Scenario-driven Analysis of Intelligent Charging Strategies Caused by the Market Ramp-Up of Electric Vehicles

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***Abstract*— The accelerating market ramp-up of electromobility in the sector of road-bound passenger and freight transport leads to an increase in the installation of charging infrastructure connected to the distribution grids. The additional power and energy demand of electromobility affects the power flow through operating equipment. In case of high load caused by electromobility, local grid congestion can occur. If no suitable countermeasures are taken, this might induce a need for grid reinforcement. To reduce the need for grid reinforcement, using intelligent charging strategies combined with other smart grid communication systems might be a feasible solution. In this paper, a methodology to forecast the market ramp-up of electric vehicles is introduced as well as intelligent charging strategies and a method to quantify grid reinforcement measures. Based on the market ramp-up scenario, the ability of intelligent charging strategies to prevent the need for grid reinforcement is examined. Depending on the structure of the examined grid area, the costs for a grid reinforcement are significantly reduced by applying the intelligent charging strategies proposed in this paper.**

Keywords: market ramp-up; charging infrastructure; EV load; intelligent charging; charging control; grid reinforcement

I. Introduction

Due to the increasing greenhouse gas concentration as the main driver for climate change, the German government facilitates, among other things, electric vehicles (EV) to reduce CO_2 emission in the transport sector [1][2]. To ensure security of supply in the distribution grids in the long term and to avoid disinvestment in grid reinforcement measures, it is necessary to take the influence of electromobility into account at an early stage when planning network expansion. Against this background, the long-term prognosis of the electromobility load and the grid relief potential of intelligent charging strategies is of central importance. To examine the grid relief potential of intelligent charging strategies in various stages of the market ramp-up, a method for forecasting the local load induced by electric vehicles needs to be developed. Therefore, a model is developed to emulate the adoption decisions of potential buyers of electric vehicles. The resulting scenario for the market ramp-up is locally disaggregated based on an analysis of mobility data as well as socio-economic parameters. Considering the mobility behavior and the forecasted charging behavior, charging use cases are defined and local load time series for electromobility are generated. These display cost-optimal integration of battery storage and local generation in charging parks as well as intelligent strategies for both global and local charging control. Subsequently, the developed methodology is applied on an exemplary rural grid area and load flow simulations are performed. The potential of intelligent charging strategies to avoid needs of grid reinforcement and its costs is examined by applying a developed heuristic. The proposed methodology is schematically depicted in Fig. 1.

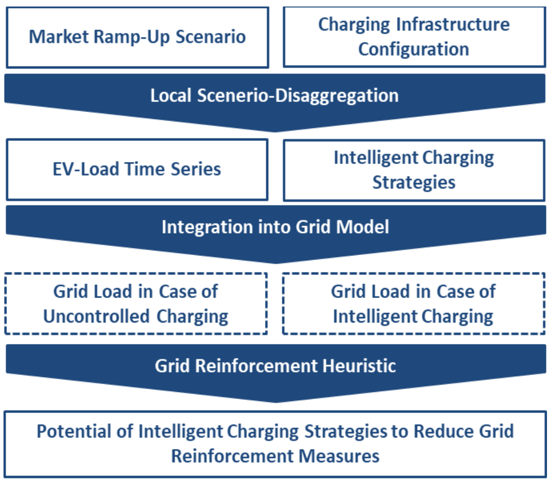

Figure 1. Schematic of proposed methodology.

II. Methodology

A. *Market Ramp-Up Scenario*

The forecast of the electromobility market ramp-up is based on the diffusion process of the electromobility innovation. The decision of purchasing a vehicle is based on the relative economic advantages of the available alternatives and the compatibility with existing mobility needs, as well as the technological risk of the drive type to be selected for both commercial and private costumers.

The forecasting model depicts the economic decision of potential users based on the economic advantages derived from a break-even analysis of the total cost of ownership (TCO). To consider the changes in the TCO over time, the factors that will influence its future development, like the specific characteristics of the vehicle, energy industry framework and possible political measures were considered.

The TCO-annuity, when the purchase is done at a year t, is calculated for the drive type r and the vehicle category s according to (1).

$$TCO^{a}_{r,s,t} = a^{r,s,t}_{capex} + a^{r,s,t}_{opex} \tag{1}$$

$$a^{r,s,t}_{capex} = \left(AC_{r,s,t} \cdot (1+i)^T - RV_s \cdot AC_{r,s,t}\right) \cdot \frac{i}{(1+i)^T - 1}$$

$$a^{r,s,t}_{opex} = YM \cdot (s_{e_r} c_{e_{r,s,t}} k_{e_t} + (1 - f_{e_r}) c_{v_{r,s,t}} k_{v_{r,t}} + k_{w_{r,s}}) + K_{S_{r,s,t}}$$

$TCO^{a}_{r,s,t}$	annuity of total cost of ownership
$a^{r,s,t}_{capex}$	annuity of capital expenditures
$a^{r,s,t}_{opex}$	annual operational expenditures
$AC_{r,s,t}$	acquisition cost
i	interest rate
T	holding period
RV	relative residual value at end of the holding period
YM	annual mileage
s_{e_r}	electric driving share
$c_{e_{r,s,t}}$	electricity consumption
k_{e_t}	electricity cost
$c_{v_{r,s,t}}$	fuel consumption
$k_{v_{r,t}}$	fuel cost
$k_{w_{r,s}}$	annual cost for maintenance and repair
$K_{S_{r,s,t}}$	annual contribution to the motor vehicle tax

The TCO values are forecasted up to the year 2050 based on the investigated development of the input parameters acquisition costs, energy consumption and costs of the respective energy source as well as the contribution to the motor vehicle tax. These parameters are mainly determined by technological and energy industry developments and the political framework associated with monetary and legal measures as well as possible support programs at national and European level. As an example, the European CO_2-framework is considered to derive future acquisition cost for vehicles with internal combustion engines [3]. Another factor to be considered are the future mobility needs that especially demand an increase in the electrical driving-range [4]. The resulting increase in battery pack size is considered when determining future acquisition cost for electric vehicles.

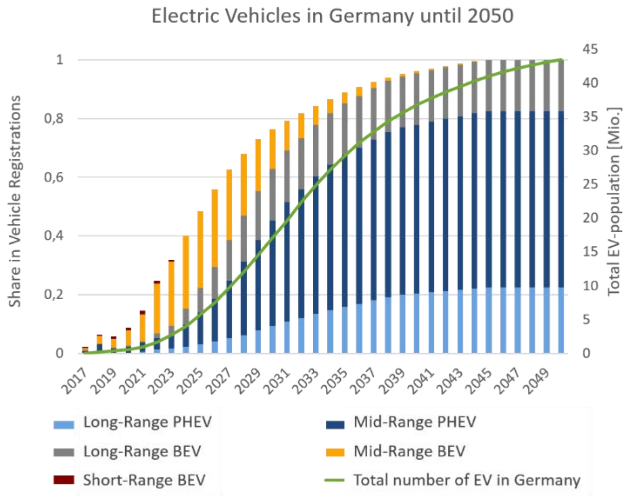

Figure 2. Prognosis for EV market ramp-up in Germany.

The future TCO values, as a function of the annual mileage, are used to forecast the market penetration of electric vehicles over time. A Break-Even-Analysis is executed to determine the proportion of new registrations that can be economically substituted by electric vehicles.

For the estimation of the diffusion process over time the economic substitutability works as a main influencing parameter but is not sufficient. The overriding regulatory framework and the individual factors influencing the purchase decision of individual customers are also relevant. The proportion of new vehicle registrations substituted by electric vehicles, for the year under consideration, is finally calculated by taking the previously found value of new registrations and multiplying it by a factor that considers the individual behavior of adoption.

Fig. 2 shows the market ramp-up for the category of passenger vehicles. For each year until 2050 the share of new registrations replaced by electric vehicles and the resulting number of electric vehicles in the total vehicle population of Germany are depicted.

B. *Charging Infrastructure Configuration*

The local effects in the distribution grids and therefore the need of grid reinforcement measures is determined by the number of electric vehicles in each vehicle category and by the characteristics and use of the charging infrastructure deployed for the expected penetration of electric vehicles. The configuration of the charging infrastructure depends on the mobility behavior and charging needs of the electric vehicle users that determine energy and power demand for each charging session. The preferences of the customers and the purpose of use of an electric vehicle can be described from the perspective of private and commercial users. Depending on the owner group and vehicle category different use cases for charging electric vehicles can be distinguished according to the potential charging location.

For privately used vehicles four main categories are to be distinguished. The first category is “Private Charging”. This refers to electric vehicles being charged at a designated parking space that is not publicly accessible for other electric vehicles. This includes the locations “Home” and “Workplace”. The second category refers to “Central

Charging" and describes charging at the destination of a trip or at central locations in urban areas. The charging points are usually operated commercially and are accessible to the public or potential customers. In this study the locations "Car Park", "Supermarket" and "Filling Station" are considered for "Central Charging". The third category of refers to "Public Charging" where charging takes place at charging infrastructure in public parking lots. The charging points are installed, for example, on behalf of the city or local administration. In this study, it is assumed that this does not represent a comprehensive use case for charging electric vehicles in the long term. The fourth category is "Long-distance Charging". The charging infrastructure is located along long-distance routes, e.g. motorways, to enable electric vehicle users to recharge on longer journeys that may exceed the vehicle's electrical range. The configuration of the charging points corresponds to the use case "Filling Station" due to the same customer requirement for fast charging.

For commercially used vehicles, a division according to vehicle category is necessary due to different mobility requirements and vehicle parameters. The first division corresponds to commercial passenger vehicles for which the use case "Car Fleet" is defined. The electric vehicles are charged at the respective company location and outside of the operating hours. The use case "Truck Fleet" corresponds to vehicles primarily used for inner-city distribution transport that take a daily round trip starting and ending at the respective company premises. It is assumed that the electric vehicles will be charged outside the time of operation at a designated parking space. The third relevant use case that is considered for commercially used vehicles within this study is "Bus Fleet" and refers to motorbuses that charge at a central depot.

Besides the previous classification according to charging location, the use cases mentioned above can also be differentiated by the charging behavior of the electric vehicle users. The required charging power is derived from the energy demand and the time the vehicle remains at the charging location. To determine the energy demand of an electric vehicle, the distance traveled between two consecutive charging sessions as well as the specific energy consumption of the vehicle need to be evaluated. The former depends on the use case and the housing structure in the examined grid area. Drivers in sparsely populated areas are travelling longer distances than those in urban areas [5]. These regional differences in mobility behavior are taken into consideration when generating local electromobility load time series. The installed maximum power of the charging infrastructure sufficient to satisfy the customers charging needs is determined by the energy to be recharged and the assumed average length of stay at the charging location as well as consumer preferences.

In Fig. 3 the assumed charging power according to the average residence time is shown for each of the considered use cases within the scope of this study.

	Charging Power	Residence Time
Home	11 kW	8-12 h
Workplace	11-22 kW	4-10 h
Car Park	11-22 kW	1-4 h
Supermarket	11-22 kW	0,5-2 h
Filling Station	150-400 kW	5-20 min
Car Fleet	11 kW	8-12 h
Truck Fleet	11-22 kW	6-12 h
Bus Fleet	50 kW	6-10 h

Figure 3. Assumed charging infrastrucure configuration per use case.

C. Local Scenrio-Disaggregation

The local load flow caused by the charging of electric vehicles is determined by the local characteristics of the charging infrastructure for each use case as well as the local energy demand of the electric vehicles. The aim of the local electromobility scenario disaggregation is to determine the significance of the use cases for a specific grid area and to derive specific parameters that influence the local power and energy demand.

To determine the number of charging sessions for each use case in a specific grid area, the number of locally registered vehicles needs to be considered. Thus, the local vehicle density for each of the different vehicle categories defined above is investigated. This number is then multiplied by the penetration rate of electromobility for the corresponding year and the vehicle category. This results in the number of vehicles located in the network area under consideration.

In addition to the locally registered vehicles, the local balance of commuters inter- and intra-area is particularly relevant for the use case "Workplace". The expected value is determined by the means of a heuristic model. The probability for each commuter entering or leaving the grid area under consideration by car is dependent on the distance traveled. Based on statistics on the distance between home and work place and the means of transportation chosen by the commuters such as [5] and [6], the developed model determines commuter hotspots within the examined grid area. Fig. 4 depicts the identified commuter hotspots for the grid area of an exemplary medium voltage (MV) grid within the service area of MDN.

Furthermore, potential charging locations for "Central charging" are identified and site-specific data is collected to determine the extent to which the use cases are relevant in the specific grid area. The number of electric vehicles that are relevant for a central charging location depends on its catchment area. The relevant number of vehicles within this area and the average distance travelled to the charging location are analyzed and then used as input parameters to determine the local power and energy demand of the electric vehicles.

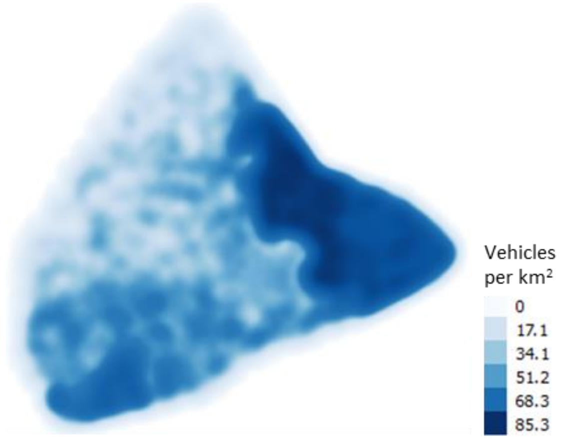

Figure 4. Commuter-hotspots in exemplary grid area.

Following this methodology to derive local electromobility scenarios, all relevant use cases for specific grid areas and thus the local characteristics of the charging infrastructure can be determined for each studied year. Also, specific input variables regarding the local power and energy demand are derived to derive local load time series for electromobility.

D. *Load Time Series for Electromobility*

Possible network congestion is caused by the characteristic of local peak loads. The local simultaneity factors and the time pattern of the required power per use case are of crucial importance. In this context, a model for generating individual load curves for each charging point is developed, so that the time curve of the electromobility load can be mapped as a local load time series based on the input parameters derived from the scenario disaggregation. The model for generating load time series is based on a "bottom-up" approach. First, the number of electric vehicles that charge according to one of the use cases defined above in the period under consideration is determined from the specific local frequency of use and the number of relevant vehicles in the examined area.

The individual power demand of each electric vehicle depends on vehicle-specific parameters, local parameters of the examined area and the selected use case. These factors determine both the vehicle battery state-of-charge (SOC) at the time of arrival and the required charging power at the charging point and thus the charging curve assigned to the vehicle.

The start and end time of each individual charging process is also relevant for the time profile of the total load. It is assumed that the charging process will start immediately upon arrival at the charging point. Hence, a probability distribution for the arrival times at the respective charging location is defined for each use case. To derive the probability of arrival, available studies on current charging and mobility behavior such as [7] and [8] are analyzed. Depending on the SOC at the beginning of the charging session and the power rating of the charging infrastructure, a potential charging curve is assigned to each vehicle, which is derived from real time series in the database of P3.

E. *Intelligent Charging Strategies*

The need for additional grid reinforcement arises due to the power drawn at the charging infrastructure facilities at times of high grid load. By implementing intelligent charging strategies, the maximum electromobility load and thus the number of necessary grid reinforcement measures can be reduced [9]. At first, the possibility of integrating battery storage, renewable energy generation systems or a combination of both options in a commercially viable manner is examined for each potential charging park in the given grid area. For this purpose, an existing optimization model for the integration of battery storage and distributed power plants into charging parks is used. In addition, intelligent operating strategies to control the exchange of energy and the power flow between the charging park components are implemented to reduce the power drawn from the grid.

In addition to battery storage and local generation, the aggregated maximum power drawn from the grid can also be decreased by reducing the number of charging sessions at times of critical grid load. This can either be achieved by conditioning the EV-owners to expand the intervals between charging sessions or by implementing intelligent strategies for charging control. To implement the latter option in real-world applications, communication between the EV, vehicle users, electric vehicle supply equipment (EVSE), energy suppliers, the distribution system operator (DSO) and billing service providers is necessary. These parties exchange data to control the charging process, such as the power demand and the SOC, as well as customer preferences and payment information. As a communication node, the EVSE is of crucial importance for the implementation of intelligent charging strategies. The regulatory framework for communication at the interface between EVSE and the network control system is given by the Open Charge Point Protocol (OCPP) and IEC TR 61850-90-8. While the OCPP is used to authorize charging sessions at publicly accessible charging stations, the technical report of IEC 61850-90-8 also offers functions for implementing an integrated control system to the DSO [10]. The model developed within the scope of this study takes intelligent charging control strategies into consideration that can already be implemented today.

For charging the lithium-ion batteries of electric vehicles the CCCV-method (Constant Current Constant Voltage) is most commonly used. Hence, the charging power reaches its maximum value just after the start of the charging session and decreases afterwards. Thus, the total aggregated electromobility load is high especially at times when many charging sessions are started simultaneously.

Therefore, the aim of the implemented charging control strategies is to limit the number of simultaneously starting charging sessions considering the required customer satisfaction. In this way, charging sessions are shifted from times of critical grid load to non-critical periods. Postponing charging sessions in this manner decreases the total electromobility peak load in the examined grid area by reducing the simultaneity factor. For the simulations in this study, two possible options for charging control are evaluated, a local and a global option. While local charging control only affects charging sessions in the subordinate grids of overloaded local transformer substations, global charging control is implemented for the entire vehicle population.

III. Results

A. Grid Load in Case of Uncontrolled Charging

To examine the grid load under increasing penetration of electric vehicles, local electromobility scenarios are derived according to the methodology described in chapter II. Based on these scenarios, local electromobility load time series representing the electromobility impact in 2020, 2030 and 2050 are generated. The charging infrastructure facilities are then mapped as additional loads in models of real-world distribution grids.

Single charging infrastructure facilities for electric vehicles are connected to low-voltage (LV). Fast-charging parks such as for the use case “filling station” or charging parks with many charging points such as for the use case “supermarket” are connected directly to the MV-grid due to the high power installed in total. To comprehensively map all relevant charging use cases and charging infrastructure configurations for electric vehicles, exemplary studies of the power flow within medium-voltage grids are carried out in this study. Especially in rural MV-grids, the supply task of the DSO is changing due to the grid integration of large wind and solar parks. To investigate the interaction of electromobility load and high supply of renewable energies (RE), a grid area with a high feed-in from RE is selected for further investigation within this study.

Based on load flow simulations, the grid load under consideration of an increasing electromobility load until 2050 is evaluated. Limitations for the layout of an electric grid are given by the required voltage quality and the maximum load of operating equipment. The permissible supply voltage at relevant nodes within the MV-grid is given by the EN 50160. The latter is determined by the applicable network planning principles of the DSO. In the simulations within the scope of the study, the load of operating equipment and the supply voltage at relevant grid nodes in the years 2020, 2030 and 2050 are examined. Fig. 5 shows the local transformer substations within the rural MV-grid and their distribution in the gird area. Those transformers with violations of the permissible supply voltage in the year 2050 are colored yellow.

In 75 cases, the supply voltage on the MV-side of local transformer substations is below the permissible limit according to EN 50160. After further evaluation of the equipment data resulting from the power flow simulations, a developed heuristic is applied to determine and evaluate the necessary grid reinforcement measures. Fig. 6 shows the resulting amount of grid reinforcement measures and its costs in 2020, 2030 and 2050.

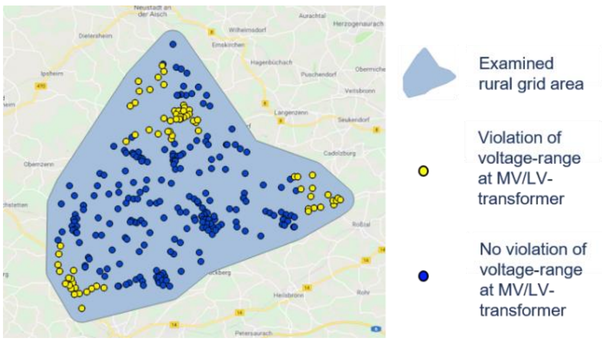

Figure 5. Voltage-range deviations in exemined rural grid area.

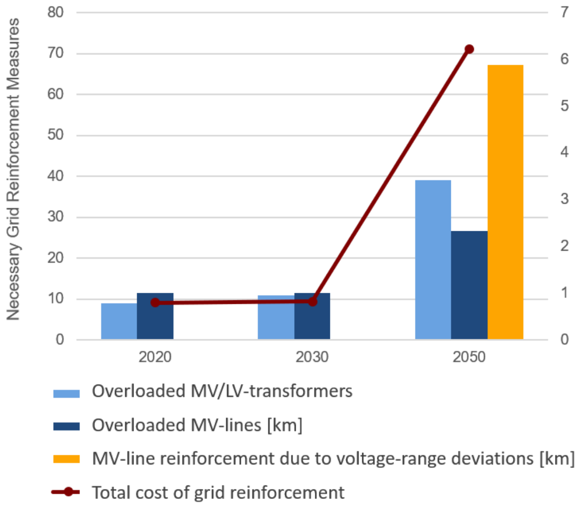

Figure 6. Grid reinforcement measures for rural MV-grid.

In case of uncontrolled charging, limits for the load of operating equipment and the supply voltage at the network nodes are increasingly being violated in the rural MV-grid. In addition to the above-mentioned violations of the supply voltage for 75 local transformer substations, 16.5% of the MV/LV-transformers and MV-lines with a total length of 26.7 km are overloaded in 2050. This results in necessary grid reinforcement measures with total costs of over six million euro.

B. Grid Relief Potential of Intelligent Charging Strategies

The grid load of the examined rural MV-grid in case the proposed intelligent charging strategies are implemented is illustrated in Fig. 7. The number of overloaded operating equipment and voltage-range deviations under the assumption of cost-optimized design of the charging park components combined with intelligent charging control strategies is shown for global as well as for the local implementation. In addition, the total decrease compared to uncontrolled charging is depicted for 2020, 2030 and 2050.

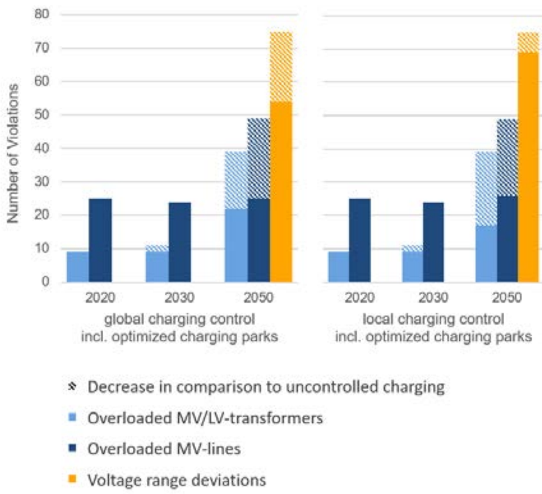

Figure 7. Overloaded operating equipment and voltage-range deviations in rural MV-grid considering intelligent charging strategies.

The amount of overloaded operating equipment occurring in 2020 and 2030 at times of high distributed generation cannot be reduced by implementing intelligent charging strategies for electric vehicles. However, both the local and global implementation in 2050 will lead to a decrease of the number of overloaded MV/LV-transformers. It will drop from 39 to 22 for global charging control and to 17 for local charging control. The number of overloaded MV-lines is reduced from 49 to 25 for the global option and 26 in case of local implementation. Regarding voltage range deviations at local transformer substations, a higher potential for network relief can be identified in case of global implementation of charging control. In fact, the number of voltage range deviations within the examined MV-grid drops by 21 to a value of 54. Fig. 8 shows the economic potential of implementing intelligent charging strategies regarding the resulting grid reinforcement costs.

The high grid reinforcement costs in rural MV-grids that arise due to the emerging electromobility can effectively be reduced by implementing intelligent charging strategies. In the examined grid area within this study, the costs of reinforcement measures arising from overload of operating equipment decreases by up to 51 %.

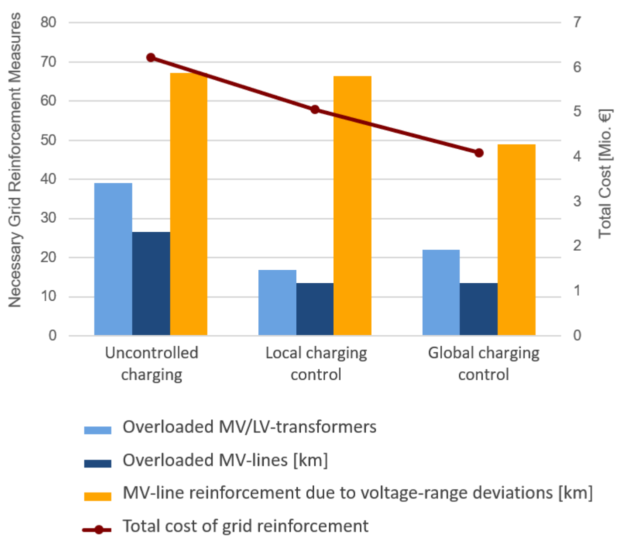

Figure 8. Grid reinforcement measures for rural MV-grid considering intelligent charging strategies.

By implementing global charging control, the scope of grid reinforcement measures due to voltage range deviation is also reduced. In total, the grid reinforcement costs in the examined grid area until 2050 can be decreased by over 2.1 million euro. However, reinforcement of MV-lines with a total length of 49.1 km is still necessary due to low supply voltage in times of electromobility peak load.

IV. Conclusion

The grid analyses reveal that until 2050, in case of uncontrolled charging, a need for grid reinforcement can arise within the considered rural MV-grid despite high supply of distributed generation. In this case, the implementation of intelligent charging strategies can reduce the number of overloaded operating equipment by up to 51 % and the number of voltage range deviations at local power transformers by up to 28 %. Thus, the costs of grid reinforcement of 6.23 million euro which occur in case of uncontrolled charging can be reduced by up to 34 %. In examined urban grid areas, the additional load caused by electromobility induces grid reinforcement costs until 2050 which can be reduced by 70 to 85 % by implementing the proposed intelligent charging strategies.

Furthermore, it is revealed that especially due to the differing locations of renewable energy power plants and charging parks for electric vehicles connected to the MV-grid, large spatial disparities of load and generation occur. This leads to voltage range deviations and a need of grid reinforcement. Hence, it may be necessary for the DSO to adjust existing grid reinforcement plans and site planning of future distributed power plants.

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