AI-based Decision Support for Sustainable Operation of Electric Vehicle Charging Parks

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Abstract

The widespread adoption of electric vehicles makes investments in charging parks both immediate and necessary to lower range anxiety and allow longer trips. However, many charging park operators struggle with sustainable and profitable operation due to high fees on peak loads and volatile availability of renewable energy. Smart charging strategies may enable such operation, but the computational complexity of most available algorithms increases significantly with the number of charging points. Thus, operators of larger charging parks need information systems that provide real-time decision support without immense cost for computation. This paper presents a model that uses recent methods from the field of Reinforcement Learning. Our model is trained on a charging park simulation with real-world data on highway traffic and day-ahead energy prices. The results indicate that Reinforcement Learning is a feasible solution to improve the sustainable and profitable operation of large electric vehicle charging parks.

1. Introduction

Electric vehicles (EVs) are widely regarded as an important means to increase the sustainability of individual transport [1, 2]. However, the uptake of EVs critically hinges on the ready availability of closely-knit charging infrastructure [3], which reduces range anxiety [4, 5] and enables long-distance trips. Moreover, the sustainability of EVs essentially depends on the share of renewable energy used during the charging

process. These two requirements prove challenging because operators of charging parks often struggle with sustainable and profitable operation due to the volatility of renewable generation and peaks in charging demand. Especially charging peaks are a significant cost driver because energy contracts for industrial consumers typically include an additional fee for these peaks, namely a demand charge [6, 7]. This demand charge bills consumers for the highest strain they induce into the power grid over the billing period. These challenges make it hard to establish the profitability of investments in charging parks, and therefore, slow down the transition to sustainable mobility [8, 9].

Green IS enabled smart charging strategies is one essential means to promote sustainable transport by improving the profitability and sustainability of charging parks [10]. Such strategies are especially relevant for large-scale charging parks where multiple EVs can charge simultaneously with high charging power [11, 12], which can result in high and costly peak loads. Smart charging strategies are often implemented as mathematical optimization models [13–16] and machine learning algorithms [17, 18]. These strategies can be very effective; however, they are often designed for charging parks with a small number of charging points [19] and scale poorly. This is problematic for larger ones such as the EV charging park planned near Zusmarshausen along Germany's A8 highway, which will comprise 144 charging points [20]. Further examples include a planned charging park at the intersection of Germany's A3 and A46 highways near Dusseldorf, which will be equipped with 114 charging points [21], and a charging park with 200 charging points in an underground parking lot in

Beijing [22]. Operators of large EV charging parks require profitable and sustainable charging strategies with low computational complexity that scale easily and provide real-time decision support to manage peak loads. Furthermore, these charging strategies have to be able to factor in customer preferences like the time to leave (TTL) and the desired amount of energy for charging as well as the preferred usage of cheap and sustainable on-site photovoltaic (PV) generation available at many large charging parks [21]. Therefore, Green IS that enable real-world operation of smart charging contribute to a sustainable development [23, 24]. Crucially, it improves usage of renewable generation which accelerates the transition to clean energy. It also promotes the shift to EVs and the adoption of sustainable transport alternatives.

In this paper, we present a Green IS artefact to implement a smart charging strategy that schedules the charging processes of multiple EVs. From a methodological point of view, we apply Reinforcement Learning (RL), a machine learning algorithm suitable for complex and large scale optimization problems [25]. RL outperforms mathematical heuristic models by finding more robust solutions [26] and learning while being used in production [27]. Our model is trained on a charging park simulation with real-world data on highway traffic and day-ahead energy prices, and simulated solar radiation for own PV energy generation of the charging park. Our results indicate that RL is a feasible solution to implement a smart charging strategy for profitable and sustainable operation of large EV charging parks. Specifically, peak loads are reduced, and PV energy is utilized appropriately while maintaining high throughput, allowing less expensive charging.

The remainder of this paper is structured as follows. In Section 2, we explain concepts and summarize related work in the fields of EV charging and RL. In Section 3, we present our model, including the RL framework, the case description and implementation, the simulation components, and the evaluation strategy, followed by the presentation of our results in Section 4. We conclude our work with a discussion of the results in Section 5 and an overview of limitations and opportunities for future work in Section 6.

2. Background and Related Work

2.1. Electric Vehicle Charging

EV charging usually creates high peak loads on the energy grid [28, 29]. This impact can be further amplified by fast charging mechanisms for recent EVs [11, 12]. Electricity tariffs for industrial consumers

are typically compound by the total energy consumed and the highest peak load during a specific time interval; for example, 15 minutes [30]. This additional fee is often referred to as demand charge [6, 7]. It accounts for up to 90% of the total cost of EV charging, depending on the charging speed, the number of simultaneously charging EVs, and the tariff design [31]. Therefore, high demand charges may primarily be responsible for unprofitable investments in charging infrastructure and particularly large charging parks [31]. To save energy costs [32] and operate their business more profitable, industrial consumers try to minimize the peak load. Minimizing peak loads on the consumer side [33] has been the subject of related work using different approaches, for example, machine learning [34] or dynamic programming [35]. More in detail, O'Neill et al. [34] present an approach to reduce residential energy costs by estimating future energy prices and customer decisions using classical Q-Learning and thereby schedule residential device usage. Dimitrov and Lguensat [17] apply this algorithm to maximize EV charging park revenue, achieving an increase of income between 40% and 80% on a charging park with three charging points. Other promising approaches such as the ones of Hegele et al. [36] and Lee et al. [19] using small alterations of the more advanced RL method Deep Q-Learning (DQL) [37] are only evaluated on similarly small charging parks (3 and 1 charging point(s), respectively). For a comprehensive review of RL applications for demand response, we refer to the review of Vázquez-Canteli and Nagy [38]. Keeping these and further recent studies in mind [13–16], we conclude that charging strategies that enable the reduction of peak loads is an ongoing issue in energy research. The scheduling is mainly enabled by customers offering flexibility in their need for charging [39] and, thus, can be exploited by operators of EV charging parks to reduce peak loads with a simultaneous increase of PV energy generation.

Although the related approaches achieve noteworthy results, they lack an evaluation of their model's performance on large charging parks. In practice, such an approach seems to be a compelling necessity for the sustainable and profitable operation of EV charging parks, and thus, the creation of incentives for investments in EV charging infrastructure [8].

2.2. Reinforcement Learning

RL [25], with its multitude of algorithms, for example, Q-Learning [40], Deep RL [41], and Proximal Policy Optimization [42], is a promising part of decision support systems for solving optimization problems

of sustainable mobility. Typically, RL consists of an agent who repeatedly chooses a single action offered by the current state of an environment. The latter is referred to as an observation (algorithm input). As a result of the action, the environment returns a reward. Through maximizing this reward, the algorithm can learn which actions led to a positive and which led to a negative reward during the training phase [43]. Since DQL, many advances were made in the field of RL. The novel method Proximal Policy Optimization (PPO) [42], is an improvement on DQL in multiple aspects and has led to a widespread adaption of this method for complex optimization problems. PPO is a sophisticated training algorithm that uses many different improvements, including two Neural Networks (NNs), to increase training performance [42]. The first NN, referred to as the policy network, computes the best action to take, whereas the second NN estimates the reward it expects to get, and is therefore referred to as the value network. Using this approach, PPO can compute the “advantage”, i. e., the difference between the expected reward and the real reward received by taking the predicted action. By learning from the advantage, the algorithm is independent of the actual reward and learns directly from being better or worse than expected.

Particularly in the field of energy research, PPO has turned out as a feasible approach for a vast amount of problems. For example, Zhang et al. [44] present an approach to reduce system operators’ operating costs using a PPO-based renewable energy conversion algorithm. Similarly, Filipe et al. [45] achieve a significant reduction in wastewater pumping stations’ electrical energy consumption. Using distributed PPO, Zhou et al. [46] developed an approach for combined heat and power system economic dispatch. In the latter study, the authors build upon the capabilities offered by RL and its algorithms in comparison to mathematical models. Although training is complex and typically takes a long time, the actual use of a trained machine learning model has far superior speeds to mathematical models, which have to perform complex computations every time they run. In the case of high-dimensional objective functions and many non-linear constraints, mathematical models are frequently linearized to reduce solution time [46], which is not required using RL.

Instead of finding the global maximum like typical optimization algorithms, RL finds a more generalized solution, which might not be perfect; however, it is significantly more robust [26]. Particularly in rare cases, for example, negative energy prices, RL algorithms can produce useful results with sufficient training. In combination with transfer learning [47] and an option

to perform learning while in production use [27], makes RL a prime candidate for real-world use. In turn, mathematical algorithms often perform differently in simulation environments compared to when applied in real-world situations, due to imperfect feature modeling or high sensitivity to input parameters. Finally, feature modeling (i. e., transforming raw data into meaningful inputs) is not required with neural networks. Adding new data, such as a different traffic distribution, changed energy prices, or an extension of the charging park by more charging points as inputs, is straightforward and leads to high flexibility and extensibility of RL models.

3. Methods

The optimization objective for scheduling an EV charging park can be defined as the profit, a certain generated revenue minus the accumulated cost. Due to our focus on scheduling, we expect to earn a fixed price per kWh charged p . For the charged amount of power a_t^{charged} , we use all available PV energy with no marginal cost for each time step $t \in T$. Missing energy is bought from an electricity market or the main grid a_t^{emarket} where we need to consider the cost per kWh c_t^{emarket} . The overall cost also includes the demand charge, which is calculated by the peak load of energy bought from an electricity market d_t^{emarket} in each demand charge interval w and the cost per kW c^{peak} , i. e., if a time step t is the last in a demand charge interval w , the resulting demand charge is subtracted from the revenue. Δw describes the length of each demand charge interval. Therefore, the profit to be maximized for each time step t that is not the last in a demand charge interval w can be described as

$$\text{profit}_t = p \cdot a_t^{\text{charged}} - c_t^{\text{emarket}} \cdot a_t^{\text{emarket}} \quad (1)$$

and for all other time steps t as

$$\begin{aligned} \text{profit}_t = & p \cdot a_t^{\text{charged}} - c_t^{\text{emarket}} \cdot a_t^{\text{emarket}} \\ & - \max\{d_{t-\Delta w+1}^{\text{emarket}}, \dots, d_t^{\text{emarket}}\} \cdot c^{\text{peak}} \end{aligned} \quad (2)$$

We developed a fictive charging simulation to train and test the algorithm. In a simulated time step, first PV, electricity price, and traffic are simulated (see Section 3.3). Second, vehicles arriving are accepted until the charging park’s capacity limit is reached. Third, to keep the guarantee of charging EVs to their desired amount, vehicles are force charged, where this is the only possibility to keep the guarantee [18]. Next, all remaining EVs are charged based on a schedule, a list of which vehicles to charge how much, determined by the RL algorithm.

3.1. Reinforcement Learning Framework

The RL algorithm's input is the current state of the environment encoded as the vector observation_t from Equation (3). The charging park has several charging points $n \in N$. The observation vector includes for each EV that is connected to a charging point n the desired amount of energy $a_{1,n}^{\text{des}}$ in kWh and a remaining TTL $l_{t,n}$. The vector includes the amount of PV energy generation a_t^{pv} at time t and the cost per kWh for the energy bought from the electricity market c_t^{emarket} , the last calculated demand charge h_t^{last} , and the time t .

$$\text{observation}_t = (a_{t,1}^{\text{des}}, \dots, a_{t,|N|}^{\text{des}}, l_{t,1}, \dots, l_{t,|N|}, a_t^{\text{pv}}, c_t^{\text{emarket}}, h_t^{\text{last}}, t)^T \quad (3)$$

All inputs are floating-point numbers, except t , which is one-hot-encoded (i.e., as a binary vector) for all days, hours, and steps per hour. The output of the algorithm, called action_t , can be interpreted as the charging schedule and can be modeled in multiple ways. To mitigate the complexity, we choose a discrete output of charging powers in kW $k \in K$ for every charging point $o_{k,n,t}$ resulting in Equation (4).

$$\text{action}_t = (o_{1,1,t}, \dots, o_{|K|,1,t}, \dots, o_{1,|N|,t}, \dots, o_{|K|,|N|,t})^T \quad (4)$$

Finally, profit maximization can be achieved by setting the reward equal to the profit.

3.2. Case Description and Implementation

We chose the simulation parameters based on the current real-world example of the upcoming EV charging park at the A8 highway near Zusmarshausen in Germany with 144 charging points. The maximum charging power in Zusmarshausen is 350 kW, but as most EVs do not support such high charging power, we set the maximum charging power to 100 kW for all charging points. All EVs are assumed to have a maximum battery capacity of 100 kWh. The battery's state of charge at arrival at the charging park is modeled using a log-normal distribution [48, 49] with a location parameter of 0.5 and a scale parameter of 0.15. Hence, the desired amount of energy can be calculated by subtracting the state of charge from 1, which is finally multiplied by the battery capacity. The TTL, after which an EV should be charged by the desired amount, is modeled using a Poisson distribution [50] with a mean of $\mu = 1.5$. For the price of load peaks, we assume a value of € 5.50 per kW. One simulated time step corresponds to 15 minutes. Thus, one hour equals four, one day 96, one week 672, and one year 34944 time steps.

We encode the environment state as a vector observation_t , to serve as input for the RL algorithm. To allow the NN flexibility, for every charging point, the algorithm can choose to charge with 0 kW, 10 kW, 20 kW, 50 kW, or 100 kW, resulting in the action space of Equation (5). Charging decisions for empty charging spots will be ignored, and vehicles will automatically stop charging when they are full, i.e., no power will be wasted.

$$\text{action}_t = (0_{1,t}, 10_{1,t}, 20_{1,t}, 50_{1,t}, 100_{1,t}, \dots, 0_{|N|,t}, 10_{|N|,t}, 20_{|N|,t}, 50_{|N|,t}, 100_{|N|,t})^T \quad (5)$$

We use the PPO algorithm with its default hyperparameters and adjust the NN architecture to a three-layer policy network with 128 neurons per layer and a value network with the same structure. The networks share the first layer, which allows both networks to learn high-level features together. The training loop is configured with 1024 steps, 32 instances of the environment, four optimization iterations, and 32 mini-batches. One training run consists of 25 loops of 819200 steps (1024 steps multiplied by 32 instances), which results in ~23.44 years of simulation using time steps of 15 minutes.

3.3. Simulation Components

To achieve reliable results in the simulation, we thoroughly implement simulation components for the model's inputs with real-world data on traffic distribution and day-ahead energy prices and modeled solar radiation.

3.3.1. Traffic Simulation. Based on the example of the real-world EV charging park near Zusmarshausen [20], we use data from the German Federal Highway Research Institute for the respective road section in 2018 [51]. The data set contains, among others, the number of passenger vehicles observed in both directions of the highway for every hour in a previously specified period. To improve data quality, we removed all outliers exceeding the interquartile range by a factor of 1.5, which mainly arose from public holidays. Given the hourly time interval, we grouped the data set by the day of the week and the hour of the day to account for the two factors we consider essential for modeling traffic distribution. We fitted an individual gamma distribution for each of the resulting 168 intervals (7 days multiplied by 24 hours), which we observed as most suitable after plotting the data for each interval. Figures 1 and 2 visualize two examples for the traffic distribution. The blue buckets represent the distribution, the green and orange lines show a

Figure 1. Traffic distribution of the highway A8 near Zusmarshausen on Mondays between 2 and 3 pm, normal distribution suitable

fitted normal and gamma distribution, respectively. A Shapiro-Wilk test with an alpha level of 0.05 rejected our initial hypothesis of normally distributed samples for 35 time intervals. For example, the test reported a p -value of $\sim 4.84 \times 10^{-5}$ for the distribution on Saturdays between 4 and 5 am (see Figure 2). Given these results, we decided to model the traffic distribution for each time interval with an individual gamma distribution for two reasons. First, we can still approach the possibly normal distributed samples without losing accuracy, since the gamma distribution converges to a normal distribution with an increasing shape parameter. Second, we analyzed the plots for all 168 time intervals and observed that the gamma distribution captured all samples precisely (see the orange graph in Figure 1). Since the distribution contains all passenger vehicles, the number of EVs can be obtained by multiplying with a factor representing an appropriate share of EVs. In the current implementation of the simulation, all EVs are initialized using the TTL parameters and the state of charge, as described in Section 3.2, which qualifies them to charge on the charging park. However, to ensure the charging guarantee for the previously arrived EVs, a fraction or even all qualified EVs are rejected randomly if the charging park's capacity would be exceeded.

3.3.2. Solar Radiation Simulation. For modeling solar radiation, we initially make two assumptions. First, to obtain robust results, the day of the week should not affect the radiation. Second, the operator in our case study aims to provide half of the charging park with PV energy at the radiation peak. Given the characteristics of solar radiation, which reaches its peak at noon, begins between 5 and 8 am, and ends between 5 and 9 pm, the probability density function of the normal distribution with a mean of $\mu = 12$ and a standard deviation of

Figure 2. Traffic distribution of the highway A8 near Zusmarshausen on Saturdays between 4 and 5 am, gamma distribution suitable

$\sigma = 3$ seems suitable. Therefore, we compute the solar radiation at time t using the function in Equation (6). Since N represents the set of charging points, $|N|$ represents the number of charging points, whereas the parameter r^{stat} represents the maximum charging power of each charging point.

$$f(t) = \frac{0.5 \cdot |N| \cdot r^{\text{stat}}}{\sigma \sqrt{2\pi}} e^{-(t-\mu)^2 / 2\sigma^2} \quad (6)$$

3.3.3. Day-ahead Energy Price Simulation. For the day-ahead energy price simulation, we take a similar approach as for the traffic simulation. We gathered the hourly day-ahead price for Germany as reported in Open Power System data [52] between 2015 and 2018 and grouped the data set by the hour of the day. Again, we removed outliers by dropping all values exceeding 1.5 times the interquartile range. Although the samples' plots indicated normally distributed values, a Shapiro-Wilk test with an alpha level of 0.05 rejected normality for all 24 groups, which we trace back to the high number of samples per group ($364.25 \times 4 = 1457$). This observation is visualized in Figure 3 for the distribution at 9 pm from 2015 to 2018. Therefore, we again fitted an individual gamma distribution for all 24 groups which we validated by comparing the plots of the sample and the fitted distribution (see the orange graph in Figure 3).

3.4. Evaluation

To evaluate RL's performance on charging process scheduling, we compare our model on multiple metrics with simple baseline charging rules during a long-term simulation on our EV charging park environment.

3.4.1. Charging Rules. For comparison, we implement two kinds of simple baseline charging rules:

Figure 3. Day-ahead energy price distribution at 9 pm between 2015 and 2018

The “Constant Charging Rule” ($C(x)$) charges all vehicles currently in the charging park with a predefined constant power of x , e. g., with $x = 100$ kW, until the EV reaches its desired amount.

The “Average Charging Rule” (Avg) charges each EV connected to a charging point n in every time step with equal charging power. The average charging power for each EV x_n^{avg} is calculated by dividing the desired amount of energy a_n^{des} by the parking time t_n^{park} of the EV at the charging point: $x_n^{\text{avg}} = a_n^{\text{des}} / t_n^{\text{park}}$. Thus, the Average Charging Rule spreads the charging over the time the EV is connected to the charging point to reduce peaks.

We compare RL with Avg and $C(x)$ with $x \in [10, 20, 50, 100]$. Since both baseline charging rules (except $C(50)$ and $C(100)$) try to reduce peaks on the energy grid by spreading the charging process over multiple hours, they seem suitable for evaluating our model. We chose these charging powers because charging 10 kW is similar to charging at home, 20 kW corresponds to most public charging points, common fast chargers provide 50 kW, and 100 kW is the current maximum charging capacity offered by a small fraction of EVs. Even though the charging rules $C(50)$ and $C(100)$ represent fast charging mechanisms and do not aim for peak reduction, we use them to validate that peak reduction is sensible in our model. In case the profits are maximized using these rules, charging as many EVs as possible would be economically reasonable.

3.4.2. Evaluation Metrics. To compare the RL model with the baseline charging rules and analyze the model’s charging strategy, we use multiple metrics. The first metric is the mean over the weekly profits in cent. We also compute the number of charged EVs per week. Further, we measure the weekly demand charge cost as

demand charge in Euro. As a fourth metric, we record the maximum charging park load fraction per week. A peak load of 0 represents an empty EV charging park, whereas, in the case of 1, the full capacity was reached. Finally, we also analyze the distribution of weekly unused PV energy.

4. Results

We simulate all charging rules from Section 3.4.1 as well as the trained RL model for eight weeks. Further, we repeat the simulation for multiple variations of the EV percentile in the total simulated traffic. The variations include 0.2% as realistic baseline while also including 1%, 5%, and 10% for future evaluation.

Figure 4 illustrates the distribution of weekly profits, and Figure 5 the weekly number of charged EVs for all charging rules at a penetration rate of 0.2% EVs. By charging all EVs as soon as possible, applying the charging rules $C(50)$ and $C(100)$, no revenue is lost, resulting in the highest profits compared to the other charging rules. Due to overall low traffic, no towering peaks are created. In this case, we do not observe substantial differences in profit between the charging rules. Although the RL approach does not outperform other approaches, it still produces similar results. Since the choice of a different charging rule neither seems to affect the profit or the number of charged EVs significantly, we increase the share of EVs in the following.

With a higher penetration rate of EVs, namely 1%, 5%, and 10%, the charging rules perform significantly different. Figures 6, 7, and 8 visualize how in a 10% scenario, the fast charging of EVs results in losses due to high demand charges and no regard for current electricity prices. Slow charging helps to reduce the demand charge, but the RL model gains 30% more profit by efficiently using all factors. Figure 9 illustrates how the RL model learns to efficiently use the available PV energy, allocating it reasonably for charging EVs and contributing to sustainability. Consistently over all metrics and fractions of EVs, the RL model performs well, while our baseline charging rules excel only under specific conditions. Although this points out good generalizability of the approach, further optimizations of the training, such as hyperparameter tuning of the underlying neural network, seem to be required to outperform the baseline charging rules in most possible configurations. Finally, we measure the time to run a single time step, including environment simulation and NN inference, to be average, ten milliseconds, thus validating feasibility for live operation. Overall, we conclude a promising approach that fulfills the objective

Figure 4. Distribution of weekly sum of profits in Euro (0.2% EVs)

Figure 5. Distribution of weekly number of charged EVs (0.2% EVs)

Figure 6. Distribution of weekly sum of profits in Euro (10% EVs)

Figure 7. Distribution of maximum weekly charging park load fraction (10% EVs)

Figure 8. Distribution of weekly demand charge in Euro (10% EVs)

Figure 9. Distribution of weekly unused PV in kWh (10% EVs)

of being profitable and sustainable and aim to improve the algorithm in a future version of this paper.

Further remarks: In line with existing literature, we first simulated one-hour intervals instead of the now more fine-grained intervals of 15 minutes. However, we could not find a significant difference in the results. Training a larger network (256 neurons per layer) also did not produce different results. We also did training runs where the reward is equal to the negative cost, resulting in the model learning to charge fewer vehicles, thus, not making profits even with low cost.

5. Discussion

The evaluation of our model shows that Green IS, using RL, helps in reducing peak loads. However, traffic distribution, as revealed in our real-world data set, puts an upper limit on the reduction. On weekdays, during morning and evening rush hours, the model assesses it more profitable to quickly charge as many EVs as possible by allocating a maximum of available charging capacities. This causes a trade-off for operators as no customers are lost, but neither peak loads are

avoided. The effectiveness of RL is further limited by the charging volume. At current EV penetration rates, there are no significant differences between the charging strategies. With growing shares of EVs, however, the benefit of RL increases, and our model outperforms other charging strategies.

Although the model increases the degree of utilization of the charging park, there remains unused capacity, particularly during periods with low traffic, such as nighttime hours. We trace this observation back to our current modeling of a single customer group with a relatively low expected TTL. So far, we do not measure the effect of heterogeneous customer groups, as proposed in other related approaches [9, 18]. In particular, customer groups with a high TTL could further increase the scheduling algorithm's flexibility and, thus, further increase the use of sustainable PV energy and decrease peak loads. Heterogeneous customer groups might also spread charging demand more equally over time and help to exploit periods with low traffic better.

Our work contributes to Green IS and towards achieving sustainability goals, outlined in the taxonomy of Kossahl et al. [53]. Specifically, we address the two sub-domains energy and automotive, combining smart grid and e-mobility technologies, by developing, and importantly, implementing a smart charging strategy. The ability of our artefact to deploy such a smart charging strategy in real-world and real-time provides a valuable contribution to the need of pushing IS research beyond theories emphasized by vom Brocke et al. [54]. Thereby, we outline pathways for Green IS research, highlighting its contribution and importance for a development of sustainable mobility.

In practice, operators could attempt to influence charging demands proactively to achieve an effective reduction of peak loads. For example, an integrated view of revenue management and smart charging could enable a tariff design for EV charging where the price is based on the peak load of the charging park. For a more sustainable operation, the operators should consider incorporating stationary energy storage (e.g., battery storage), which might increase the use of PV energy with a simultaneous further reduction of peak loads [55–57].

An advantage of using Deep RL to solve the underlying problem over mathematical optimization models is computational. While PPO can be trained ahead of time using an arbitrary amount of resources, the trained model's actual prediction process is an efficient and scalable computation. In turn, mathematical optimization models need to run for every prediction, taking more computational resources during live

operation combined with often poor scaling capability. However, Deep RL has inherent weaknesses, e.g., the lack of transparency of NNs, raising liability and responsibility questions that need to be addressed prior to real-world deployment.

6. Conclusion

In this paper, we present a Green IS artefact for a smart charging strategy of large EV charging parks controlled by a Deep RL model. Our results indicate that a Green IS design using RL is a promising alternative to implement smart charging strategies with low computational overhead and good scalability properties. It enables the reduction of peak loads and considers the sustainable PV energy while maintaining high throughput, thus, allowing for more profitable operation of large-scale charging parks.

Our contribution to IS research and practice is twofold. First, we use real-world data and demonstrate the scalability of RL. Our results for the EV charging park near Zusmarshausen match related approaches for significantly smaller charging parks [17, 18]. Second, we show that Deep RL models can solve computational complexity and thereby reduce cost, making it a prime candidate for deployment as a real-time decision support system.

Nevertheless, we also encounter limitations of our approach. First, even though our approach robustly generates the most profit, due to the black-box nature of deep NNs, we can neither prove nor clearly view the strategy the model is following. Upcoming approaches should therefore work on testing scenarios and transparency of models. Second, we only tested our model with traffic data of one particular highway section and German electricity prices. Naturally, every charging park application needs location-specific training and might yield different results. To validate the performance and to provide more generalization to the findings, the model requires testing for multiple EV charging parks including the adaption of traffic data to other places as well as other countries.

In future work, a combination of revenue management and smart charging could explore how the willingness to pay of customers can shift the number of EVs at the charging park and increase profit from balanced levels of charging traffic. Since highways are popular sites for wind turbines, wind energy could be incorporated as an alternative source of renewable energy. Regarding the ongoing development of machine learning, the current RL model could be improved, for example, using hyperparameter optimization, testing different NN designs (e.g., convolution kernels for

more complex feature detection), or (bidirectional) Long Short-Term Memory Networks [58, 59] for enhanced learning of temporal interrelationships. Training with more and versatile data (e.g., rain simulations, seasonal data), are levers to make the current model more robust against unseen scenarios.

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