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The value of EV forecasts for microgrid energy management – A case study

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Summary

The emergence of electric vehicles comes along with the global trend towards microgrids which are a key element of a more decentralized and more digitized energy system. This coincidence generates great opportunities for both technologies. On the one hand, microgrids with their locally produced renewable energy enable a sustainable and cheap way to recharge the electric vehicles' batteries. And on the other hand, electric vehicles can provide additional flexibility to the microgrid thanks to their energy storage. For instance, the charging process can be shifted to hours where a roof-top photovoltaic system produces "free" energy, or to off-peak hours where energy from the grid is cheap.

Most of today's state-of-the art microgrid energy management systems rely on Model Predictive Control, where at each control instant forecasts of external inputs (e.g. renewable production, variable energy price,…) are taken into account to find the optimal control strategy. For an efficient integration of electric vehicles into such energy management systems, the availability of forecasts about the vehicles' arrival- and departure times and their energy needs is crucial. In this work, the economic value of electric vehicle forecast information is analysed in the context of a microgrid equipped with a photovoltaic system, a stationary battery and an electric vehicle charging station. Full year simulation results show that energy savings of up to 18% can be achieved if reliable EV forecasts are available compared to a situation without forecast information.

Keywords: microgrid, optimization, energy, control system, forecast

1 Introduction

The on-going energy transition towards a more decentralized and more digitized grid comes along with numerous challenges for the energy systems worldwide. The increasing amount of renewable energy installations at distribution grid level (mainly solar) and the decreasing cost of battery storage have made microgrids an economically attractive alternative to the classic top-down energy supply scheme [1]. Electric vehicles (EV) have the potential to further accelerate the emergence of microgrids thanks to the energy flexibility which they naturally provide through their battery. Many studies have shown the high potential electric vehicles may provide to the energy system. In [2] for instance, the impact of EVs on the distribution grid in Belgium is assessed using a dynamic programming model. The study shows that advanced microgrid control methods can significantly limit the negative impact of large amounts of EVs on the distribution grid in terms of peak load, over-voltage and line currents. [3] furthermore points out that advanced energy management systems (EMS) are crucial to achieve a reliable and efficient operation of energy systems including EV charging stations.

According to [4] the control methods reported in the literature can be categorized into forecasting-based optimization (also known as Model Predictive Control) and rule-based decision-making. In general, Model Predictive Control (MPC) outperforms rule-based control methods thanks to its natural way of adapting to a changing system context and to its ability to consider forecasts in the control decision making. For example, in [5] a MPC controller is proposed that optimally uses the in advance declared flexibility of EV users.

While the power of MPC stems from the consideration of forecasts in the decision making, this is also the reason why in situations where the forecast quality is bad, the control performance may be unsatisfying. This has been put into evidence at an EV charging station located at the Euref campus in Berlin [6] where an MPC controller has been tested in real life. Due to the difficulty to obtain reliable EV behavior forecasts for this e-Car sharing station, an unsatisfying control performance had been observed. In [7] an alternative energy management system relying on a probabilistic certification method has been proposed to deal with such strong uncertainties in the EV availability at public EV charging stations. These works assume that no forecast information at all is available for the individual EVs. This is the most conservative assumption one can make and in many practical cases the situation is luckily more comfortable. For instance, at a residential charging point located in a private garage, the availability of the EV can be forecasted quite well thanks to the repetitive behavior of most humans, especially during a working week. In other situations, for instance at a public charging station in a residential area, this may quickly become more complicated if there was no possibility to identify which user connects to a given charging point.

In this work the impact of available EV forecast information on the performance of a microgrid energy management system using MPC is evaluated. The considered microgrid is a small office building equipped with a photovoltaic system, a stationary battery and a public EV charging station as shown by figure 1.

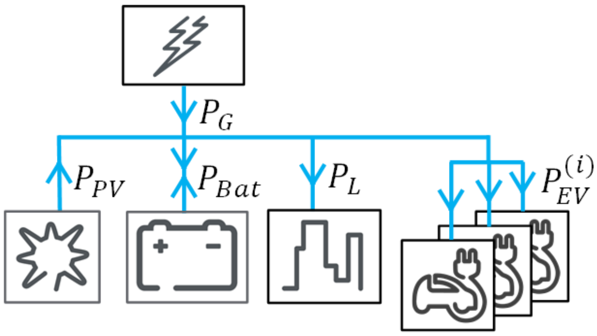

Figure 1: Microgrid composed of a photovoltaic system, a battery, a building load and an EV charging station.

Furthermore, the system is subject to a variable time-of-use tariff and it is assumed that the charging power can be modulated between zero and the vehicles' nominal charging power. Note that vehicle-to-grid technology is not considered in this work. The following four scenarios in terms of availability of EV forecast information are considered and their impact on the control performance compared with each other:

1. EVs are not considered as a controllable system and are directly charged at their nominal power when they arrive. The EMS only controls the stationary battery and does not consider any forecast information about the EVs' power consumption.
2. As in the previous case EVs are non-controllable, however, in the EMS the aggregated power consumption of the charging processes, averaged over the past days is considered as a forecast in the MPC controller which still controls only the stationary battery.
3. EV users declare their vehicle to the charging station after they arrive and provide the planned departure time, for instance through a mobile app. Here, not only the stationary battery is controlled by the EMS, but also the EV charging process.
4. Perfect forecasts are available on a day-ahead basis. This scenario achieves the best possible control performance, but is unrealistic in practice. However, it provides very useful results which can serve as a theoretical upper bound for the performance achieved with the previous three scenarios.

2 Model Predictive Controller

In this section the MPC-based microgrid energy management system is explained.

2.1 System model

Among the sub-systems depicted in figure 1, only the stationary battery and the batteries of the electric vehicles are controllable. The building load and the renewable photovoltaic production are non-controllable, but will be considered in the MPC controller by their forecasted power profiles over the 24 hour prediction horizon.

The dynamic model of the stationary battery is as follows:

$$b_{t+1} = b_t + \eta \, P_{Bat,t} \, t_S \qquad \text{where} \quad \begin{cases} \eta = \eta^+ & \text{if} \quad P_{Bat} \geq 0 \\ \eta = (1/\eta^-) & \text{otherwise} \end{cases} \qquad \forall \, t \, \in \{0,1, \dots H-1\} \tag{1}$$

b_t is the energy stored in the battery at time *t*, η^+ and η^- are the charging and discharging efficiencies, t_S is the sampling period and *H* is the number of discrete time steps in the prediction horizon. Similarly, the battery model of the *i*-th vehicle is as follows:

$$b_{t+1}^{(i)} = b_t^{(i)} + \eta^+ \, P_{EV,t}^{(i)} \; t_S \qquad \forall \, t \, \in \left\{t_{arr}^{(i)}, t_{dep}^{(i)} \right\} \tag{2}$$

with the arrival and departure times of the vehicle $t_{arr}^{(i)}$ and $t_{dep}^{(i)}$.

2.2 Control objective

The control objective is to maximize the self-consumption of locally produced PV energy and to minimize the costs for buying energy from the grid. This is achieved by the following objective function:

$$Minimize \quad \sum_{t=0}^{H-1} C_t^{Buy} \cdot \max(0, P_{G,t}) \tag{3}$$

where C_t^{Buy} is the variable energy buying price and $P_{G,t}$ is the power consumed from the grid at time *t*. Note that the self-consumption objective is realized implicitly, since the locally produced PV energy is free of cost.

2.3 Control model constraints

The following set of linear constraints represents the system model in the control optimization problem:

$$P_{G,t} = P_{L,t} - P_{PV,t} + P_{Bat,t} + \textstyle\sum_i P_{EV,t}^{(i)} \qquad \forall \, t \, \in \{0,1, \dots H-1\} \tag{4}$$

$$b_{t+1} = b_t + \eta^+ \, P_{Bat,t}^+ \, t_S - \eta^- \, P_{Bat,t}^- \, t_S \qquad \forall \, t \, \in \{0,1, \dots H-1\} \tag{5}$$

$$P_{Bat,t}^+, P_{Bat,t}^- \geq 0 \qquad \forall \, t \, \in \{0,1, \dots H-1\} \tag{6}$$

$$b_0 = b_{measured} \tag{7}$$

$$b_{t+1}^{(i)} = b_t^{(i)} + \eta^+ \, P_{EV,t}^{(i)} \; t_S \qquad \forall \, t \, \in \left\{t_{arr}^{(i)}, t_{dep}^{(i)} \right\}, \quad \forall i \tag{8}$$

$$b_{t_{arr}^{(i)}}^{(i)} = b_{arr}^{(i)} \qquad \forall i \tag{9}$$

Constraint (4) is the energy balance equation. Constraints (5) – (7) implement the model of the stationary battery with the measured state-of-charge $b_{measured}$ and $P_{Bat,t}^+, P_{Bat,t}^-$ which represent the charging and discharging powers respectively. Note that the non-linear constraint $P_{Bat,t}^+ \cdot P_{Bat,t}^- = 0$ which prevents simultaneous charging and discharging of the battery can be omitted, because it is implicitly respected by the control model. This is because simultaneous charging and discharging is economically not interesting. Finally, the constraints (8) and (9) represent the battery model of the *i*-th vehicle. $b_{arr}^{(i)}$ is either the forecasted state-of-charge at the forecasted arrival time $t_{arr}^{(i)}$ of the vehicle, or the measured state-of-charge in case the vehicle is already connected to the charging point at t=0.

3 Case study

The considered microgrid is a small commercial building with an average electric load around 25 kW. The building is equipped with a roof-top PV installation of 60kW and a stationary battery of 50kWh. Furthermore, a charging station composed of 6 charging points, each with a maximum power of 7.4 kW is installed at the site. Three charging points are used by private vehicles which typically arrive in the morning and stay connected during the whole day. Some of them also leave during the lunch hours. The other three charging points are used by professional EVs owned by a small business (e.g. a post office or a food delivery service for elderly people) located in the building. They are typically connected during the night and are used during the day with a short recharge period during the lunch break.

To generate realistic EV behavior data (arrival time, departure time and required energy), a statistic model has been created based on the EV usage patterns described above. The statistic EV behavior data generated from this model for a one-year period is then used by the simulation model and – depending on the forecast scenario – by the MPC controller. Concerning the electric energy consumption of the building and the photovoltaic production, perfect forecasting models are assumed, which provide at each control step the actual power load and photovoltaic power profiles for the next 24 hours to the MPC controller.

3.1 Illustration of the control behaviour with perfect forecast information

Figure 2 illustrates an exemplary simulation result which has been achieved using the MPC controller with ***perfect forecast*** information. This is the best possible control behavior which can be achieved, since at each control instant the MPC controller made its decision based on the precise forecast of when each vehicle was going to arrive at the charging station and when it was going to depart. The figure shows how the vehicles connected during the whole day (charging point 1 & 2 in the second subplot) are partially charged during the mid-peak period where energy is relatively cheap, and during the afternoon hours where a surplus of locally produced "free" PV energy is available.

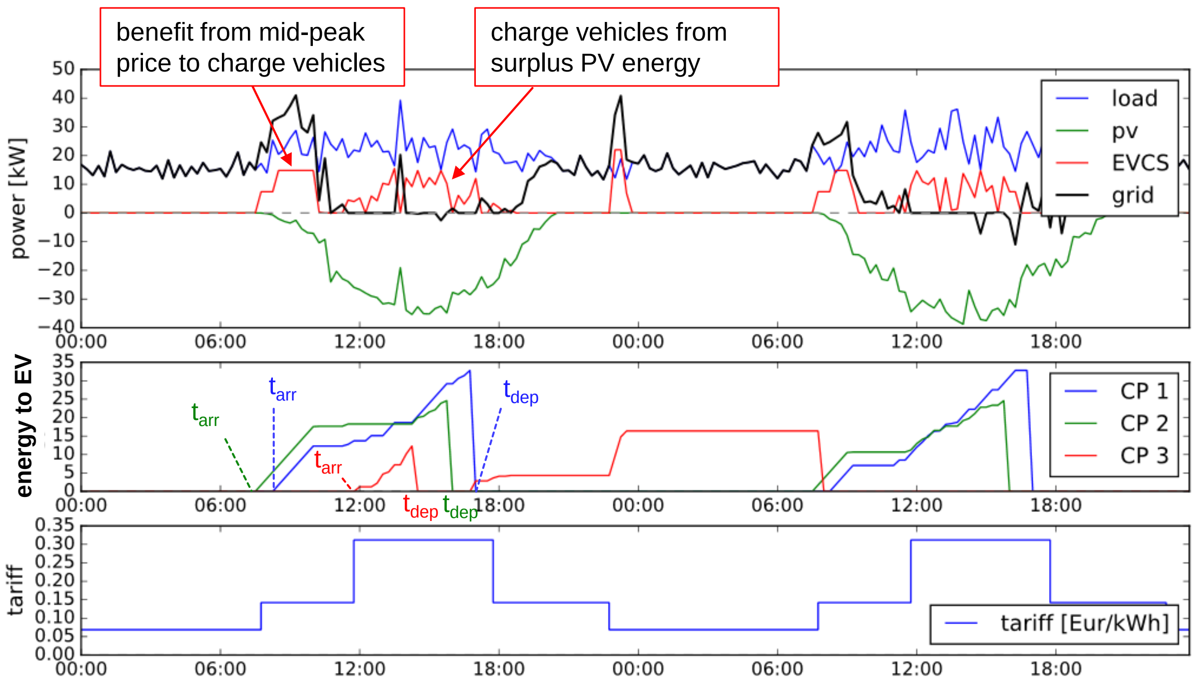

Figure 2: Exemplary result using perfect forecast information. It shows how the EV charging process is adapted to the variable time-of-use prices and to the surplus PV power which is available in the afternoon.

3.2 Impact of the EV forecast information on the control performance

This section provides detailed simulation results. The following four levels of forecast information are compared with each other through simulations covering a full year:

(i) ***no forecasts:*** EVs are recharged directly after their arrival at nominal power, since their planned departure time is unknown and the battery should be recharged as much as possible before the next departure. The MPC controller only manages the stationary battery and does not consider any forecast of the power consumption of the EV charging process.

(ii) ***average power forecast:*** the EVs are still recharged directly after their arrival, since no information regarding a specific EV's schedule is available. However, in the MPC controller for the stationary battery, a forecast of the aggregated power consumption of the EV charging points is considered. More precisely, the average daily EV power consumption profile over the last 10 days is used as the forecast for the next day.

(iii) ***departure forecast:*** EV users declare their planned departure time and the state-of-charge of their vehicles' battery after their arrival to the charging station. The charging process of the EVs is managed by the MPC controller based on this forecast information.

(iv) ***perfect forecast:*** It is assumed that EV arrival- and departure times and the state-of-charge of the vehicle's batteries at their arrival can be precisely forecasted on a day-ahead basis. While this scenario is unrealistic in most cases, it is highly interesting, because it allows to assess the hypothetical maximal cost savings which might be achieved in a given use case.

Table I shows the detailed simulation results. Note that in total 12 full year simulations have been run. More precisely, each of the four forecast information scenarios has been simulated three times with different sizes of the stationary battery (0, 50 and 100 kWh). This battery size study allows to gain some additional insights regarding the value of installing a stationary battery in such a microgrid.

Table I. Simulation results showing the yearly energy cost and the self-consumption ratio of locally produced PV energy as a function of the available forecast information and the size of the stationary battery at the microgrid.

	battery size = **0 kWh**		battery size = **50 kWh**		battery size = **100 kWh**	
	Energy Cost [€]	Self-cons. ratio [%]	Energy Cost [€]	Self-cons. ratio [%]	Energy Cost [€]	Self-cons. ratio [%]
no forecasts	6828	69.9	5856	82.7	5178	90.2
average power forecast	6828 *(-0.0 %)*	69.9 *(+0.0 %)*	5762 *(-1.6%)*	83.7 *(+1.0 %)*	4926 (-4.9%)	90.6 *(+0.4 %)*
departure forecast	5650 *(-17.3 %)*	77.1 *(+7.2 %)*	4686 *(-19.9%)*	88.1 *(+5.4 %)*	4030 *(-22.2%)*	93.9 *(+3.7 %)*
perfect forecast	5650 *(-17.3 %)*	77.1 *(+7.2 %)*	4676 *(-20.2%)*	88.4 *(+5.7 %)*	4006 *(-22.6%)*	94.2 *(+4.0 %)*

For each of the simulated battery sizes, two KPIs are shown, namely the annual energy cost and the self-consumption. Regarding the energy cost, for each battery capacity, the ***no forecasts*** scenario serves as a reference for the achieved cost savings. A closer look at the results with the 50 kWh battery shows that taking into account the ***average power forecast*** of the EV charging points to better control the stationary battery only results in a cost reduction of 1.6%. In contrast, the availability of ***departure forecasts*** results in a much more significant cost reduction of 19.9%. Interestingly, the additional gains that could be achieved with ***perfect forecasts*** are very small. For the simulations with the 100 kWh battery, similar observations can be made. A slight difference is the higher cost reduction of 4.9% with the ***average power forecasts*** scenario. The self-consumption ratio measures the percentage of produced PV energy which is consumed locally within the microgrid. The results show that considering ***average power forecasts*** does not have a significant impact on this KPI (< 1.0%), whereas the availability of ***departure forecasts*** and the fact that the EV charging process is optimized in this case, results in an increased self-consumption ratio of up to 7.2%.

Finally, considering the sensitivity of the achieved results to the size of the stationary battery, two observations can be made. The first one is that the introduction of a stationary battery significantly reduces the energy costs, independently of the four considered forecast scenarios. For example, with the ***departure forecast*** scenario, a 50 kWh battery reduces the annual energy costs by 5650 – 4676 = 974 € which corresponds to a reduction of 17.2%. The second observation is that a stationary battery also increases the self-consumption ratio. The increased self-consumption ratio is one of the two reasons for the quite significant energy cost reduction. The other reason is the strong variation in the energy price between the off-peak, mid-peak and on-peak periods, which allows to buy and store energy while it is cheap and consume it later when the price is high.

4 Conclusion

Recent research has demonstrated the potentials of using the flexibilities in the EV charging process to overcome the challenges arising from the massive EV integration into our energy systems. This contribution investigated the value of EV forecast information for an MPC-based microgrid energy management system through a case study. The results obtained through full year simulations show that significant energy cost reductions of up to 18% can be achieved when EV owners provide their planned departure time to the microgrid energy management system. Moreover, the gap to the ideal case where full information of the EV behavior is known in advance (including the forecasted arrival times) is shown to be very small.

While the quantitative results achieved in this case study are very sensitive to the load and PV power profiles as well as to the underlying energy tariff, a general conclusion one that can be drawn is that the availability of forecasts of EV departure times and the EVs' required energy will be highly beneficial for the cost-effective integration of EVs into microgrids and into energy systems in general. Beyond the demonstrated energy cost reductions and improved self-consumption of local renewable energy, future research should also focus on the impact of EV forecast information on the mitigation of power peaks which are considered as a major threat for the distribution grid.

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