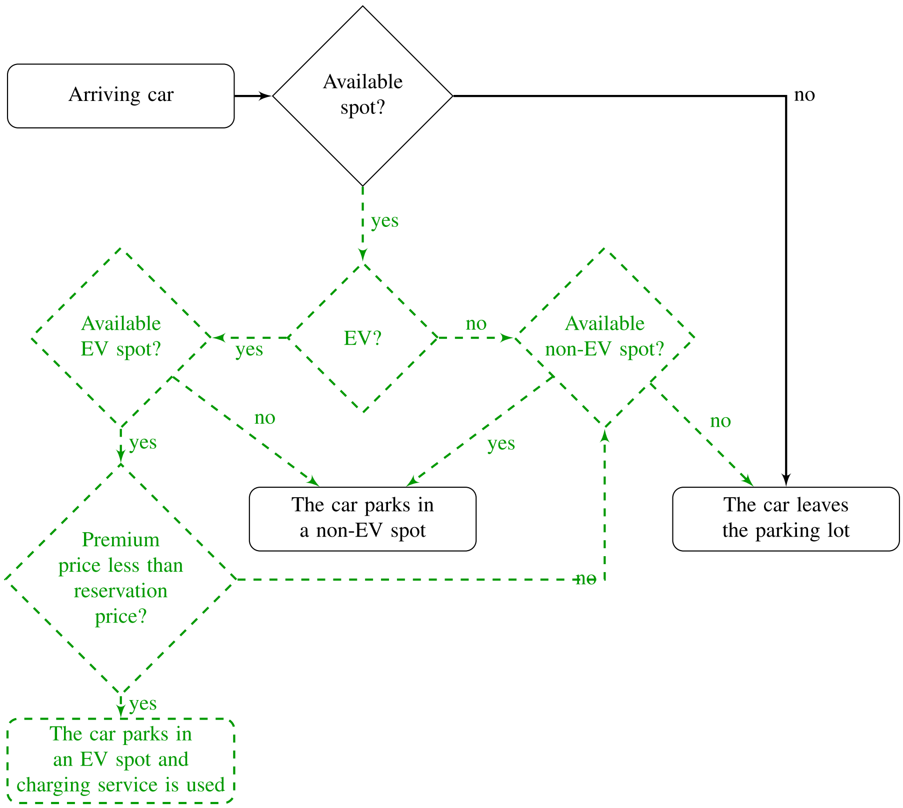


FIGURE 5. **Flowchart of the charging-exclusive (CHARG-EXCL) parking policy. The green dotted elements outline the changes w.r.t. the default parking policy.**

that EV spots can be used by non-EVs in only extraordinary circumstances, *i.e.*, when all non-EV spots are occupied. In practice, for example, the S-EVPL can dynamically mark an EV spot as a non-EV spot by providing the appropriate information on a digital display above the parking spot.

V. EVIDENCE FROM A CASE STUDY: MELBOURNE'S PARKING LOT

In this section, we explain the case study concerning parking lots in Melbourne, Australia, used to benchmark the parking policies described in Section IV.

A. EXPERIMENTAL CONFIGURATION

To find the most appropriate parking policy from the perspective of the parking lot operator's profitability, we consider one-year simulation scenarios where a parking lot operates under certain parking policies, *i.e.*, CHARG-EXCL, EV-EXCL and DYNAMIC. To perform detailed sensitivity analysis, the experimental configuration includes a range of values for *charging fees* (p_{EV}), the *number of EV parking spots* (n_{EV}), and the *EV adoption rate*. Furthermore, to account for the diversity among different parking lots, we used real-world data from some parking lots in the city of Melbourne. Figures 8a, 8b, and 8c illustrate per hour car arrivals for the month of February, 2012, for the public parking lots in the neighborhoods of *Chinatown*, *City Square* and *Tavistock*, respectively. We note that, since the simulation duration has 8,784 simulated hours (*i.e.*, a leap year), we are able to derive and use arrival rates for the whole year in

TABLE 2. **Experiment configuration.**

Variable	Value
Parking policy	CHARG-EXCL EV-EXCL DYNAMIC
EV adoption rate	0%, 25%, 50%, 75%, 100%
Areas (n_{total})	Chinatown (91) City Square (111) Tavistock (14) Halved Chinatown (45) Quartered Chinatown (23)
n_{EV}	from 0 to n_{total} by 1
p_{park}	5.5 \$/h
p_{EV}	0.00 \$/h, 0.05 \$/h, ..., 1.00 \$/h
$p_{reservation}$	dynamically calculated
Charger speed (S)	7.7 kW
Simulation duration	8,784 h (one simulated year)
Scenario replications	300

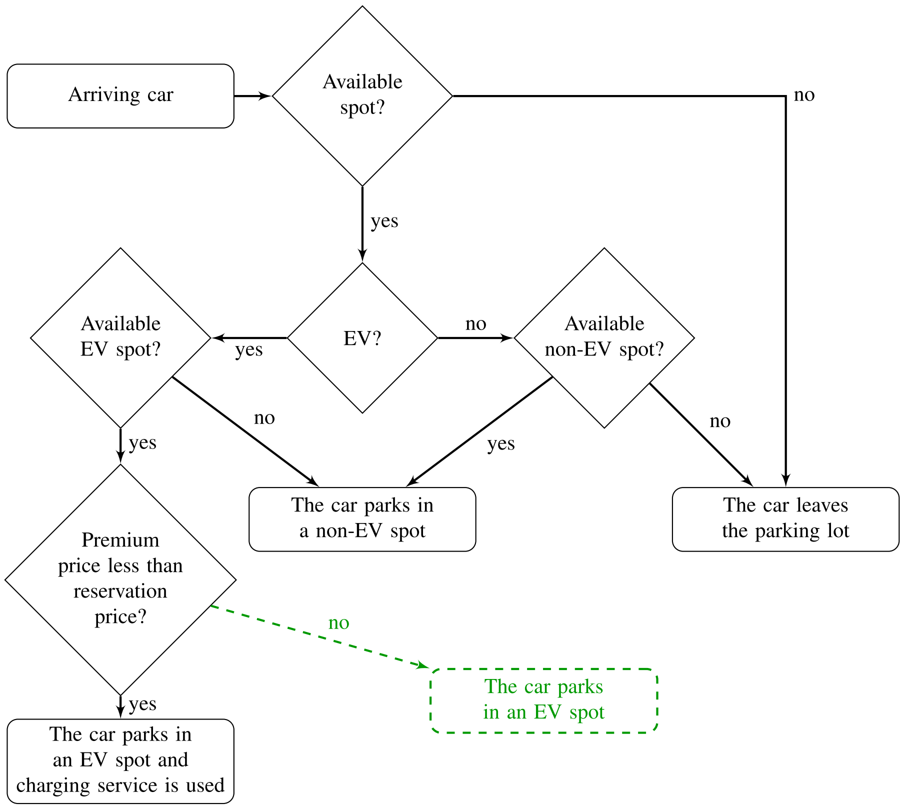


FIGURE 6. Flowchart of the electric vehicle exclusive (EV-EXCL) parking policy. The green dotted elements outline the changes w.r.t the charging-exclusive parking policy.

our simulations. As we detail in Section VI, we also include the so-called *Halved Chinatown* and *Quartered Chinatown* parking lots to investigate the impact of different parking lot sizes on our results, *i.e.*, what happens for different number of parking spots (n_{total}) when the parking demand remains fixed.

Table 2 summarizes the values used for each of the variables. In total, the experiment considered 91,035 distinct scenarios for the (S-)EVPL ecosystem. Finally, to account for the stochastic nature of our computational model, we replicated each scenario 300 times. All of our analyses are then based on average values resulting from these multiple runs.

B. PERFORMANCE MEASURES

We now briefly mention and explain the metrics used for assessing the impact of the parking policies on the (S-)EVPL's operations.

1) ADDITIONAL GROSS PROFIT AGAINST BENCHMARK SCENARIO

The additional gross profit against the benchmark scenario (GPBS) in expressed in percentages. It is a key metric that informs the parking lot operator how well a certain parking policy does in comparison to the benchmark scenario. Recall that the benchmark scenario uses the DEFAULT policy, which does not differentiate between different types of cars, and it only works when all parking spots are non-EV spots. The GPBS for the *ith* scenario is calculated as:

$$GPBS^{(i)} = \frac{GP^{(i)} - GP^{BS}}{GP^{BS}} * 100\% \tag{1}$$

where $GP^{(i)}$ is the gross profit from the *ith* scenario and $GP^{(BS)}$ is the gross profit from the benchmark scenario. The gross profit takes into account positive cash flows regarding the parking service and the charging service as well as the negative cash flow from electricity procurement, *i.e.*, the amount of money the parking lot pays to obtain the required electricity to charge the EVs.

2) REJECTION RATE

The rejection rate (RR) of the *ith* scenario is the percentage of cars that are rejected, *i.e.*, leave the parking lot due to not being able to park:

$$RR^{(i)} = \frac{N^{(i)}_{carsLeft}}{N^{(i)}_{carsParked}} * 100\% \tag{2}$$

where the $N^{(i)}_{carsLeft}$ is the number of cars that left without parking, and $N^{(i)}_{carsParked}$ is the number of cars that parked in the (S-)EVPL. Given the (S-)EVPL ecosystem dynamics (*i.e.*, arrival patterns and EV adoption rates) and the underlying parking policy, the *RR* may provide crucial information regarding the size of the S-EVPL (*i.e.*, whether it is

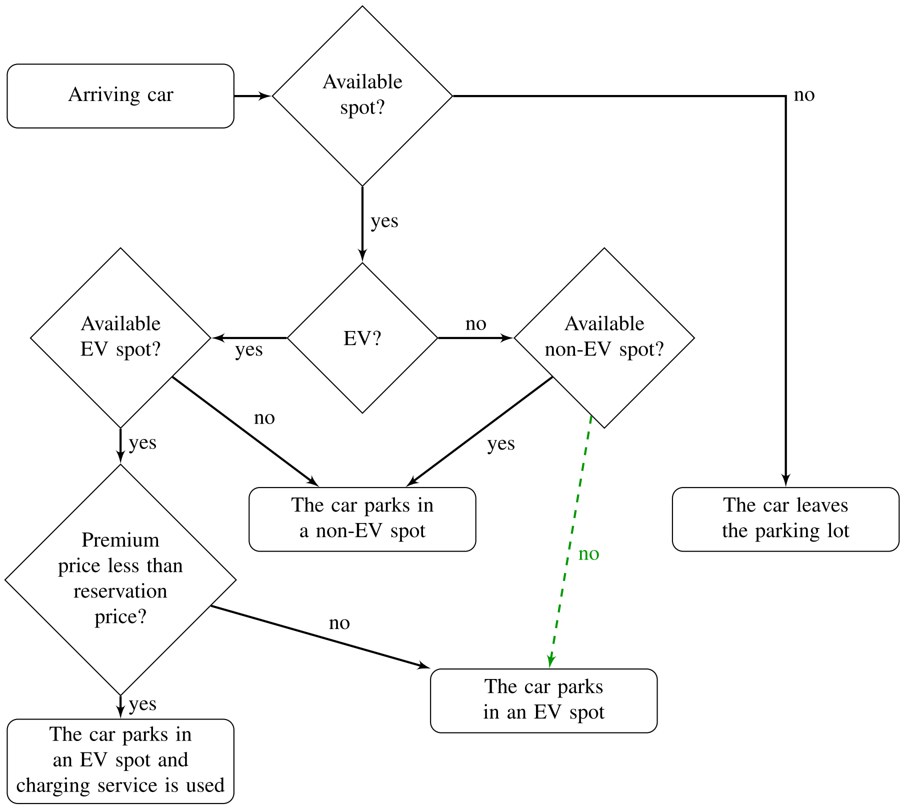


FIGURE 7. Flowchart of the dynamic (DYNAMIC) parking policy. The green dotted arrow outlines the change w.r.t the electric vehicle exclusive parking policy.

undersized or not) and whether a particular parking policy is applicable to a given scenario.

3) CHARGING UTILIZATION

The charging utilization (ρ_{charge}) is defined as the ratio between the total sum of kilowatts charged into EVs and the theoretical maximum sum of kilowatts that could have been charged if chargers were operating at 100% during the time vehicles were parked on EV spots. Mathematically speaking:

$$\rho_{charge} = \sum_{i=1}^{|E|} \frac{\gamma^{(i)}}{t_{park}^{(i)} * S} * 100\% \tag{3}$$

where $|E|$ is the total number of parking events from a set E of parking events related to EV spots, $\gamma^{(i)}$ is the amount of electricity charged into a vehicle during the ith parking event, $t_{park}^{(i)}$ is total parking time during the ith parking event, and S is the charger power, which determines the speed at which a vehicle is charged. In our simulations, we only consider Level II chargers that are able to provide 7.7 kW of power.

The charging utilization metric allows one to measure how efficiently the charging infrastructure is being utilized. Clearly, apart from external parameters (*e.g.*, charging demand from EVs and their willingness to pay for the charging service), ρ_{charge} is also affected by the underlying parking policy.

VI. RESULTS AND DISCUSSION

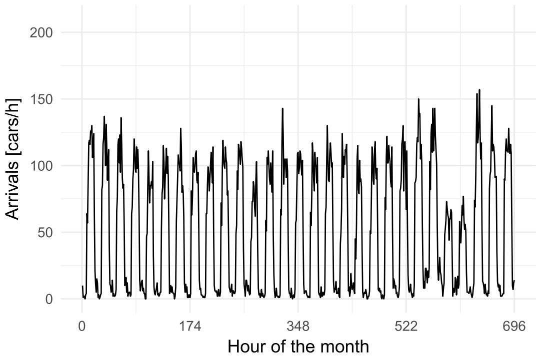
In this section, we present the results from our case study as well as explain how the derived key insights can be used to guide parking lot development and management.

A. SENSITIVITY ANALYSIS

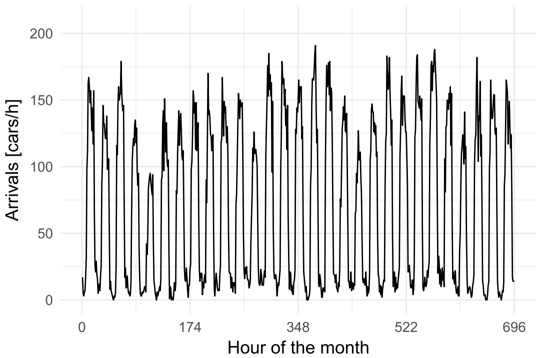
In order to evaluate the parking policies, we present an extensive sensitivity analysis whose underlying context changes based on three different aspects. First, we explore how the parking policies perform for different parking lots having different arrival rates, departure rates, and the total number of available parking spots (n_{total}). Second, the context changes through different EV adoption rates. Third, the context changes through different parking lot sizes (n_{total}), while having similar arrival and departure rates. Once again, it is worth mentioning that the reported results represent the average values of 300 simulation runs of each scenario.

1) PARKING LOTS

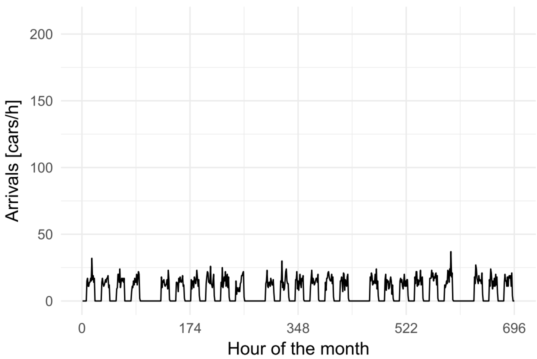
Fig. 9 graphically presents the performance of the policies CHARG-EXCL, EV-EXCL and DYNAMIC, represented, respectively, as the red, blue, and green curves. Each scenario is defined by a fixed EV adoption rate, fixed charging and parking fees, and three different parking lots. In particular, the EV adoption rate is set at 50%, the number which is expected to be reached in Australia by 2030 [26]. The charging fee, *i.e.*, the premium price per hour an EV owner pays



(a)



(b)



(c)

FIGURE 8. The one-month excerpts (*i.e.*, February 2012) of the arrival rates for parking lots used in the experiment configuration. (a) Arrival rates for Chinatown. (b) Arrival rates for City Square. (c) Arrival rates for Tavistock.

for consuming the charging service, is fixed at 0.45 \$/h, the number which was found to bring the highest profit to all three parking policies.

Recall from Section V-B that we defined three KPIs. In order to make the results comparable across different parking lots, each row in Fig. 9 displays a certain KPI on the Y-axis, *i.e.*, gross profit against the benchmark scenario (GPBS), rejection rate (*RR*), and charging utilization (ρ_{charge}). The x-axis always represents the percentage of available EV spots. Finally, each column in Fig. 9 corresponds to a parking lot, *i.e.*, Chinatown, City Square, and Tavistock.

Looking at the columns, one can immediately notice that the first two columns, representing respectively Chinatown (Fig. 9a 9d, and 9g) and City Square (Fig. 9b, 9e, and 9h), have similar curves for all the KPIs, albeit with slightly different values. Although the identified trends, upon which we elaborate next, are the same for all three parking lots, the exact curves for Chinatown and City Square are different than curves for Tavistock (Fig. 9c, 9f, and 9i). The main reason for this emergent behavior lies in the fact Tavistock is inherently *undersized*, whereas Chinatown and City Square are *well-sized*. We further elaborate upon the impact of parking lot sizing (*i.e.*, the total number of parking spots) later on.

Starting with the gross profit against the benchmark scenario (GPBS). Recall that GPBS measures how much more money, percentage-wise, a parking lot operator makes when compared to the benchmark scenario where all parking spots are non-EV spots and the parking lot operates under the DEFAULT parking policy. It is evident from Fig. 9a, 9b, and 9c that the GPBS for both CHARG-EXCL and EV-EXCL increases up to a certain point after which the GPBS decreases. The same does not hold true for DYNAMIC, which increases to the point of saturation for Chinatown and City Square (Fig. 9a and 9b), which are well-sized parking lots, after which the GPBS remains constant. In contrast, the GPBS for Tavistock (Fig. 9c) continually increases even when the number of EV spots approaches 100%, suggesting that the undersized parking lot may become more profitable by increasing the number of parking spots (n_{total}).

Regarding the relative GPBS performance of the parking policies, we can identify that CHARG-EXCL marginally outperforms EV-EXCL before the maximum GPBS of CHARG-EXCL is reached. It is also evident that the maximum GPBS of EV-EXCL is consistently higher than the maximum GPBS of CHARG-EXCL. Next, in well-sized parking lots (Fig. 9a and 9b), the GPBS of DYNAMIC follows the GPBS of EV-EXCL to its maximum, after which the GPBS of DYNAMIC still marginally increases. Also, the GPBS of DYNAMIC seems to substantially increase when used in the undersized parking lot (Fig. 9c). Clearly, this is not surprising when we consider the fact that parking demand is high and the value of parking service (*i.e.*, $p_{park} = 5.5$ \$/h) is much greater than the value of the charging service (*i.e.*, $p_{fee} = 0.45$ \$/h).

Fig. 9a, 9b, and 9c not only shows which parking policy performs best, but they also reveal the *margin of error in investment decision* a parking lot operator has for each of the parking policies. For example, for similar GPBS values, the *latus rectum* of the red curve is smaller than for the blue curve, indicating that the decision on the number of EV spots is more critical for CHARG-EXCL than for EV-EXCL. DYNAMIC trivially circumvents such a challenge when the number of EV spots is increasing towards 100%.

We now move to the rejection rate (*RR*). From Fig. 9d and 9e, one can see that the lines for CHARG-EXCL and EV-EXCL remain close to zero from the start until the number of EV spots increases to a certain point, indicating that Chinatown and City Square are well-sized

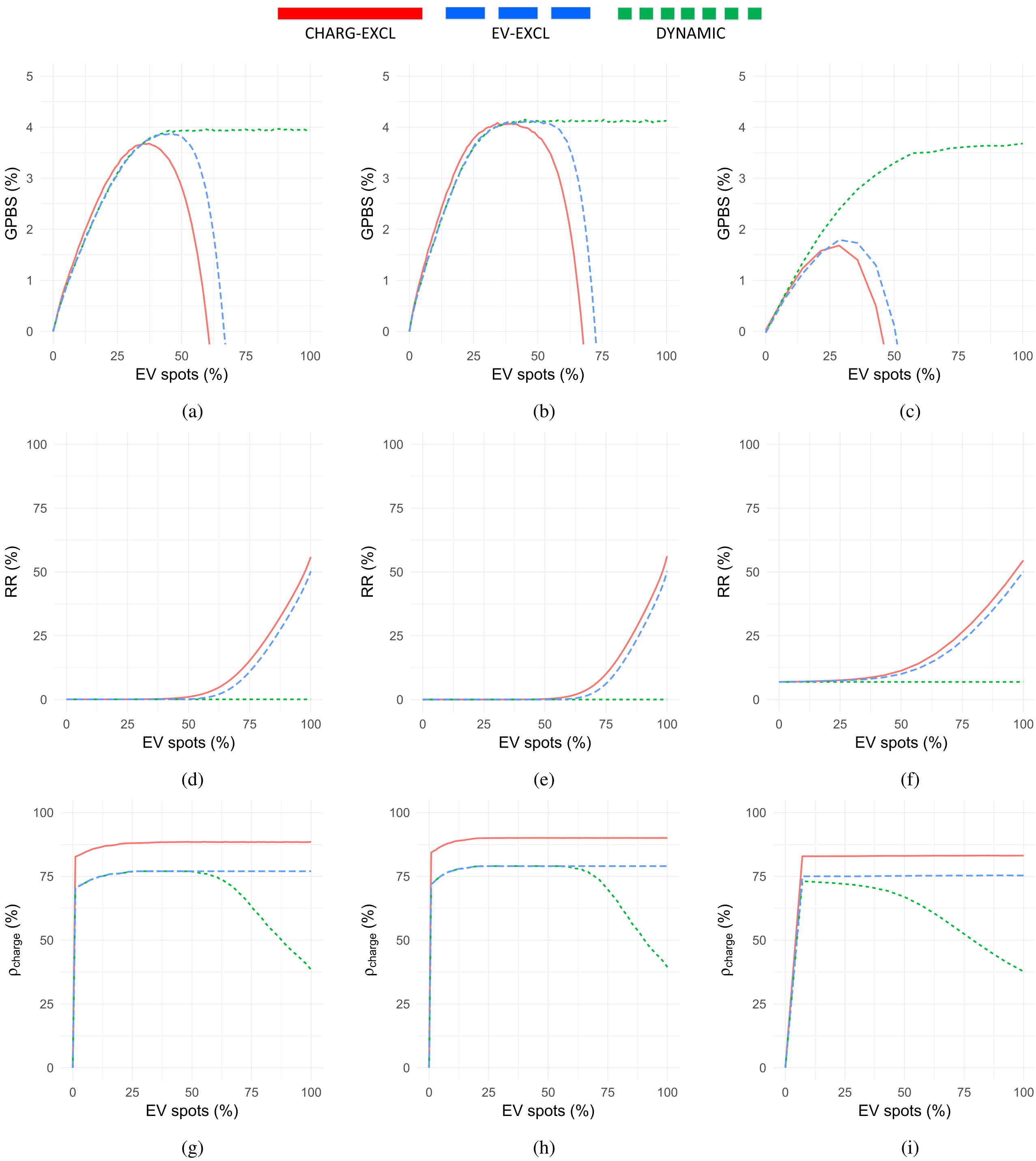


FIGURE 9. The impact of the parking policies on a certain parking lot when the EV adoption rate is 50% and the charging fee is set at 0.45 $/h. (a) GPBS for Chinatown. (b) GPBS for City Square. (c) GPBS for Tavistock. (d) Rejection rate for Chinatown. (e) Rejection rate for City Square. (f) Rejection rate for Tavistock. (g) Charging utilization for Chinatown. (h) Charging utilization for City Square. (i) Charging utilization for Tavistock.

parking lots, *i.e.*, on average, n_{total} is enough to support the parking demand. As already mentioned, Tavistock (Fig. 9f) is different because the minimum RR is around 10%, suggesting that the parking lot is inherently undersized, *i.e.*, on average, parking demand exceeds n_{total}. Evidently, CHARG-EXCL has the highest RR as the focus is placed on utilizing the charging service, followed by EV-EXCL which results in a slightly lower RR when the number of chargers increases. It is also noticeable that the RR in DYNAMIC is the lowest.

Finally, Fig. 9g, 9h, and 9i represent charging utilizations (ρ_{charge}). When comparing different parking lots, it is evident that Chinatown (Fig. 9g) and City Square (Fig. 9h) follow similar trends, with City Square having consistently higher ρ_{charge} than Chinatown. We attribute this emergent behavior to different arrival patterns among parking lots. More concretely, on average, City Square had more EVs parked during the time when the prices on the electricity market were low in comparison to Chinatown. Not surprising, CHARG-EXCL has the highest ρ_{charge}, followed by EV-EXCL, while DYNAMIC performs the worst. Finally, ρ_{charge} of DYNAMIC in Tavistock is always lower than EV-EXCL, proving once again that the parking lot is undersized.

2) ELECTRIC VEHICLE ADOPTION RATES

We now discuss how different EV adoption rates affect CHARG-EXCL, EV-EXCL, and DYNAMIC parking policies. To do so, the focus of the analysis is placed on the scenario where the observed parking lot is Chinatown and the charging fee is fixed at the optimal value of 0.45 \$/h. In particular, Fig. 10 presents the results for 0% (low extreme), 25% (first midpoint), 50% (forecast for the year of 2030), 75% (second midpoint), and 100% (high extreme) EV adoption rates, which in turn are represented as the red, brown, green, blue, and purple curves, respectively. Each row in Fig. 10 represents a certain KPI, while each column contains information for one parking policy.

Starting with the first row, which represents the GPBS for CHARG-EXCL, EV-EXCL, and DYNAMIC parking policies in Fig. 10a, 11b, and 10c, respectively. The decline of the red curves indicates that it does not make sense financially to deploy new parking policies when there are no EVs as customers. DYNAMIC is the only exception because it allows non-EVs to be parked on both EV and non-EV spots. Furthermore, one can notice that the maximum GPBS increases with the increase of the EV adoption rate, meaning that the profitability of the charging service increases with the increase of the EV adoption rate. Looking at the maximum GPBS for CHARG-EXCL (Fig. 10a) and EV-EXCL (Fig. 10b), it can be seen that the relative benefits of choosing the optimal number of EV spots increases with the EV adoption rate. Lastly, the GPBS for DYNAMIC, shown in Fig. 10c, reveals that for the observed scenario, the parking lot operator can get the maximum GPBS of 2%, 4%, 6% and 8% by investing in the appropriate number of chargers for, respectively, 25%, 50%, 75% and 100% of the total number of parking spots.

Moving on to the RR in Fig. 10d, 10e, and 10f. For CHARG-EXCL and EV-EXCL, it is clear that the number of EV spots positively affects the RR, with CHARG-EXCL having slightly higher RR than EV-EXCL. This is most noticeable by looking at the RR when the number of EV spots is set at 100%, *i.e.*, the rightmost values in the curves in Fig. 10d and 10e. Note that the values in Fig 10e are the complement of the EV adoption rate, meaning that the RR is 25% for scenarios where the EV adoption rate is 75% and so on. This is very much expected because, for example, when all the spots are equipped with chargers, EV-EXCL will no longer be able to serve non-EVs. Looking at DYNAMIC in Fig.10f, it is clear that EV adoption rate does not affect the RR.

Lastly, the maximum ρ_{charge} is reported to be around 87.5% for CHARG-EXCL (Fig. 10g) and around 76% for EV-EXCL and DYNAMIC (Fig. 10h and 10i). When DYNAMIC is used in a setting where there are more EV spots than needed by EV users, the ρ_{charge} will decrease, meaning that chargers will not be used as frequently as they could be given the demand for charging service.

3) PARKING LOT SIZES

In our final sensitivity analysis, we investigate how a certain parking policy behaves when the size of the parking lot (n_{total}) changes, while arrival rates and parking time remain the same. Again, we fix the EV adoption rate at 50% and the charging fee at 0.45 \$/h. The observed parking lot is Chinatown, displayed in Fig. 11 with red, blue, and green curves to denote, respectively, the original Chinatown parking lot ($n_{total} = 91$), halved Chinatown ($n_{total} = 45$), and quartered Chinatown ($n_{total} = 23$). Chinatown is particularly well-suited for analysis because, in its original state, it is *well-sized* by design, as we discussed in Section VI-A1. For the sake of consistency, note that Fig. 11 organizes the same level of information as Fig. 10 does, with each row representing a certain KPI and each column representing a certain parking policy.

Regarding GPBS, CHARG-EXCL, and EV-EXCL have similar trends regardless of the n_{total} (Fig. 11a and 11b). Also, it is interesting that the maximum GPBS of the original, well-sized Chinatown (*i.e.*, around 4%) noticeably outperforms the halved and quartered counterparts (*i.e.*, around 2%). However, as shown in Fig. 11c, the maximum GPBS for DYNAMIC reaches around 4% for all three parking lot sizes, thus suggesting that DYNAMIC is more versatile than the other two parking policies.

Fig. 11d, 11e, and 11f reveal that for the current arrival rates: (i) the original Chinatown is *well-sized* by design because its *RR* is 0% when there are no chargers installed in the parking lot; and (ii) both halved and quartered Chinatown parking lots are *undersized* because their *RR*s are greater than zero.

Finally, Fig. 11g and 11h capture the trends for CHARG-EXCL and EV-EXCL similar to the ones already shown in Fig. 10g and Fig. 10h, thus suggesting that the parking lot size does not affect ρ_{charge} as much when either CHARG-EXCL or EV-EXCL is used. However, as shown in Fig. 11i, parking lot sizing positively affects charging utilization when DYNAMIC is used. The reason behind this emergent behavior lies in the fact that parking demand in undersized parking lots (*i.e.*, green and blue curves in Fig. 11i) outweighs demand for the charging service.

B. IMPACT ON PARKING LOT DEVELOPMENT AND MANAGEMENT

Based on the performed sensitivity analysis, one can conclude that the *relative share of EV spots* within the total number of parking spots is crucial when deciding which parking policy should be used. We conclude that:

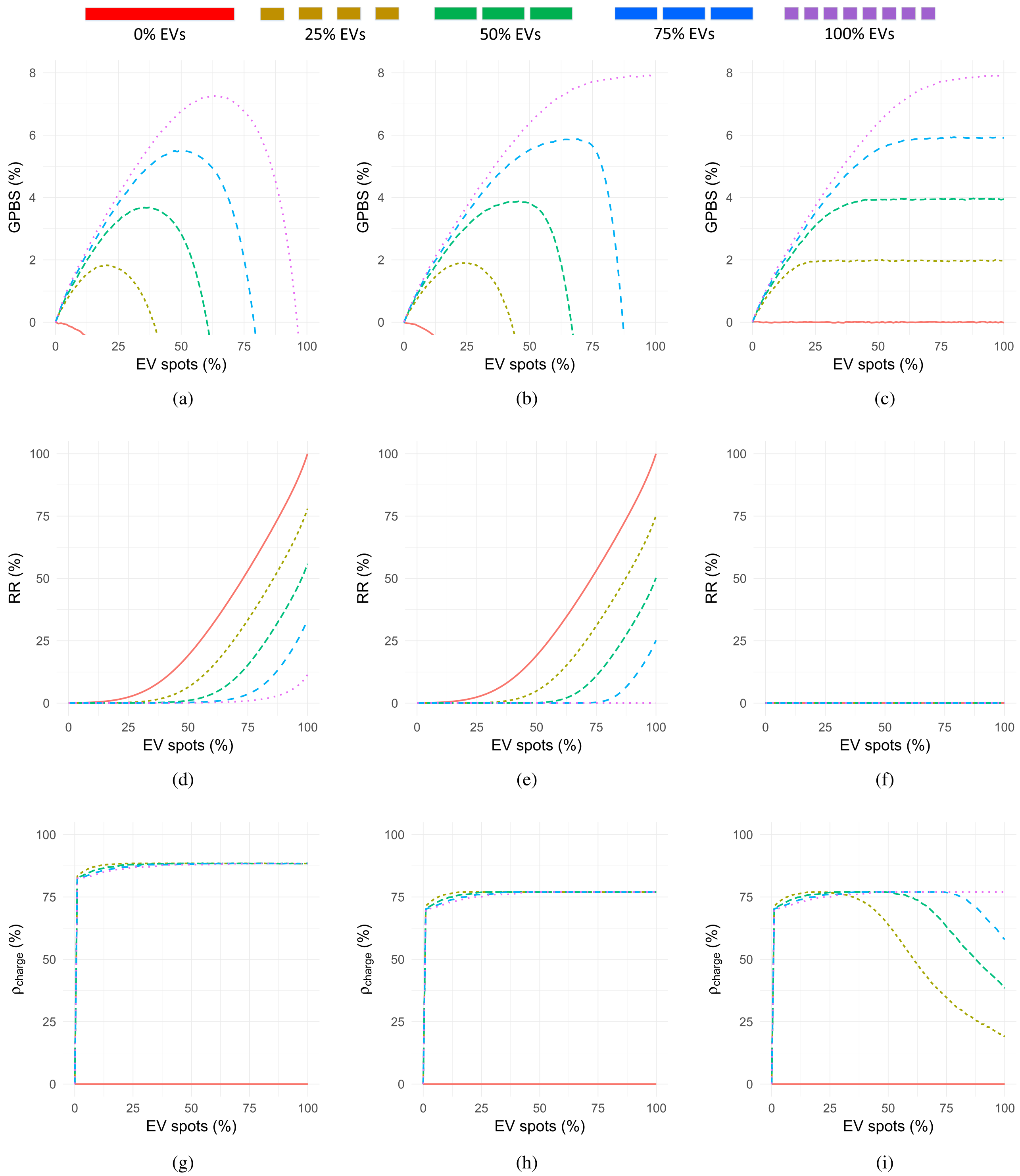


FIGURE 10. **The impact of the parking policies on different EV adoption rates when the observed parking lot is Chinatown and the charging fee is set at 0.45 $/h. (a) GPBS for the CHARG-EXCL parking policy. (b) GPBS for the EV-EXCL parking policy. (c) GPBS for the DYNAMIC parking policy. (d) Rejection rate for the CHARG-EXCL parking policy. (e) Rejection rate for the EV-EXCL parking policy. (f) Rejection rate for the DYNAMIC parking policy. (g) Charging utilization for the CHARGEXCL parking policy. (h) Charging utilization for the EV-EXCL parking policy. (i) Charging utilization for the DYNAMIC parking policy.**

- When the number of EV parking spots is small, it is preferable to use CHARG-EXCL. The reason behind this lies in the fact that such a policy promotes efficient usage of EV spots for the charging service. In other words, CHARG-EXCL has the best return on investment as it minimizes the number of chargers needed to be

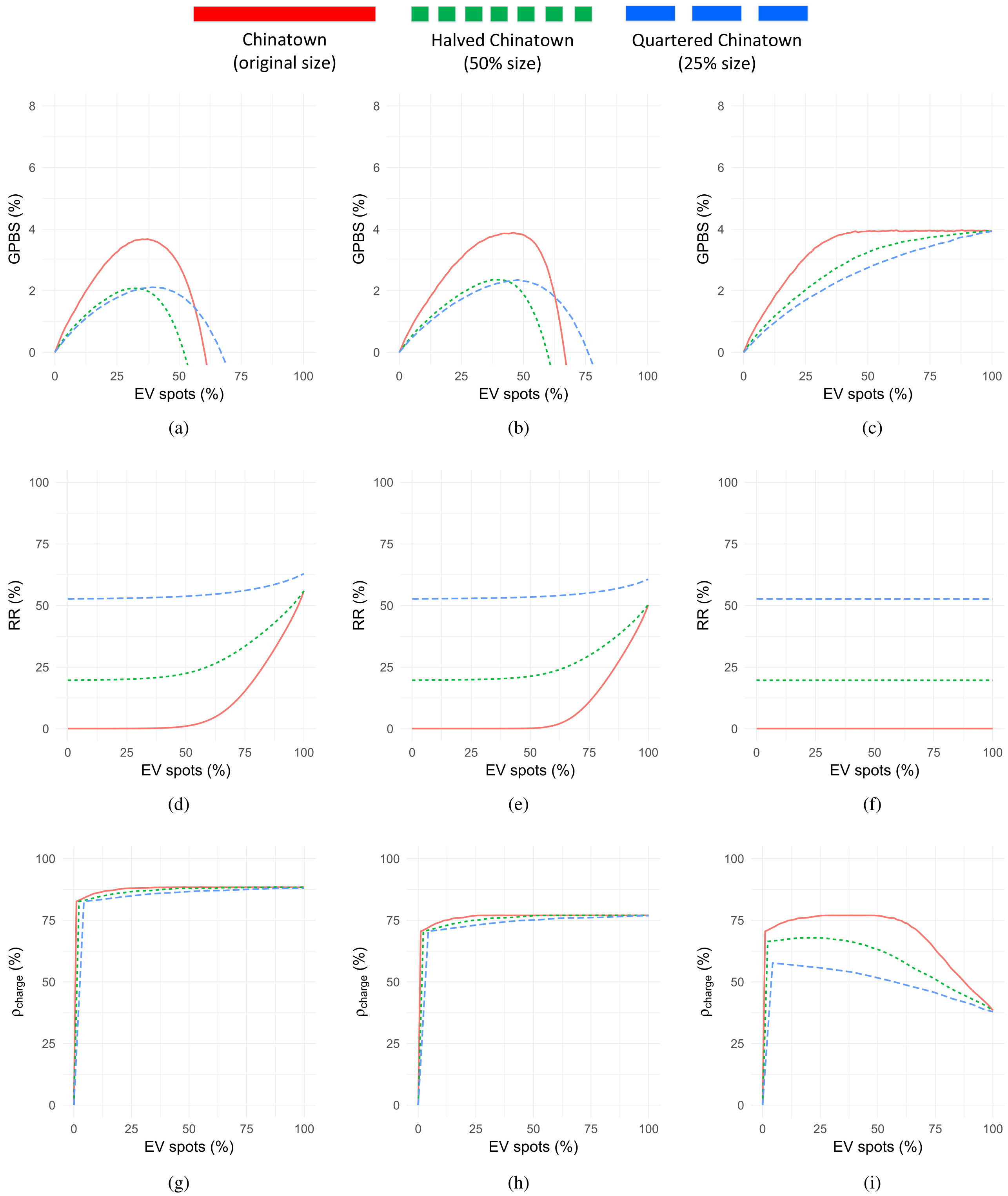


FIGURE 11. The impact of the parking policies and parking lot size for the Chinatown parking lot when the EV adoption rate is 50% and the charging fee is set at 0.45 $/h. (a) GPBS for the CHARG-EXCL parking policy. (b) GPBS for the EV-EXCL parking policy. (c) GPBS for the DYNAMIC parking policy. (d) Rejection rate for the CHARG-EXCL parking policy. (e) Rejection rate for the EV-EXCL parking policy. (f) Rejection rate for the DYNAMIC parking policy. (g) Charging utilization for the CHARGEXCL parking policy. (h) Charging utilization for the EV-EXCL parking policy. (i) Charging utilization for the DYNAMIC parking policy.

installed. This policy also results in a low rejection rate and relatively high GPBS for a small number of chargers.

- EV-EXCL is a valuable upgrade of CHARG-EXCL when the number of EV spots is further increased because profit will increase and the rejection rate will

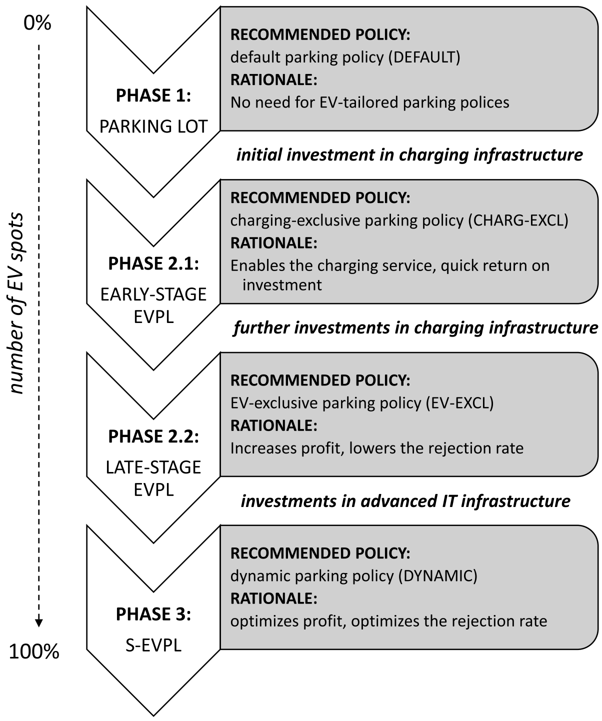


FIGURE 12. **Parking policies deployment.**

decrease. It is a preferable parking policy when a parking lot operator is able to accurately forecast parking and charging demand.

- DYNAMIC is the optimal parking policy for a parking lot whose number of EV spots exceeds the demand for the charging service. Consequently, it is the preferable parking policy when a parking lot operator is not able to cope with uncertainties related to parking and charging demand. Also, DYNAMIC is favorable among car owners as the rejection rate is minimized.

The aforementioned observations seem to be general to all parking lots operating in different contexts (*e.g.*, EV adoption rates). Clearly, as the *EV adoption rate* increases, the impact of the three proposed parking policies increases as well. Finally, the *parking lot size* is shown to be an important variable when choosing the appropriate parking policy. In *well-sized* parking lots, the parking lot operator can theoretically (*i.e.*, if he/she is able to deal with uncertainties related to parking and charging demand) obtain the optimum GPBS by using EV-EXCL. However, DYNAMIC in the *undersized* parking lots is able to significantly outperform both CHARG-EXCL and EV-EXCL. The reason for this lies in DYNAMIC's flexible nature when dynamically assigning EV spots to non-EVs.

Taking into account all the identified patterns related to a parking lot's operations, Fig. 12 shows how a parking lot operator, *i.e.*, a decision maker, can choose the right parking policy given the phase a parking lot is currently in. In the first phase, it makes no sense to use any parking policies other than DEFAULT as there is no need for the charging service. The initial investment in charging infrastructure marks the transition to the early-stage EVPL, which operates with CHARG-EXCL so as to optimize charging utilization and, consequently, to quickly monetize the installed chargers. Once the extra chargers are added, we refer to a parking lot as late-stage EVPL. In such a parking lot, it is advisable to switch to EV-EXCL as it increases profit and lowers the rejection rate. Also, the introduced chargers implicitly help a parking lot operator in scenarios where he or she is not able to accurately predict parking and charging demands. Finally, after significant investments in advanced IT infrastructure, the newly-formed S-EVPL should be operated under the DYNAMIC policy so as to maximize profit and minimize the rejection rate.

VII. CONCLUSION

Although the need for appropriate parking policies, tailored to both internal combustion vehicles (ICVs) and electric vehicles (EVs), may be an understandable and obvious idea, the context under which a certain parking policy should be deployed is not immediately known *a priori* due to the inherent uncertainties related to the (smart) electric vehicle enabled parking lot (S-EVPL) ecosystem. Therefore, we used a data-driven approach coupled with simulations to propose a technology roadmap for transforming parking lots into smart EV-enabled parking lots and evaluate three parking policies that extend the *default parking policy* (DEFAULT), which in turn only offers the parking service: 1) the *charging-exclusive parking policy* (CHARG-EXCL) ensures that the parking spots with chargers (*i.e.*, EV spots) are only used by EVs that will accept the price for charging; 2) the *EV-exclusive parking policy* (EV-EXCL) relaxes such a constraint by allowing EVs to be parked on EV spots regardless of whether the charging service is used; and 3) the *dynamic parking policy* (DYNAMIC) may allow non-EVs to be parked in EV spots if there are not enough available non-EV spots.

Based on the obtained results and detailed sensitivity analysis, it was shown that CHARG-EXCL is a particularly suitable policy for parking lots that tend to have less chargers than what EV owners charging demand would require. EV-EXCL is a valuable upgrade of CHARG-EXCL when there is a small redundancy in the number of chargers as profit increases and the number of cars being rejected decreases. Once the number of chargers increases substantially and the required advanced IT infrastructure is deployed, the resulting S-EVPL operates the best when the DYNAMIC policy is used as it optimizes profit and minimizes the rejection rate at the same time. From a methodological point of view, the strength of our approach lies in the fact that we are able to specify scenarios in a detailed manner as well as to determine the boundaries at which certain parking policies operate optimally with respect to profit, rejection rates, and charging utilization.

We strongly believe that the prescriptive nature of the insights derived from our simulations are highly relevant to practitioners involved in parking lots. For example, the results from the case study concerning parking lots in Melbourne suggest that, by 2030, a Chinatown parking lot operator can expect almost 4% more profit if the price of the charging service is set at an optimal value, *i.e.*, at 0.45 $/h. Of course, when choosing the appropriate parking policy, careful planning needs to be considered. Our results suggest that, if the decision maker is able to perfectly predict the demand for both the charging and parking services, the parking lot should adopt CHAR-EXCL and install chargers in around 37% of the parking spots. To increase profit slightly and to lower the impact of demand prediction error, our results suggest that the decision maker should adopt EV-EXCL and install chargers in around 49% of the parking spots. Finally, to completely hedge the risk of a wrong demand prediction, the decision maker should equip all the parking spots with chargers and invest in advanced IT infrastructure in order to adopt DYNAMIC.

For future work, we aim at performing more experiments to study the performance of parking policies in other contexts. For example, in our current simulations, the EV owners' willingness to pay function for the charging service remains the same throughout the experiment (see [35]), although in real-life that may be context-specific. In particular, early adopters may want to pay differently than late adopters, suggesting that such a willingness-to-pay function can incorporate EV adoption rate as a predictor. Furthermore, the methodology we proposed can be used to assess the impact of various charging technologies that have different charging speeds. Also, a particularly interesting future direction is the development of a real-time algorithm that is able to switch parking policies given a tactical horizon, meaning that parking policies are not fixed, but they can change on a daily or hourly basis based on relevant variables.

REFERENCES

[1] F. Kley and M. Wietschel, "Evaluation of European electric vehicle support schemes," in *Paving the Road to Sustainable Transport: Governance and Innovation in Low-Carbon Vehicles*. London, U.K.: Routledge, 2012, pp. 75–95. [Online]. Available: https://www.routledge.com/Paving-the-Road-to-Sustainable-Transport-Governance-and-innovation-in/Nilsson-Hillman-Rickne-Magnusson/p/book/9780415683609, doi: 10.4324/9780203119716.

[2] C. Kemfert, "Promoting electric vehicles in Germany via subsidies—An efficient strategy?" *CESifo DICE Rep.*, vol. 14, no. 4, pp. 65–70, 2016.

[3] G. Tal and M. Nicholas, "Exploring the impact of the federal tax credit on the plug-in vehicle market," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2572, pp. 95–102, 2016.

[4] T. Higgins and C. Rollet, "Tesla sales fall to zero in hong kong after tax break is slashed," *Wall Street J.*, Jul. 2017. [Online]. Available: https://www.wsj.com/articles/teslas-hong-kong-sales-gutted-by-tax-change-1499598003

[5] Z. Shahan. (2014). *ABB Conversations Electric Vehicle Market Share in 19 Countries*. [Online]. Available: https://www.abb-conversations.com/2014/03/electric-vehicle-market-share-in-19-countries/

[6] Statista. (2017). *Worldwide Number of Battery Electric Vehicles in Use From 2012 to 2016*. [Online]. Available: https://www.statista.com/statistics/270603/worldwide-number-of-hybrid-and-electric-vehicles-since-2009/

[7] W. Young and C. F. Miles, "A spatial study of parking policy and usage in Melbourne, Australia," *Case Stud. Transp. Policy*, vol. 3, no. 1, pp. 23–32, Mar. 2015.

[8] G. Marsden, "Parking policy," in *Transport and Sustainability*, vol. 5, S. Ison and C. Mulley, Eds. Bingley, U.K.: Emerald Group Publishing Limited, Sep. 2014, pp. 11–32.

[9] G. Mingardo, B. van Wee, and T. Rye, "Urban parking policy in Europe: A conceptualization of past and possible future trends," *Transp. Res. A, Policy Pract.*, vol. 74, pp. 268–281, Apr. 2015.

[10] R. Arnott, "Spatial competition between parking garages and downtown parking policy," *Trans. Policy*, vol. 13, no. 6, pp. 458–469, Nov. 2006.

[11] W. Ketter, J. Collins, and P. Reddy, "Power TAC: A competitive economic simulation of the smart grid," *Energy Economics*, vol. 39, pp. 262–270, Sep. 2013.

[12] W. Ketter, M. Peters, J. Collins, and A. Gupta, "A mutual competitive gaming platform to address societal challenges," *Manag. Inf. Syst. Quart.*, vol. 40, no. 2, pp. 447–460, Jun. 2016.

[13] P. A. Barter, "Off-street parking policy without parking requirements: A need for market fostering and regulation," *Transp. Rev.*, vol. 30, no. 5, pp. 571–588, Sep. 2010.

[14] M.-T. Tsai and C.-P. Chu, "Evaluating parking reservation policy in urban areas: An environmental perspective," *Transp. Res. D, Transp. Environ.*, vol. 17, no. 2, pp. 145–148, Mar. 2012.

[15] J. van Ommeren, D. Wentink, and J. Dekkers, "The real price of parking policy," *J. Urban Econ.*, vol. 70, no. 1, pp. 25–31, Jul. 2011.

[16] A. O. Kotb, Y.-C. Shen, X. Zhu, and Y. Huang, "iParker—A new smart car-parking system based on dynamic resource allocation and pricing," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 9, pp. 2637–2647, Sep. 2016.

[17] I. Benenson, K. Martens, and S. Birfir, "PARKAGENT: An agent-based model of parking in the city," *Comput., Environ. Urban Syst.*, vol. 32, no. 6, pp. 431–439, 2008.

[18] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 371–380, Feb. 2010.

[19] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, "Integration of electric vehicles in the electric power system," *Proc. IEEE*, vol. 99, no. 1, pp. 168–183, Jan. 2011.

[20] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," *IEEE Trans. Smart Grid*, vol. 2, no. 3, pp. 456–467, Sep. 2011.

[21] E. Sortomme, M. M. Hindi, S. D. J. MacPherson, and S. S. Venkata, "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 198–205, Mar. 2011.

[22] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 131–138, Mar. 2011.

[23] P.-Y. Kong and G. K. Karagiannidis, "Charging schemes for plug-in hybrid electric vehicles in smart grid: A survey," *IEEE Access*, vol. 4, pp. 6846–6875, 2016.

[24] Z. Duan, B. Gutierrez, and L. Wang, "Forecasting plug-in electric vehicle sales and the diurnal recharging load curve," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 527–535, Jan. 2014.

[25] R. Segal, "Forecasting the market for electric vehicles in California using conjoint analysis," *Energy J.*, vol. 16, no. 3, pp. 89–111, 1995.

[26] A. Higgins, P. Paevere, J. Gardner, and G. Quezada, "Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles," *Technol. Forecast. Soc. Change*, vol. 79, no. 8, pp. 1399–1412, Oct. 2012.

[27] M. R. Mozafar, M. H. Amini, and M. H. Moradi, "Innovative appraisement of smart grid operation considering large-scale integration of electric vehicles enabling V2G and G2V systems," *Electr. Power Syst. Res.*, vol. 154, pp. 245–256, Jan. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378779617303498

[28] M. H. Amini, M. P. Moghaddam, and O. Karabasoglu, "Simultaneous allocation of electric vehiclesŠ parking lots and distributed renewable resources in smart power distribution networks," *Sustain. Cities Soc.*, vol. 28, pp. 332–342, Jan. 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2210670716304966

[29] H. A. Bonges and A. C. Lusk, "Addressing electric vehicle (EV) sales and range anxiety through parking layout, policy and regulation," *Transp. Res. A, Policy Pract.*, vol. 83, pp. 63–73, Jan. 2016.

[30] M. V. Faria, P. C. Baptista, and T. L. Farias, "Electric vehicle parking in European and American context: Economic, energy and environmental analysis," *Transp. Res. A, Policy Pract.*, vol. 64, pp. 110–121, Jun. 2014.

[31] J. Babic, A. Carvalho, W. Ketter, and V. Podobnik, "Electricity trading agent for EV-enabled parking lots," in *Agent-Mediated Electronic Commerce. Designing Trading Strategies and Mechanisms for Electronic Markets*. Cham, Switzerland: Springer, May 2015, pp. 35–49.
[32] L. Tesfatsion, "Agent-based computational economics: Modeling economies as complex adaptive systems," *Inf. Sci.*, vol. 149, no. 4, pp. 262–268, Feb. 2003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0020025502002803
[33] J. Babic and V. Podobnik, "A review of agent-based modelling of electricity markets in future energy eco-systems," in *Proc. Int. Multidisciplinary Conf. Comput. Energy Sci. (SpliTech)*, Jul. 2016, pp. 1–9.
[34] J. P. Davis, K. M. Eisenhardt, and C. B. Bingham, "Developing theory through simulation methods," *Acad. Manag. Rev.*, vol. 32, no. 2, pp. 480–499, 2007.
[35] J. Babic, A. Carvalho, W. Ketter, and V. Podobnik, *A Data-Driven Approach to Manage Charging Infrastructure for Electric Vehicles in Parking Lots*. Rochester, NY, USA: SSRN, Sep. 2017. [Online]. Available: https://papers.ssrn.com/abstract=3035913
[36] M. Nesenbergs, "A hybrid of erlang *B* and *C* formulas and its applications," *IEEE Trans. Commun.*, vol. COM-27, no. 1, pp. 59–68, Jan. 1979.
[37] T. R. of the University of Michigan. (2017). *Electric Vehicle Charging Stations—Time Limit And Enforcement*. [Online]. Available: https://ltp.umich.edu/alt-trans/ev-charge.php

JURICA BABIC (GS'12) is currently pursuing the Ph.D. degree with the University of Zagreb. He is currently a Research and Teaching Associate with the Telecommunication Department, Faculty of Electrical Engineering and Computing, University of Zagreb. His teaching and research activities are in a field of energy informatics, which aims to foster Information System (IS) skills and IS thinking to create sustainable systems of the future. His current research is focused on design of sustainable parking lots with electric vehicles. He is a member of the Social Networking and Computing Laboratoryand the Laboratory for Assistive Technologies and Alternative and Augmentative Communication. He is a member of INFORMS associations.

ARTHUR CARVALHO received the M.Math. and Ph.D. degrees in computer science from the University of Waterloo in 2010 and 2014, respectively. He was as an Assistant Professor with the Rotterdam School of Management, Erasmus University. He is currently an Assistant Professor of information systems and analytics with the Farmer School of Business, Miami University. In particular, he involves in the development of mathematical techniques and decision support systems that assist decision makers in making better decisions, with a particular focus on applications in the crowdsourcing and energy domains. His research has been published in academic journals, such as the *Annals of Mathematics and Artificial Intelligence*, the *APA Decision*, *INFORMS Decision Analysis*, the *Judgement and Decision Making*, and the *Journal of Prediction Markets*. His research interests lie at the intersection of information systems, analytics, and decision analysis.

WOLFGANG KETTER has been a Chaired Professor of information systems with the Faculty of Management, Economics, and Social Sciences, University of Cologne, Cologne, Germany, since 2017. He also serves as the Director of the Institute of Energy Economics, University of Cologne and the Erasmus Centre for Future Energy Business, Rotterdam School of Management, Erasmus University, Rotterdam, The Netherlands. His research exploits rapidly evolving computing power and techniques to build and explore new solutions that could not be thought of before. Traditionally, research in business and social environments is built over time, as researchers pick interesting and promising ideas and build a body of research over decades. He is currently changing this paradigm by building a community of researchers who compete and learn from each other in rapid competitive environments for important societal challenges such as the future of energy markets.

VEDRAN PODOBNIK (M'05–SM'17) received the M.Eng. degree in electrical engineering and the Ph.D. degree in computer science from the Faculty of Electrical Engineering and Computing (FER), University of Zagreb, Zagreb, Croatia, in 2006 and 2010, respectively, and the M.Phil. degree in technology policy from the Judge Business School, University of Cambridge, Cambridge, U.K., in 2013.

Since 2006, he has been with the Department of Telecommunications, FER, where he has been an Associate Professor since 2016. He is the Founder and Director of the Social Networking and Computing Laboratory and Co-Coordinator of the FER's student startup incubator SPOCK. He led several national and international scientific and industrial projects. His teaching and research activities are in transdisciplinary fields of network and data science, social computing, and technology policy. He has co-authored over 80 papers, including publications in Information Sciences, Information Technology and People, *AI Magazine* and *Cybernetics, and Systems* journals.

Prof. Podobnik is a member of the ACM, INFORMS, AIS, and KES International associations. He was a Leader of an interdisciplinary team which was a recipient of the Highest National Award for notable achievements in the education activity by the Croatian Parliament in 2015 and the annual national PMI Project of the Year Award by the world's leading project management professionals association PMI in 2016. As a Junior Researcher, he received the Croatian Annual National Award for Science in the field of technical sciences by the Croatian Parliament in 2011.