Potential Grid-Oriented and Market-Oriented Optimisation of a Local Charging Infrastructure Through a Genetic Algorithm

David Cano-Tirado(*)[1], Maximilian Forchheim[2], Martin Asman[2], Markus Zdrallek[2], Sebastian Palmer[3]

[1] Institute of Power Systems Engineering, University of Wuppertal, Rainer-Gruenter-Str. 21, 42119 Wuppertal, Germany, +49 202 439 1109, david.cano@uni-wuppertal.de, https://www.evt.uni-wuppertal.de/

[2] Institute of Power Systems Engineering, University of Wuppertal

[3] Phoenix Contact Deutschland GmbH, Unterhombach 5b, 32825 Blomberg, Germany

Abstract: This contribution assesses the operational potential of the charging infrastructure at the Freudenberg Campus of the University of Wuppertal in both grid-oriented and market-oriented contexts, taking into account the Day-Ahead market. Genetic algorithms are employed to optimize the operation schedule. The optimisation considers the mathematical modelling of the charging processes and utilises a tool based on probabilistic methods to determine the standing times of electric vehicles. In the presented scenarios, the results prove the potential to reduce electricity costs. Moreover, in most cases, these algorithms fulfil the power-shifting requirements that may be requested by a Smart Grid system in the short term.

Keywords: Day-Ahead Scheduling, Grid-Oriented Operation, Electric Vehicles in Smart Grids, Genetic Algorithm optimisation

1 Introduction

The electrification of the mobility sector is one of the implemented strategies to meet the challenges imposed by the climate change crisis. This initiative has significantly increased the total number of electric vehicles (EVs) in Germany from 84 thousand in 2018 to almost 620 thousand by the end of 2022 [1]. The growth of the EV and Plug-in hybrid electric vehicles (PHEVs) fleet resulted in the development of public charging infrastructure (CI) and, consequently, charging points (CPs). The total number of CP increased from almost 20 thousand in 2018 to 84 thousand in 2022, of which 17 % corresponded to fast CP [2]. This fact results in a potential simultaneous charging power demand of 2.8 GW [2], which could lead to critical operational conditions in the power grid. By managing the charging processes, it is possible to exploit the flexibilities of EVs and PHEVs. On the one hand, these flexibilities could have a grid-oriented character to support grid operation to mitigate potential grid bottlenecks, such as voltage limit violations and overloads [3]. On the other hand, in the absence of grid requirements, these flexibilities can be traded in suitable energy markets to enable a market-oriented operation to generate economic revenues [4].

Determining the operating schedule of a CI that takes into account the two discussed modes of operation is not trivial. On the contrary, its optimisation must deal with the non-linearities present in the charging process models for EVs. It must also consider not only the technical characteristics of the EVs involved but also the constraints related to user comfort. In particular, the willingness and expectations that a user would have if the EV’s state of charge (SoC) is affected by one of the operation modes. Therefore, Genetic Algorithms (GA) appear as an alternative to conventional optimisation methods as they can consider non-linear models and multiple constraints [5]. They can consider approaches to examine a wider range of potential solutions that are not intuitively easy to determine [6].

This contribution aims to determine the potential of the CI for EVs at the Freudenberg Campus of the University of Wuppertal to operate optimally considering energy markets and grid requirements. For this purpose, this paper is divided into four additional sections. In "Conceptual framework", general relevant topics for this paper are introduced. In "Methodology" the general technical characteristics of the considered local CI are described; the used models and the way the optimiser works are also outlined; the scenarios are presented. In "Results and Analysis" the results of the market-oriented operation and the grid-oriented operation of the local CI are discussed for each scenario. Finally, "Conclusion and outlook" summarises the most relevant findings and the strengths and weaknesses of GA as an optimisation method for EVs.

2 Conceptual framework

2.1 Spot and Flexibility market

Owners and operators of CI for EVs often pay for the electricity demanded through long-term contracts in the forward market. Such contracts are typically prevalent in, for example, non-residential buildings [7]. For most cases, and under conventional energy market conditions, this can lead to higher operating costs compared to a flexible operation in the Spot Market. Furthermore, the end consumer should have the possibility to purchase electricity flexibly in the most suitable energy market.

Otherwise, the end electricity consumer should have the possibility to purchase electricity flexibly from wherever it is most profitable. The timeframe of the trading options in the Spot Market is highlighted in grey in Figure 1. The Day-Ahead and Intraday auctions and the Intraday trading belong to the Spot Market [8, 9]. The smallest tradable transaction in the Spot Market is 0.1 MWh which may lead to aggregate users to be able to participate in it.

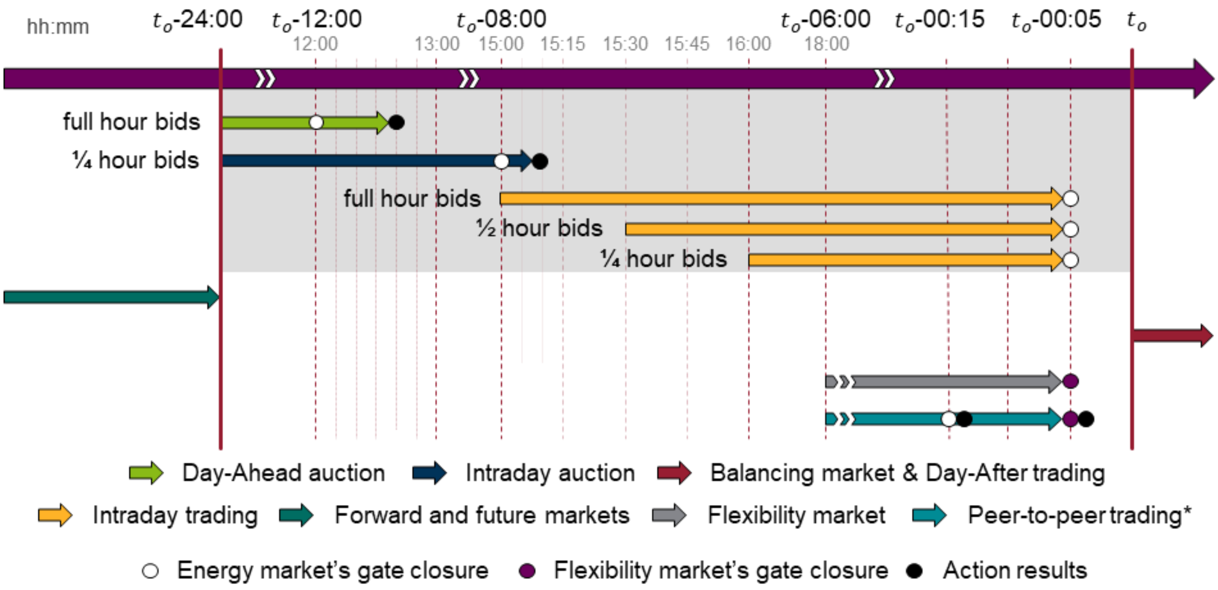


Figure 1: Time frame conditions of the potential trading markets for CI for EVs

The retrofitting of conventional grids with modern information and communication technology to Smart Grids paves the way for introducing Smart Markets [10]. With the grid state information from the Smart Grid system, the available grid capacity can be monitored and transferred to intelligent trading as an indirect offer. This concept is used in local Flexibility markets, where efficiency services such as the curtailment of controllable loads and energy management are mapped by shifting energy flows over time as part of a smart market.

In addition to the Spot Market and the Flexibility market, Peer-to-Peer (P2P) trading* appears to be a decentralised market option. Here, members of a distribution grid can trade more precise products, such as energy or flexibility, on a short-term basis. Trading volumes could also be less than 0.1 MWh. Thus, no aggregation is necessary. An example of such a market is considered in the PEAK research project [11]. Its timeframe is presented in Figure 1, but it can vary from one P2P market to another, as well as the type of products that are traded [11].

2.2 Grid-oriented operation

A Smart Grid system enables the grid-oriented operation of the CI. Since not all nodes are equipped with measurement devices, it uses methods of grid state estimation. These methods accurately determine the current grid's status with limited information and detect critical conditions that may compromise the grid operation [12, 13]. Once a bottleneck is detected, the Smart Grid system determines the operating points to be reached by grid members capable of contributing to clearing the fault. Such operating points are transmitted to the involved participants in the form of a request for a change of operating power [14]. After clearing the bottleneck, the CI can return to a normal operating mode.

2.3 Electric vehicle charging process models

Conventional mathematical models aim to describe the charging process through the power demanded from the battery $P(t)$ and its respective state of charge $SoC(t)$. Given the characteristics of lithium-ion batteries, which have a high energy and power density, it is common to find them nowadays in most EVs [15]. Their charging process generally occurs in two stages and they are separated by the switching point S^* (from eq. 1). In the constant current (CC) stage, the battery voltage gradually increases until the maximum terminal voltage is reached. This is followed by the constant voltage (CV) stage which targets to keep the voltage value constant while the charging current is reduced exponentially until it falls below a predefined threshold value [16, 17].

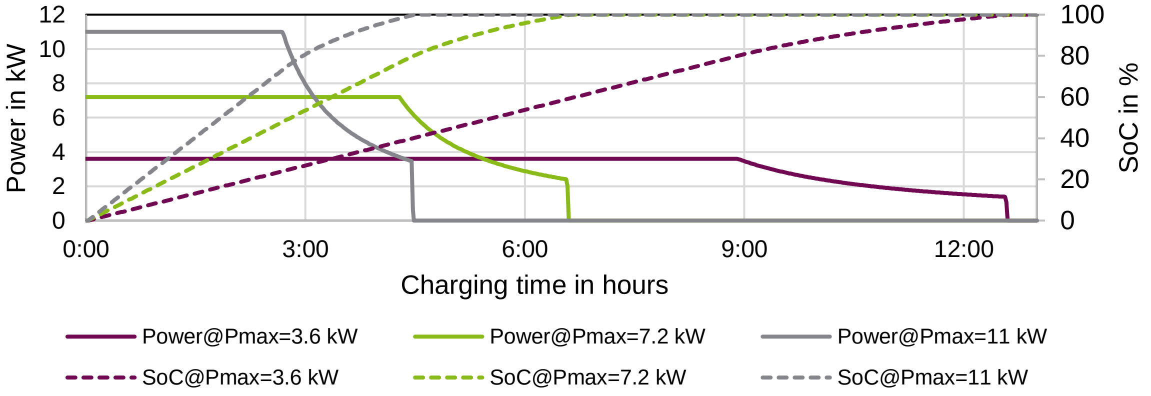


Figure 2: Effects of maximal charging power on power and SoC in a charging process

Figure 2 shows how different levels of maximum charging power ($P_{\max}$) affect the charging process. The intervals where the charging power remains constant correspond to CC, while the exponential drop corresponds to CV. These curves were obtained through a tool implemented in the framework of this research. This tool considers eq. 1, eq. 2 and eq. 3, which are the results of Fasthuber's research. These equations depend on the intrinsic parameters of the EV battery [17]. These parameters are: the maximum charging power $P_{\max}$, the maximum battery's usable capacity $E_{\max}$, the cell battery's nominal voltage U_{N}, the cell battery's maximum final charging voltage U_{LS} and its final charging current I_{LS}.

$$P(t) = \begin{cases} P_{\max} & , \; SoC(t) < S^* \\ P_{\max} \cdot \exp\left(\frac{S^* - SoC(t-1)}{\tau}\right), & SoC(t) \geq S^* \end{cases} \tag{1}$$

$$SoC(t) = SoC(t-1) + \frac{P(t) \cdot \Delta t}{E_{\max}} \tag{2}$$

$$\tau = (100 - S^*) \left[ln\left(\frac{P_{\max}}{\frac{U_{\mathrm{LS}}}{U_{\mathrm{N}}} \cdot I_{\mathrm{LS}} \cdot E_{\max}} \right) \right]^{-1} \tag{3}$$

2.4 Standing times forecast for electric vehicles

The methods for determining the standing times of EVs can be done in different ways. Today, the computational power of computers has enabled the widespread use of techniques such as machine learning, even in electromobility. Through machine learning, it is possible to forecast driving profiles [18], the occupancy of CPs [19, 20] and the power demand of a CI [21]. However, the forecast accuracy depends to a large extent on the quality of the data used to train the model [19]. On the other hand, conventional alternatives, such as those based on probabilistic methods, seek to determine the mobility behaviour of EV users through electromobility studies. At the Institute of Power Systems Engineering, a tool to generate driving profiles was developed, and this tool has been able to support several research projects [22].

The tool generates driving profiles according to input variables such as date (weekday, weekend day, holiday, etc.), CP amount and details of their charging power characteristics. The CI location (metropolis, urban area, rural area, etc.) plays also a decisive role and has also been considered. The model provides the EV's standing times based on their SoC at the arrival time based on the probabilistic mobility behaviour.

2.5 Optimisation of electric vehicle charging processes

There are extensive research studies involving the optimisation of EV charging processes. Some of them take a deterministic approach (i.e. the outcome of the model is fully determined by the parameter values and the initial values) and seek to minimise operation costs and maximise ancillary service revenue [23]. Others consider a stochastic approach (i.e., involving random variables and probabilities) to schedule the potential EV combined charging and discharging process in a microgrid, prioritising the use of renewable energies [24]. These stochastic processes have market-oriented applications to determine the Day-Ahead pricing to minimise the peak power demand [25]. Although these optimisation methods can converge quickly, in many cases they can only be applied for small-sized problems where the number of constraints is reduced and multiple optimisation objectives are not considered. Usually, in these cases, the processes involved have a linear behaviour [24].

Apart from the conventional optimisation methods hereby presented, there are other methods based on the natural evolutionary process. Among these, Genetic Algorithms (GA) are primarily used to solve complex optimisation problems. Their metaheuristic character (i.e., they adapt independently of the objective or the search field) enables them to offer great flexibility in considering multi-objective functions and can consider several constraints. These optimisation methods start from an initial random population of individuals. Throughout iterations (or generations) they recombine and mutate to improve the population of suitable candidates, via fitness assessment, in order to solve the optimisation problem. Figure 3 shows the general GA's workflow. In each iteration, it is possible to explore beyond the search field so far considered, providing the GAs insight to avoid local minima or maxima, without being immune to falling into them. [5, 6]

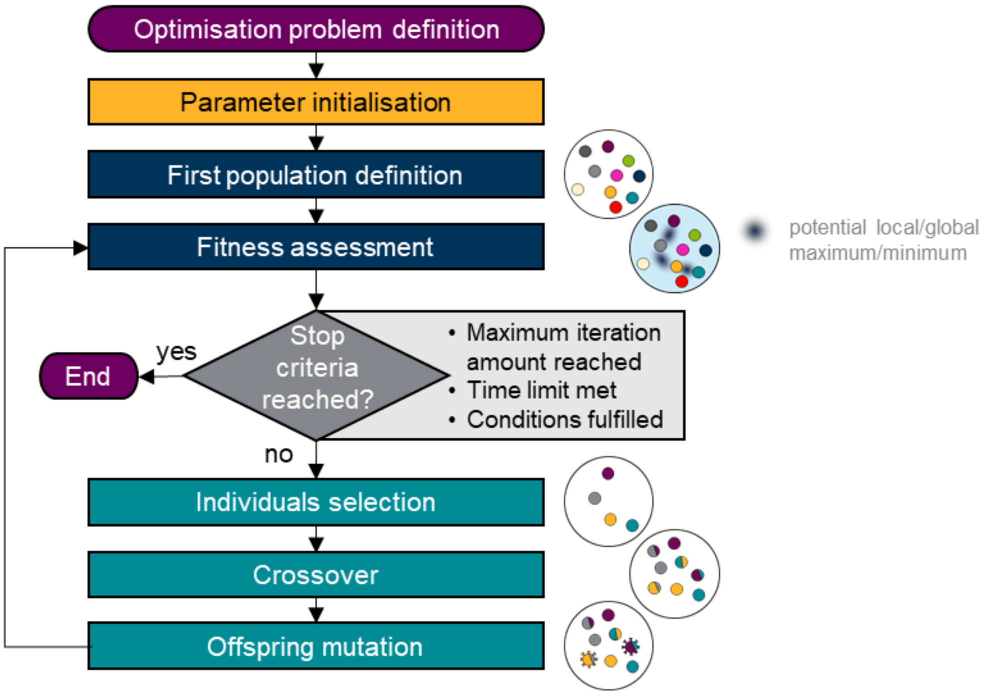


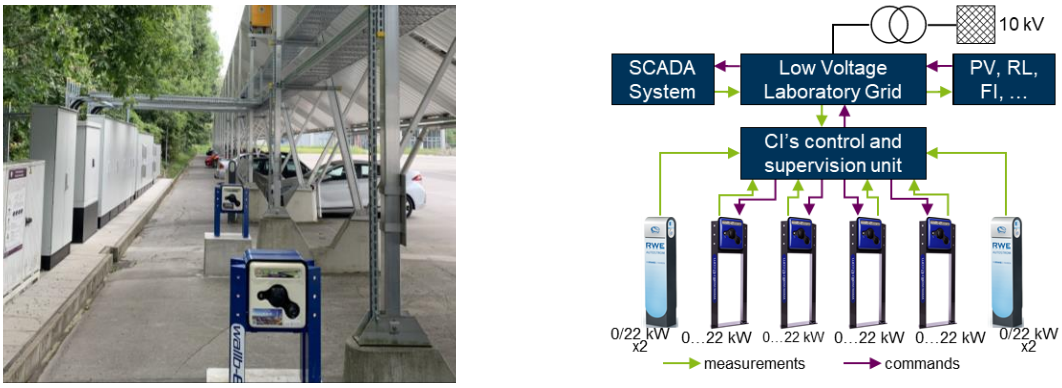
Figure 3: Conventional flowchart of a GA

3 Methodology

This section describes the methodology used to optimise the charging processes of the local CI in a market-oriented and grid-oriented approach. This section also describes the scenarios considered for the analysis.

3.1 Description of the local charging infrastructure

The Smart Grid Laboratory (SGL) is located at the Freudenberg Campus of the University of Wuppertal. A low-voltage Test Grid was conceived and implemented there, in which different devices are used to emulate realistic scenarios that can occur in the power distribution grid [26]. In addition to frequency inverters (FI), resistive loads (RL), a photovoltaic (PV) system, and a structure capable of considering multiple grid topologies, it also has a CI for EVs. The CI can simultaneously deliver up to 176 kW through its six charging stations, two of which have two CPs, while the rest have one. Figure 1 illustrates generally the described hardware. It is worth highlighting that the charging stations that have two CPs do not allow the regulation of the charging processes. Given this limitation, these CPs are not regulated in the optimisation.



a) Hardware layout in the low voltage Test Grid of the SGL b) Schematic representation of the CI

Figure 4: Local CI at Freudenberg Campus of the University of Wuppertal

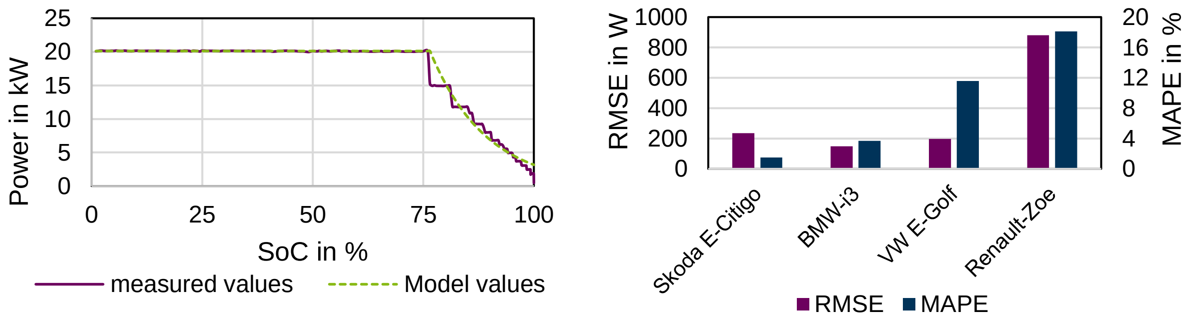
3.2 Validation of the charging process model

By monitoring the charging processes of some EVs charged via the local CI, the measurements are used to identify the corresponding parameters of the implemented model for EV charging processes presented in section 2.3. These are summarised for specific EVs and shown in Table 1.

Table 1: EVs' relevant model parameters

EV	$P_{\max}$ in kW	U_N in V	U_{LS} in V	$E_{\max}$ in kWh	I_{LS} (C-rate) in 1/h [17]
Skoda E-Citigo	7.6	3.6	4.2	36.8	0.123
BMW-i3	7.6			37.9	0.025
VW E-Golf	3.5			32	0.026
Renault-Zoe	20.1			22	0.123

A comparison between measurements (x) and the simulation ($\hat{x}$) of a charging process is presented in Figure 5a). The stepwise behaviour of the power measured is an effect of the EV's charging strategy. The charging management systems may differ, but the general process can be reproduced by the model.



a) Renault-Zoe's model validation b) RMSE and MAPE indicators for different EVs

Figure 5: Validation results for different EV charging process models

In Figure 5b, typical indicators such as Root Mean Squared Error (RMSE) (eq. 4) and Mean Absolute Percentage Error (MAPE) (eq. 5) are used to compare the model's performance for the considered EVs.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_\mathrm{i} - \hat{x}_\mathrm{i})^2} \tag{4}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_\mathrm{i}-\hat{x}_\mathrm{i}}{x_\mathrm{i}}\right| \tag{5}$$

The presented model has however potential for improvement especially when the maximum charging power approaches the maximum technical operating power of the CP.

3.3 Optimisation model for EV charging processes through Genetic Algorithms

An insight into the developed genetic algorithm for market-oriented optimisation and grid-oriented optimisation for given scenarios is presented in this section. For this purpose, the optimisation objective functions are defined and the GA parameters with which the algorithm works are listed. Finally, the calibration process of the GA parameters is presented.

3.3.1 Optimization problems: Objective functions definition

The implemented genetic algorithm operates in two stages: one schedules the CI operation up to twelve hours in advance, and the other seeks to adjust it within a narrow time horizon to meet a requirement identified and requested by a Smart Grid system. For both cases, the genetic algorithm seeks to find the fittest individual that satisfies the governing mode of operation. In this context, an individual of a generation has the information of the set points for the maximum charging power P_max for every CP in each time block throughout the day. With each iteration, a new generation is created and every generation undergoes fitness assessment, individual selection, crossover and mutation.

For the optimised definition of the schedule of the market-oriented operation (mo), the objective function of eq. 6 is used. This aims to shift the CP's demanded power (P^{mo}) to the times of the day (i) when the Day-Ahead prices (k) are most profitable. This is done from the first time block to the last time block of the day (N) by considering the charging processes at the controllable charging points (ccp). Finally, the demanded electricity price is obtained by considering the simulation time step (Δn), which is 15 minutes. The result of the optimisation is the operation schedule with the maximum charging power (P_{max}) setpoints for each time slot for each CP in the CI, which minimises the operating costs for the next day.

$$GA_\mathrm{mo} = \min \sum_{i=1}^{N} \sum_{j=1}^{ccp} \left\{P_j^{mo}(i) \cdot \Delta n \cdot k(i)\right\} \tag{6}$$

Once the above schedule starts running, the grid-oriented optimisation (go) takes place. The control and monitoring system of the CI is aware of possible requests from a Smart Grid system. If there were no requirements, the market-oriented schedule would be executed. Such requests are commands to reduce or increase the load power (ΔP_{go}) for the next time block. In the event of a request, the optimiser uses the objective function presented in eq. 7. It aims to minimise the differences between the market-oriented schedule (P^{mo}), which includes the request of the Smart Grid system ΔP_{go} at the needed moment (i_{go}), and the new grid-oriented schedule (P^{go}). Eq. 7 seeks not only to satisfy the Smart Grid system's requirement but also to minimise the potential variations between both schedules. This prevents possible penalties or additional costs due to non-compliance with the original schedule.

$$GA_{\text{go}} = \min \sum_{i=i_{go}}^{N} \left| \left\{ \sum_{j=1}^{CP} [P_j^{mo}(i) + \Delta P_{go}(i = i_{go})] \cdot \Delta n \right\} - P_j^{go}(i) \cdot \Delta n \right| \tag{7}$$

subject to:

$$\text{SoC}_j \geq \text{SoC}_{\text{min}}$$

The objective function also takes into account the user's willingness to have a smaller SoC value than expected through a minimum SoC (SoC_{min}) condition to be satisfied. The grid-oriented operation may affect the expected SoC value at the time when the EV leaves the CP.

In case variations persist between the market-oriented schedule and the grid-oriented schedule, they can be traded in intraday trading, in Flexibility markets or in P2P markets [27]. However, redispatch is not the focus of this paper.

3.3.2 Parameter optimisation of the Genetic Algorithm

GA-optimisation considers multiple parameters which must be calibrated to accelerate the convergence of the optimisation model [28]. Furthermore, the search field that the optimiser may consider can significantly affect the quality of the results obtained. In general, the parameters considered in the framework of this contribution are:

- *nIt*: Maximum number of iterations (generations)
- *Pop*: Size of the population of candidate solutions of each generation
- *pCh*: Offspring rate as a proportion of population size
- *ParSel*: Parent selection criteria
- *beta*: Pressure factor for the selection of suitable individuals
- *CrossMod*: Crossover mode
- *gamma*: Crossover's exploration factor for new potential solutions
- *mu*: Mutation factor
- *sigma*: Mutation step size
- *zeta*: Damping factor of the mutation factor after each generation

The parameters involved in “Individuals selection” phase of Figure 3 are *ParSel* and *beta*. Those belonging to the "Crossover" phase are *CrossMod* and *gamma*. Lastly, the parameters that impact “Offspring mutation” are *mu, sigma* and *zeta.*

A Monte Carlo analysis is performed to determine the values of the GA parameters that provide the fastest solution for both optimisation problems. The solution of the optimisation problem considered to calibrate the GA parameters is known beforehand. This analysis iteratively sweeps the values of the following GA parameters within a given range: *Pop, pCh, beta, gamma, mu,* and *sigma*. The same seed was used throughout the random number generator to ensure reproducibility and thus to understand the effects of parameter variation on the results and the speed with which results are obtained.

The GA parameters that remain constant during the parameter calibration are [29]:

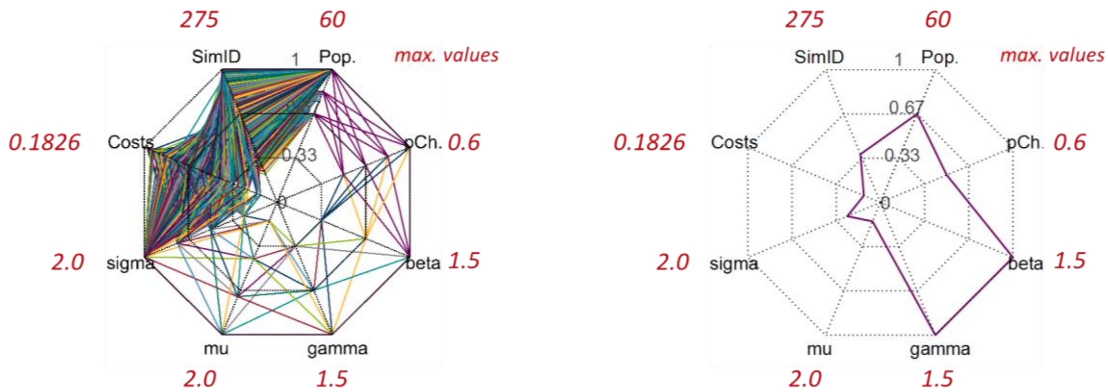
- *nIt*: set to 6 to force fast convergence
- *ParSel*: usually roulette wheel
- *RecMod*: usually uniform distribution

- *zeta*: usually 0.99

As control variables for the GA-parameter calibration are considered:

- *Sim ID*: Unique simulation ID for a generation's individual
- *Costs*: Total operational costs (fitness assessment value of the individual)

The objective of the GA-parameter optimisation is to find the fastest individual to emerge that generates the most cost-effective results. This is achieved through the smallest *Sim ID* number, as this parameter increases by one each time the assessment of an individual is completed. After almost 20 hours of evaluating 1750 generations (iterations), which corresponds to more than 320 thousand individuals, the set of parameters that obtained the fastest solution is chosen through the control variables. A GA-parameter optimisation overview is presented in Figure 6. The concentration of information in the upper left part of Figure 6a) is due to several factors. Not only does the number of possible parameter combinations influence this result, but also the unit increment of the control variable *SimID*, along with the unique *Cost* variable for each iteration. The *Costs* variable measures the quality of each iteration, with lower values indicating better fitness.



a) Normalised GA -parameter optimisation chart b) Optimised GA-parameter values

Figure 6: GA-Parameter optimisation overview

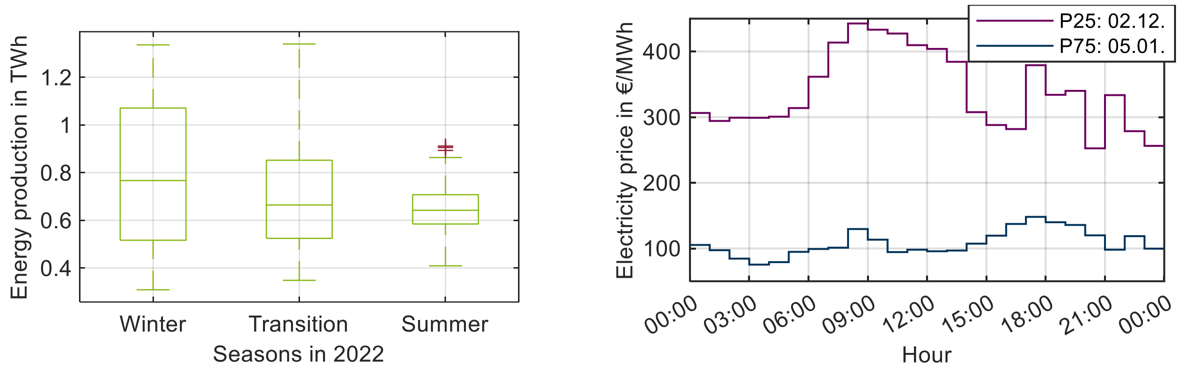
3.4 Scenario description

3.4.1 Market-oriented scenario

The scenario selection is based on the analysis of the energy generation type in Germany in 2022. This is to ascertain the daily generation of renewable energies for each season [30]. This information enables the selection of representative days by analysing the quartile data of the seasons presented in Figure 7a). The resulting representative days are those around the 25th percentile (1st quartile) for low renewable energy contribution and the 75th percentile (3rd quartile) for high renewable energy contribution. The Day-Ahead prices of these days [31] are extracted exemplary and presented for the winter season in Figure 7b).

These electricity prices are used as input variables in the market-based optimisation. Based on the probabilistic standing time forecasts for EVs from the tool presented in section 2.4 and the models of the EV involved, the market-oriented GA optimisation is performed.

Two additional operation modes are considered to highlight the advantages of an optimised operation. The first one considers the dynamic prices of the Day-Ahead market while the CI's operation is not optimised. It is assumed that for the spot-market-depending operation modes, the CI can participate directly or indirectly (via an aggregator) in the energy markets. The second operation mode considers a fixed electricity tariff for commercial customers, whose average value for the first half of the year 2022 was 0.2658 €/kWh and 0.5066 €/kWh for the other half [32]. The presented tariffs do not include the following additional costs: renewable energy fees, network charges, taxes and other levies. It also does not include administrative and management costs resulting from the operation through aggregation.



a) Daily energy production in Germany from renewable energies by season

b) Prices for the Day-Ahead market for the winter season 2022 considering the quartile distribution of a)

Figure 7: Market-oriented optimisation day selection criteria [30, 31]

3.4.2 Grid-oriented scenario

After determining the CI's operation schedule taking into consideration the Day-Ahead market prices, determined time blocks are selected. In these time blocks the CI must meet the requirements set by a Smart Grid system, in which the power demanded must be reduced during a 15-minute time slot (e.g., a 50 % reduction of the power demanded between 10:00 and 10:15) while the bottleneck is cleared. On the one hand, it must be taken into account that grid-oriented operation may lead to differences between the original market-oriented operation plan. On the other hand, the reduction of the charging power may reduce the EV's SoC once it leaves the CP affecting the user's comfort. For this reason, minimum SoC requirements that the EV must meet at the time of departure from the CP are included in the optimisation conditions. The minimum SoC value for the charging EVs at the time of leaving the CP must be at least 85 %. This scenario is only considered for the 5th of January 2022.

4 Results and analysis

This section presents the results and the corresponding discussions of the market-oriented and the grid-oriented optimisation, considering the presented scenarios.

4.1 Market-oriented optimisation results

Exemplarily, Figure 8 shows the results for 5 January of the GA-optimised schedule (marked in green and named GA) and the non-optimised operation schedule (marked in purple and named Dx), which operates, as does GA, considering dynamic electricity tariffs from the Day-Ahead market on the 5th of January 2022. The main difference between the two modes of operation is that GA uses dynamic values of the maximum charging power at each time block, while the Dx mode of operation uses the maximum operative charging power of the CP, taking into consideration the Day-Ahead market as well. As shown in Figure 8, the GA aims to avoid demanding power during time blocks where electricity costs are high. An example of this can be evidenced in the time slot between 15:00 and 20:00 when the GA avoids charging at maximum power and shifts consumption to the time slot between 20:00 and 24:00.

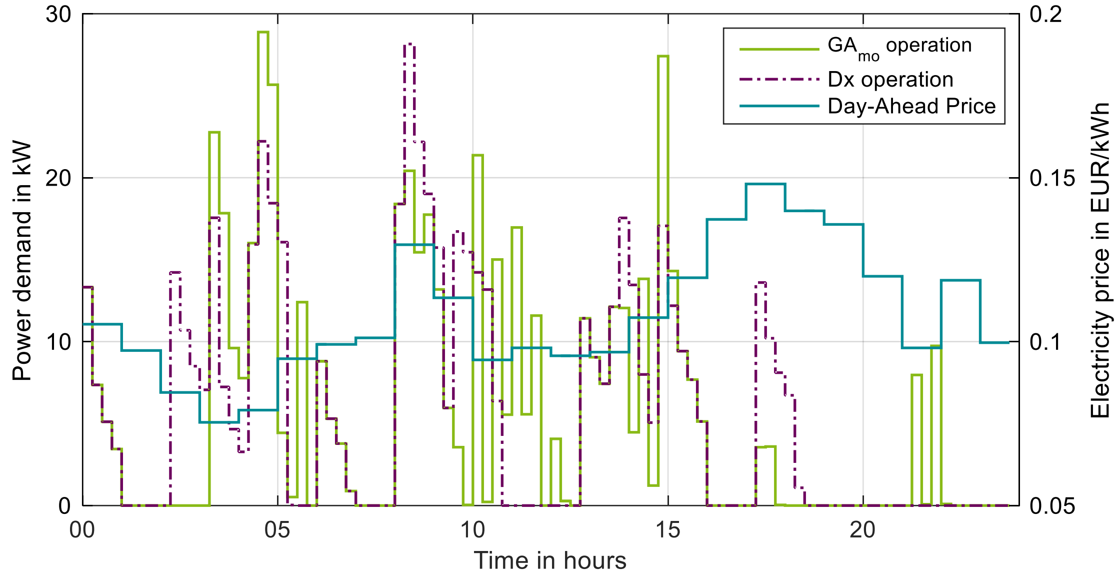


Figure 8: Market-oriented optimisation results for the scenario "Winter – P75: 05.01."

A summarised overview of the electricity costs associated with the modes of operation just presented (GA and Dx), as well as the cost of the mode of operation that considers fixed electricity tariffs (Fx) are presented in Figure 9 for all scenarios considered.

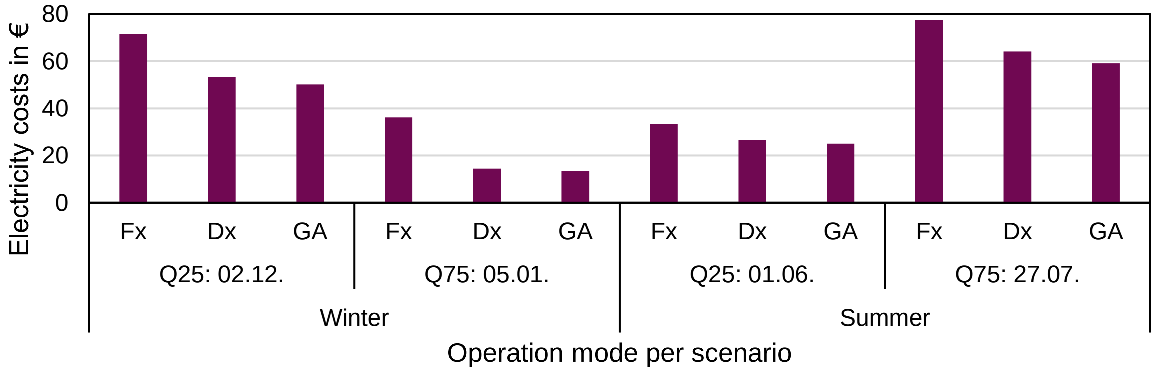


Figure 9: Overall market-oriented results by scenario

Figure 10 shows a comparison between the economic saving potential that the GA-based operation mode can offer compared to the other modes. On the one hand, compared to the Dx operation mode, the GA-based optimised operation is between 6.3 % and 8 % more cost-effective for the selected days. This is because GA aims to shift the demanded power to times when the electricity price is most profitable, as previously discussed.

On the other hand, without considering the "Winter - P75: 05.01." scenario, GA offers for the other scenarios an economic savings potential between 23 % and 30 % compared to the Fx operation. For the scenario "Winter - P75: 05.01.", it offers a savings potential of 63 %. Given that the contribution of renewable energies in electricity generation for the analysed day corresponds to the third quartile of 2022, the average cost of electricity is expected to be low compared to other days.

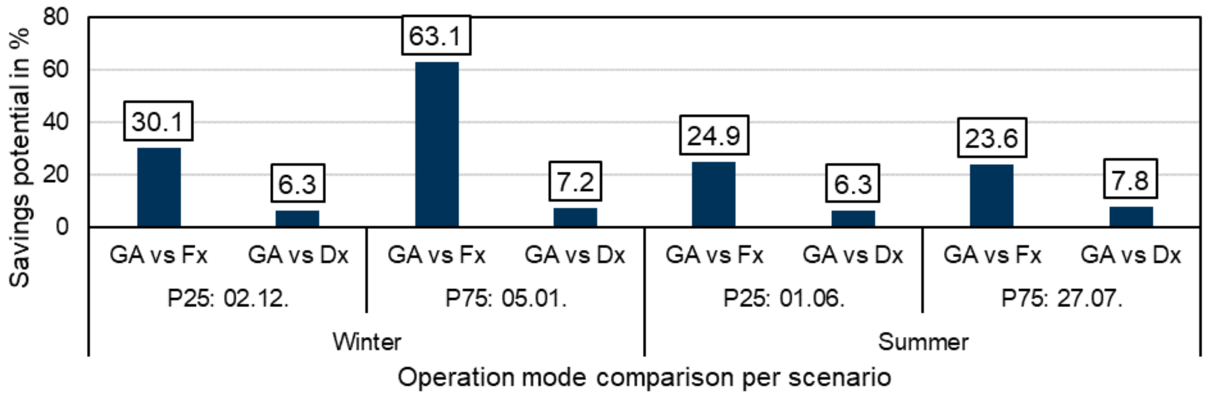
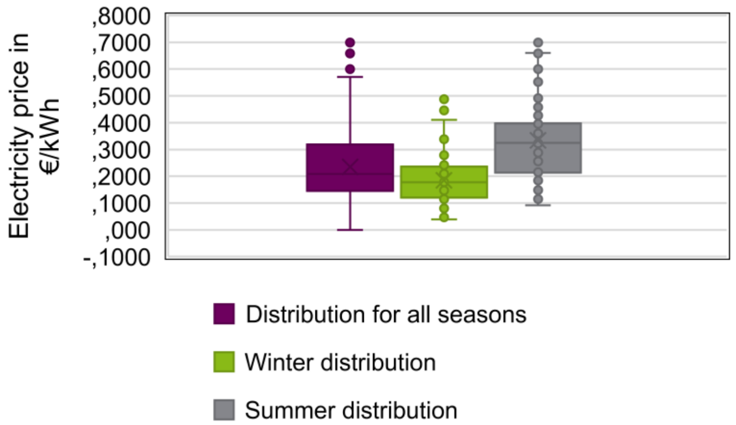


Figure 10: Saving potential between the GA market-oriented operation and the other considered operation modes

Figure 11 shows the average electricity price in the Day-Ahead market for that day is 0.11 €/kWh. This price is not only lower than the first quartile of the daily average price distribution for winter but for the entire year. This translates into a higher savings potential than the other considered scenarios, given the fixed energy tariffs presented in 3.4.1.



Day	Daily average electricity price in the Day-Ahead market in €/kWh
05.01.	0.11
06.01.	0.22
27.07	0.42
02.12	0.34

a) Seasonal analysis b) Daily average prices for given days

Figure 11: Daily average electricity price on the Day-Ahead market in 2022

Finally, at least for the selected days, there seems to be a close relationship between the days of high and low contribution of renewable energies in electricity generation and the electricity tariff in the Day-Ahead market.

4.2 Grid-service-oriented optimisation results

Figure 12 exemplifies the results of grid-oriented optimization for January 5, 2022. The green line represents the results of market-oriented (G_{mo}) as shown previously in Figure 8. Before the peak demand period in the afternoon, occurring between 14:45 and 15:00, a request (ΔP_{go}) is received from a Smart Grid system to reduce the demanded power by 10 kW during that time block. This request is highlighted in red and may have been triggered by a bottleneck in areas adjacent to the electricity distribution grid to which the CI belongs. The grid-oriented optimisation determines the new $P_{\max}$ setpoints for each CP to meet this requirement while simultaneously ensuring a value at the time of leaving the CP of at least 85 % thereafter. The grid-oriented optimised schedule of the entire CI (G_{go}) is represented by the blue line.

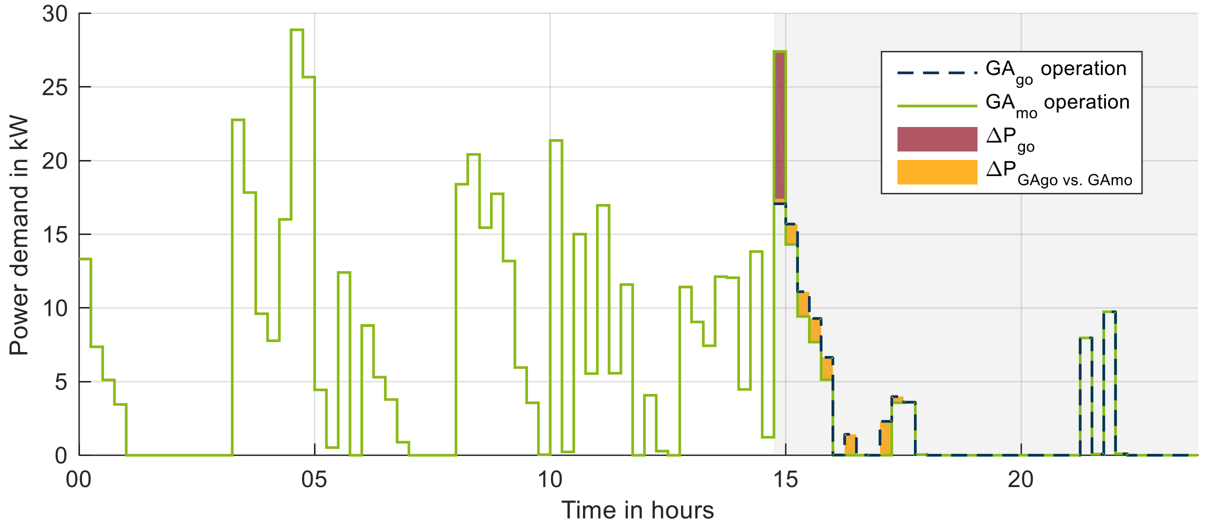


Figure 12: Results of grid-oriented optimization in response to a 10-kW power reduction request on January 5, 2022

The grid-oriented operation can introduce subtle variations in the power demand of the CI compared to the original market-oriented schedule, while still meeting grid requirements. The areas marked in yellow from 14:45 onwards represent these aforementioned variations, coinciding with the time when the grid-oriented optimization scheduling is active (region marked in light grey). As presented in Figure 12, the 10-kW reduction request is addressed by 96.6 %. Figure 13 presents the results of the power deviation between the grid-oriented optimisation P_{dev} and the target set by the Smart Grid system. It also shows the deviation between the demanded energy E_{dev} by operation mode GA_{mo} and operation mode GA_{go}. This percentage value provides insights into the energy that may need to be re-traded in short-term energy markets, such as Intraday trading [27], Flexibility markets or even P2P. However, this is not considered in the scope of this contribution.

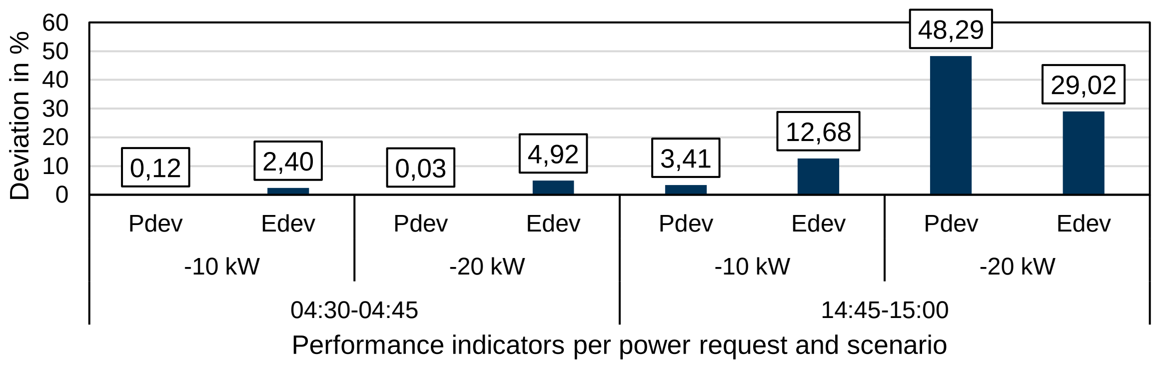


Figure 13: Power and energy deviation overview of the grid-oriented operation with respect to the market-oriented operation considering the power request of the Smart Grid system

The two selected time blocks for grid-oriented operation align with the peak power demand of the CI during the day—one in the morning and the other in the afternoon. In each time block, two requests are initiated to assess the potential flexibility that the associated charging processes can provide at those specific moments. During the morning time block, the grid-oriented optimization not only achieves accurate matching of setpoints, enabling a demand reduction of 10 kW and 20 kW with an accuracy exceeding 99 % for both cases. Simultaneously, the grid-oriented optimisation provides small variations concerning the original market-oriented operating schedule. For the 20-kW request in the afternoon time block, the involved charging processes exhibited limited flexibility. Within the considered iterations, it was challenging to determine setpoint values that would guarantee the EVs would leave the CP with the defined minimum SoC value.

5 Conclusion and outlook

Operating in the considered scenarios, the CI at the Freudenberg Campus of the University of Wuppertal demonstrates the potential for both market-oriented and grid-oriented operations. According to the results obtained, participating in the Day-Ahead market and employing metaheuristic optimization methods —specifically, Genetic Algorithms— can effectively reduce electricity-related costs. On one hand, an optimised market-oriented operation proves to be 20 % to 30 % more cost-efficient than an operation with a fixed electricity tariff. It is worth noting that the savings potential could have been higher, as only half of the load points were controllable. On the other hand, comparing the operation of the CI when using the dynamic electricity tariffs of the Day-Ahead market against its operation considering the GA-based operation, the optimised schedule still offers a saving potential of about 6 % to 8 %.

The grid-oriented operation was successful in almost all considered cases. In three of the discussed scenarios, the Smart Grid system's requirements were met by more than 96 %, ensuring that the resulting schedule did not significantly deviate from the original schedule of the market-oriented operation. However, in instances where user comfort must not be compromised, meeting Smart Grid system requirements may prove challenging. This was evident in the scenario on the right in Figure 13, where the charging process had to ensure that the EV could leave the CP with a minimum SoC value.

Given that the optimization processes heavily rely on the quality of the EVs' standing time forecasts, employing a machine-learning-based model instead of a probabilistic-based one could enhance the CI's scheduling. Additionally, for future work, a scheme to determine the price of electrical energy that can be sold in short-term markets, resulting from variations between market-oriented schedules and grid-oriented schedules, can be considered.

6 References

[1] Kraftfahrt-Bundesamt, *Neuzulassungen nach Umwelt-Merkmalen.* [Online]. Available: https://www.kba.de/DE/Statistik/Produktkatalog/produkte/Fahrzeuge/fz14_n_uebersicht.html?nn=3514348 (accessed: Oct. 24 2023).

[2] Bundesnetzagentur, *Elektromobilität: Öffentliche Ladeinfrastruktur.* [Online]. Available: https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/E-Mobilitaet/start.html (accessed: Oct. 24 2023).

[3] C. Gschwendtner, C. Knoeri, and A. Stephan, "Mind the goal: Trade-offs between flexibility goals for controlled electric vehicle charging strategies," *iScience*, vol. 26, no. 2, 2023.

[4] X. Lei, Y. Shang, Z. Shao, Y. Jia, and L. Jian, "Grid integration of electric vehicles for optimal marginal revenue of distribution system operator in spot market," *Energy Reports*, vol. 8, pp. 1061–1068, 2022.

[5] M. Alonso, H. Amaris, J. Germain, and J. Galan, "Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms," *Energies*, vol. 7, no. 4, pp. 2449–2475, 2014, doi: 10.3390/en7042449.

[6] X. Zhao and G. Liang, "Optimizing electric vehicle charging schedules and energy management in smart grids using an integrated GA-GRU-RL approach," *Frontiers in Energy Research*, vol. 11, 2023.

[7] TenneT, "Market Review 2017: Electricity market insights," 2018.

[8] EPEX SPOT SE, "Trading at EPEX SPOT," 2022. [Online]. Available: https://www.epexspot.com/sites/default/files/2022-07/22-07-12_TradingBrochure.pdf

[9] R. Kiesel, "Modelling Day-Ahead and Intraday Electricity Markets: Ökonomik der Energiewende," University of Duisburg-Essen, 2016.

[10] C. Aichele and O. D. Doleski, *Smart Market*. Wiesbaden: Springer Fachmedien Wiesbaden, 2014.

[11] M. Kilthau *et al.,* "Integrating Peer-to-Peer Energy Trading and Flexibility Market with Self-Sovereign Identity for Decentralized Energy Dispatch and Congestion Management," *IEEE Access*, vol. 11, 2023.

[12] N. Neusel-Lange, "Dezentrale Zustandsüberwachung für intelligente Niederspannungsnetze," Diss., Bergische Universität Wuppertal, 2013.

[13] N. Neusel-Lange, C. Oerter, and M. Zdrallek, "State identification and automatic control of smart low voltage grids," in *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, Berlin, Germany, 2012, pp. 1–6.

[14] C. Oerter, "Autarke, koordinierte Spannungs- und Leistungsregelung in Niederspannungsnetzen," Diss., Bergische Universität Wuppertal, 2014.

[15] P. Keil and A. Jossen, "Charging protocols for lithium-ion batteries and their impact on cycle life—An experimental study with different 18650 high-power cells," *Journal of Energy Storage*, vol. 6, 2016.

[16] W. Shen, T. T. Vo, and A. Kapoor, "Charging algorithms of lithium-ion batteries: An overview," in *2012 7th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, Singapore, Singapore, 2012.

[17] D. Fasthuber, "Integration der Ladeinfrastruktur in das elektrische Energiesystem," *Elektrotechnik & Informationstechnik*, vol. 137, 4-5, pp. 156–160, 2020.

[18] S. Moecker, "Driving Profile and Energy Demand Analysis for Electrical Vehicles based on GPS Trajectories," Master's Thesis, Technische Üniversität München, 2014.

[19] M. Forchheim, D. Cano-Tirado, G. Puleo, M. Wazifehdust, M. Zdrallek, and S. Palmer, "Forecast of Charging Processes of a Local Charging Infrastructure for Potential Flexibility Provisioning Based on Methods of Artificial Intelligence," *Energies*, vol. 13, no. 20, p. 5429, 2020, doi: 10.3390/en13205429.

[20] A. Ostermann, Y. Fabel, K. Ouan, and H. Koo, "Forecasting Charging Point Occupancy Using Supervised Learning Algorithms," *Energies*, vol. 15, no. 9, p. 3409, 2022.

[21] M. Clerc, "Short-term Forecasting of EV Charging Stations Power Consumption at Distribution Scale," Master's Thesis, KTH Royal Institute of Technology, 2022.

[22] R. Uhlig, M. Stötzel, M. Zdrallek, and N. Neusel-Lange, "Dynamic grid support with EV charging management considering user requirements," *CIRED Workshop*, 2016.

[23] N. DeForest, J. MacDonald, and D. Black, "Day ahead optimization of an electric vehicle fleet providing ancillary services in the Los Angeles Air Force Base vehicle-to-grid demonstration," *Applied Energy*, Volume 210, pp. 987–1001, 2018.

[24] H. Cai, Q. Chen, Z. Guan, and J. Huang, "Day-ahead optimal charging/discharging scheduling for electric vehicles in microgrids," *Protection and Control of Modern Power Systems*, vol. 3, no. 1, 2018.

[25] Q. Zhang, G. Raman, and J. C.-H. Peng, "EV Charging Optimization based on Day-ahead Pricing Incorporating Consumer Behavior," *2020 IEE Region 10 Conference (TENCON)*, vol. 2020, pp. 325–330.

[26] M. Koch *et al.,* "Low Voltage Laboratory Grid for Smart Grid Systems with Bidirectional Power Flows," *ETG Congress 2023*, Kassel, Germany, pp. 1–5, 2023.

[27] J. Messe, B. Dahlmann, M. Zdrallek, and A. Völschow, "International ETG Congress 2017," *International ETG Congress 2017*, pp. 1–6, 2017.

[28] M. Shaygan, A. Alimohammadi, A. Mansourian, Z. S. Govara, and S. M. Kalami, "Spatial Multi-Objective Optimization Approach for Land Use Allocation Using NSGA-II," *Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, no. 3, pp. 906–916, 2014.

[29] S. M. Kalami, *Practical Genetic Algorithms in Python and MATLAB.* [Online]. Available: https://yarpiz.com/632/ypga191215-practical-genetic-algorithms-in-python-and-matlab (accessed: Jan. 17 2024).

[30] ENTSO-E Transparency Platform, *Actual Generation per Production Type.* [Online]. Available: https://transparency.entsoe.eu/generation/r2/actualGenerationPerProductionType/show (accessed: Jan. 17 2024).

[31] ENTSO-E Transparency Platform, *Day-ahead Prices.* [Online]. Available: https://transparency.entsoe.eu/transmission-domain/r2/dayAheadPrices/show (accessed: Jan. 17 2024).

[32] Bundesverband der Energie- und Wasserwirtschaft e.V., "BDEW-Strompreisanalyse - Dezember 2023: Haushalte und Industrie," 2023.