Power-Dependent Efficiency Model of EV Chargers for Distribution Grid Simulations

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***Abstract*—The growing adoption of Electric Vehicles (EVs) and their integration into electrical distribution grids present various challenges. Among others, the efficiency of bidirectional chargers is critical for accurate energy demand forecasting and charging schedule optimisation. This study adapts a mathematical efficiency model, originally developed for photovoltaic inverters, for application to bidirectional EV chargers and incorporates the charging operation into a distribution grid simulation. To account for the power-dependent efficiency of chargers under diverse charging conditions, an approximation based on a step-function is employed. Simulation results indicate that incorporating variable charger efficiency leads to a moderate increase in total EV energy demand (9.4 %) and a minor increase in transformer loading during charging events (0.4 %), while the impact on line loading remains negligible in the considered scenario. The developed variable efficiency model provides a foundation for future research in larger networks with higher EV penetration levels also incorporating functionalities such as Vehicle-to-Grid.**

***Index Terms*—electric vehicle charging, charger efficiency, charging optimisation, modelling, distribution grid simulation.**

I. Introduction

The transition towards a widespread adaption of Electric Vehicles (EVs) poses various challenges to the electrical power grid. In power system simulations, the strongly nonlinear efficiency of chargers in partial load condition is often neglected and considered with a constant value only [1]. Charging schedule optimisations commonly target the mitigation of peak load through reduction of charging power, leading to a discrepancy between simulation and practice, if partial load efficiency is not accounted [2]. Previous studies analysing the impact of smart charging or partial load situations highlight the importance of accurately modelling charger efficiency to better understand its impact on energy demand and grid performance:

The work in [2] implements and evaluates the impact of limited charging efficiency on EV charging optimisation. The efficiency data originate from measurements obtained from chargers during frequency regulation operation, i.e., a highly dynamic operation mode. This yields a high variation in the partial load efficiency values, which is not expected in normal charging operation. The conducted case study simulation highlights an on-off charging strategy to overcome the limited partial load efficiency and reduce the peak load while avoiding low-efficiency operation. However, from a practical point of view, intermittent charging is problematic for many EVs available today [3].

Sevdari et al. [4] provide a detailed experimental insight into the AC-to-DC conversion efficiency of 38 EVs at varying current setpoint and State of Charge (SoC). The additional energy required due to smart charging is estimated as 1-10 % and confirms the importance of efficiency modelling in power system simulations. However, only aggregated fitting curves are provided without explicitly stating the parameters.

The study performed in [5] evaluates the grid-to-battery and battery-to-grid efficiency of a DC charger under various power setpoints, reporting charging efficiencies from 88.9 % to 91.3 %, with similar values for discharging. A comprehensive loss analysis of the electrical components, from the building transformer to the bidirectional EV, is presented in [6]. Losses range from 12 % to 36 %, highlighting the significant influence of battery SoC and charging power variations. In [7], the impact of charger losses on the revenues of Vehicle-to-Grid (V2G) operations for primary frequency regulation is assessed. Given the high energy exchange, efficiency plays a critical role, with an average hourly efficiency of 80 % in this scenario.

In contrast to the previous laboratory-based studies, [8] uses real home energy management data to calculate the efficiency of 5.9 kW DC chargers in a Vehicle-to-Home (V2H) application. Efficiency significantly drops below 0.5 kW during discharging and 1 kW during charging. At higher power levels, efficiency stabilises at around 90 %.

This study focuses on the application of a mathematical model to laboratory measurements obtained with a commercially available bidirectional charger. In contrast to previous studies, full model parameters are provided, so it can be directly used for accurate charger simulations. A step-function approximation with reduced complexity is developed for application in distribution grid simulations.

The rest of the paper is structured as follows: in Section II, the process of efficiency measurement as well as the application of an empirical converter model is detailed. Section III describes the integration of the approximation to a distribution

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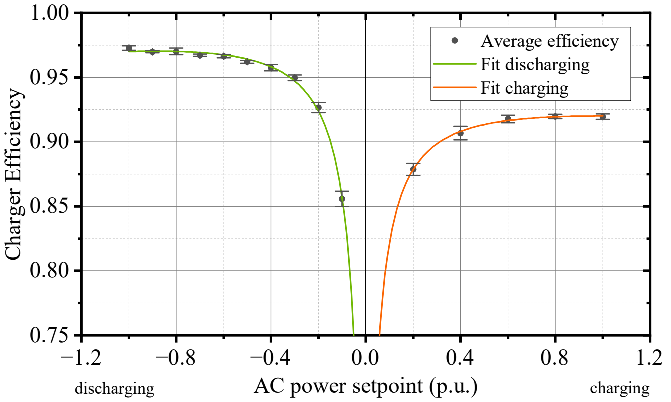

Fig. 1. Average partial load charger efficiency, determined from grid and DC output power. Data points represent the weighted mean across both vehicles and varying SoC, using the inverse of the variance as the weight. Error bars indicate the standard deviation between these conditions, confirming their similarity. The solid lines represent the corresponding data fits.

grid simulation. The results in Section IV highlight the impact of limited partial load charger efficiency on the total charging energy demand and load of grid assets. Section V discusses the main conclusions and provides an outlook.

II. Model Application

Firstly, the efficiency of a bidirectional DC EV charger is calculated in various charging power scenarios. An empirical model is then fitted on the basis of these results.

A. *Efficiency measurements*

The partial load efficiency of a bidirectional EV charger is calculated based on the dataset [9] obtained at Smart Grid Technology Lab at TU Dortmund University [10]. The dataset includes measurements from Nissan Leaf and Honda-e Advance in conjunction with an EVTEC coffee&charge 3in1 charger with a rated power of $\pm 10\,\mathrm{kW}$. Grid-side and DC output parameters are available at sub-second intervals, losses occurring in the EV are therefore not considered. Within the so-called dynamic test type in [11], the AC power setpoint of the charger is varied in a stepwise manner based on a defined time series scenario. A detailed description of the referred test case and calculation of the efficiency is provided in [11].

To generalise the $10\,\mathrm{kW}$ charger results, setpoints are converted to per-unit (p.u.). As shown in Fig. 1, the efficiency is nearly independent of the vehicle and its SoC. The data points are therefore means of all underlying measurements, weighted by the inverse of their variance to give more influence to results with a lower spread. The small resulting error bars confirm this high similarity. Efficiency drops for loads below $\pm 0.4\,\mathrm{p.u.}$, with discharging ($97.3\,\%$ at -1 p.u.) being generally more efficient than charging ($92.0\,\%$ at +1 p.u.).

The results align with [7] on efficiency independence from SoC and with [8] on higher discharge efficiency. However, [6] found higher charge efficiency, likely due to the use of modified onboard chargers rather than discharge-optimised offboard bidirectional chargers like those in this study and [8]. An increase in efficiency at higher power setpoints was also noted in [5], but is more pronounced here. The values in Fig. 1 are higher than the average curve from [2] and instead closer to the maximum observed efficiencies. This highlights the significant impact of the charger's characteristics.

TABLE I
Fitted parameters and corrected R^2 for the discharging and charging operating ranges.

	k_0	k_1	k_2	Corrected R^2
Discharging	-0.0173	-0.0084	-0.0220	0.9957
Charging	0.0162	0.0543	0.0164	0.9886

B. *Efficiency model*

Since Fig. 1 shows similar efficiency for both EVs without SoC dependence, a weighted average for each setpoint is calculated based on data variance, with lower variance values influencing the average more. To derive an efficiency model from the data, multiple mathematical models for power converters are considered, which are discussed in [12]. The model developed by Jantsch et al. in the context of photovoltaics (PV) inverters is given by (1) [13]. Due to similar power electronics principles and comparable loss mechanisms in PV inverters and bidirectional chargers, this model appears viable to represent the data. Other approaches, such as quadratic polynoms, show a significant inaccuracy towards higher power setpoints where the efficiency reaches saturation.

$$\eta(p) = \frac{p}{p + \left(k_0 + k_1\, p + k_2\, p^2\right)}, \tag{1}$$

where p is the inverter power in p.u. and k_0, k_1 and k_2 are the parameters to be fitted. For the fitting process, using a least squares algorithm, charging and discharging are considered separately yielding the parameters and corrected R^2 listed in Table I. As can be seen from the plot of the fitted function in Fig. 1 and the high corrected R^2, the measured efficiencies can be accurately represented using the model.

III. Implementation in Grid Simulation

In this section, the power-dependent efficiency of EV charging stations, as depicted in Fig. 1, is integrated into a distribution grid simulation environment. The focus of the simulation is solely on charging processes. Discharging operations, while representable by the underlying efficiency model, are not considered in this study but are designated as a subject for future work. First, a simplified overview of the key aspects of the simulation environment is provided. Then, the existing EV modelling approach and the specific model extensions required to integrate the power-dependent charging efficiency are described.

A. *Distribution grid simulation environment*

The distribution grid simulation applied in this study is detailed in [14]. It is fully implemented in MATLAB, with the integrated optimisation formulated using YALMIP and solved

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by Gurobi. Grid states are determined at each time step by performing an AC load flow calculation, taking into account exogenously specified time series data for connected load and generation units. Since the simulation environment is designed to investigate distribution grids in scenarios with high penetration of new electrical loads (such as heat pumps or EVs) and decentralised generation units, a flexibility optimisation is integrated to examine grid-supportive adjustments in the operational behavior of these flexible units.

The flexibility optimisation is activated in any time step where the AC load flow calculations detects grid congestions (i.e., transformer overloading, violations of permissible line current limits, or voltage band deviations) caused by the initially exogenously specified behavior of the connected units. The primary goal of the optimisation is to adapt the operation of flexible units in a way that resolves these congestions. However, since it is generally desirable to avoid or minimise any intervention in the originally planned operation schedule of a unit, the following objective function is defined:

$$\min \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} \left(\Delta P_{u,t}^{\mathrm{pos}} + \Delta P_{u,t}^{\mathrm{neg}} \right). \tag{2}$$

Accordingly, the deviation in the operation of flexible units is to be minimised. In distribution grids with a high penetration of decentralised generators and flexible loads, a wide range of grid conditions can occur (e.g., reversed load flows, over- and undervoltages, etc.). Therefore, the optimisation must enable flexible units to adjust their operational behavior in both directions (i.e., increasing or decreasing of generation and/or consumption) while respecting their respective operational limits. To reflect this, the term $\Delta P_{u,t}^{\mathrm{pos}}$ represents an increase in power generation or a reduction in consumption, while $\Delta P_{u,t}^{\mathrm{neg}}$ represents a decrease in power generation or an increase in consumption. The deviations are minimised for each flexible unit $u \in \mathcal{U}$ and in every time step $t \in \mathcal{T}$. These decision variables (as well as all the other decision variables in the optimisation problem), are restricted to positive values. Compliance with grid constraints is ensured through the formulation of corresponding constraints, meaning that the operational behavior of flexible units is to be adjusted only to the extent necessary to satisfy the grid requirements.

B. EV Modelling with fixed efficiency

Flexible EV charging processes can be considered within the optimisation. Their boundary conditions are definded by exogenously provided driving profiles, specifying key information such as the arrival time t_{arr}, departure time t_{dep}, and required energy E_i^{req} per charging session $i \in \mathcal{I}$. For simplification, each charging station is assigned exactly one EV and thus one corresponding driving profile.

With reference to the decision variables $\Delta P_t^{\mathrm{pos}}$ and $\Delta P_t^{\mathrm{neg}}$ minimised in the objective function, which represent the deviation from the initial, exogenously specified charging power $P_{v,t}^{\mathrm{EV,init}}$, the modified charging power $P_{v,t}^{\mathrm{EV,mod}}$ of an EV $v \in \mathcal{V}$ at time step t is given by:

$$P_{v,t}^{\mathrm{EV,mod}} = P_{v,t}^{\mathrm{EV,init}} - \Delta P_{v,t}^{\mathrm{pos}} + \Delta P_{v,t}^{\mathrm{neg}} \quad \forall v \in \mathcal{V}, \forall t \in \mathcal{T}. \tag{3}$$

When utilising flexibility (i.e., modifying the initial charging schedule), it must be ensured that the operational limits of EVs and charging stations are respected. Since only flexible, unidirectional charging is modeled, the charging power must not become negative, which would correspond to feeding power back into the grid.

$$\Delta P_{v,t}^{\mathrm{pos}} \leq P_{v,t}^{\mathrm{EV,init}} \quad \forall v \in \mathcal{V}, \forall t \in \mathcal{T} \tag{4}$$

Constraint (4) ensures that the reduction in charging power $\Delta P_{v,t}^{\mathrm{pos}}$ cannot exceed the initial charging power $P_{v,t}^{\mathrm{EV,init}}$ in the respective time step. When adjusting the initial charging power $P_{v,t}^{\mathrm{EV,init}}$ according to constraint (3), the modified charging power $P_{v,t}^{\mathrm{EV,mod}}$ can therefore only be reduced to a maximum of zero. Conversely, constraint (5) guarantees that increases in charging power $\Delta P_{v,t}^{\mathrm{neg}}$ do not violate the maximum allowable charging power P_v^{max}.

$$P_{v,t}^{\mathrm{EV,init}} + \Delta P_{v,t}^{\mathrm{neg}} \leq P_v^{\mathrm{max}} \quad \forall v \in \mathcal{V}, \forall t \in \mathcal{T} \tag{5}$$

In addition, it must be ensured that each EV v receives the required amount of energy E_i^{req} in each charging session i:

$$\sum_{t=t_{\mathrm{arr,i}}}^{t_{\mathrm{dep,i}}} P_{v,t}^{\mathrm{EV,mod}} = E_{v,i}^{\mathrm{req}} \quad \forall v \in \mathcal{V}, \forall i \in \mathcal{I}. \tag{6}$$

As constraint (6) only requires the sum of the modified charging power $P_{v,t}^{\mathrm{EV,mod}}$ to match the energy demand E_i^{req} of each charging session i, and losses are not explicitly considered, a constant efficiency of $\eta = 100\,\%$ is assumed for simplification.

For the purpose of this study, the presented flexibility optimisation is slightly adapted. This adaption primarily concerns the activation of the flexibility optimisation. Since the general effects of incorporating power-dependent efficiency of EVs in distribution grid simulations are to be analysed (where grid congestions do not necessarily occur), the flexibility optimisation is executed in every investigated time step rather than being triggered only when grid congestions arise. Additionally, no initial charging schedule is specified for the EVs. Instead, only the corresponding driving profiles are provided, allowing the solver to determine each EV's charging schedule endogenously. Therefore, the optimisation of the charging schedule is guided solely by the constraints imposed by the driving profiles and technical limits, while ensuring that no violations of grid constraints occur.

C. Integration of the power-dependent efficiency

To integrate the power-dependent charging efficiency into the existing modelling approach [14], the flexibility optimisation is extended by additional constraints. Constraints (3) - (5) continue to serve as the basis for determining the modified

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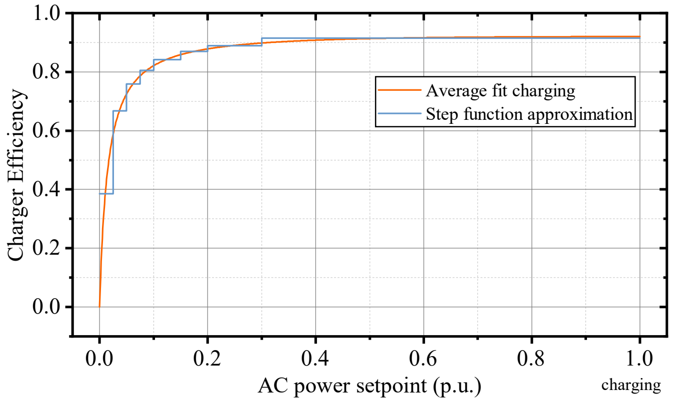

Fig. 2. Partial load charger efficiency fit and step function approximation

charging power $P_{v,t}^{\mathrm{EV,mod}}$ while ensuring it remains within the technical operating limits. However, constraint (6) is extended by an additional term to account for the power-dependent charging efficiency.

Before applying this extension, additional constraints are introduced to represent the variable charging efficiency, as illustrated in Fig. 1. Since the fitted efficiency curve (1) is a second-order polynomial, it is approximated by a simplified step function to reduce model complexity. This function assigns fixed efficiency values to defined power intervals. Narrow step widths are used at low charging power due to the steep slope of the efficiency curve, while wider intervals are applied at higher power levels where the curve flattens. This modelling approach aims to represent the efficiency curve with sufficient accuracy while reducing the complexity of the optimisation problem. A total of eight efficiency levels are defined as shown in Fig. 2, by integrating the original function over each power interval. The step function approximation yields a corrected $R^2 = 0.9201$ with regard to model (1) when evaluated at 1000 points, indicating a good representation at significant reduction of model complexity.

To integrate the step function into the optimisation model, binary variables are introduced. For each efficiency level, a binary variable B indicates whether the corresponding efficiency value is applied for a given EV v in time step t.

$$\eta_{v,t} = \eta_1 \cdot B1_{v,t} + \cdots + \eta_8 \cdot B8_{v,t} \quad \forall v \in \mathcal{V}, \forall t \in \mathcal{T} \tag{7}$$

An additional constraint using the same binary variables is formulated to ensure the correct assignment of efficiency values depending on the modified charging power $P_{v,t}^{\mathrm{EV,mod}}$. Therefore, a piecewise case distinction is modeled, where L and U represent the lower and upper bounds of the respective efficiency interval according to Fig. 2:

$$\begin{aligned} B1_{v,t} \cdot L_1 + \cdots + B8_{v,t} \cdot L_8 \leq P_{v,t}^{\mathrm{EV,mod}} \leq B1_{v,t} \cdot U_1 \\ + \cdots + B8_{v,t} \cdot U_8 \quad \forall v \in \mathcal{V}, \forall t \in \mathcal{T}. \end{aligned} \tag{8}$$

Finally, a constraint must be included to ensure that only one binary variable is active at any given time step.

$$\sum B1_{v,t} + B2_{v,t} + \ldots + B8_{v,t} = 1 \quad \forall v \in \mathcal{V}, \forall t \in \mathcal{T} \tag{9}$$

As a result of the described modelling approach, exactly one of the predefined efficiency values is selected per time step, depending on the interval in which the modified charging power $P_{v,t}^{\mathrm{EV,mod}}$ falls. Since constraint (9) ensures that only one binary variable is active (and thus equal to 1), only the relevant interval and its corresponding efficiency value are considered in constraint (7) and (8). All other terms in the respective constraint are multiplied by inactive binary variables (equal to 0) and therefore do not affect the constraint.

Once the power-dependent efficiency is formulated, it can be incorporated into the constraint that ensures the fulfillment of the energy demand in each charging session.

$$\sum_{t=t_{\mathrm{arr,i}}}^{t_{\mathrm{dep,i}}} P_{v,t}^{\mathrm{EV,mod}} \cdot \eta_{v,t} = E_{v,i}^{\mathrm{req}} \quad \forall v \in \mathcal{V}, \forall i \in \mathcal{I}. \tag{10}$$

Since only driving profiles are specified for the purpose of this study, and no initial charging time series is provided for EVs, the optimizer is incentivised to select charging powers that yield high efficiency values in order to reduce losses and minimise the required deviation $\Delta P_{v,t}^{\mathrm{neg}}$. However, if simultaneous charging of multiple EVs is not feasible in certain time steps due to grid constraints, charging processes may need to be shifted to other time steps and potentially carried out at lower power level, resulting in lower efficiencies.

IV. Results

The described method and its extension are applied to evaluate the impact of power-depending charging efficiency using the distribution grid benchmark "1-LV-rural1–0-no_sw" from the SimBench dataset [15]. The low-voltage (LV) grid includes 13 nodes, four feeders, and a 160 kVA transformer. All relevant grid data is available in [16]. EV charging stations (resp. the corresponding EVs) are randomly assigned to the grid nodes, with two scenarios (12 and 15 EVs) used to assess the effects of increasing EV penetration. For simplification, all charging stations are assumed to support a maximum charging power of 11 kW, and identical driving profiles are applied to all EVs. The simulation is first run without, and then with, power-dependent efficiency to evaluate its influence on the grid assets and EV energy demand. Each run covers one year at hourly resolution (8,760 time steps).

Selected simulation results are shown in Table II. Since the original model assumes 100 % EV charger efficiency, the integration of power-dependent efficiency leads, as expected, to an increase in total EV energy demand. This increase amounts to approximately 9.4 % in both scenarios, which is consistent with the findings in [4].

Average transformer utilisation during charging sessions increases slightly when including power-dependent efficiency (0.44 % and 0.43 %). In the 15 EV case, the smaller increase can be attributed to grid losses, which depend on the EVs'

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TABLE II
EXEMPLARY RESULTS FROM MULTIPLE SIMULATION SCENARIOS

	12 EVs		**15 EVs**	
	Power-dep.	**Fixed** ($\eta = 1$)	**Power-dep.**	**Fixed** ($\eta = 1$)
Total EV energy demand (MWh)	19.56	17.88	24.45	22.34
Mean transformer utilisation during charging sessions (%)	16.41	15.97	17.13	16.70

location within the grid. The optimisation minimises deviations from the initial schedule (set to 0 kW for all EVs in all time steps), without explicitly considering transformer loading, as long as limits are not violated. In the 12 EV case, lower efficiencies are observed in some cases for EVs located further from the transformer, leading to higher grid losses. As this is not penalised in the objective function, a slightly higher increase in transformer utilisation results. Although the increase appears minor in both scenarios, this is mainly due to the small test grid and limited number of EVs. In larger LV grids with higher EV penetration or medium-voltage (MV) grids, the effect is expected to be significantly more pronounced, making power-dependent efficiency increasingly relevant for asset utilisation assessment.

Analysis of the average line loading during charging sessions shows only a marginal increase. This is mainly due to the line types used in the test grid, which (with a maximum current of 270 A) provide high capacity for a rural 13 nodes grid. In more constrained grids or scenarios with higher EV penetration, stronger effects are expected.

The average annual charging efficiency of an EV is approximately 88 %, meaning that EVs do not consistently operate at the highest possible efficiency of 92 % (see Fig. 2). This is mainly due to two factors: 1) Grid constraints may require reduced charging power in certain time steps, leading to lower efficiency. 2) In some charging sessions, the required energy demand is relatively small. Given the simulation's hourly resolution, charging must then be performed at reduced power to avoid overcharging, which also reduces efficiency.

V. CONCLUSION

The presented methodology highlights the application of a mathematical PV inverter efficiency model to measurements obtained with a bidirectional charger. The derived model parameters can either be used directly for bidirectional charger emulation or applied to grid simulations. Two scenarios are simulated in a rural benchmark distribution grid, revealing a total EV energy demand increase by around 9.4 %. While the impact on asset utilisation (transformer and lines) is minor in this exemplary grid, stronger effects are expected in larger or weaker LV grids with higher EV penetration, and in MV grids due to aggregated impact.

Future work includes implementing the nonlinear efficiency model in a power-hardware-in-the-loop emulation of a bidirectional charger to improve level of detail and accuracy. Further model validation could involve measurements on different charger types. The step-function approximation will be expanded to the discharging realm and integrated in larger grid simulations. A significant increase in computation time was observed due to the use of binary variables, highlighting the need to evaluate the method's scalability for larger grids and higher EV shares. Furthermore, a finer temporal resolution and individual EV driving profiles will be considered to improve simulation accuracy by enabling more flexible charging adaption and better reflecting user behavior.

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