Grid Load Relief by Smart Charging of Electric Vehicles

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***Abstract*—This paper analyzes a possibility to reduce the grid impact of electric vehicles (EV) by curtailing the charging power in case of necessity. The focus lies on the development of a decentralized charging algorithm with minimum communication needs. The only communication needed is uni-directional communication to broadcast the current transformer status. The goal is to evaluate if the local voltage at the charging station is a sufficient indicator to keep the grid within its operation boundaries instead of supplying every charging station with the minimum voltage of the corresponding power line, which would result in high communication needs. To reduce the impact of the local voltage an urgency-factor is included as a further input parameter. It determines how close the vehicles are to the departure time and increases the charging power in case of insufficient charge.**

The proposed charging is based on a fuzzy controller. It converts the described input parameters into a change of charging power via a predefined control matrix. In the first step, the input values are transferred into fuzzy-areas and thereafter interpreted by the inference engine. In a final step, the results of the inference engine are transformed into a change of charging power by the point of gravity method. Additionally to the fuzzy controller it is assumed that the vehicles are able to support the grid voltage by changing the powerfactor between 0.9 underexcited and 0.9 overexcited alongside a cos(φ)(U)-curve.

Deterministic models for the active load of households, heat pump and photovoltaic systems were introduced in a previous paper. The existing model is advanced by including reactive power dependencies, car classes and more realistic charging behavior of EV-owners.

The functionality of the charging algorithm is tested under difficult grid conditions. A low voltage grid with long power lines and a relatively small transformer in an urban environment is chosen. At first it is shown that the grid can be kept stable even at maximum EV-penetration without causing limitations for the vehicle owners. In a second evaluation the grid is further burdened with heat pumps close to the point of the minimum voltage level even before including EV's. In this case the charging algorithm is not able to keep the voltage above the voltage threshold because only local voltage measurements are considered. Bi-directional communications could solve the problem but grid expansion should be the preferred method at this point because average EV-charging power is below 23% of its nominal value. Lastly the impact of additional photovoltaic (PV) systems in the grid is evaluated. It can be concluded that photovoltaic systems are not able to prevent grid expansion caused by increasing load from heat pumps and electric vehicles, due to the volatility of the technology.

I. Introduction

Originally low voltage grids were not designed to include the additional load of charging electric vehicles (EV). Instead of grid expansion, one possible solution could be to migrate the charging power away from times of high grid load by an appropriate charging algorithm. Chapter II shows the importance of communications to evaluate the grid stability which at the same time leads to a more complex and costly design. Therefore a charging algorithm is proposed which uses very little communication (chapter III). For testing purposes, a simulation model is introduced in chapter IV while taking into consideration a deterministic model discussed in the paper "Probabilistic Modeling of Charging Profiles in Low Voltage Networks" [1]. Afterwards the simulation results are presented in chapter V and a final summary is given.

II. Communications

Before deciding on the charging algorithm, general communication constrains are evaluated. The goal is to create a functional EV-charger with minimum communication effort, to reduce potential communication errors and cost of the necessary technologies.

The simplest solution for omitting communication is to use the local voltage as indicator for the state of the grid. Unfortunately this does not allow to get any reliably information on the loading of transformers and lines. As the transformer is typically the weakest link when it comes to overloading, it has been decided to use additionally to the local voltage the state of the transformer as parameter in the charging algorithm. Thus a uni-directional communication link to broadcast the transformer load to all participants via a radio station is included.

When implementing bi-directional communications global optimization becomes possible. Advantages lie in potentially better results although come at the price of reduced scalability compared to local charging algorithms. The power quality is mostly known and could further be improved by monitoring individual line load. General disadvantages of bi-directional communications are a high increase in data transfer and potential data protection issues.

This paper sets the focus on developing a charging algorithm based on uni-directional communication to investigate if the grid can still be kept inside the operation boundaries.

III. Charging Algorithm

As shown in a previous paper [1] maximum grid load only occurs avery seldom. Instead of expensive grid expansion, charging algorithms could mitigate additional impact of EV-charging by load shifting. The proposed charging algorithm is a combination of existing charging strategies by [2] [3] [4].

Teng et al. [2] designed an algorithm based on Fuzzy-Control. Fuzzy-Control calculates a percentile change of the output value by evaluating multiple input parameters via a predefined fuzzy rule control matrix. At first the input parameters are transferred into fuzzy areas inside the fuzzifier. In the next step the areas are evaluated by the inference engine and the fuzzy rules. Finally the values are transferred into the output inside the defuzzifier.

The input parameters differ from Teng et al. Transformer load, local voltage and a newly developed urgency factor are used instead of local voltage and state of charge (SOC) of the EV-battery. The transformer load is known to the charging algorithm by the previously described radio signal. It is broadcasted as a percentage of the maximum transformer load. The local voltage is obtained at the charging station. Both factors are used to evaluate the momentary grid impact. The urgency factor is further introduced to reduce the impact of the charging algorithm on EV-holders. The vehicle owner expects that the vehicle is fully charged before the upcoming journey. Therefore, when considering the same SOC of two different cars, the one with closer departure time should be charged faster to satisfy the owners. Equation 1 displays the introduced urgency factor u_i.

$$\begin{aligned} u_i &= \frac{t_{C;min,i}}{t_{rest,i}} && \mid t_{C;min,i} < t_{rest,i} \\ u_i &= 1 && \mid t_{C;min,i} \geq t_{rest,i} \\ t_{C;min,i} &= \frac{BatCap}{P_{max}} \cdot (SOC_{max} - SOC_i) \end{aligned} \tag{1}$$

The urgency factor is calculated by comparing the time until departure $t_{rest,i}$ with the minimum time to fully charge the vehicle using maximum charging power P_{max}. The remaining charging capacity is calculated by multiplying the EV-battery-capacity $BatCap$ with the maximum state of charge SOC_{max} minus the current state of charge SOC_i. Figure 1 shows an exemplary development of the charging power until departure in case the car is not charged during the displayed charging time. Once the urgency reaches 100% it is at its maximum value. Unless the grid is close to collapse the EV's should be charged with maximum power no later than this point.

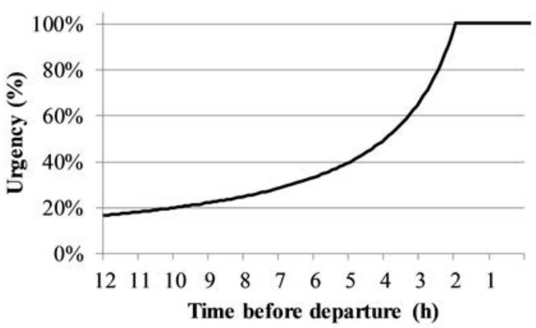

Fig. 1. E.g. change of urgency factor when approaching departure time without charging simultaneously.

For the grid to stay within the operation boundaries the transformer load must not exceed 100%. Furthermore, because the medium voltage grid is not considered in the simulation, the nominal voltage is set to 1 p.u. on the medium voltage level right before the transformer. Norm EN 50160 allows a maximum voltage deviation of 0.1 p.u. for low and medium voltage grids combined. The deviation is split equally for both voltage levels. Therefore the minimum grid voltage has to be above 0.95 p.u. in the following evaluation. In reality the level would be set to 0.9 p.u.

In the first step of the fuzzy control the input values are transformed into two fuzzy-areas for each input value. The fuzzy-areas range from negative big (NB) to positive big (PB) while including negative small (NS), zero (ZE) and positive small (PS). The value NB is equal to 0.955 p.u. for the voltage control. No later than this point should the charging power be reduced immensely. The minimum voltage for power reductions is set slightly above the minimum level to account for safety margins for households drawing power down the power line.
"Positive Big" is set to 1 p.u. for maximum EV-charge. The values in between are set in an exponential manner. EV-charging should only be curtailed when necessary. Al-Awami et. al have shown that orthographic dependencies can be reduced when using exponential instead of linear area sizes proposed by Teng et. al for voltage control.

The start and end values for transformer load and urgency factor are set similarly. Transformer load is uncritical until reaching 80% (PB-Value) and gradually reduced until reaching 99% (NB-Value). The remaining 1% are a safety margin against dynamic changes. For the urgency factor, the value for maximum charge (PB) is set to 100% and the value for minimum charge to 45%. Vehicles with an urgency level below this point only get charged when the grid is far from its maximum operation point.

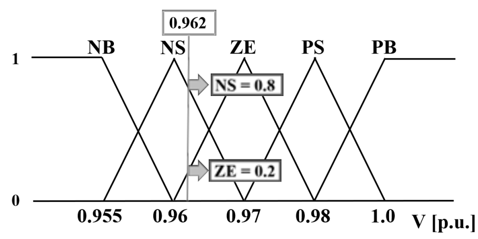

Fig. 2. Evaluation of Fuzzy-Control for local voltage values.

If, for example, the local voltage equals 0.962 p.u., the corresponding fuzzy-areas are "negative small" and "zero" (figure 2). Both are given values interpolated linearly between 0 and 1 alongside the area boundaries (NS_V = 0.8; ZE_V = 0.2). Calculations for the transformer load and urgency-factor follow the same pattern.

In the next step a one dimensional value has to be calculated via the predefined control matrix and the inference engine. The control matrix sets the correlations between the input values. In case the transformer load is far from its operational maximum (PB_T), but the local voltage is below 0.955 p.u. (NB_V), then the charging power should not increase regardless of the urgency-factor. Exemplary dependencies between the local voltage and the urgency factor in case of uncritical transformer load (PB_T) can be taken from table I. For example, if the voltage area is NS_V, the urgency area PS_U and the transformer load PB_T, the resulting combined area is ZE_I as highlighted in table I.

In the fuzzifier two areas with corresponding values for each input parameter were calculated. Each area is combined

TABLE I
CONTROL MATRIX SHOWING DEPENDENCIES BETWEEN LOCAL VOLTAGE (COLUMN) AND URGENCY FACTOR (ROW) WHILE THE TRANSFORMER LOAD IS UNCRITICAL (PB_T).

Voltage/Urgency	NB_V	NS_V	ZE_V	PS_V	PB_V
PB_U	ZE	PS	PB	PB	PB
PS_U	NS	ZE	PS	PB	PB
ZE_U	NB	NS	ZE	PB	PB
NS_U	NB	NS	ZE	PS	PB
NB_U	NB	NB	NS	PS	PB

with the corresponding areas of the other input data as shown in the previous example. In total eight combinations are possible.
In the next step for each area a value is calculated by the inference engine. The lowest value of all three combined input parameters is chosen as seen in equation 2 to stabilize the algorithm.

$$\mu_i = min(\mu_V; \mu_T; \mu_U) \tag{2}$$

The resulting areas are evaluated in the defuzzifier by a simplified point of gravity method for trapezoids. Figure 3 visualizes the approach. Each area is given a percent change of charging power. While ”negative big” leads to a 10% decrease in charging power, ”positive big” is assigned a 10% increase. The remaining areas are set linearly.
For visualization purposes, only two values PB=0.8 and PS=0.2 are assumed as a result of the inference engine. The areas are shaded in figure 3 according to the area type and the height of the corresponding value. The resulting point of gravity is at 9% and can be calculated by equation 3, while N_i represents the number of areas taken out of the inference engine. Therefore, the charging power would increase 9% of the maximum charging power.

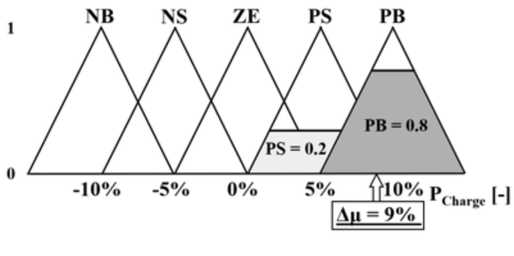

Fig. 3. E.g. simplified gravity method for trapezoids.

$$\Delta\mu = \frac{\sum((-10\% + \frac{20\%}{N_i}) \cdot \mu_{min,i})}{\sum \mu_{min,i}} \tag{3}$$

The created control algorithm is extended by a reactive power controller taken from [3]. It is assumed that all EV’s are able to change the power factor between 0.9 underexcited and 0.9 overexcited charging depending on the local voltage level. Close to 1 p.u. a dead band is set to reduce the risk of reactive power transfer between charging stations in case of PV-integration. The control characteristic can be taken from figure 4.

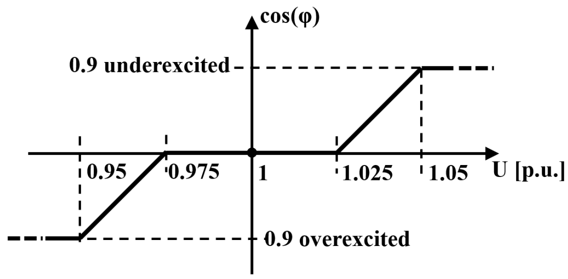

Fig. 4. Reactive control characteristic depending on local voltage.

IV. SIMULATION DESIGN

The developed algorithm will be evaluated in a low voltage grid with a relatively small transformer compared to grid size and long power lines. The grid topology was designed and validated by Kerber [5]. It consists of 9 power lines with the longest containing 61 households over a length of 621 meters. A total number of 192 households are connected. It is assumed, that the grid is already heavily loaded.

To evaluate maximum load impact all vehicles in the grid are electrified. Each household owns an average of 0.89 vehicles [6]. Furthermore, three vehicle types are defined. The vehicle types differ in battery size and electric energy consumption and does cover a certain market share. The classification follows a method designed by the Fraunhofer ISI [7], but uses updated data. The specific values can be taken from table II.

TABLE II
OVERVIEW OF THE DEFINED CAR CLASSES

	cheap	average	expensive
Battery capacity [kWh]	21,1	40,0	81,4
El. energy consumption [kWh/100km]	16,8	22,1	25,8
Percentage of cars [%]	29,2	51,8	19,0

EV-charging efficiency can be taken from figure 5. For the simulation it is assumed that the efficiency does not drop below the values of 30% charging power compared to the maximum charging power. In reality, if vehicles have to curtail the charging power below this point, some cars would stop charging completely. In consequence other cars could keep charging with a minimum charging power of 30%. Potentially resulting grid impact is neglected for simplification reasons.

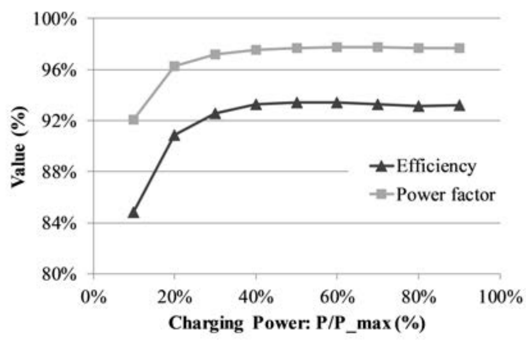

Fig. 5. Charging efficiency and power factor depending on the charging power [8].

Usually vehicles are not charged after each journey. Field experiments of the University of Denmark have shown that the average SOC of EV's is 55% at the point of recharge [9]. Therefore, in the simulation, vehicles are connected to the grid when the SOC at arrival is below 55% unless the time until the next departure is less than 30 minutes. Additionally, cars are charged earlier when the following journey cannot be successfully completed without recharging.
It is assumed that cars are exclusively charged at home, but in case the battery is empty during the journey, it is charged externally to the point of successful trip completion. This event is recorded for later analysis in case the trip was unsuccessful due to insufficient SOC at departure.

Generally the simulation is based on methods introduced in the paper "Probabilistic Modeling of Charging Profiles in Low Voltage Networks" [1]. It discusses the probabilistic development of driving profiles and active power curves for household loads, heat pumps and PV-systems. Each household has a characteristic load profile selected randomly via Monte-Carlo-Method. The simulation is therefore repeated 1000 times with changing load profiles to increase statistical significance.

Furthermore, this paper introduces reactive power dependencies to improve the simulation results. The underexcited power factor for EV's charging at full capacity is 0.977 as shown in figure 5 taken from experiments conducted by Zhang et.al [8]. In case of controlled charging the previously described reactive power controller is used.

The power factor of the household load is derived from experimental data from the HTW Berlin [10]. Figure 6 displays the power factor distribution. 39.1% of the net loads in a household are overexcited. The rest is underexcited. The power factors are randomly assigned to the simulated households alongside the given distributions.
The underexcited heat pump power factor is distributed uniformly between 0.7 and 0.8, due to high reactive power consumption of usually installed asynchronous motors. For photovoltaic systems the underexcited power factor is kept constantly at 0.95 to evaluate the worse case scenario of maximum voltage drop.

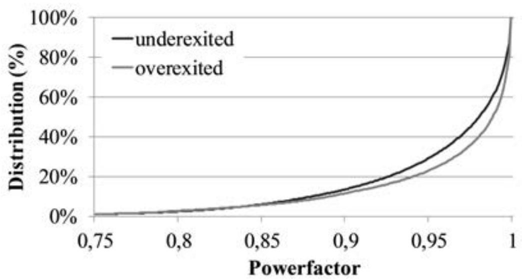

Fig. 6. Power factor distribution for underexited and overexited household loads.

V. Calculations and Results

The general setup is designed to show boundaries of the charging algorithm. An already heavily loaded grid is chosen and evaluated on a cold winter day. Furthermore, maximum EV penetration is assumed. At first no heat pumps and photovoltaic systems are installed in the grid. In a second evaluation additional impact of heat pumps an photovoltaic systems is analyzed.
On weekdays vehicles are used more than on weekends, while household load peaks are almost the same over the course of a week. Therefore the highest grid impact is expected during a working week and the simulation focus set on this type of day.

A. *Influence of EV's*

To evaluate the grid impact figure 7 displays the apparent power over the course of a weekday at the transformer substation. At first uncontrolled charging is considered (light gray). As represented by the 99.73% (+3-sigma) graph the transformer is in danger of overload from about noon until midnight. Instead of the maximum values, the +3-sigma values are chosen because for statistical analysis with a limited set of data, the quantils have a higher significance [11]. Extremely rare load combinations (less than 0.27% are ignored.
By introducing the proposed charging algorithm the transformer load stays below 100% for all time intervals. The transformer load does not exceed 90% due to later described voltage restrictions.
Only in a few scenarios is the EV-charging power curtailed, which can be seen when comparing the mean values for controlled and uncontrolled charging. Both values vary by less than 15%. After 10 pm the mean for controlled charging is above uncontrolled charging because previously curtailed energy is transferred to the EV's to close the energy gap.

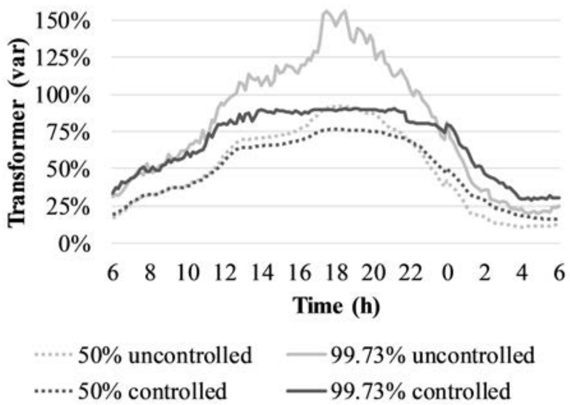

Fig. 7. Transformer load over the course of a weekday for controlled and uncontrolled charging.

Along with transformer load, the voltage also has to be kept within the boundaries of 0.95 p.u. and 1.05 p.u. to keep the grid inside operational boundaries. In this scenario, the upper value is never reached due to missing photovoltaic(PV)-systems in the grid. The lowest local voltage is found at the household furthest from the transformer. As seen in figure 8 it decreases down to 0.89 p.u. in the case of uncontrolled charging. Already at 10 am charging power is curtailed by the charging algorithm to keep the grid voltage above 0.95 p.u. Curtailment due to transformer overload is theoretically only needed after 12 am, therefore in this scenario the algorithm is primarily voltage driven.

As previously shown, the charging-algorithm is capable of keeping the transformer load and local voltage at a normal

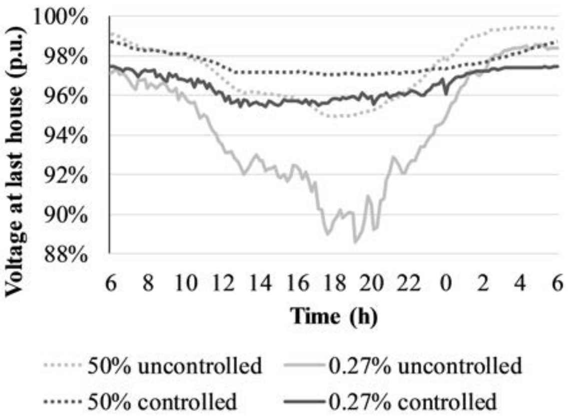

Fig. 8. Local voltage at the last household over the course of a weekday for controlled and uncontrolled charging.

operating point for all time steps even when considering maximum EV-penetration in an already heavily loaded grid. Power line overload could still lead to grid failure as power line evaluation is not part of the charging algorithm to reduce costs and communication effort. The risk of power line overloading is typically lower compared to the risk of transformer overloading, as this is typically dimensioned for higher simultaneously factors of the load compared to the transformer. The heaviest loaded line is expected between the transformer and the first household on the longest power line with the most households connected. The power line time dependency is similar to the transformer load due to same influencing factors. Therefore, the power line stability is assessed globally by the amount of time it is overloaded in minutes per month. Without a charging algorithm the power line is overloaded for 178.8 minutes per month on average. No overload occurs when the charging algorithm is used. Table III shows the results of the global evaluation not only for power lines but also for the transformer and the voltage level.

TABLE III
AVERAGE GRID OVERLOAD IN MINUTES PER MONTH FOR TRANSFORMER, VOLTAGE AND POWER LINES DEPENDING ON EV-PENETRATION AND THE CHOSEN CHARGING STRATEGY.

EV's	Algorithm	Transformer	Voltage	Power line
0%	NO	0,0	0,0	0,0
25%	NO	0,0	29,6	0,0
25%	YES	0,0	0,0	0,0
50%	NO	6,3	366,0	2,6
50%	YES	0,0	0,0	0,0
75%	NO	243,5	1581,2	39,5
75%	YES	0,0	0,0	0,0
100%	NO	1227,3	3631,1	178,8
100%	YES	0,0	1,3	0,0

In Table III the average time in minutes over all the simulations for the specific grid impact factors is shown. When applying the charging algorithm, the grid can be kept within the operational boundaries to a very high degree. Without the use of the proposed charging algorithm, violations occur already at a 25% penetration level of EV's. Grid expansions would be needed early in the transition towards more eco-friendly transportation. In case the charging algorithm is applied, only at maximum EV-penetration the average voltage level falls below the threshold for 1.3 minutes. To understand the impact of an on average 1.3 minutes overloading, individual simulations are analyzed. Only in one of 1000 simulations the voltage falls below the voltage threshold of 0.95 p.u. The maximum detected voltage boundary violation per day is 30 minutes long. EN 50160 allows voltage drops below the voltage threshold for 5% of the time over the course of a week. Even in case the voltage would be out of bounds for half an hour each consecutive day the voltage violations would only occur 2% of the time. Especially when considering the remaining margin of the medium voltage grid the total voltage drop of 10% should happen even more seldom. Additionally in more than 99.73% of the simulations no boundary violations occurred at all. Therefore it can be concluded, that the grid can be operated within its allowed boundaries, even for maximum EV penetration in already heavily loaded grids in case the charging algorithm is used.

Next, the impact of power curtailment by the charging algorithm on the EV's usability is evaluated. The individual average charging power is reduced exponentially with an increasing amount of EV's. At maximum EV-penetration it is 24% lower than without curtailment (table IV).

As previously described the charging algorithm only takes into account the local voltage level at each household instead of the global minimum voltage. Therefore, EV's close to the substation are generally charged faster than cars further downstream on the line due to gradually decreasing voltage levels. The average urgency factor is slightly higher at the end of the line due to the increased energy gap but does not prevent different charging speeds depending on the location. In case of maximum EV penetration, vehicles close to a substation are charged up to twice as fast compared to cars at the end of the line (table IV). Never the less cars approaching departure time are charged faster than the average regardless of the position.

As previously described, every trip which requires recharging during the journey is recorded and divided by the number of total journeys. This factor does not include trips exceeding battery capacity because in this case recharging depends on the EV-technology rather than grid limitations. Independent of the charging strategy and EV penetration level 3.2% of the trips will require recharging before completion. The charging power of 11 kW is sometimes insufficient to recharge the vehicles to the desired capacity to complete the next journey. The charging algorithm has no influence on the car usability as long as the owners supply the correct departure time because the urgency factor is essential to enable cars at the end of the power line to charge quickly when needed.
The urgency factor is important even when the minimum grid voltage is known to all participants. Bi-Directional Communications would equalize charging along the power line at the cost of average charging power. Vehicles close to the transformer would need to reduce their charging power at a higher rate than cars at the end of the line could increase the charging power. The necessity of the urgency factor would even increase.

TABLE IV
IMPACT OF CURTAILMENT ON CHARGING POWER AND LOCATIONAL CHARGING DIFFERENCES.

EV's	Charging Power	Location Impact
25%	10.6 kW	58%
50%	10.0 kW	131%
75%	9.3 kW	168%
100%	8.4 kW	192%

B. *Further influence of heat pumps*

As shown in the previous section, the simulated grid is able to handle maximum EV penetration. Without EV's, the grid can contain heat pumps at up to 20% of the households. The power factor of asynchronous motors, which are normally used in heat pumps, affects voltage stability to a high degree. Hence the low number of heat pumps the grid can endure until voltage issues occur. Under the additional influence of heat pumps, it is then evaluated if the grid is still able to cope with loads from controlled EV-charging.

As seen in figure 9 the transformer load is below 100% in the case of no connected EV's and also in case of maximum EV-penetration as long as the charging algorithm is used.

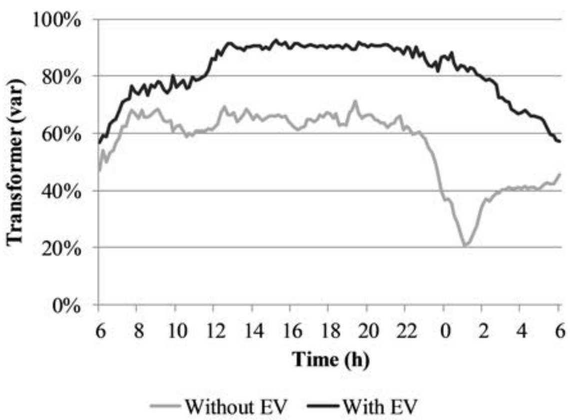

Fig. 9. Transformer load over the course of a weekday for controlled charging and no connected EV's displayed for the 99.97% quantil.

The local voltage of the 0.27% quantil at the last household is already very close to the minimum value of 0.95 p.u. even without additional load from EV-charging (figure 10). Further EV-charging can lead to a voltage drop below the lower voltage theshold. This is the greatest disadvantage of uni-directional communications. Each charging station only knows the local voltage level. In case of a high urgency factor, vehicles charge as long as the voltage is above 0.955 p.u. as specified in the algorithm. In case the minimum voltage has already been reached in the middle of the power line, the remaining safety margin of 0.005 p.u. is not enough to keep the voltage above the minimum value.

Heat pump inclusion into the low voltage grid does not only have an effect on grid stability it also further influences the SOC of the vehicles. Figure 11 displays the 0.27% quantil for controlled charging with and without additional heat pumps and uncontrolled charging. At the end of the night the minimum SOC in case of controlled charging without heat pumps in the grid is the same as in case of uncontrolled charging. The curtailed energy during peak

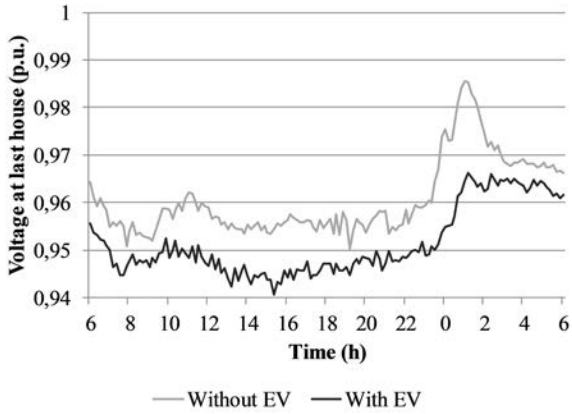

Fig. 10. Local voltage at last household over the course of a weekday for controlled charging and no connected EV's for the 0.27% quantil.

hours is equalized at this point. It does not hold true for controlled charging with addtional heat pumps. The minimum SOC stays low throughout the day. Some cars, especially at the end of the power line, only get charged when approaching departure. Still the algorithm is able to keep the number of unsuccessful trips due to insufficient charge at 3.2%. Nevertheless, the vehicles are not available for spontaneous use anymore. The average charging power is reduced to 2.5 kW. Latest at this point, grid expansions are inevitable.

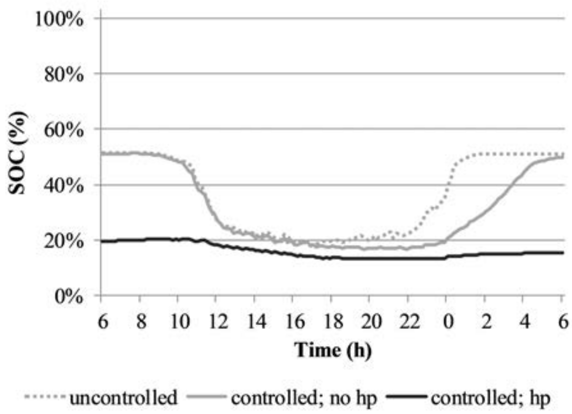

Fig. 11. Minimum SOC over the course of a weekday for controlled charging with and without additional heat pumps and uncontrolled charging.

C. *Influence of photovoltaic systems*

As a final analysis photovoltaic systems are included into the grid. Up to 50% of the household can connect a photovoltaic system, when considering the average German PV-system size. Above this value the grid would face overloading in summertime.

Table V shows the monthly time in minutes the grid is operated outside the boundary values for 20% heat pump penetration with and without EV's or photovoltaic systems. Voltage deviations in wintertime do decrease by more than 40% but do not vanish completly. Photovoltaic power production is close to zero during cloudy periods or at night time. During these periods, photovoltaic power is not available to stabilize the grid. In general, photovoltaic systems also have a positive effect on the average charging power of EV's. It increases from 2.5 kW to 3.2 kW. Therefore photovoltaic systems support power quality up to a certain point but do not prevent grid expansion because of increased load.

TABLE V
AVERAGE GRID OVERLOAD IN MINUTES PER MONTH FOR TRANSFORMER, VOLTAGE AND POWER LINES DEPENDING ON EV AND PV-PENETRATION.

EV	HP	PV	Transformer	Voltage	Power line
0%	20%	0%	0,0	13,2	0,0
100%	20%	0%	0,0	722,6	0,0
0%	20%	50%	0,0	6,5	0,0
100%	20%	50%	0,0	404,3	0,0

VI. CONCLUSION

The paper has shown, that the charging algorithm based on a fuzzy controller is able to keep a critical urban grid within the given boundaries for high penetration levels of electric vehicles even when bi-directional communication is not used. For the case where algorithm is used, the grid would be outside operational boundaries even for a small amount of EV's.

In case of additional loads which heavily reduce the voltage level, such as heat pumps, the charging algorithm is not able to keep the voltage above the threshold anymore. At this point grid expansion is necessary.

Bi-directional communications would theoretically enable the charging algorithm to keep the voltage in balance but the resulting charging power would not be enough to sufficiently charge all vehicles. Therefore, after considering all results, the introduction of a fuzzy controlled charging algorithm has proven successful.

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