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

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Motivation

Simultaneous charging of electric vehicles (EVs) creates high peak loads on the energy grid. The tariff design for industrial customers, which is based on the highest peak load during a certain period of time, impedes a profitable operation of large EV charging parks if conducted unsupervised. To mitigate expensive peak loads and to optimally incorporate volatile renewable energy, such as photovoltaic (PV) energy, operators require profitable and sustainable charging strategies that provide real-time decision support. In our paper, we present a Green IS artefact to implement a charging strategy that schedules the charging processes of multiple EVs using Reinforcement Learning (RL), a machine learning algorithm suitable for complex and large-scale optimization problems.

Approach

Our simulation model is based on the example of the real-world EV charging park near Zusmarshausen. along Germany's A8 highway, which will comprise 144 charging points. The model quarter-hourly simulates the highway traffic, the PV energy, and the electricity price based on real-world data in a first step. Next, a guarantee algorithms ensures that all customers leaving in this timestep are charged and rejects arrivals where requests are impossible to fulfill. Consequently, a charging rule computes which EVs will be charged how much energy. For evaluation purposes, we compare RL with constant charging (10, 20, 50, and 100 kW) as well as average charging (i.e., desired amount of energy divided by desired charging time). Finally, the energy cost is calculated based on the used PV energy and the cost for energy bought from the electricity market. The latter is furthermore reported for a weekly calculation of the demand charge for the highest peak load. The reward for the RL model is equal to the profit of the charging park and is calculated by subtracting the charging cost from the revenue. Figure 1 illustrates the simulation process graphically.

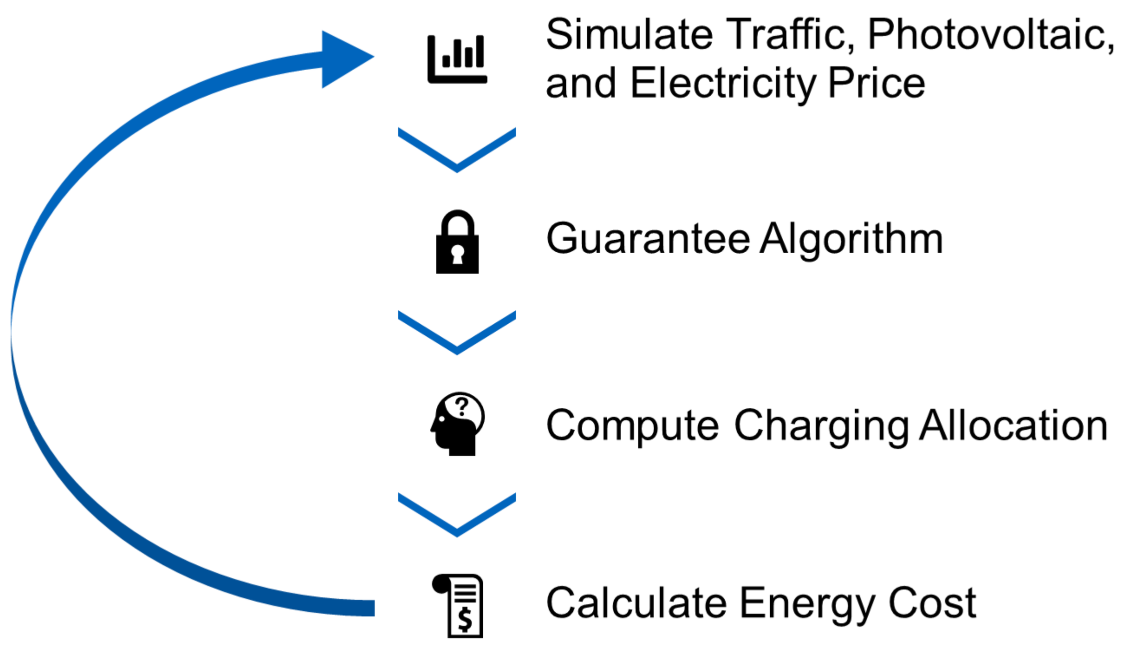

Figure 1. Simulation process

Results

After training the model for a period which corresponds to an equivalent of ~23 years, we measured its performance for eight weeks of simulation. We repeated the simulation with all charging rules as well as with different shares of EV penetration (0.2%, 1%, 5%, 10%). Figure 2 visualizes two of our evaluation metrics, the profit (to measure the profitability objective) and the unused PV energy (to measure the sustainability objective).

Simulating with a share of 0.2% EVs, charging all EVs as soon as possible results in the highest profits. However, this observation reverses with an increased share of EVs, particularly at 10%. In this case, fast charging of EVs results in high losses due to high demand charges and no consideration of current electricity prices. In contrast, the RL model enables a profitable operation and learns to efficiently use the available PV energy, allocating it reasonably for charging EVs and contributing to sustainability.

Discussion

Due to the traffic distribution of our real-world data, there is an upper limit of the peak reduction, particularly during morning and evening rush hours. During periods with low traffic, for example, nighttime hours, there remains unused capacity which we trace back to our current modeling of a single customer group. Furthermore, the effectiveness of RL is limited by current EV penetration rates, however, with growing shares, our model outperforms other charging strategies.

In practice, operators could attempt to influence charging demands proactively to achieve an effective reduction of peak loads using a revenue management approach with a tariff design based on the current peak load of the charging park. For a more sustainable operation, the operators should consider incorporating stationary energy storage, which might increase the use of PV energy with a simultaneous further reduction of peak loads.

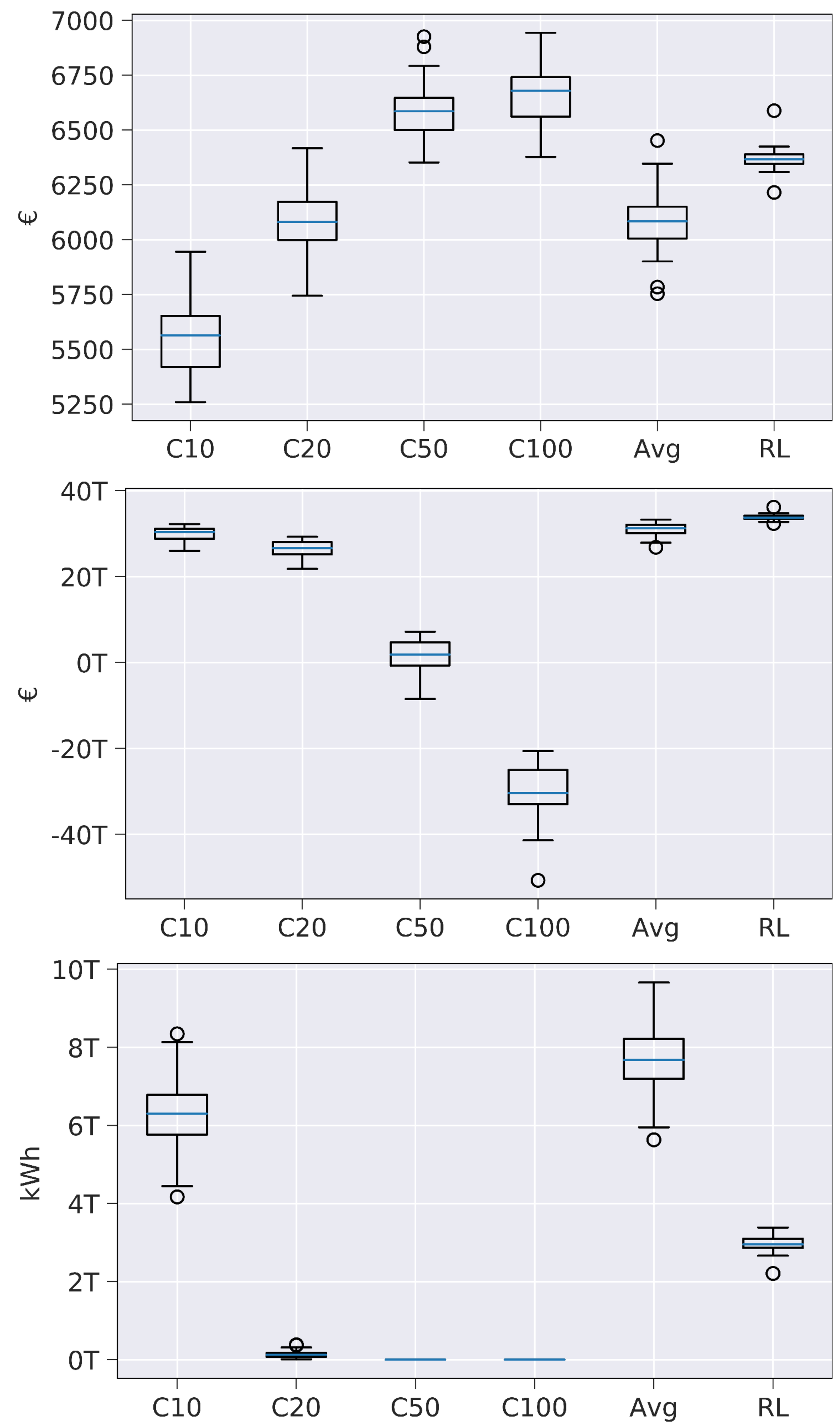

Figure 2. a) Profit (0.2% EVs), b) Profit (10% EVs), c) Unused PV energy (10% EVs)

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