

## CONTROLLING EV CHARGING AND PV GENERATION IN A LOW VOLTAGE GRID

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### ABSTRACT

*Increasing amounts of local power generation and loads are challenging the management of low voltage (LV) grids. This paper proposes a low voltage grid monitoring and control solution enabling a grid operator to: 1) assess available capacity in an LV grid for planning purposes, 2) provide grid constrained electrical vehicle (EV) charging control, and 3) optimize the injection of photovoltaic (PV) energy in the grid. The ability to increase LV grid utilization and to minimize critical grid events are shown in Park & Ride and Shopping Mall EV charging scenarios. Relying on the prediction of domestic demand and PV generation, the ability of the EV charging strategy to handle prediction errors is analyzed.*

### INTRODUCTION

Two factors, that will threaten the power quality in the low voltage grid in the future, are the massive deployment of distributed generation (DG) using renewable resources (photovoltaic, wind) and of charging stations for electric vehicles. In order to tackle these and other future problems, it is necessary to gradually replace the current, tedious and inaccurate offline grid planning process, which is usually, based on standard profiles, with an automated, online process.

In this paper we propose a grid component called low voltage grid controller (LVGC) that enables:

- Online monitoring of the LV grid using existing smart meter data to provide a grid state estimate
- Computation of a feasible region in which the grid can be loaded within grid constraints (voltages, currents, transformer limits, etc.) considering fairness among users
- Planning the Electrical Vehicle (EV) demand under uncertain forecasts of photovoltaic (PV) generation and domestic power.
- Controlled EV charging and limitation of PV active power in case of over-generation.

Recent work shows that new LV grid load scenarios from e.g. electrical vehicles require a degree of control [1]-[4]. Analysis on macroscopic level shows how smart-charging allows an increase of EV penetration to more than 50% without overload of current grids (Portugal [1]), while the authors of [3] show how grid investments can be reduced by up to 25% for transformers with 75% of household owners owning a car (year 2040 scenarios, Holland). For household charging scenarios (aiming for 100% charge) different control techniques have been proposed. Key examples are a) basic house-hold peak avoidance approaches [3] b) dynamic charging intensity control co-

optimized with grid constraints for energy loss optimization [4], and c) sophisticated charging schedule planning on a day basis based on historical trip forecasting, desired load curves (price controlled) and grid constraints [2].

Our work recognizes the recent approach of [2] to derive power limitations on busses in LV grids for EV planning purposes, but extends the view by:

- Proposing a new formulation of how available power resources are estimated to ensure fair allocation of free bus resources, with applications for both planning, charging control and general control purposes.
- Proposing an explicit smart meter based architecture for LV grid management enabling short-term (15 min) adaptation of charging schedules based on: plug-in events and changes in the available power resources (caused by errors in the load prediction and PV output).
- Defining a smart charging control approach aiming to eliminate grid overload events.
- Studying new EV public charging scenarios (Park & Ride and Shopping Center). We clarify their different requirements and the achieved charging service quality when minimizing grid events and accommodating to photovoltaic production.

The rest of the paper is structured as follows: in Section 2 we describe the system high-level architecture. Section 3 presents details on the developed control and support mechanisms. In Section 4, we present results from selected evaluation scenarios, and finally in section 5 conclusions and further research directions are provided.

### 2. SYSTEM ARCHITECTURE

The architecture studied in this work is based on a LV Grid Controller (LVGC) located at a secondary substation level, as depicted in Figure 1. A main motivation for this approach is to utilize the availability of smart meter measurements and provide grid operators new options for LV grid management. In practice the LV grid controller enables the following features:

- A) Online LV grid monitoring that enables operators to identify situations, where real consumer patterns frequently lead to grid events. A grid event is here defined as an *over-current (OC)*, *over-voltage (OV)* or *under-voltage (UV)*.
- B) What-if analysis to enable simulated deployment of new EV charging stations or PV generation which may be power curtailed in certain cases.
- C) Provide online load and generation management here emphasized by electrical vehicle charging control as well as power limitation control of photovoltaic systems. This paper only focuses on the charging control.

This proposed architecture is compatible with other hierarchically controlled smart grid architectures. Thus, future versions the LVGC will comply with the objectives of virtual power plant controllers [6]. In its current version,

a stand-alone solution may however be integrated by grid operators to provide services as described in A)-C) independently of other control architectures.

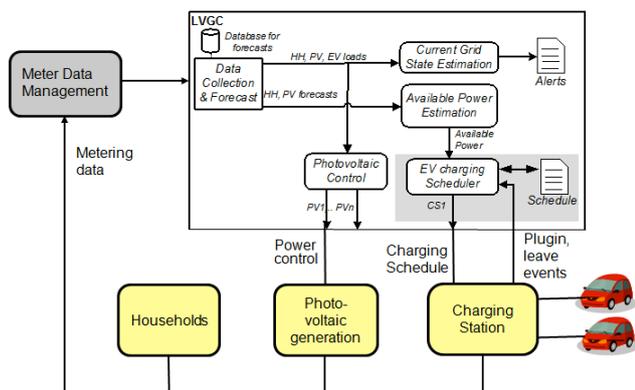


Figure 1 - Architecture for LV grid control

The LVGC operates in the following manner. A smart metering system collects periodically (every 15 minutes) metering data from smart meters (in households and at charging points). Based on meter observations, a local prediction function that uses historical measurements further predicts household consumption and local generation. Based on observations and prediction data, three mechanisms are executed: 1) A grid state estimator that performs a power flow calculation and logs/reports alarms in case grid constraints are violated. It uses a local model of the grid topology and parameters.

2) A control mechanism to reduce the output of PV inverters in order to prevent overvoltage and overcurrent. 3) An electrical vehicle charging scheduling algorithm that produces and maintains a rolling schedule based on EV plug-ins, currently charging EVs and EV departures. The schedule is constrained by a profile of the available power resources on the bus of charging point attachment. At vehicle plug-in events, the scheduler further receives from the vehicle: *plug-in time, desired energy to be charged* (in the following a desire for full battery is assumed) as well as supported charging speeds.

The scheduler also needs to know the expected stay durations of individual cars. However, as such information would require particular user interaction and assumptions of new features in electrical vehicles, it is considered that the scheduler itself estimates the expected stay duration based on learned user statistics for a given charging station. It should here be noted that a grid operator may not be interested in running charging control operations. In such cases, a valid solution could be to locate the scheduling functionality in local controllers situated at the charging stations. This aspect is not considered further in this paper. In the following section, details of the available power estimation and scheduling approach are provided.

### 3. ENERGY CONTROL MECHANISMS

#### 3.1 Available Power Estimation

The available power is defined as the maximum charging power at a grid bus, before any voltage or current constraint in the grid is violated. In order to calculate the available power  $P_{av}[k]$  for all the nodes  $k$ , we saturate the grid by maximizing the percentage  $EVg$  of the allowed EV charging power at each node,  $EVmax_k$ . We call this modified OPF problem Proportional Maximum Power Flow (PMPF), equations (1)-(5). The power flow equations (2)- (3) take into consideration the PV generation ( $P_{gk}$ ,  $Q_{gk}$ ), the domestic loads ( $P_k$ ,  $Q_k$ ) and the proportional EV load  $EVg \cdot EVmax_k$ .

$$\text{PMPF:} \\ \max EVg \tag{1}$$

subject to:

$$Pg_k - P_k - EVg \cdot EVmax_k - \sum_{(k,m) \in YBUS} V_k V_m (G_{km} \cos(\phi_k - \phi_m) + B_{km} \sin(\phi_k - \phi_m)) = 0 \tag{2}$$

$$Qg_k - Q_k - \sum_{(k,m) \in YBUS} V_k V_m (G_{km} \sin(\phi_k - \phi_m) - B_{km} \cos(\phi_k - \phi_m)) = 0 \tag{3}$$

$$V_{min} \leq V_k, k \in BUS \tag{4}$$

$$|I_{km}| \leq I_{max_{km}}, (k,m) \in BRANCH \tag{5}$$

If one maximizes the total charging demand, instead of  $EVg$ , then those locations, which are near to the feeder, will be better served than the locations far away from it. The reason for that is, that a shorter power path consumes less resources and will violate current limits at a higher level than a longer path transporting the same power. However, this kind of allocation is unfair because the remote parking lots starve, whereas the closer locations will be served to a high percentage. Therefore, the proportional allocation provides better fairness. Fairness can also be applied to represent future extension options in other busses. Thus, it can also be used as a feature for operators to pre-plan free bus resources e.g. for future EV charging points.

The PMPF problem is solved for several timeslots into the future based on the predicted load and production. The resulting variables  $EVg \cdot EVmax_k$  form an available power array, which defines the feasible region for EV loads at every grid bus. Based on this load upper bound, a discrete scheduling algorithm can be used to schedule the cars as needed.

#### 3.2 EV Scheduling

A scheduler component controls the start and end of charging times of individual EVs at a charging station. The objective of the scheduler is to maximize for all cars the percentage of the demand actually charged in the available (parking) time. The scheduler can select between different charging speeds (Low: 3.7kW, Medium: 8kW and High: 11kW), but as lower speeds leads to less component wear these are preferred. In the same time, the cumulative load shall not exceed the available power at any time. In order to

achieve a feasible solution, the charging interval is shifted, or shortened by selecting a higher charging speed. The scheduler can also choose to reduce the targeted battery demand (which by default is 100%) to allow some charging rather than rejecting EVs. The optimization problem (also called bandwidth allocation problem) has been described in detail in [3] and the references therein.

#### 4. EVALUATION RESULTS

##### 4.1 Evaluation Methodology & Scenarios

In this paper, the overall evaluation aims are to clarify the impact of control using dynamically available power ( $P_{av}$ ) compared to no control or other conservative planning approaches. We study two deployment scenarios of a Shopping Centre (SC) and a Park & Ride (P&R) with, and without, collocated PV generation.

To evaluate the proposed control architecture and its impact in different scenarios, the system has been integrated in an emulation framework. The latter enables to playback real smart meter data measurements from households as well as to run different e-mobility models.

To consider the challenges faced in a real LV grid, KELAG Netz has provided topology, line data, 400 kVA substation data and smart-meter data from a LV grid in Kärnten, AT. In summary, the grid consists of 156 households, 96 timer controlled water heaters and 1 small enterprise distributed over 11 feeders. Smart-meter data (15 min sampling time) is available from 1/3 of the meters, but has been extrapolated to cover all consumers.

The grid model and emulation framework enables different configurations of charging places and PV generation. For the studied scenarios both 50 kWp PV generation and a charging station with 35 charging spots are located on the same bus, situated 4 busses away from the feeder.

The grid limits are defined on bus voltage ( $\pm 5\%$ ), line currents (60% of nominal capacity) and transformer capacity (80% of nominal capacity).

The two scenarios mainly differ by their traffic model: **Park & Ride:** Bursty independent arrival of 35 cars in interval from 07.00-09.00. Demand is normally distributed ( $\mu=6kWh$ ,  $\sigma=1000Wh$ ), corresponding to 30 km driven before arrival. The stay duration is normally distributed: ( $\mu=7.5h$ ,  $\sigma=0.5h$ ).

**Shopping Centre:** 110 cars arrive between 06.00-20.00 according to a mobility profile obtained from a real EV user study [7]. The demand is between 3kWh (06.00) and increases linearly with the time up to 10kWh. The duration of stay is normally distributed ( $\mu=2.5h$ ,  $\sigma=0.5h$ ).

To capture both the charging service received and the grid impact, the following metrics are evaluated: Total Energy Charged, Number of grid events observed, Fraction of cars getting full charge.

The controller is configured to run every 15 min. A run manages the latest EV events, leads to a calculation of a new  $P_{av}[k]$  array and a new schedule and charging speed assignment (if needed). It is assumed that new smart meter

data is available for each run. For non-controlled scenarios, cars are assumed to charge at low speed (3.7kW) until they plug-out or are fully charged.

##### 4.2 Charging Control Results

Figure 2 depicts the resulted EV load in the Shopping Centre scenario during a normal weekday in April assuming perfect prediction of household loads and PV production (6 hours ahead).

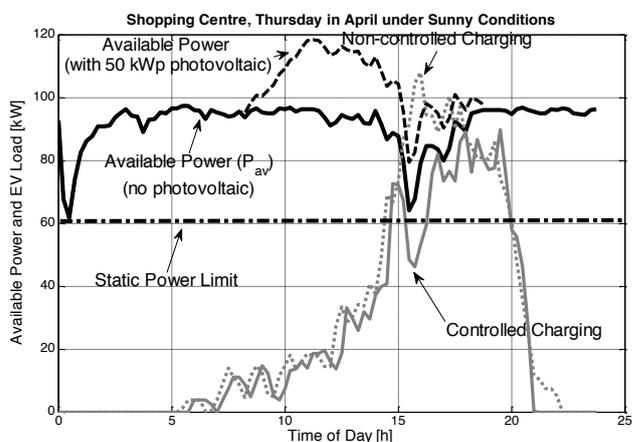


Figure 2 - Shopping Centre Scenario.

The figure shows  $P_{av}$  with and without a PV system installed. No EV loads are planned on other busses. A nominal level of 95 kW is available except around 01.00 and 15.00 where water heaters are operating. With PV, a higher  $P_{av}$  is obtained, as expected. Note that the controlled charging load closely follows the dynamically calculated  $P_{av}$  (here displayed for a case without PV).

	Energy Charged [kWh]	Grid Events [#]	Full Charge Fraction [%]
P&R, (REF)	199.52	12 (OC)	100
No Control	199.52	7 (OC)	100
P&R, Static AP	89.44	0	45.70
P&R, Dynamic Control	191.98±2.38	0	84.60±1.9
	192.30±2.2	0	87.42±2.9
Shopping, (REF)	662.66	35 (UV+OC)	68.2
No Control	662.66	13 (OC)	68.2
Shopping, Static AP, No Control	418.96	0	48.00
Shopping, Dynamic Control	562.61±4.5	0.4±0.8 (OC)	51.00±1.2
	593.55±3.7	0	58.94±1.5

Table 1 – EV charging results for Park & Ride and Shopping Centre scenarios. Grey rows represent cases where 50 kWp photovoltaic is installed.

The results summaries for all scenarios are presented in Table 1. Reference scenarios (REF) show the full demand. 95% error bounds are provided for 5 repetitions as the scheduler does not provide deterministic solutions.

We start by considering results with no PV installed. In the P&R case, long stay durations enable all cars to fully

charge. Due to short stay durations, this is not true for the SC case.. In both cases several grid events occur. Without control, a conservative planning approach would be the typical way to avoid grid events. Here, a fixed static power limit can be derived. In this case, such a limit has been identified (61.6 kW – see Figure 2) using a 99% percentile of available power distributions for a whole year of smart meter data (considering that short-duration overload situations can be accepted). Based on the fixed power limit, a maximum capacity of 16 charging points has been identified. As can be observed, this configuration does not lead to grid events, but nearly half of arriving cars are being rejected (no parking place). Considering instead the same scenario with controlled charging, close to zero grid events are generated, but a significant increase in charged energy for both scenarios is achieved. It should here be noted that the few grid events observed in the controlled case are of a limited magnitude (~3A larger than the line limit of 165A). They can be attributed to delayed “stop charging” signals to cars not planned to fully charge. In the current implementation such signals are only sent every 15 minutes. The results show that the used smart charging scheme enables to provide more charging points and thereby fewer rejected EVs than static scenarios. The best gain is here achieved, when parking durations are large as in the P&R scenario. Adding PV power to the controlled charging shows improvements primarily for the shopping scenario. One reason is the correlation of sun hours and charging need. Moreover, in case of short stay durations the controller can utilize the increase in  $P_{av}$  to raise the charging speed and improve thereby the charging performance.

**4.3 Impact of Prediction Errors**

In reality,  $P_{av}$  will be subject to errors in the prediction. Assuming that the error increase with  $\alpha\%/h$  into the future starting at 0% at  $t=0$ , the following prediction model is defined:

$$\bar{P}(t) = \bar{O}(t)(1 + \alpha * t),$$

Where  $\bar{P}(t)$  is a prediction vector of either household loads or PV production and  $\bar{O}(t)$  is the real value (perfect prediction).

	Energy Charged [kWh]	Grid Events [#]	Full Charge Fraction [%]
+28.8%/h	553.31±2.8	0	48.4±1.4
+14.4%/h	558.40± 4.1	1±0.9	50.72±2.2
Perfect Prediction	562.61±4.5	0.4±0.8	51.00±1.2
-14.4%/h	564.54±7.9	1±1.2	52.0±1.7
-28.4%/h	564.16±3.3	1±1.2	53.12±1.8

**Table 2 – Impact of Prediction Error (Shopping Centre)**

The results for the Shopping Centre scenarios without PV installed are summarized in Table 2. Most predominantly, the high positive simulated prediction error in the left column causes a slight decrease in charging efficiency (the overestimate in household loads corresponds to an

underestimate in the available power). On the contrary, a negative prediction error leads to a overload schedule (more grid events). Generally, it can however be concluded that the periodically updated scheduling provides high robustness towards prediction errors, given that such errors can be continually reduced through new measurements.

**5. CONCLUSIONS**

The presented work proposes mechanisms to plan and schedule the charging of electric vehicles in a low voltage grid. The power upper bound to be used for charging is calculated for scheduling the EV demand. This method makes the tacit assumption that the LV grid infrastructure is currently the main energy bottleneck for massive EV charging. Future work will consider additional schedulable loads such as storage, and demand constraints at the LV level as a whole.

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