Chapter 7

Distributed Load Management using Additive Increase Multiplicative Decrease based Techniques

Sonja Stüdli, Emanuele Crisostomi, Richard Middleton, Julio Braslavsky and Robert Shorten

Abstract Due to the expected increase in penetration levels of Plug-In Electric Vehicles (PEVs), the demand on the distribution power grid is expected to rise significantly during PEV charging. However, as PEV charging in many cases may not be time critical, they are suitable for load management tasks where the power consumption of PEVs is controlled to support the grid. Additionally, PEVs may also be enabled to inject power into the grid to lower peak demand or counteract the influence of intermittent renewable energy generation, such as that produced by solar photovoltaic panels. Further, PEV active rectifiers can be used to balance reactive power in a local area if required, to reduce the necessity for long distance transport of reactive power. To achieve these objectives, we adapt a known distributed algorithm, Additive Increase Multiplicative Decrease, to control both the active and reactive power consumption and injection. Here, we present this algorithm in a unified framework and illustrate the flexibility of the algorithm to accommodate different user objectives. We illustrate this with three scenarios, including a domestic scenario and a workplace scenario. In these scenarios the various objectives allow us to define a type of "fairness" for how the PEVs should adapt their power consumption, i.e. equal charging rates, or charging rates based on energy requirements. We then validate the algorithms by simulations of a simple radial test network. The simulations presented use the power simulation tool OpenDSS interlinked with MATLAB.

Keywords Power Sharing • Load Management • AIMD • Reactive Power Compensation • PEV Charging • G2V • V2G

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7.1 Introduction

The increased integration of renewable energy into the electricity grid has stimulated significant interest in designing "demand side management" and "load management" strategies to support the distribution grid [4]. In this context, "peak shaving" and "load tracking" are two important support services required for proper functioning of the grid with highly variable renewable power generation, see for example [18] and more recently [22].

Peak shaving is an instance of time-shifting power demand. Peaks in aggregate demand experienced in the power grid may be reduced by shifting the power usage of controllable loads to other times of the day. Load tracking is a network service where controllable loads are driven to follow a given varying power signal. Load tracking is particularly useful to follow the fluctuating power generated from renewable sources, and to limit the use of electricity from more polluting power plants at times when demand exceeds the power available from renewable sources.

There is a general consensus that should widespread adoption occur, Plug-In Electric Vehicles (PEVs), will play an important role in demand side management. In fact, PEVs can be often treated as controllable loads and their charging can be postponed to some later time of the day (unless the owner has some urgency in using the vehicle) see [23,31]. With the capability to act as energy storage, PEVs may also be utilized to inject power into the grid, often referred to as vehicle to grid (V2G) operation. Especially during day-times, such a functionality can be used to flatten the peak demand and to help regulate the grid frequency, see for example [1], [20]. When injecting power into the grid, it is important to take into account the needs of the PEV owner such that their energy requirements are met, see for example [30]. This can be implemented in several ways, for example by limiting the energy that is allowed to be used for V2G operation [1]. In that way it is guaranteed that the battery of the PEV is not completely depleted when the vehicle is needed, due to providing V2G services.

In addition, PEV charging infrastructure can also support the power grid, by exchanging reactive power with the grid, as mentioned in for example [5]. In this case, the PEVs can either consume or inject reactive power into the grid to compensate for the reactive power required locally where they are connected. The advantage of using PEVs for reactive power balance, is that in some cases this can be done without affecting the charging process, see for instance [5].

The aim of this chapter is to explore how PEVs may be integrated into the distribution grid for peak shaving, load tracking and reactive power support purposes without imposing a significant impact on the existing infrastructure. In doing so, we use algorithms well-known to the communication community, namely, additive increase multiplicative decrease (AIMD) algorithms, and adapt them for the PEV charging problem. Preliminary work in this direction is reported in [28-29]. In the present chapter we combine the previous work in a unified framework, and evaluate the performance of the proposed approach in a more realistic simulation setting.

7.2 PEV Charging Problem Description

We formulate the active load management task as the task of sharing a limited resource (here, the power) among several loads. Some of the loads may be controllable (e.g. PEVs where we use the term 'agent' to describe local management of charge rate) and some uncontrollable (i.e., lights, televisions, and other appliances whose power consumption cannot be shifted to a later time without inconvenience to the user). We denote the aggregate power limit at time step k by $P(k)$. Note that this power is generally time-varying, as it depends itself on the power generated from renewable sources, and is subject to some physical constraints, such as limitations at power lines or distribution transformers. Further, note that we operate in discrete time with the time index denoted by k.

We denote by $p_i(k)$ the active power drawn by the i'th controllable load. This power can be either positive or negative, as we assume that PEVs can both draw power from the grid and inject power into the grid. We say that when the PEV absorbs real power, it operates in grid to vehicle (G2V) mode, and when it injects power into the grid, it operates in the V2G mode. The admissible power drawn or injected into the grid is also subject to constraints such as a limit on the apparent power, i.e., $-\overline{s}_i \leq p_i(k) \leq \overline{s}_i$ for all k. This limit may arise, for example, due to inverter current limitations where we assume there is negligible variation in supply voltage. In addition, we denote by $\tilde{p}(k)$ the aggregated demand of the uncontrollable loads. Then, neglecting losses in the local distribution grid, the sum of the (controllable and uncontrollable) loads should be smaller than the available power, i.e. ,

$$\sum_{i=1}^{N} p_i(k) + \tilde{p}(k) \leq P(k) \qquad \forall k. \tag{7.1}$$

In most cases, we treat Equation (7.1) as a hard constraint, though in some cases, we allow minor transient excursions beyond this limit. This is allowed, for instance, if the power limit is due to thermal constraints at a power distribution transformer.

By inspecting Equation (7.1) it is clear that in some cases the problem can be infeasible depending on the values of $P(k)$ and of the demand by uncontrollable loads $\tilde{p}(k)$. This happens, for instance, if the demand of the uncontrollable loads is greater than the available power plus the maximum power that may be injected by the PEVs into the power grid. In such cases, we will be interested in a "best-effort" solution, where the PEVs will be required to provide as much power as possible to mitigate the effects of the power mismatch. The exchange of active power between the grid and the PEVs can be used to implement the peak-shaving and load-tracking functionalities described previously.

As the most important service remains the charging of the vehicles, the first part of the PEV charging problem that we consider here is to govern the active power consumption of the vehicles such that the constraint in Eq. (7.1) is not violated, while maximizing the energy transferred to the vehicles. This can be expressed by

$$\begin{aligned} & max_{p_1(k),\dots,p_N(k)} && \sum_{i=1}^{N} p_i\,(k) \\ & \text{s.t.} && -\bar{\mathrm{s}}_{\mathrm{i}} \le p_i(k) \le \bar{\mathrm{s}}_{\mathrm{i}} \text{for all } i,k \\ & && \sum_{i=1}^{N} p_i\,(k) + \tilde{p}(k) \le \mathrm{P(k)} \text{for all } k, \end{aligned}$$

which represents the first part of the PEV charging problem.

This objective assumes that PEV owners permit the reduction of their charge rates in order to lessen the stress on the distribution grid. To encourage the owners of PEVs to participate in such a program energy distirbutors may give incentives to the owners in form of electricity price reductions.

As the primary objective of the PEVs is to use them as a mode of transportation, it is important that the batteries of the vehicles have enough stored energy to accommodate the needs of the owners. In the case that the PEV is a hybrid model which combines a combustion engine with an electric motor, the combustion engine can be used to compensate for the required energy, possibly given to the grid. In this case, it is important that the customers are compensated for the inconvenience or for the costs incurred after using the combustion engine (e.g., fuel costs). If the PEVs do not have a combustion engine, the missing energy could even prevent the owners from doing a trip, and this situation is clearly very undesirable. In some studies, it was shown that the average traveled distance per day usually lies around 40km [9], [24]. The charging levels define a power rate of 2.4kW as Level 1 [2] which corresponds to an approximate charging time of 200mins for 40km. This implies that if we assume as in [9] that most vehicles charge at least while staying at home where they are connected for seven to eight hours [9], [24] less than half of the time is required to charge the 40km that are required for the next day. The range of fully electric vehicles lies between 90km and 395km with a battery sizes ranging from 9kWh to 53kWh [2]. Hence, for most drivers it is not necessary to fully charge their PEV batteries every day.

Obviously, there are some exceptions, as when the PEVs are required to travel long distances. In such cases, we allow the owners of the PEVs to temporarily stop their participation to the energy exchange program and treat the PEVs as uncontrollable loads. They would then pay a higher tariff if charging occurs at peak times.

On the other hand, when the owners decide to participate in an energy exchange program with the grid, they automatically allow signals from the grid to influence their local power consumption. Also, note that it is reasonable to believe that the problems regarding the limited range of PEVs will likely lessen in the future as the technology progresses and charging points become available at additional places than just residential houses, such as at the parking lots at shopping centers, restaurants, working places, and many others. In [24], it is assumed that vehicles stay parked for an average duration of three hours at work places, while parking at shopping facilities lasts two hours on average. If charging facilities are available at such places, then the necessity to fully charge the battery at each of these locations is clearly reduced. This further means that we can safely assume that even with the limitations imposed by our algorithm, the PEV will have enough power to complete the next trip.

It remains to define how the power should be shared among the vehicles. As in principle there are many ways in which the power can be shared among the connected PEVs, in Sect. 7.3 we define different scenarios that give rise to different ways of sharing the available active power.

In addition, the PEVs can also exchange reactive power with the grid to balance the reactive power required locally. Reactive power management is particularly attractive when a large fleet of PEVs is connected to the grid in close proximity to industrial areas where a large amount of reactive power is required. We denote by $q_i(k)$ the reactive power drawn by the i'th PEV at time step k. Accordingly, the upper bound on the active and reactive power injected or drawn from the grid becomes in practice

$$\sqrt{p_i(k)^2 + q_i(k)^2} \leq \bar{s}_i. \tag{7.2}$$

Ideally, the PEVs can be used to balance all the reactive power consumed in the area of interest, for instance by the uncontrollable loads, i.e.,

$$\sum_{i=1}^{N} q_i(k) + \tilde{q}(k) = 0 \qquad \forall k, \tag{7.3}$$

where $\tilde{q}(k)$ denotes the total reactive power consumed by the uncontrollable loads in the area of interest at time k. However, we will not consider Eq. (7.3) as a hard constraint. In fact, if it is not possible to achieve a full balance, the generators and other devices nowadays used for reactive power balancing connected to the grid can be used to balance the residual reactive power, though at the price of transporting reactive power over a longer distance. Not being a critical task, we give a lower priority to reactive power management compared to active power management. However, if needed by the grid, it is possible to exchange the priorities of active and reactive power management.

The reactive power management is the second part of the PEV charging problem.

7.3 Charging Scenarios

We assume that PEVs can modulate the active and reactive power exchanged with the grid to accommodate their own charging needs, the energy needs of the other PEVs connected, and also the needs of the distribution grid itself. Hence, at each time step the PEVs are supposed to adjust their active and reactive power consumption such that ideally the constraints in Eqs. (7.1)-(7.3) are fulfilled.

In the future with a higher penetration of PEVs, it will be possible to recharge the vehicles at a variety of different locations, such as at homes, work places, fast charging stations, shopping centers, hospitals, and airports. Accordingly, the needs and desires of PEV owners and the providers of the charging service, for example at a shopping center, should be considered and the PEV charging problem should reflect the different scenarios of interest. In this section we will illustrate three specific scenarios, which give rise to three different concepts of "fairness" among the participating vehicles. These scenarios are:

- Power Fairness (PF): In this scenario each connected PEV will receive (or provide) exactly the same share of the available power, hence the power consumption (or injection) is equalized. This is fair in the sense that each PEV receives exactly the same quantity of power;

- Energy Fairness (EF): In this scenario the power consumption is proportional to the expected needs of the users, while the power injection is inversely proportional (e.g., smaller power is given to the PEVs that will not need to travel anytime soon). Hence, the scenario is fair in regard to the energy needed;

- Time Fairness (TF): In this scenario the PEVs are categorized depending on the time they have already been connected. Thus PEVs that have been connected for a long time consume (or inject) a smaller amount of power compared to recently connected PEVs. Hence, this scenario is fair in a way that short connection times are not penalized.

In the remainder of this section, we illustrate each scenario in greater detail.

7.3.1 Power Fairness (PF) scenario

The most obvious and simple way to share the available active power among a fleet of PEVs is to give exactly the same amount of power to each PEV. Such a solution can, for instance, be adopted in a domestic charging scenario, where it might be too complicated, and also unfair, to give higher charging rates to some particular vehicles. Note that the power shared among the connected vehicles will change during the day; either due to the presence of a high power demand from uncontrollable loads in the same area, or as a consequence of a reduction of energy produced from renewable energy generation (e.g., using the energy produced by solar panels on top of buildings).

In this scenario, all PEVs should on average consume, or inject, the same amount of power. We mathematically model the complete PEV charging problem as a prioritized optimization problem. This means that we have an objective with very high priority, denoted $O_1(t)$, which is solved first. This objective represents rapid charging while maintaining the constraint on the active power demand by the grid. If the solution of this objective allows additional degrees of freedom, an objective with lower priority, denoted $O_2(t)$, is solved. This objective represents the power fairness condition imposed in this scenario. If further flexibility is available (for example if the total power available means that many chargers are not operating at their individual complex power limits), the third objective, which has even lower priority, denoted $O_3(t)$, is then solved to balance the reactive power. These prioritized optimizations can be represented by

$$
\begin{aligned}
O_1(k) = & \max_{p_1(k),\ldots,p_N(k)} \sum_{i=1}^{N} p_i(k) \\
\text{s.t.} \quad & -\bar{s}_i \le p_i(k) \le \bar{s}_i \qquad \text{for all } i,k \\
& \sum_{i=1}^{N} p_i(k) + \tilde{p}\,(k) \le \mathrm{P} \qquad \text{for all } k \\
O_2(k) = & \min_{p_1(k),\ldots,p_N(k)} \|B\,\boldsymbol{p}(\boldsymbol{k})\,\|_1 \\
\text{s.t.} \quad & -\bar{s}_i \le p_i(k) \le \bar{s}_i \qquad \text{for all } i,k \\
& \sum_{i=1}^{N} p_i(k) = O_1(k) \qquad \text{for all } k \\
O_3(k) = & \min_{q_1(k),\ldots,q_N(k)} \left| \sum_{i=1}^{N} q_i(k) + \tilde{q}\,(k) \right| \\
\text{s.t.} \quad & \sqrt{p_i(k)^2 + q_i(k)^2} \;\le\; \bar{s}_i \qquad \text{for all } i,k
\end{aligned}
\tag{7.4}
$$

$$\sum_{i=1}^{N} p_i(k) = O_1(k) \qquad \text{for all } k,$$
$$\|B\,\boldsymbol{p(k)}\,\|_1 = O_2(k) \qquad \text{for all } k,$$

where $\boldsymbol{p(k)}$ is the vector containing the power consumption of each PEV and B is a matrix containing 1, -1, and 0 such that $B\,\boldsymbol{p(k)}$ contains the difference between the power consumptions. For example

$$B = \begin{bmatrix} 1 & -1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 & -1 \\ 1 & 0 & -1 & \ldots & 0 \\ \ddots & \ddots & \ddots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 & -1 \end{bmatrix}$$

is such a matrix.

Note that in the above mathematical formulation, we implicitly assumed that all PEVs participating are also able to participate in the V2G program. In some cases this might not be true and only a subset of the participating PEVs would allow reverse power flows. However, Eq. (7.4) can easily be modified to include such situations by making the lower bound on real power absorbed zero.

The previous optimization problem explicitly requires that the charge rates of two vehicles must be exactly the same at every time step. However, our interpretation of “fairness” in this scenario can also be relaxed if we require only the running average of the power consumption by each PEV to be equal, which in the following will be denoted by ρ_i. The average can either be computed from the beginning of the charging procedure by

$$\rho_i(k) = \frac{1}{k}\sum_{l=0}^{k} p_i\,(l)$$

or over the past τ time steps (e.g., the last few minutes of charging) by

$$\rho_i(k) = \frac{1}{\tau}\sum_{l=k-\tau}^{k} p_i\,(l).$$

Accordingly, the second optimization objective in Eq. (7.4) can be reformulated to

(7.5)

$$
\begin{aligned}
O_2(k) = &\min_{p_1(k),\dots,p_N(k)} \|B\,\boldsymbol{\rho}(\boldsymbol{k})\|_1 \\
\text{s.t.}\quad & -\bar{s}_i \le p_i(k) \le \bar{s}_i \qquad \text{for all } i, k \\
& \sum_{i=1}^{N} p_i(k) = O_1(k) \qquad \text{for all } k,
\end{aligned}
$$

where $\boldsymbol{\rho}(\boldsymbol{k})$ is the vector containing the average power consumption of each vehicle and B is the same matrix as above.

Note that there is no objective in Eq. (7.5) that states how the reactive power should be provided by the vehicles if there are multiple possibilities. However, extensions of this work could be pursued in the future to introduce a type of “fairness” for the reactive power compensation as well as for the real power. For example if the PEV owners get paid according to the amount of reactive power they compensate, it is important to impose a “fairness” on the reactive power compensation. This is simply possible by adding a forth objective $O_4(k)$ with even lower priority that represents a “fairness” notion for the reactive power compensation.

7.3.2 Energy Fairness (EF) scenario

The PF scenario of Sect. 7.3.1 shares the instantaneous power among the participating PEV in the same way, independently from the actual power requirements of the PEVs connected. As a consequence, some PEVs might be fully charged long before they are actually needed, while other PEVs might not be fully recharged by the time their owners require the vehicle for transportation. To include different energy needs by the owners in this scenario we design charging strategies that prioritize the PEVs according to the time they are connected to the grid for charging their batteries, and their energy requirements. Note that such a solution cannot be implemented in a competitive scenario where all the PEV owners are only interested in their own needs. Hence, it is more realistic to implement it in a scenario like a work place, where employees are not in competition with one another.

In this scenario, let us assume that at time step k a PEV requires a certain amount of energy $E_i(k)$ to fully charge its battery to a desired level. Note that the required energy is non-negative. In addition, let $T_i(k)$ denote the remaining time the PEV is expected to remain connected to the grid at time step k, before it is used again. Then, the objective in the EF scenario is to give an amount of energy $E_i(k)$ to the i'th PEV within time $T_i(k)$. This corresponds to a desired average charging rate $\hat{p}_i(t)$ and is computed as

$$\hat{p}_i(k) = \min\left(\frac{E_i(k)}{T_i(k)}, \bar{s}_i\right), \tag{7.6}$$

namely, that rate to allow the PEV to finish the charging procedure in the desired time. Note that we explicitly bound the desired charging rate by the maximum power consumption that is physically allowed by the electrical power outlet and the charger. This upper bound makes it impossible to obtain an unrealistically large amount of energy in a small time. Note that the desired charge rate $\hat{p}_i(k)$ has 0 as natural lower bound, since the required energy is larger than or equal to 0. In that case, it might still make sense to connect the vehicle to the grid to perform V2G services, or to exchange reactive power.

In this scenario, we prioritize the vehicles according to their desired charge rates, i.e., vehicles with a high desired charge rate $\hat{p}_i(k)$ actually receive more power than the ones with a lower desired charge rate. The PEV charging problem related to this scenario can be formulated as in the previous scenario where we order in total three objectives depending on their priorities. This leads to

$$\begin{aligned}
O_1(k) = & \max_{p_1(k),\ldots,p_N(k)} \sum_{i=1}^{N} p_i(k) \\
\text{s.t.} \quad & -\bar{s}_i \le p_i(k) \le \bar{s}_i \qquad \text{for all } i, k \\
& \sum_{i=1}^{N} p_i(k) + \tilde{p}\,(k) \le \mathrm{P} \qquad \text{for all } k \\
O_2(k) = & \min_{p_1(k),\ldots,p_N(k)} \|B\,\boldsymbol{\zeta}(\boldsymbol{k})\,\|_1 \\
\text{s.t.} \quad & -\bar{s}_i \le p_i(k) \le \bar{s}_i \qquad \text{for all } i, k \\
& \sum_{i=1}^{N} p_i(k) = O_1(k) \qquad \text{for all } k \\
O_3(k) = & \min_{q_1(k),\ldots,q_N(k)} \left|\sum_{i=1}^{N} q_i(k) + \tilde{q}\,(k)\right| \\
\text{s.t.} \quad & \sqrt{p_i(k)^2 + q_i(k)^2} \ \le \ \bar{s}_i \qquad \text{for all } i, k \\
& \sum_{i=1}^{N} p_i(k) = O_1(k) \qquad \text{for all } k \\
& \|B\,\boldsymbol{\zeta}(\boldsymbol{k})\,\|_1 = O_2(k) \qquad \text{for all } k,
\end{aligned} \tag{7.7}$$

where B is a matrix as in Sect. 7.3.1 and $\boldsymbol{\zeta}(\boldsymbol{k})$ is a vector with the j'th element

$$\zeta_j(k) = \frac{p_j(k)}{\tilde{p}_j(k_0)}$$

whenever the vehicles consume power from the grid and

$$\zeta_j(k) = p_j(k)\tilde{p}_j(k_0),$$

whenever the PEVs inject power into the grid.

In the above notation, k_0 corresponds to the initial (or intermediate) time step at which the desired charge rate is computed, according to Eq. (7.6).

As for the PF scenario, the second objective $O_2(k)$ can be relaxed by using the running average $\rho_i(k)$ instead, as in Eq. (7.5). The running average can again be taken over the whole connection period, or over a smaller time window τ.

Another similarity with the PF scenario is that we are not interested in how much reactive power each PEV consumes (or injects) as long as the aggregated reactive power consumption (injection) compensates the reactive power by uncontrollable loads in the region. As mentioned before, additional, lower priority reactive power objectives can easily be incorporated by adding an additional objective $O_4(k)$.

7.3.3 Time Fairness (TF) scenario

The two scenarios presented in Sect. 7.3.1 and 7.3.2 accommodate situations where the PEVs are connected for long periods of time. However, during the day a lot of situations arise where the vehicle is parked for short periods of time, for example in shopping centers, restaurants, cafes, parking lots in a city center, etc. While it is currently unlikely to find charging facilities at such locations, the increasing amounts of PEVs on the roads can increase the desire for them. In addition, local authorities or shopping mall owners may wish to provide incentives for PEV owners to visit there and therefore provide charging infrastructure.

In such a framework, one possible way to charge the PEVs of the customers to encourage short connections and avoid excessively long stays (e.g., to encourage people to leave as soon as they have finished shopping, so they make their parking spot available for new customers). In this case, we suggest a to allow a higher power consumption (or injection) to PEVs that are connected more recently than the PEVs that have been connected for a longer period.

First, we categorize the vehicles into groups with different priorities depending on the length of their connection. Accordingly, upon connection a PEV automatically joins the group with highest priority. Then after a predefined period has elapsed, the PEV is moved into a group with lower priority. The PEV is then repeatedly shifted to a group with lower priority, until, after another predefined period of time, it ends up in the group with lowest priority. We assume that there are L groups, where group 1 has priority 1 (the lowest) and group L has priority L (the highest). Also, we assume that the time period before a PEV is moved into another group is constant and the same for all PEVs. In the following, we denote such a time period by κ and it is measured in time steps. Further, let T_i be the time step at which the i'th PEV connects to the power grid. Then, the priority of the i'th PEV at time step k, denoted $\Upsilon_i(k)$, can be computed as

$$\Upsilon_i(k) = \min\left(L-1, \left\lfloor \frac{k - \mathrm{T_i}}{\kappa} \right\rfloor\right), \tag{7.8}$$

where $\lfloor x \rfloor$ denotes the integer part of x.

Now, the power should be shared according to user priority. This can again be formulated as a prioritized optimization problem similar to the ones before,

$$\begin{aligned}
O_1(k) = & \max_{p_1(k),\ldots,p_N(k)} \sum_{i=1}^{N} p_i(k) \\
\text{s.t.} \quad & -\bar{s}_i \leq p_i(k) \leq \bar{s}_i \qquad \text{for all } i, k \\
& \sum_{i=1}^{N} p_i(k) + \tilde{p}\,(k) \leq P \qquad \text{for all } k \\
O_2(k) = & \min_{p_1(k),\ldots,p_N(k)} \|B\Xi(\boldsymbol{k})\,\|_1 \\
\text{s.t.} \quad & -\bar{s}_i \leq p_i(k) \leq \bar{s}_i \qquad \text{for all } i, k \\
& \sum_{i=1}^{N} p_i(k) = O_1(k) \qquad \text{for all } k \\
O_3(k) = & \min_{q_1(k),\ldots,q_N(k)} \left| \sum_{i=1}^{N} q_i(k) + \tilde{q}\,(k) \right| \\
\text{s.t.} \quad & \sqrt{p_i(k)^2 + q_i(k)^2} \;\leq\; \bar{s}_i \qquad \text{for all } i, k \\
& \sum_{i=1}^{N} p_i(k) = O_1(k) \qquad \text{for all } k \\
& \|B\;\Xi(\boldsymbol{k})\,\|_1 = O_2(k) \qquad \text{for all } k,
\end{aligned} \tag{7.9}$$

where B is the same as in the previous sections and $\Xi(\boldsymbol{k})$ is the vector with i'th element

$$\Xi_i(k) = \frac{p_i(k)}{\Upsilon_i(k)}.$$

Analogously to the previous two scenarios it is possible to relax objective $O_2(k)$ by using the running average of the power consumption $\rho_i(k)$.

Finally, in the current formulation we are not interested in the reactive power consumed or injected by each vehicle, but only in the aggregated reactive power.

7.4 The Additive Increase Multiplicative Decrease Algorithm (AIMD)

To solve the PEV charging problem for the different scenarios defined in Sect. 7.3, we propose a distributed algorithm. Distributed algorithms are attractive for a number of reasons. Firstly, such solutions are known to be robust against possible failures. Secondly, the requirements for distributed algorithms usually place a smaller burden than centralized algorithms on the communication infrastructure. Finally, distributed solutions sometimes lead to "plug-and-play" type functionalities which could be convenient in the future where a large but unknown number of PEVs connect to the same power distribution grid and compete for power. Note that after the preliminary work [29], other papers have been published to solve the charging problem in a distributed fashion, see for instance [3], [32] and [11].

The PEV charging problem formulated in Sect. 7.2 is a typical resource-sharing problem, where several agents compete to acquire their share of the resource (in this case, power). This is similar to what occurs in the Internet, where the connected devices compete with each other to obtain as much bandwidth as possible. The similarity between the power distribution network and the communication network have already been observed by a number of authors [17], [19]. Algorithms developed for the transmission control protocol (TCP), namely additive increase multiplicative decrease (AIMD) type algorithms, have recently been used in power networks [8], and in the PEV charging problem [28], [3], [19] and [29]. AIMD based algorithms are known to be flexible and reliable, require a small amount of communication between a central management unit and agents, such as PEVs, and have been extensively investigated and tested in the past twenty years [6], [16], [15], [25], [26] and [27].

The AIMD algorithm is a distributed algorithm that relies on a central management unit to broadcast a binary control signal. The PEVs autonomously react to this control signal by changing their power consumption and injection in a stochastic manner. As the PEVs, or the charger outlet they are connected to, are themselves in command of their reaction, it is possible to accommodate for the individual needs of the PEVs. Thus, AIMD-like algorithms are perfectly suitable for distributed resource allocation problems found in smart grid applications.

As mentioned in Sect. 7.2, the PEV charging problem involves management of active and a reactive power. Normally, the PEVs will draw power (active and/or reactive) from the grid. However, in some cases it might be desired to reverse one or both of the power flows, and make the vehicles inject power into the distribution grid. This situation occurs if, for instance, the grid at a given moment does not have enough power to supply the uncontrollable loads.

The AIMD algorithm can be extended to allow management of active and reactive power exchange and both G2V and V2G power flows. We call such an algorithm double (prioritized) AIMD (in the following, DAIMD). The DAIMD algorithm comprises an active power AIMD algorithm, which manages the active power consumption, and a reactive power AIMD algorithm, which governs the reactive power consumption. Each of these AIMD sub algorithms is able to operate in two modes: the G2V mode, in which the PEV draws power from the grid, and the V2G mode, in which the PEV injects power into the grid.

In the following, we first present the active power AIMD algorithm as it operates in G2V mode, which is the most basic form of the algorithm. Afterwards, we show how we can extend this algorithm, so that the PEVs can also operate in V2G mode, and how the PEVs can autonomously determine in which mode they should operate. We then illustrate how the reactive power AIMD algorithm works and how it can be implemented to obtain the DAIMD algorithm. In Sect. 7.4.1 to 7.4.3 we illustrate three ways to tune the DAIMD to accommodate for the three charging scenarios presented in Sect. 7.3.

While the PEVs operate in G2V mode, the active power AIMD algorithm controls the active power consumption of each PEV by switching between two distinct phases. The first phase is the additive increase (AI) phase, where the PEVs gently increase their charging rate, according to equation

$$f_p(k+1) = p_i(k) + \alpha_i(k)\overline{\alpha}. \tag{7.10}$$

The additive increase is scaled by a fixed scalar $\overline{\alpha}$, which is identical for all PEVs. This allows for some control over the increase from a central management unit, if necessary, where occasional broadcast of $\overline{\alpha}$ may be desirable. Further, the charging rate cannot exceed some value $\overline{s}_i$ (given by the physical constraints of the individual charging infrastructure).

The second phase is called the multiplicative decrease (MD) phase which occurs when Eq. **Error! Reference source not found.** is violated, i.e., when the sum of the consumed power by all connected PEVs and the demand by uncontrollable loads exceeds the maximum amount of power allowed by the power grid. We will refer to such an event as a capacity event (CE). When a CE occurs, the central management unit notifies all the connected PEVs of such an event by broadcasting a binary feedback signal. In response, the PEVs decrease their charge rate by a multiplicative factor ${\beta_i}^{(1)}(k)p_i(k)$ with probability $\lambda_i(k)$, or by another multiplicative factor ${\beta_i}^{(2)}(k)p_i(k)$ with residual probability $1-\lambda_i(k)$. In addition, when a PEV decreases its power consumption from an already small value, we force the decrease to be greater than a fixed threshold ψ. In this way, it is possible to handle the situations where the power is near zero e.g., when transitioning between V2G and G2V modes.

If the PEVs operate in the V2G mode, the AIMD algorithm described above is inverted. This means that upon receiving a CE the PEVs increase their power injection additively, which corresponds to an actual decrease of the power consumption. Similarly, when no CE is received the PEVs decrease their power injection multiplicatively, which corresponds to an increase in power consumption.

The PEVs can automatically recognize at which point they need to change the operating mode (i.e., from V2G to G2V or vice versa) in the following way. The switch from G2V to V2G mode occurs after a CE if the actual power consumption is very small. Let $m_i(k)$ indicate whether the i'th PEV operates in G2V mode at time step k, i.e. $m_i(k) = 1$ if at time step k vehicle i is in G2V mode and $m_i(k) = 0$ if at time step k vehicle i is in V2G mode. Then, the indicator is updated after a CE by

$$m_i(k+1) = \begin{cases} 1, & \text{if } p_i(k+1) > \varepsilon \text{ and } m_i(k) = 1, \\ 0, & \text{if } p_i(k+1) \le \varepsilon \text{ and } m_i(k) = 1, \end{cases}$$

where ε is a positive scalar parameter. The return from V2G mode to G2V mode occurs when no CE is received, and the indicator changes as

$$m_i(k+1) = \begin{cases} 1 & \text{if } p_i(k+1) > -\varepsilon \text{ and } m_i(k) = 0 \\ 0 & \text{if } p_i(k+1) \le -\varepsilon \text{ and } m_i(k) = 0 \end{cases}.$$

Figure 7.1 illustrates the active power AIMD algorithm executed by the vehicles for both G2V and V2G mode operation.

Different values of the parameters $\alpha_i(k)$ in the AI phase, and $\lambda_i(k)$, $\beta_i^{(1)}(k)$ and $\beta_i^{(2)}(k)$ in the MD phase give rise to different solutions, and this flexibility will be used in the Sect. 7.4.1 to 7.4.3 to handle the different scenarios presented in Sect. 7.3.

To handle both the active and the reactive power exchange with the grid, the above active power AIMD algorithm is embedded in a DAIMD, which also includes a reactive power AIMD algorithm. Figure 7.2 shows a flow chart implementing such a DAIMD. In a first step the active power AIMD algorithm is executed as previously explained, and as illustrated in Fig. 7.1. Afterwards, a second AIMD algorithm, the reactive power AIMD algorithm, is executed, where the PEVs aim at computing the value of the reactive power $q_i(k)$ to be exchanged with the grid.

The reactive power AIMD algorithm depends on reactive CEs. Such events occur whenever the reactive power at a defined measuring point, for example placed at a transformer, is larger than 0. This indicates that all reactive power in the area has been compensated and additional consumption of reactive power would lead to over-compensation. Similarly to the active power AIMD, the PEVs are able to draw or inject reactive power depending on the requirements of the power grid. The reactive power consumption (or injection) additively increases if no reactive CE occurs, and multiplicatively decreases otherwise. Figure 7.3 illustrates this algorithm in detail. To distinguish between the parameters used in the reactive power AIMD from the ones used in the active power AIMD, we denote the additive parameter $a_i(k)$, its additive scaling factor $\bar{a}$, the two multiplicative factors $b_i^{(1)}(k)$ and $b_i^{(2)}(k)$, the associated probability $\gamma_i(k)$, and the indicator $z_i(k)$.

Naturally, at all times, the charger outlet gives a maximum bound on the apparent power that can be exchanged between the vehicles and the grid

$$\sqrt{p_i(k)^2 + q_i(k)^2} \leq \bar{s}_i.$$

Regarding this bound it is important to note that we first bound the active charging rate $p_i(k+1)$, and then we bound the reactive power consumption $q_i(k+1)$, see Fig. 7.2. Thus, we give a higher priority to the active power exchange rather than to the reactive power exchange. This is deliberate and based on the assumption that charging PEVs is more important than satisfying some ancillary services for the grid (i.e., exchanging reactive power). If necessary the priorities can easily be reversed, giving reactive power exchange first priority and active power a lower priority.

One of the main advantages of AIMD-like algorithms is that they can be easily implemented in a distributed way with small communication constraints. In particular, the basic active and reactive power AIMD algorithms as described above only require a central management unit to broadcast binary CE signals. In this case, no communication between the PEVs, or from the PEVs to the central management unit is required. Other studies that deploy a central controller require more communication, see for examples [10], [21], [23] or [33]. This requires higher investments to equip each charger outlet with two-way communication capabilities and stringent communication requirements, especially in larger scale deployments, to mitigate the effects of increased delays and signal loss. In addition, two-way communications may face user resistance from PEV owners who might not be willing to share all the required data with the central controller.

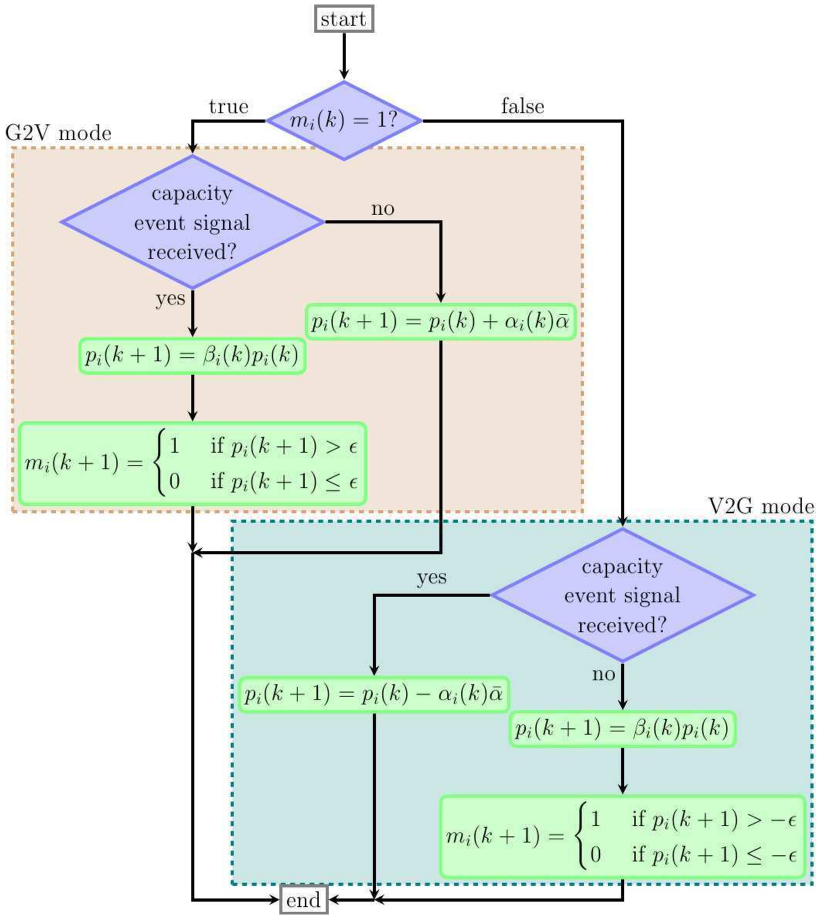


Fig. 7.1. Illustrative diagram of the active power AIMD for PEVs.

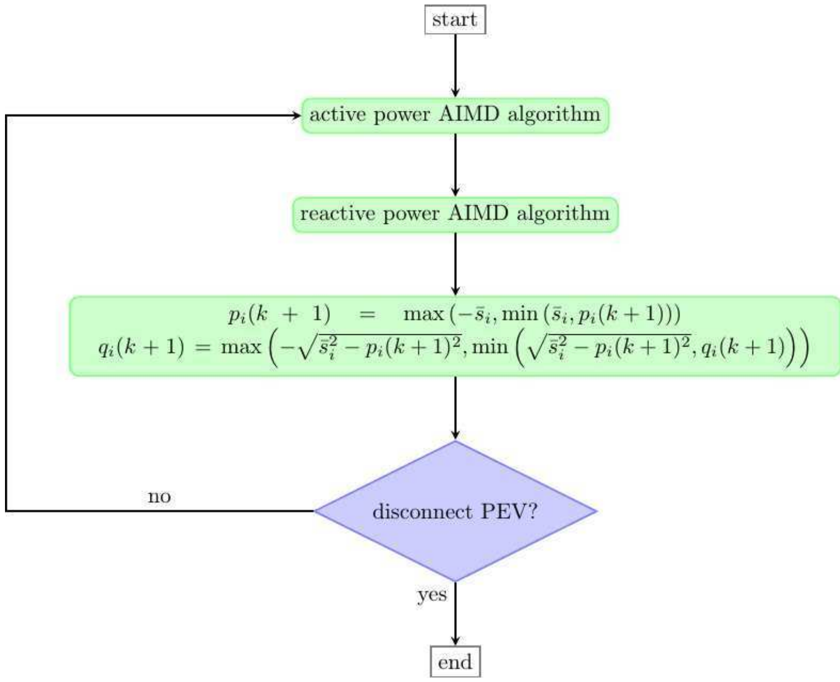


Fig. 7.2. Illustrative diagram of the DAIMD, where the active power AIMD is illustrated in detail in Fig. 7.1 and the reactive power AIMD in Fig. 7.3.

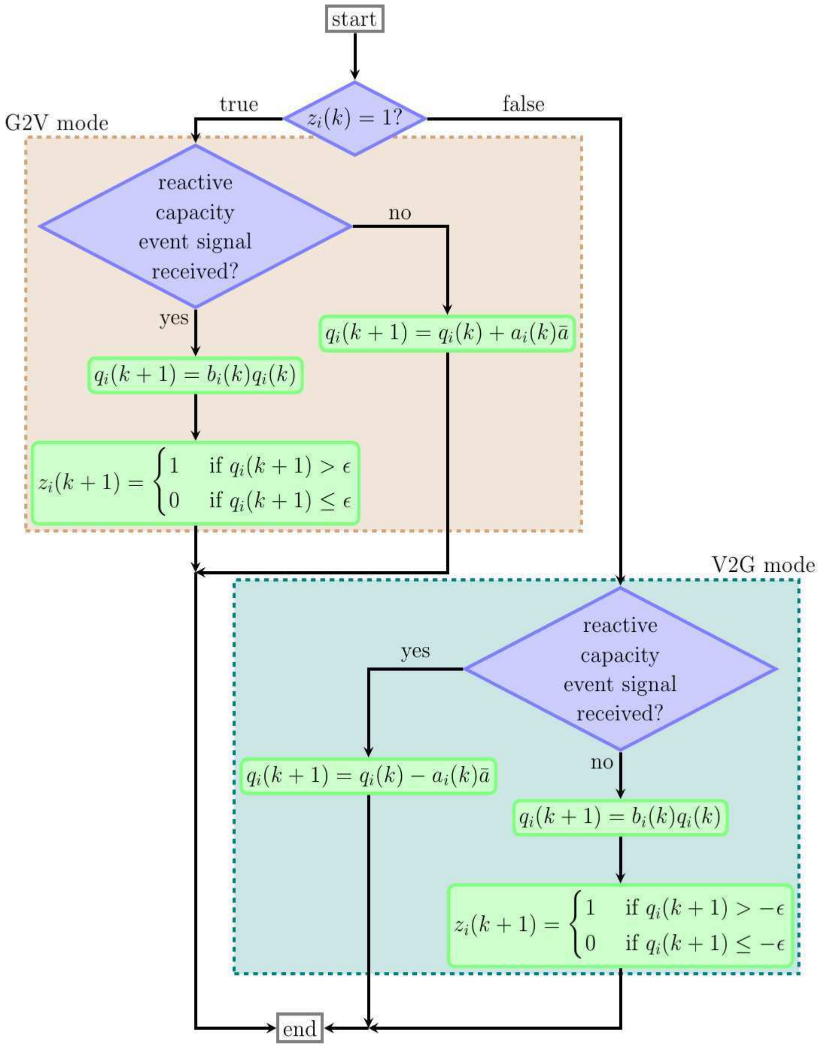


Fig. 7.3. Illustrative diagram of the reactive power AIMD for PEVs**.**

7.4.1 Algorithm for the Power Fairness scenario

In [26] it is shown that an equal share of the available active power can be achieved by setting the AIMD parameters identical for all participating vehicles.

This means that $\alpha_i(k) = \alpha$, $\beta_i^{(1)}(k) = \beta^{(1)}$, $\beta_i^{(2)}(k) = \beta^{(2)}$, and $\lambda_i(k) = \lambda$ for all i and k. This can be done if the infrastructure informs the PEVs of the values of the parameters before beginning the charging procedure, which would require additional communication. Another possibility is to have static parameters that are coded in the charger, or dynamic ones that are broadcasted to the vehicles during CEs (in this way, different parameters can be used in different situations).

Since we are not primarily interested in reactive power exchange, the parameters of the reactive power AIMD can be selected with more freedom. Hence, we choose the reactive power AIMD parameters to be equal for all connected PEVs, i.e. $a_i(k) = a$, $b_{\mathrm{i}}^{(1)}(k) = b^{(1)}(k)$, $b_{\mathrm{i}}^{(2)}(k) = b^{(2)}(k)$, and $\gamma_i(k) = \gamma(k)$. In this way, the PEVs draw (or inject) equal amounts of reactive power.

7.4.2 Algorithm for the Energy Fairness scenario

In some cases, one is interested in sharing the power directly (inversely) proportionally to the desired charge rate in the G2V (V2G) mode. This objective can be achieved by appropriately changing the parameters of the AIMD algorithm. In the G2V mode, the parameters have to be changed such that

$$\frac{\alpha_i(\mathrm{k})}{\beta_i^{(1)}(k)\lambda_i(k) + \beta_i^{(2)}(k)(1 - \lambda_i(k))}$$

is proportional to the desired charge rates $\tilde{p}_i(k)$.

In this regard, it does not matter which of the AIMD parameters are adapted to obtain such a result. However, such a choice affects the behavior of the algorithm. In fact, adapting the additive parameter $\alpha_i(k)$ influences the ability of the demand to increase, while adapting the multiplicative factors $\beta_i^{(1)}(k)$ and $\beta_i^{(2)}(k)$, or the probability $\lambda_i(k)$, influences the ability to decrease the demand. In this section, we only adapt the additive parameter $\alpha_i(k)$ to achieve objective $O_2(k)$ this scenario, while all the other parameters are chosen identical for all the connected PEVs. Therefore, the additive parameter is adjusted as

$$\alpha_i(k) = \frac{\hat{p}_i(k)}{\bar{s}_i} \tag{7.11}$$

in the G2V mode, and as

$$\alpha_i(k) = \frac{\bar{s}_i}{\hat{p}_i(k)} \tag{7.12}$$

in the V2G mode.

This scenario requires that the PEVs are informed of the value of the other parameters $\overline{\alpha}$, $\beta^{(1)}$, $\beta^{(2)}$, and λ. As for the PF scenario, this information can be transmitted along with the CEs or be coded in the charger to avoid additional communication requirements.

As in the PF scenario, we use identical parameters for all PEVs for the reactive power AIMD. Hence, the reactive power drawn or injected by the PEVs should be equal.

7.4.3 Algorithm for the Time Fairness scenario

For the TF scenario the power has to be proportional to the priority $\Upsilon_i(k)$ assigned to the PEVs. Hence, as in the EF scenario, we adapt the parameters such that $\Upsilon_i(k)$ is proportional to

$$\frac{\alpha_i(k)}{\beta_{\mathrm{i}}^{(1)}(k)\lambda_i(k) + \beta_{\mathrm{i}}^{(2)}(k)(1-\lambda_i(k))}.$$

Here, we adapt only the additive parameter $\alpha_i(k)$, while the remaining parameters of the active power AIMD are kept identical for all connected PEVs. The parameter is updated at each time step according to

$$\alpha_i(k) = \frac{\Upsilon_i(k)}{L}. \tag{7.13}$$

Note that we scale the priority $\Upsilon_i(k)$ with L, i.e., the number of available groups, such that the additive parameter remains in the interval $]0,1]$. While it is not essential that the additive parameter lies in that interval, this is a useful property, since then $\bar{\alpha}$ is the upper limit for the increase per time step and PEV.

7.5 Simulations

In this section we illustrate the behavior of our algorithms in a simulated scenario, using a customized OpenDSS-Matlab simulation platform. In particular, Matlab was used to compute the power consumption according to the different algorithms, while OpenDSS, a power simulation tool developed by [13], was used to simulate the power grid.

We tested our algorithms on a revised version of the power distribution system based on the IEEE37 bus test feeder found among the OpenDSS examples [12].

This is depicted in Fig. 7.4. Note that Fig. 7.4 only shows the interconnections between the loads, buses, and the transformer, and is not meant to depict the real dimensions of the distribution grid. We also assumed that the actual power was measured at the transformer that connects the loads with the external grid, and we assumed a power limit at this transformer of 180kW for the active power. The transformer is depicted in Fig. 7.4 as the square block with label "SubXF". Additionally, the algorithm controls the reactive power flow to compensate it completely at the transformer, i.e., the reactive power at the transformer should be equal to $0\ \text{VAR}$.

Overall there are 25 uncontrollable three-phase loads, indicated by inverted triangles in Fig. 7.4, connected to different buses. Such loads follow a pre-specified load pattern over a day. For illustrative purposes, we made the assumption that the peak load of the uncontrollable loads would overlap the connection time of the PEVs. While this assumption is clearly not always true (PEVs could be recharged at night time when the load curve is lower), it still allows us to investigate a worst-case scenario. Also, note that there are some studies that predict that domestic charging is likely to partly occur during the evening load peak, directly after work, and this last scenario is consistent with this assumption. For example in [7] three charging periods are identified: during daytime, during the night, and during the evening. Similarly, [14] assumes that without control the charging starts around 6pm and identifies such a scenario as a worst-case, which is consistent with our simulation.

In our simulation, up to 20 PEVs can connect at the locations specified in Fig. 7.4 with ellipses. We assume that the PEVs are connected with uniform probability between hours 7 and 10 of the daily simulation. The connection is single phase, where each charger has a maximal apparent power capacity of 3.7kVA. In Fig. 7.4 the different line styles (solid, dashed, dotted) of the ellipses indicate the different phases the PEVs are connected to. The required energy is assigned using a uniform distribution between 15 and 20kWh. We also assume that the PEV is automatically disconnected when it is charged to the desired level. Note that this means that fully charged vehicles do not participate in reactive power balancing. Also, we assume that PEVs can also be disconnected after a predefined time, independently from their charging state. Further, we only simulate one scenario per time. This means that all PEVs are in the same situation and therefore deploy the same algorithm, corresponding to the simulated scenario. In the simulation, the PEVs react synchronously to the CE, and possible communication delays have not been taken into account.

The results obtained using the proposed DAIMD algorithm to control the active and reactive power consumption are compared with:

(i) the case where there are no PEVs connected at all, to evaluate the possibly different utilizations of the uncontrollable loads; and with

(ii) the case where PEVs are charged with the maximum charge rate until they are fully charged, i.e., $p_i(t) = \overline{s}_i$ for all i.

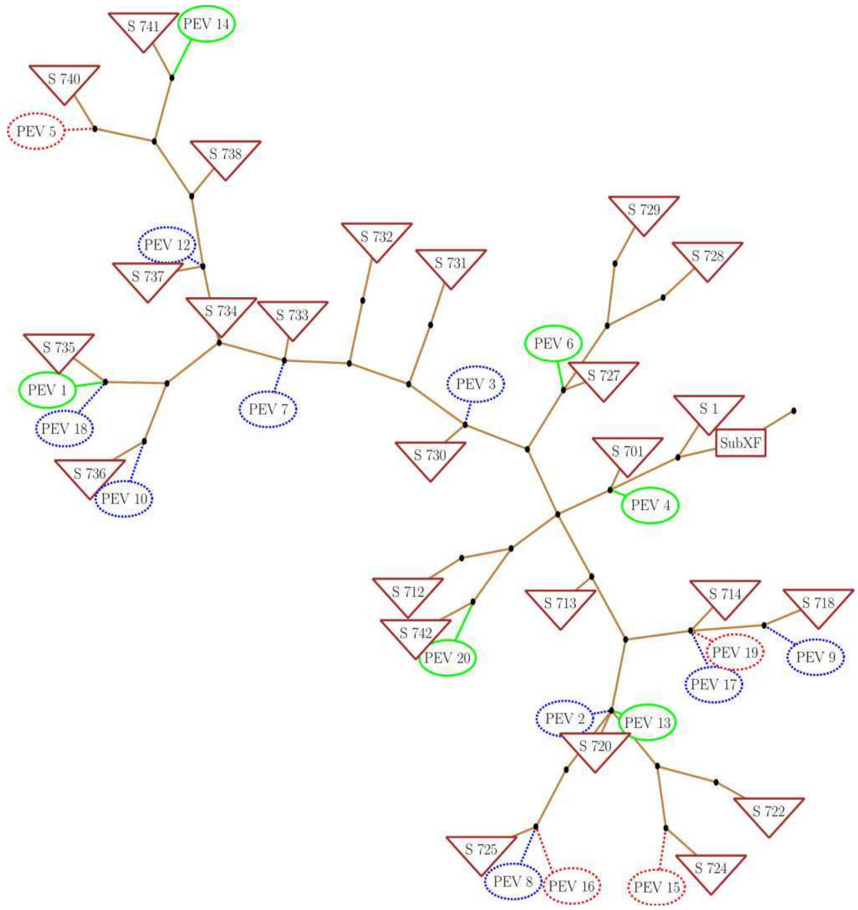


Fig. 7.4. Connection graph of the IEEE37 test feeder including PEVs. Inverted triangles symbolize uncontrollable three-phase loads. The square block represents the transformer that connects this part of the distribution grid to the external grid. The ellipses represent connected PEVs and the line style (solid, dashed, dotted) indicates to which phase the PEV is connected to.

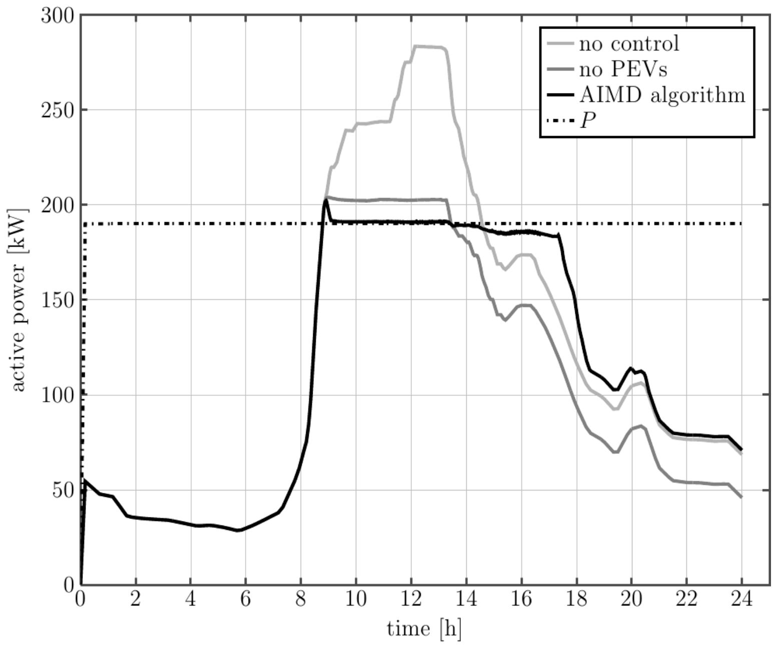
7.5.1 Simulation of the Power Fairness scenario

In this section the PEVs connected to the distribution grid, shown in Fig. 7.4, use the PF scenario algorithm described in Sect. 7.4.1. This means that they should be recharged with the same average charge rate, without exceeding the maximum active power allowed by the transformer. The active power AIMD parameters are identical for all the PEVs: $\alpha = 1$, $\bar{\alpha} = 0.1\frac{\text{kW}}{\text{s}}$, $\beta^{(1)} = 0.75$, $\beta^{(2)} = 0.99$, $\lambda = 0.7$, and $\psi = 0.15$. The values for the reactive power AIMD are also identical for all PEVs and identical to the ones used for the active power AIMD, i. e. $a = 1$, $\bar{a} = 0.1\frac{\text{kVA}}{\text{s}}$, $b^{(1)} = 0.75$, $b^{(2)} = 0.99$, $\gamma = 0.7$, and $\psi = 0.15$.

Figure 7.5 shows the active and reactive power consumption at the transformer and Fig. 7.6 shows the active power consumption of four randomly selected PEVs. The results are filtered using a moving average filter with a window length of 600 time steps which corresponds to 10 minutes.

Note that the load demand exceeds the allowed limit by a small margin for a brief period of time near 9 hours. However, when the PEVs are connected to the distribution grid, they are able to inject power into the grid and reduce the total demand to below the limit. On the other hand, if the PEVs are not controlled, then there is a peak demand which exceeds the power limit by a large margin. By appropriately controlling the charge rates, it is possible to mitigate the peak, though the overall charging time obviously increases. Furthermore, the PEVs can also support the grid with reactive power management, and successfully push the reactive power at the transformer towards zero. This is helpful both in terms of reduced grid transmission losses and local voltage support. Finally, note that in our set-up the PEVs disconnect as soon as they are charged to the desired level (e.g., fully charged).

(a)



(b)

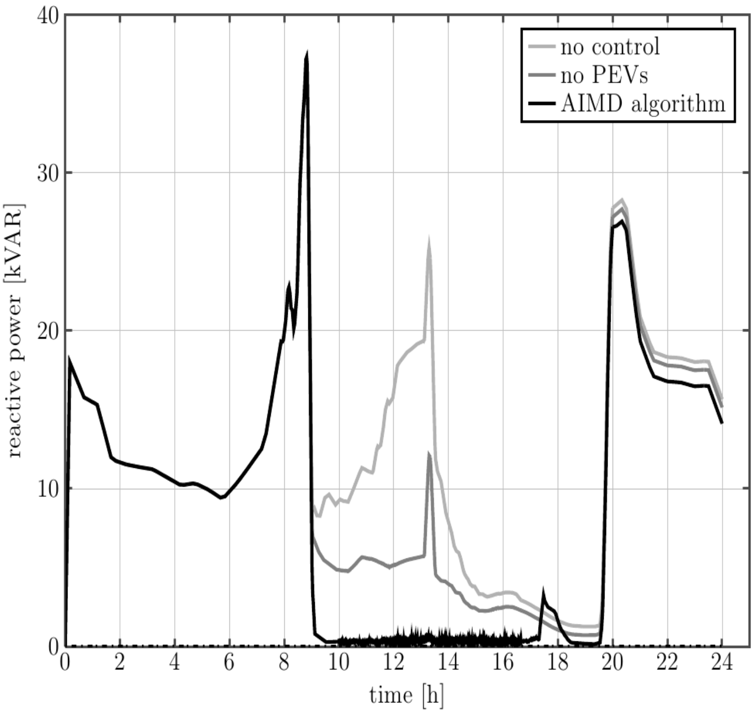


Fig. 7.5. The power consumption at the transformer "SubXF" filtered using a moving average filter with a window length of 600 time steps, while the connected PEV apply the PF scenario. The active power consumption is depicted in (a) and the reactive in (b).

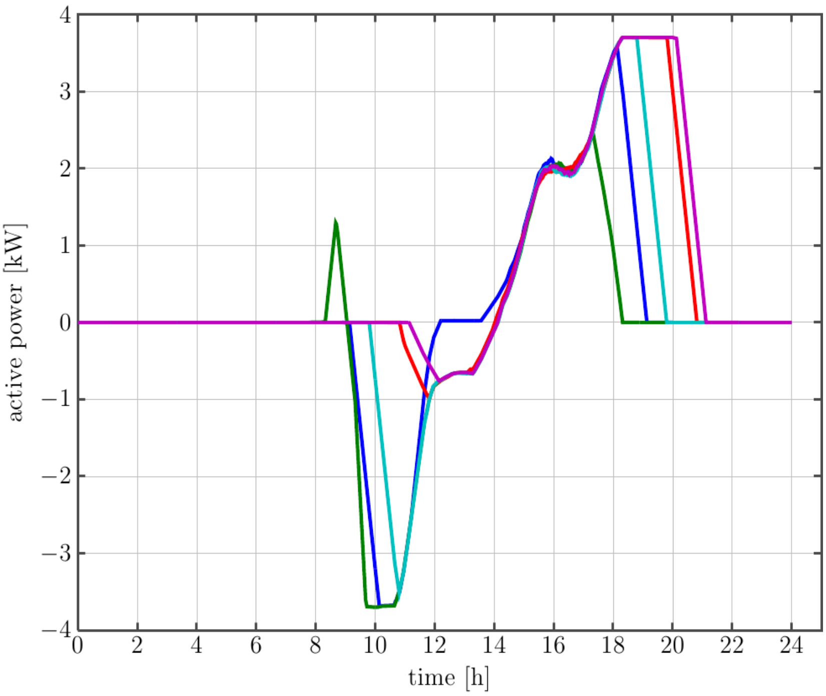


Fig. 7.6. The active charge rates of four randomly selected PEVs applying the PF scenario filtered using a moving average filter with a window length of 600 time steps.

7.5.2 Simulation of the Energy Fairness scenario

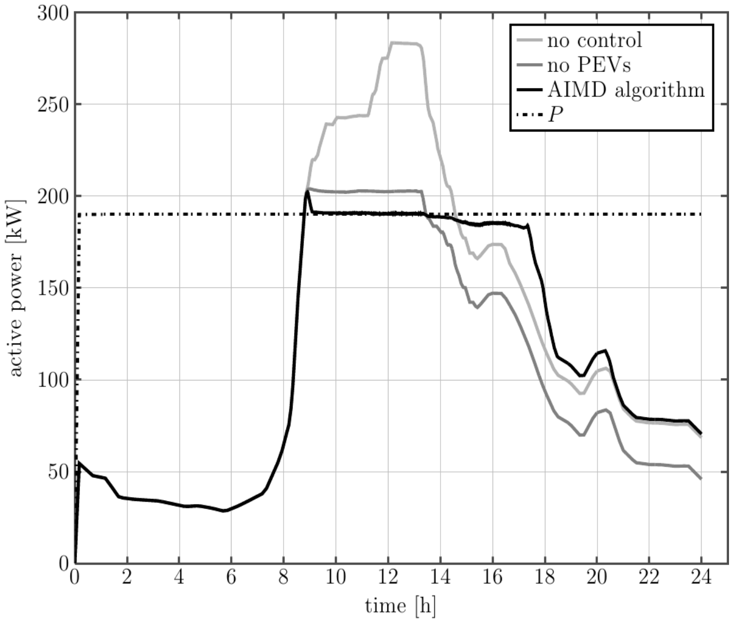
In this section, the charge rates of the PEVs are determined using the modified algorithm illustrated in Sect. 7.4.2. To make a comparison with the previous charging strategy, we use a similar setting as previously described. While the additive parameter α_i is determined by the Eqs. (7.11) and (7.12), respectively, the remaining active power AIMD parameters are chosen identically to those in Sect. 7.5.1 for the previous simulation, i.e. : $\alpha = 1$, $\bar{\alpha} = 0.1\frac{\text{kW}}{\text{s}}$, $\beta^{(1)} = 0.75$, $\beta^{(2)} = 0.99$, $\lambda = 0.7$, and $\psi = 0.15$. The values for the reactive power compensation are also chosen identically to the previous scenario, i.e. . $a = 1$, $\bar{a} = 0.1\frac{\text{kVA}}{\text{s}}$, $b^{(1)} = 0.75$, $b^{(2)} = 0.99$, $\gamma = 0.7$, and $\psi = 0.15$.

Each PEV has to know the expected time it will be connected to the power grid in advance, in order to compute the additive parameter as in Eqs. (7.11) and (7.12). In this simulation, we assumed that every PEV is expected to stay connected for nine hours. Then the desired charge rate is computed once at connection of the vehicle to the grid according to Eq. (7.6). This desired charge rate is then used to continuously update the additive parameter $\alpha_i(k)$ using Eqs. (7.11) and (7.12) while the PEVs operate in G2V and V2G mode, respectively.

Figure 7.7 depicts the active and reactive power at the transformer. Again, we show a comparison of the results relative to the case of no connected vehicles, and to the case of uncontrolled charge rates.

The second objective $O_2(k)$ in this scenario is to share the power proportionally to the desired charge rate (i.e., more power to those who need more energy in a shorter time). To investigate whether this objective is fulfilled, the ratio between the desired charge rate and the actual average power consumption is plotted in Fig. 7.8. As before, the power consumption is filtered using a moving average filter with a window size of 10 minutes.

(a)



(b)

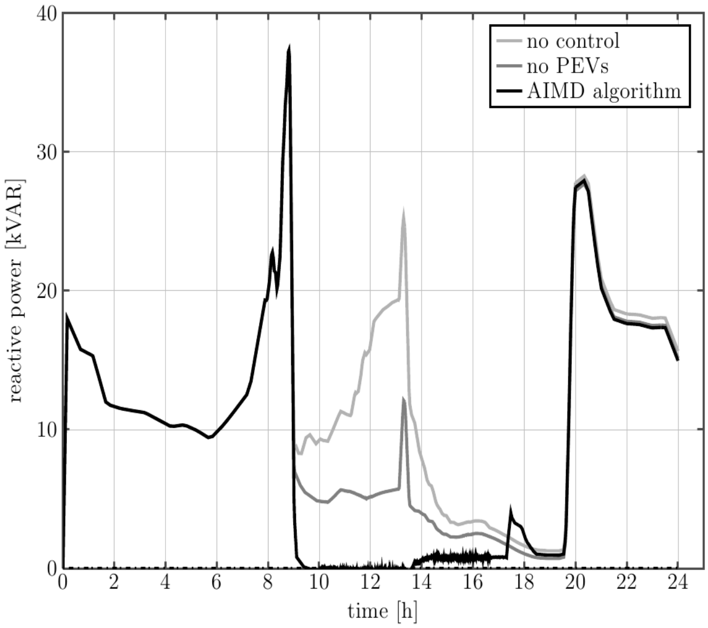


Fig. 7.7. The power consumption at the transformer "SubXF" filtered using a moving average filter with a window length of 600 time steps, while the connected PEVs apply the EF scenario. The active power consumption is depicted in (a) and the reactive in (b).

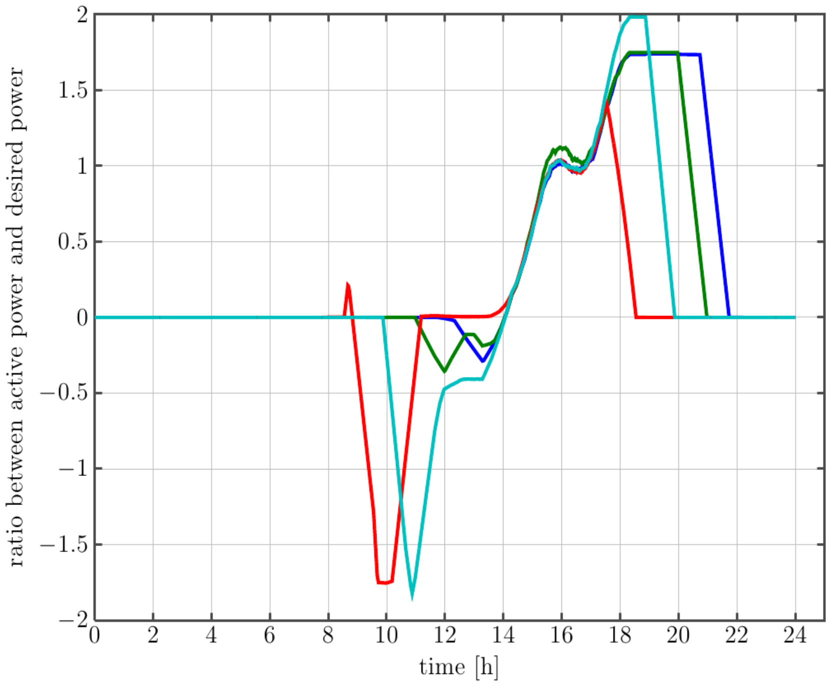


Fig. 7.8. The ratio between the active charge rates filtered using a moving average filter with a window length of 600 time steps and the desired charge rate $\tilde{\mathrm{p}}_{\mathrm{i}}(\mathrm{k})$ of four randomly selected PEVs applying the EF scenario.

7.5.3 Simulation of the Time Fairness scenario

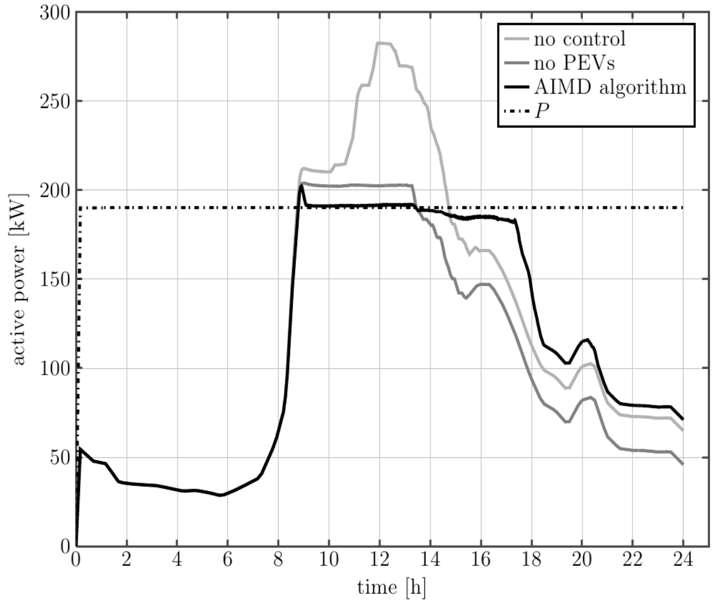
We repeat the simulation to simulate the TF scenario. As mentioned in Sect. 7.3.3 the power consumption or injection should be proportional to an assigned priority $\Upsilon_i(k)$, which can be computed by Eq. (7.8). The parameters for the scenario are such that the number of groups L is set to four and the time period κ is set to one hour. While the additive parameter of the active power AIMD is computed at each time step using Eq. (7.13), all remaining parameters of the active and reactive power AIMD are identical to the previous simulations.

Figure 7.9 depicts the active and reactive power consumption at the transformer “SubXF”. Similarly to the other scenarios, the algorithm manages to mostly push the active power below the limit, while allowing the PEVs to balance a large part of the reactive power in the area.

Here, the PEVs power consumption or injection should be proportional to their priority. In Fig. 7.10 the power consumption of four randomly selected vehicles is depicted (dashed) and their priority (solid). The power consumption or injection is higher for PEVs that have just been connected to the grid compared to those connected for a longer period, as desired in this scenario.

Similarly to the other simulations, the power consumption is filtered using a moving average filter with a window length of 10 minutes.

(a)



(b)

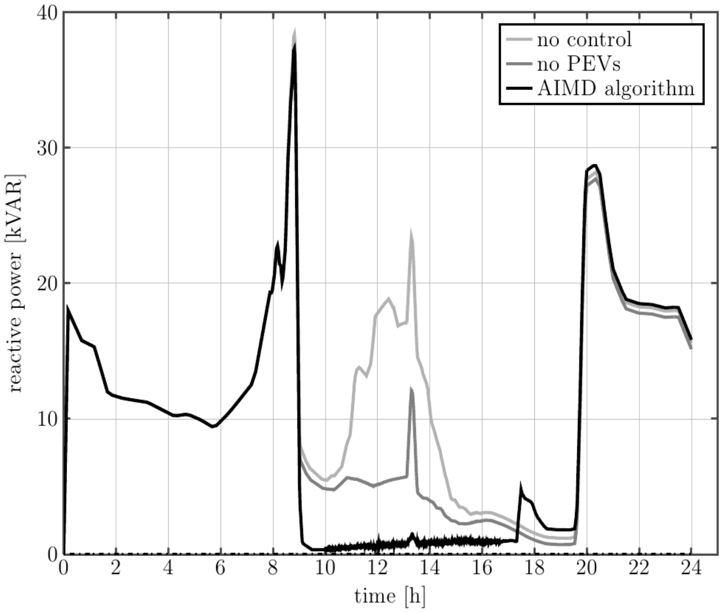


Fig. 7.9. The power consumption at the transformer “SubXF” filtered using a moving average filter with a window length of 600 time steps, while the connected PEV apply the TF scenario.

The active power consumption is depicted in (a) and the reactive in (b).

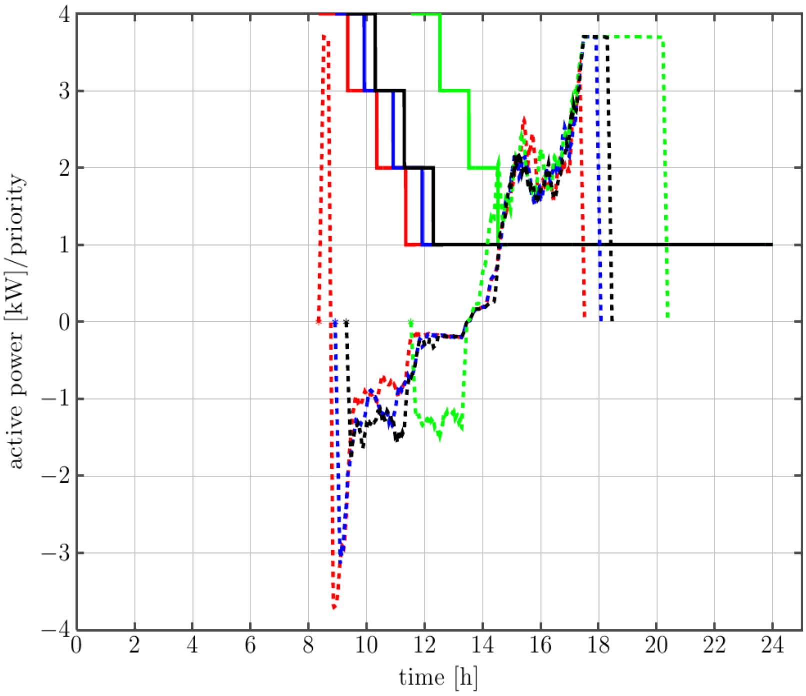


Fig. 7.10. The active charge rates of four randomly selected PEVs applying the TF scenario filtered using a moving average filter with a window length of 600 time steps (dashed, star marks connection time) and the associated priority of the PEVs (solid).

7.6 Future Work

We have simulated the algorithm proposed for managing the active and reactive power consumption of PEVs to support the distribution grid while PEVs are connected for charging. In this chapter a simple radial feeder model has been used to test the algorithm. In reality, however, the grid structures are more complex and may contain multiple feeders with different limitations. Those more complex cases with additional limitations have to be investigated to guarantee an efficient operation of the algorithm.

Similarly, different types of constraints such as line current or node voltage limits may be present. For example, a node voltage limit might be imposed to ensure all users have supply that meets the relevant standards. In that regard it may be important to carefully select a subset of nodes where excess voltage excursions are most likely to occur. In this case, further studies would be required to prevent unforeseen interactions among the different CE-generating sources.

Additionally, the algorithm proposed could be used to shape the demand curve that regions should follow instead of just limiting the demand in the region. Such a behavior can be achieved by intelligent adaption of the limit, P. This can be used to limit the rate of change in aggregate demand to allow generators which react slowly to compensate for the changes. The main problem in this case is how to find the optimal P to support the distribution grid while full-filling the needs of the owners of PEVs.

Similarly, extensions of this basic algorithm and intelligent adaptation of the limit P allows two more services of support. The first one is to balance the power among the three phases by controlling the phases separately. In that case, a limitation is introduced for each phase whose value depends on the demand in the three phases. However, it is not straightforward to include such an operation. For example it might be hard to define whether a phase should reduce its power consumption or the other phases should increase their power consumption. The second possible extension is to regulate currents according to the grid frequency and utilize this frequency as a signal, indicating when to locally reduce the power consumption.

Furthermore, we assumed throughout the paper that all participating PEVs are applying an identical scenario. It has to be verified whether the fairness can still be guaranteed if the connected PEVs apply different scenarios in the same distribution grid. For example in a region where a lot of PEVs are connected using the PF scenario, for example in a domestic setting, and a few vehicles connect using the EF scenario, for example at a small office building in the same area. This issue has to be studied, especially for a larger scale use of the algorithm. In the situations described above, one might try to use multiple levels of DAIMD. For instance, one DAIMD controls only the PEVs that apply the EF scenario, and a second one controls the PEVs that apply the PF scenario. The power limit of those two separate DAIMD algorithms is then controlled by a higher level DAIMD. Such multi-level DAIMD algorithms might also be used for the control of large scale distribution grids. However, as this adds higher levels of communication and control, the behavior has to be studied more carefully.

Due to the small communication overhead of a single bit, the PEVs are not able to react to future expectations of the demand by uncontrollable loads and the power generated by renewable power sources. By allowing the management unit to broadcast additional information, for example the expected increase in demand in the next hour, the PEVs may be able to react to such information and adapt their power consumption in response to predictions. What information is most useful and how the PEVs should react while maintaining a sense of fairness remains an open problem. Further, by relying on predictions it is important to consider that they normally are not exact. It needs to be verified that the algorithm can handle such prediction errors and whether the advantages are large enough to accept the higher communication requirements and the necessity of predictions.

7.7 Conclusions

This chapter presents a distributed algorithm to control the charging of PEVs and enables them to support the grid. While the algorithm manages to limit the peak demand and reduces the reactive power transported outside of an area, it also allows flexibility in how the PEVs are "fairly" controlled.

We presented three possible definitions of how the control can be interpreted as "fair". While there are many more possibilities to define "fairness" among the participants, those three scenarios illustrate the flexibility of the proposed algorithm.

Using a simple radial test feeder we simulated the behavior of the algorithm for the different scenarios and verified its usefulness.

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