Decentralized Charging of Plug-in Electric Vehicles and Impact on Transmission System Dynamics

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***Abstract*—This paper focuses on the impact of the charge of Plug-in Electric Vehicles (PEVs) on the dynamic response of power systems and proposes an efficient solution to control electric vehicle chargers, by dynamically allocating the available power in an optimized way. The proposed approach is based on an Additive-Increase-Multiplicative-Decrease (AIMD) stochastic decentralized control strategy to efficiently and seamlessly manage the charge of a high number of PEVs with little communication efforts. A modified version of the New England network is utilized to validate the proposed control through a variety of scenarios and control setups.**

***Index Terms*—Plug-in electric vehicles, loading margin, frequency control, decentralized control.**

I. Introduction

A. Motivation

The projections of the future electricity demand indicate that Plug-in Electric Vehicles (PEVs) will play a relevant role in power systems. It has been estimated, in fact, that there will be over 1 billion electric vehicles by 2050, making electricity the first energy carrier [1], [2].

PEVs are characterized by high flexibility, which can be a valuable resource for the system. However, an uncontrolled charging of large fleets of vehicles at peak times may pose challenges to the transmission grid [3]. There is, thus, an impelling need to develop smart strategies to accommodate an increasing number of PEVs in existing power grids. The present work proposes an efficient stochastic decentralized control that is particularly suited for large numbers of PEVs.

B. Literature Review

The literature on the impact of PEVs on system dynamics can be roughly divided into two main groups: (i) studies that exploit the flexibility of PEVs to improve system dynamics; and (ii) studies that discuss how large fleets of PEVs affect the system and possibly lead it to collapse.

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1) Studies that exploit PEVs flexibility: Smart charging strategies can be adopted by means of *ad hoc* electricity tariffs [4], and Vehicle-To-Grid (V2G) power flows [5]. Some works focus on the ability of PEVs to provide control that can improve the performance of the grid. For example, [6] lists a variety of positive aspects of the PEVs, such as their ability to facilitate the integration of renewable energy sources.

With respect to short-term time scales, in [7], the authors propose an aggregate model of PEVs for the Primary Frequency Control (PFC), which proves to help considerably regulate the frequency of the system after a large disturbance. Also [8] shows that the adoption of advanced centralized PEVs charging strategies reduces the negative impact of the electric mobility penetration, e.g. congestion problems on distribution grids, and increases the PEVs potential benefits as system ancillary services providers.

Considering longer time scales, reference [9] presents a power management scheme for Secondary Frequency Regulation (SFR) using an integrated fleet of electric vehicles. An alternative application can be found in [10], where the potential advantages of V2G and mobility are investigated for the day-ahead generation scheduling of power systems: an optimal charging/discharging schedule of PEVs fleets is studied to reduce grid operation costs and congestions in the power grid, and also to lessen the generation dispatch variability due to wind generation units; anyway, there are some restrictions for utilizing PEVs as storage facilities because of vehicles requirements for mobility.

2) Studies on the impact of a large number of PEVs on system dynamics: The impact of PEVs on system dynamics is intrinsically tied to their charging strategy. Without a suitable control, in fact, the charging of large fleets of PEVs may compromise the operation and security of a power system [6].

The transition to grid-charged cars in Ontario, Canada, is discussed in [11], and the authors conclude that about 6% of total vehicle fleet in Ontario (approximately 500,000 PEVs) can be charged without any additional power system investments, if the off-peak periods are smartly exploited. Different models and settings have been considered so far to conduct this kind of studies. In [12], for example, a probabilistic method of examining the impact of PEVs on composite power systems is presented. Results suggest that the PEVs penetration will indeed affect the system dynamic response. In [13], on the other hand, it has been shown that the evening ramp due to the PEVs domestic charge may cause a collapse of the system.

The architecture of the control strategy is also critical. Reference [14] presents a review of different strategies, algorithms, and methods to implement a smart charging control system, and [15] describes the main existing PEVs charge scheduling approaches in a smart grid context. In particular, there are two main control approaches: centralized and decentralized. Both approaches can be found in the literature. A centralized method is used for example in [16], where an event driven Model Predictive Control (MPC) approach is proposed for the management of PEVs charging in distribution grids. In [8], instead, a combination of local and centralized control methods is used to optimally coordinate the PEVs fleet charging. However, a centralized management of the charging process of a large number of PEVs may quickly become computationally intractable and impractical, therefore most charging algorithms are evolving towards a decentralized structure [15]. For this reason, this paper focuses on a decentralized approach.

This paper considers the decentralized Additive-Increase-Multiplicative-Decrease (AIMD) algorithm; this approach has been applied for a particular class of resource sharing problems, where a group of agents with limited or no communication abilities at all wish to share a given resource in an optimal fashion [17]. In our case, the algorithm coordinates the charging rates of the PEVs, so that the available power can be utilized by all vehicles in a fair and safe fashion.

AIMD-based control solutions have many significant advantages, most notably it is a fully decentralized approach, which implies that the solution is scalable and independent from the number of agents. In our case study, this implies that it is not required to count the number of PEVs connected for charging, and it is not required to know how much energy they need. Accordingly, neither PEVs, nor charging stations, require to communicate any information, contrary to the vast majority of other existing distributed charging algorithms. In fact, AIMD algorithms have been already proposed for PEV charging in some literature works. Reference [18] studies the problem of charging a number of electric vehicles via limited capacity infrastructure. In [19], the authors design a smart energy exchange algorithm based on bidirectional energy management. Reference [20] proposes an AIMD solution to fairly share the energy, and to minimize the queues.

The references above envisage the adoption of AIMD but they do not consider any model of the power grid. Recently, [21] proposes AIMD algorithms for PEV charging control supported by a distribution grid model, and measurements of local voltages are used to decentralize the charging operation. While this is similar to what it is proposed here, yet no optimization problem is formulated in [21] and, thus, the whole power capacity of the network is not fully utilized during the charging process.

C. Contributions

The main contributions of this work are twofold:

- A formulation of the charging problem of PEVs based on fully decentralized AIMD control. Such a formulation does not require PEVs or charging stations to communicate any information, e.g. their connection for charging, and the available power is automatically shared among PEVs.
- A discussion on the non-obvious result that popular strategies based on locally measured grid frequency may not be appropriate for the control of PEV charging, as these approaches sometimes fail to predict stability of the network.

The latter point may be regarded as a surprising result, given that, as discussed above, some works in the literature exploit *small devices* for supporting system frequency regulation, most notably electric vehicles [7], but also micro-grids [22], [23], or thermostatically controlled loads, such as refrigerators and air-conditioners [24]. However, in such studies, the small devices do not originate the instability, which is what happens in the PEV charging problem investigated in this work.

The charging problem is formulated as an optimization problem, so that it can flexibly include priority rules, e.g. based on the price people may be willing to pay for charging, or to prioritize vehicles that have a lower level of the battery. We validate the proposed algorithm on the popular IEEE 39-bus system, and we use the power grid simulator Dome [25], to simulate the power system behaviour and provide realistic and practical assessments.

D. Organization

The paper is organized as follows. Section II describes the models of the power system, the PEVs fleets, and the control strategies analyzed. Then, Section III presents the AIMD algorithm and the proposed control schemes; the following Section IV introduces our system set-up, and the main results obtained. Finally, Section V outlines main conclusions.

II. Modeling

We first introduce the overall dynamic model of the power system (Section II-A) and then the model of the PEV fleet (Section II-B) and the proposed control strategy (Section II-C).

A. Power System Model

The power system model is formulated as a set of stochastic differential algebraic equations (SDAEs), as follows [26]:

$$\begin{aligned}
\dot{\boldsymbol{x}} &= \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}, \boldsymbol{z}, \boldsymbol{\eta}), \\
\boldsymbol{0} &= \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}, \boldsymbol{z}, \boldsymbol{\eta}), \\
\dot{\boldsymbol{\eta}} &= \boldsymbol{a}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\eta}) + \boldsymbol{b}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\eta})\, \boldsymbol{\xi} \ ,
\end{aligned} \tag{1}$$

where $\boldsymbol{f}$ represents the differential equations, including the dynamic models of synchronous machine and their controllers, while the algebraic equations $\boldsymbol{g}$ model auxiliary variables; $\boldsymbol{x}$, $\boldsymbol{y}$, $\boldsymbol{z}$ are the state, algebraic, and discrete variables, respectively; $\boldsymbol{u}$ are the inputs, e.g. active power schedules and reference voltage of the automatic voltage regulators; $\boldsymbol{\eta}$ represents stochastic perturbations, e.g. wind speed and load variations, which are modeled through the last term in (1); $\boldsymbol{a}$ and $\boldsymbol{b}$ represent the *drift* and *diffusion* of the stochastic differential equations, respectively; and $\boldsymbol{\xi}$ represents the white noise vector. The set of equations in (1) includes lumped models of the transmission system and conventional dynamic models of synchronous machines, e.g., 6th order models, and their controllers, such as, automatic voltage regulators, turbine governors, and power system stabilizers.

B. PEVs Fleets Model

Many statistical analyses have shown that in the near future in many countries a significant number of PEVs is expected to charge in a domestic scenario [27], [28], as soon as the drivers come back home after work [8], [29]. In this case, the number of connected PEVs may quickly increase in a short time, e.g. right before dinner time, and may give rise to a new evening peak load. This peak of PEVs domestic charging can be modeled as many active power load ramps, connected to some buses of the network, where other conventional loads are present. The mathematical model of the loads at the buses where also PEVs are connected is:

$$\begin{aligned} p &= p_0 + R_{\mathrm{PEV}}(t - t_0) + \eta_p, \\ \dot{\eta}_p &= -a\eta_p + b\xi_p, \end{aligned} \tag{2}$$

where p is the total load; p_0 is the aggregated voltage-dependent pre-existing load at the bus; R_{PEV} is the ramp rate of the electric vehicles; t_0 is the time at which the evening ramp begins; η_p is a Gaussian mean-reverted stochastic process that reproduces load random fluctuations; a is the drift; b is the diffusion; and ξ_p is white noise [26].

C. Control Strategies

A decentralized control strategy relies on the ability of one PEV charger to modulate the charge rate so that the PEV gets charged as quickly as possible, without at the same time giving rise to power system stability issues. For this purpose, this section discusses the effectiveness of different measurable, or simple to estimate, quantities to trigger a control action and decrease the charge rates of PEVs when getting close to the safety limits of the network.

In principle, there are various alternative set-ups, as follows.

- ω_{COI}: the frequency of the center of inertia (ω_{COI}) of the system [30]. Since this quantity is indicative of a system balancing condition, it is reasonable to assume that it may be used to infer when getting close to unstable conditions.
- ω_i: the local frequency measured at the bus i. This quantity is indicative of the local power imbalance, and it is easier to estimate than ω_{COI} for a decentralized approach, as it can be locally measured.
- v_i: the voltage magnitude at bus i. This quantity is strictly linked to the transmission capacity of the lines.
- p_i: the PEVs power load at bus i.

A first result of our paper, that will be better illustrated through extensive simulations in a later section, is that the only control strategies that use p_i as a control variable are effective for our case study. In particular, the following facts have been noticed:

- The time scale of the PEV ramping rate allows assuming that the frequency of the system is effectively the same in every point of the grid. As a matter of fact, our simulations show that all ω_i are always very close to ω_{COI}, even when very steep ramp profiles of vehicles are simulated.
- Frequency-based control strategies (either using ω_{COI} or ω_i's, as they are equivalent as explained in the previous point) are ineffective as instability issues may occur without noticing any evident variation in the frequency signals (or they are noticed when it is too late to implement recovery strategies).
- Voltage-based control strategies are ineffective for the opposite reason, since significant voltage variations may be observed even in fully stable operations of power grids. This is due to the presence of many existing devices devoted at regulating voltages around the nominal values, e.g. under-load tap changers (ULTCs) and static VAR compensators (SVCs).

On the other side, it is reasonable to assume that grid operators can use historical data to estimate the maximum power allowed at each bus ($p_i^{\max}$) (following for instance the techniques proposed in [31], [32]), and that power-based control strategies can be used to maintain p_i below the value of $p_i^{\max}$. For this reason, in the following section we focus on power-based control strategies.

III. AIMD-based Decentralized Control of PEVs

The problem of optimal allocation of a shared resource (here, power) among a set of competing agents (here, PEVs) arises in many different scientific and engineering applications. The AIMD algorithm, which had been initially introduced to address internet congestion problems and optimally share bandwidth between connected computers, may be efficiently used to solve this problem. In particular, AIMD is known to be very attractive when the number of agents is continuously changing (here, PEVs connect and disconnect from the grid), with limited or no communication abilities at all (so, one does not need to count the number of connected PEVs, and PEVs are not required to communicate any information). The algorithm consists of two alternating phases:

1) the additive increase (AI) phase: the resource consumption of each agent increases linearly in time with a certain step $\alpha > 0$;
2) the multiplicative decrease (MD) stage: each agent decreases its consumption in a multiplicative fashion, with a certain slope $\beta > 0$.

In particular, the MD step is performed when the so-called *Capacity Events (CEs)* occur, which means that the limit of the shared resource has been reached, e.g. all the available power is fully shared by the connected PEVs.

Let $t_1 < t_2 < \cdots < t_k < \ldots$ denote the time instants when such CEs occur; if t_{k+1}^+ is the instant after the agent i performs an MD step at time t_k, its share of the resource $x_i(t_{k+1}^+)$ is:

$$x_i(t_{k+1}^+) = \beta \lim_{t \to t_{k+1}} x_i(t), \tag{3}$$

and then agent i will return to the AI phase, until the next CE occurs.

Therefore, the equation describing the behaviour of the i'th agent is the following:

$$x_i(t) = \beta x_i(t_k) + \alpha(t - t_k), \quad t \in (t_k, t_{k+1}), \tag{4}$$

where t_k and t_{k+1} represent two consecutive time instants at which a CE occurs.

We now tailor the general AIMD algorithm for our application of interest as follows: each bus of the network represents an independent system with maximum allowed power $p_s^{\max}$ that is shared among PEVs, as described in Section II-C; let us denote with $p_{i,s}$ the power consumption of i'th agent at the s'th bus. Then a capacity event occurs at the s'th bus when the sum of the charge rates $p_{i,s}$ of all connected PEVs exceeds the maximum available power $p_s^{\max}$.

A. The Unsynchronized AIMD Control

The previously described version of the AIMD algorithm is also known as the *synchronized* AIMD, as *all* PEVs reduce the charging rate in a multiplicative fashion when a CE is notified. In reality, it is a sufficient that only a subset of PEVs decrease their charge rates to fall between the safe thresholds, and this possibility is useful to prioritize some PEVs over others [33]. This can be easily achieved by implementing a so-called *unsynchronized* version of the AIMD, where only a subset of PEVs react to a CE event by reducing the charge rates, in a probabilistic way.

Priorities of single buses can be formally stated by assuming that each PEV i has its own utility function $f_{i,s}(p_{i,s})$, where for convenience we shall consider convex, strictly differentiable utility functions $f_{i,s}(\cdot)$ that have a global minimum for the maximum allowed charge rate (i.e., here 3.3 kW). Roughly speaking, this implies that the optimal value of the utility function of PEVs (i.e., the minimum) is achieved when PEVs are charged at the maximum power. Accordingly, we formulate an optimization problem for each bus as follows:

$$\begin{cases} \min\limits_{p_{i,s}\in[0,3.3]\mathrm{kW}} \sum_{i=1}^{n(s)} f_{i,s}(p_{i,s}) \\ \sum_{i=1}^{n(s)} p_{i,s} \le p_s^{\max}, \end{cases} \tag{5}$$

where $n(s)$ is the number of PEVs connected to the s'th bus. Roughly speaking, Problem (5) works as follows: when there are no stability issues, then the minimization of the sum of the utility functions is achieved when PEVs are charged at the maximum charging rate; when the aggregated vehicles load reaches the power limit, then PEVs are charged at a lower charging rate and safer system configurations are restored.

As proved in [34], the optimization problem (5) can be solved in a fully decentralized way if we let each vehicle asynchronously perform the decrease step with probability

$$\pi_{i,s}(\bar{p}_{i,s}(t)) = \Gamma \frac{f'_{i,s}(\bar{p}_{i,s}(t))}{\bar{p}_{i,s}(t)}, \tag{6}$$

where $f'(\cdot)$ is the derivative of function $f(\cdot)$ with respect to time, and $\bar{p}_{i,s}(t)$ is the average charge rate of PEV i at bus s at previous time steps (to improve smoothness of the solution):

$$\bar{p}_{i,s}(t) = \frac{1}{t}\int_0^t p_{i,s}(\tau)\ d\tau, \tag{7}$$

and Γ appearing in (6) is a constant required to map $\pi_{i,s}$ into a probability, i.e., $0 \le \pi_{i,s} \le 1$. Equation (6) means that each PEV i reacts to a CE independently from the others, with the customized probability $\pi_{i,s}(\bar{p}_{i,s}(t))$, based on its historical power consumption. For the convenience of exposition, a pseudocode to implement the AIMD algorithm at each bus is now given in Algorithm 1.

Algorithm 1 Unsynchronized AIMD algorithm at the s'th bus

```
Initialisation: k = 1; Γ is broadcast;
  while k < k_simulation do
    if Σ_i p_{i,s}(k) ≥ p_s^max(k) then
      p_{i,s}(k+1) = { β p_{i,s}(k),       with probability π_{i,s}(p̄_{i,s}(k))
                     { p_{i,s}(k) + α,     with probability 1 − π_{i,s}(p̄_{i,s}(k)) ;
    else
      p_{i,s}(k+1) = p_{i,s}(k) + α;
    end if
    k = k + 1;
  end while
```

If convex utility functions are considered as in our case, and parameters α and β are the same for all agents, then the convergence analysis described in [34, Section 4] can be used, and the AIMD Algorithm 1 produces a long-term average that converges almost surely to the optimal solution of problem (5).

Remark 1: The AIMD algorithm has a number of significant advantages that are ideal for the charging problem: for instance, it can be implemented in a fully decentralized way without requiring PEVs to communicate anything to either other PEVs or charging stations; the solution is fully scalable independently from the number of agents; unlikely many other optimization approaches it is not required to solve a new optimization problem as new PEVs connect for charging, but a new optimized solution is obtained; all the communication is restricted to a CE event, i.e. a 0 or 1 bit of communication.

Remark 2: In a practical implementation of this algorithm in a power grid, we assume that it would be too complicated, and anyway not fundamental, to change the charging rates of PEVs too often, and for this reason we assume that the occurrence of CEs only occurs every $T_p = 30$ seconds, in accordance with [23].

IV. Case Study

A. Power System Set-up

The simulations discussed in this work are based on the well-known IEEE 39-bus 10-machine, which corresponds to the New England power system [35]. Synchronous machines are equipped with turbine governors and automatic generation control (for primary and secondary frequency regulation), automatic voltage regulators and power system stabilizers [30], [36]. The original network is slightly modified by replacing two generators with wind farms with detailed dynamic models of the doubly-fed induction generator, wind turbine and MPPT and voltage controllers of the power electronic converters [30], to mimic modern power systems with significant penetration of power generated from renewable sources (see Fig. 1).

The set of SDAEs describing the system (1), including the PEVs load ramps (2), are implemented and simulated using Dome, a Python-based power system software tool [25].

All 16 loads in the New England system are connected to the grid through an ULTC with discrete control of the voltage. Moreover, aggregated models of the PEV charging stations are assumed to be located at buses 3, 4, 7, 8 and 12; for simplicity, all stations have the same maximum charging rate, i.e. 3.3 kW, which is the typical nominal rate of domestic chargers

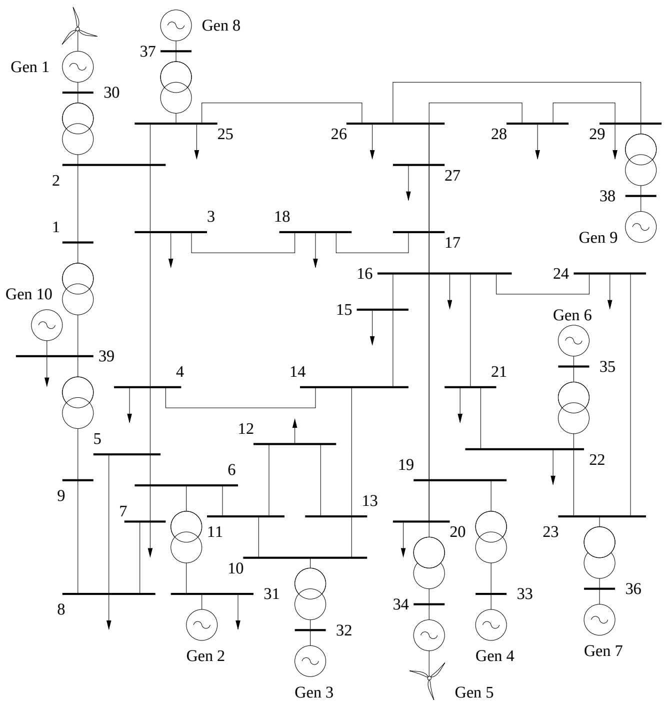

Fig. 1. Modified IEEE New England 39-bus power system. Generators 1 and 5 are modeled as wind power plants, with same capacity as the original synchronous machines.

[37]. SVCs have also been included at these buses to prevent collapses due to shortage of reactive power in the grid. Note that, since the focus is on PEVs, we have not included in the system a fast frequency control in wind power plants nor large batteries. These controllers, in fact, while can help improve the dynamic response of the system do not alter the conclusions that are drawn in this section.

The load consumption of the system has been increased by 10 pu with respect to the original data, and pre-existing loads (including industrial and residential loads) at each bus of the system are considered constant, which allows one to separate the effects of the PEVs from those of the conventional load.

Overall, the set of hybrid differential-algebraic equations that form the model of the system include 169 state variables, 398 algebraic variables, and 57 discrete variables.

Remark: The results presented in the remainder of this section refer to the specific power system described above. However, conclusions are general and may be extended to any other power system.

B. A Motivating Example: Uncontrolled Charging

The evening ramp due to the PEVs domestic charge may cause a system collapse, if it is uncontrolled [13]. We now simulate such a situation in our case study. For this purpose, we assume that PEVs are equally distributed among the 5 buses (3, 4, 7, 8 and 12, see Fig. 1), and that the arrival rate of PEVs for charging is about 120 veh/s. We do not give an exact starting time for the evening domestic charging scenario, as this may change from country to country, depending on local habits (e.g., dinner time). After 1 hour of simulation, about 432 000 PEVs would be connected for charging. Considering that the total number of cars in New England can be estimated equal to $5 \cdot 10^6$ vehicles,[1] this corresponds to assuming that about 8-9$\%$ of the total number of cars connect for charging during the evening peak within an hour. Figs. 2(a)-(c) show that actually the system is not able to cope with such a large volume of PEVs, and the system collapses.

The interesting aspect is that it may be hard to predict the upcoming instability, as the voltages and the frequency of the center of inertia ω_{COI} remain always very close to their nominal value 1 pu in all scenarios, even very close to the collapse (see Fig. 2(b) and Fig. 2(c)). In particular, Fig. 2(b) shows that the behaviour of the voltage values is mainly affected by the action of the ULTC devices. Also, we can observe that the system behaviour is independent of the Gaussian process parametrization, which characterizes the load ramp equation – see (2). Actually, we get quite the same results if we use a standard deviation ten times higher (see Figs. 2(d)-(f)) for instance. A careful handling of the reactive power is critical in the problem of charging PEVs in transmission networks. The SVCs included in the system prevent limit-induced bifurcations due to reactive power shortage. So the instability shown in this scenario refers to congestion in the transmission lines (saddle-node bifurcation) [38].

Remark: The analysis above can be conveniently carried out using a steady-state analysis, such as the well-known continuation power flow technique [39]. The goal of this simple example, however, is to show that the relatively slow time-scale of the PEVs ramp as well as the small capacity of each individual PEV prevent utilizing the frequency of the system, or the voltages of the buses, as reliable signals to implement a "smart" control. For this reason, as mentioned in advance, in the next sections we shall show examples where only power signals are used for control purposes. Finally, this example indicates that it is not enough to insert SVCs close to the charging points, as the intrinsic transfer capability limit of the grid cannot be avoided and is thus binding.

C. Synchronized AIMD

As previously discussed, we now consider the power-based AIMD controller described in details in Section III, where safety thresholds for the system are defined as a function of the static limits, i.e., the maximum power limits of the load buses.

The synchronized version of AIMD may be regarded as the maximally fair solution to solve the problem, as all PEVs have the same priority and should be charged on average with the same power rate. In this section, we present the system behaviour in the same settings of Section IV-B, with the action of our synchronized controller; the parameters of the AIMD are $\alpha = 0.34$ W, $\beta = 0.99$ and the threshold that triggers CEs is $p_s^{\max} = 180$ MW. The values of the AIMD parameters α and β are assumed to be the same in all simulations. In practice, the grid operator can tune these parameters as a trade-off between power efficiency (i.e., optimal utilization of the available power) and communication requirements (to prevent the system from frequently broadcasting CEs). Finally, the

[1] https://www.fhwa.dot.gov/policyinformation/statistics/2016/mv1.cfm#foot3

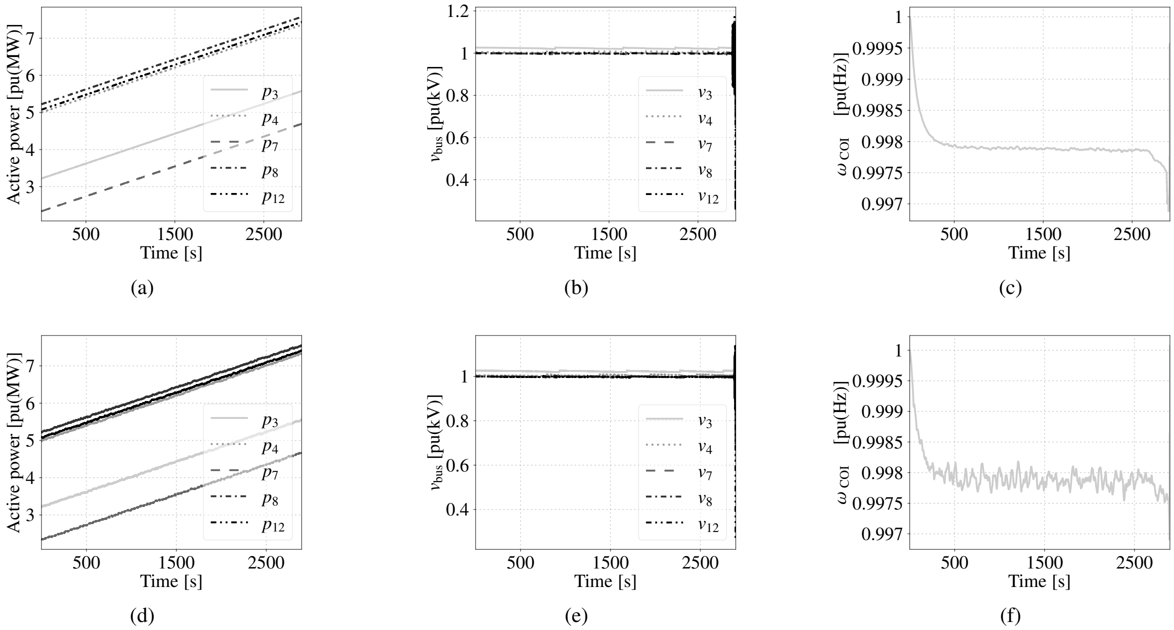

Fig. 2. Effect of uncontrolled charging of PEVs equally distributed among buses 3, 4, 7, 8 and 12, with an arrival rate of about 120 veh/s: (a) and (d) nodes power load profile; (b) and (e) nodes voltage response; (c) and (f) behaviour of the frequency ω_{COI}. The lower row shows results for a system with noise ten times higher than the upper row.

static limit $p_s^{\max}$ of each bus s is set equal to 80% of the actual bus power limit, assuming that grid operators will be conservative in estimating the maximum available power, for safety reasons.

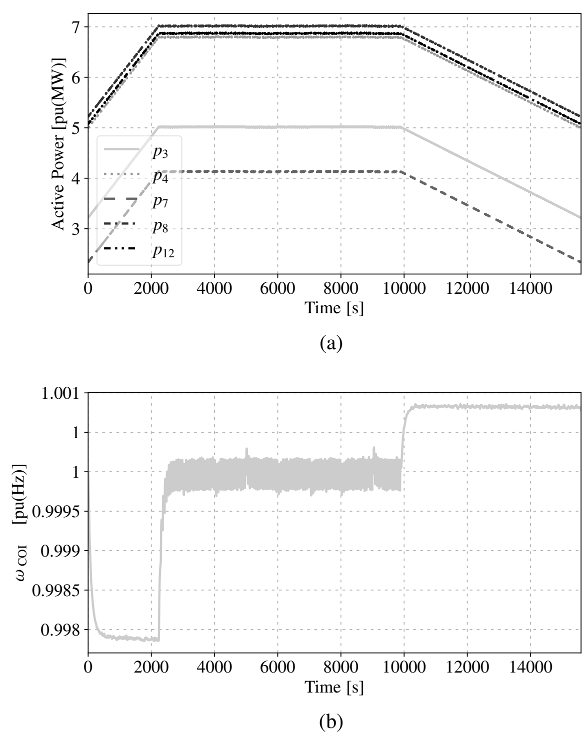

Fig. 3. Synchronized AIMD results; (a) active powers of loads at buses 3, 4, 7, 8 and 12 (where PEVs are); (b) frequency ω_{COI} response.

Fig. 3 summarizes the obtained results; the proposed control correctly manages to accomplish the charging task, as the control action prevents the power limit from being exceeded. Also, note that during the charging process, the frequency signal ω_{COI} lies within a safe range of $[0.996, 1.004]$ pu (Fig. 3(b)), thus making this control strategy realistically feasible and safe for the system stability.

Remark 1: Extensive simulations have been performed to validate the previous results, for different values of the loads, and for different PEVs spatial distribution: similar results have been obtained and for this reasons are not reported here. Moreover, it is important to note that the choice of parameters or thresholds does not change the main conclusion, i.e. that the control strategy is effective to prevent the system collapse.

Remark 2: The determination of the maximum loading condition, namely $p_s^{\max}$, of a grid is an analysis that is commonly carried out by system operators, independently from the presence of PEVs in the grid. This analysis is aimed at determining the available loading condition or, equivalently, the voltage stability margin of the grid. In the paper, we thus assume that the system operator has a good knowledge of the grid and defines $p_s^{\max}$ based on an analysis of the "available transfer capability", this takes into account an N-1 contingency analysis and the "transmission reliability margin" as defined by NERC [40]. Of course, $p_s^{\max}$ varies for different topologies of the grid but these are events that require updating the AIMD parameters periodically. For simplicity, however, in the simulations presented in the manuscript, we assume that $p_s^{\max}$ does not change during the PEV ramp-up. It should be noted that system operators often decrease the estimated value of $p_s^{\max}$ for security reasons. In the context of PEV charging, the lower the maximum loading condition limit $p_s^{\max}$, the longer the time required to charge all PEVs than strictly needed. On the other hand, the value of $p_s^{\max}$ is never increased as this would lead to a potential security issue for the grid.

D. Synchronized AIMD: a Frequency-Based Version

In Section IV-B we had noticed that it may be inappropriate to use a frequency-based control to charge PEVs, as stability issues may arise without significant changes to the frequency, until it is too late. In this section, we provide a simple simulation to support our statement. In particular, we consider exactly the same scenario of Section IV-C, but the AIMD algorithm is performed with respect to the bus frequencies, and a capacity event (and consequent reduction of power consumption by the connected PEVs) now occurs when the frequency falls below a safe threshold. AIMD parameters are $\alpha = 0.34$ W, $\beta = 0.99$ and $\omega^{\min} = 0.999$ pu(Hz) on a base of 60 Hz.

Remark 1: When PEVs perform an increasing step, and increase their charge rates, then the frequency decreases. For this reason the threshold corresponds now to a minimum allowed frequency (and not a maximum overall power).

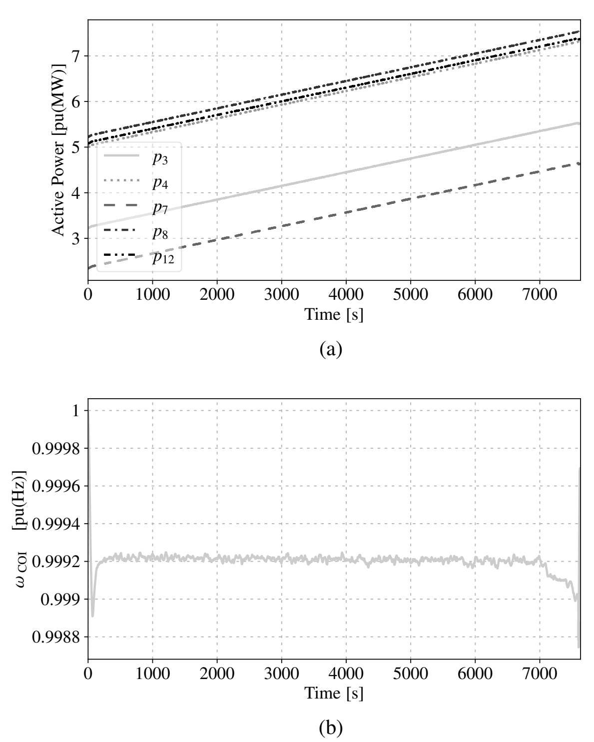

Fig. 4. Results of the synchronized AIMD frequency-based version; (a) active powers of loads at buses 3, 4, 7, 8 and 12 (where PEVs are); (b) frequency $\omega_{\rm COI}$ response.

Fig. 4 summarizes the obtained results. In particular, the charging process is very slow because a very conservative threshold for the frequency was chosen, and thus only very small changes of the load are allowed. Despite this conservative choice of the frequency threshold, instability occurs just the same, and when the system realizes of this event and starts reducing the charge rates of the connected vehicles, it is too late to prevent a network collapse from occurring.

Remark 2: Several simulations, solved with different thresholds, have confirmed that small variations of charging powers do not have a significant impact on the frequency of the system, and more importantly, that local frequency-based strategy may not be appropriate for the control of PEV charging to avoid lines congestion.

E. Unsynchronized AIMD

The unsynchronized version of AIMD is actually more interesting than its synchronized counterpart, as it is possible to prioritize PEVs as desired. This allows one to implement policies that favor certain PEVs (for instance because their owners are willing to pay more to be charged earlier, or also allow one to take into account energy requirements of the PEVs, or of the power grid). We now assume again that PEVs are be equally distributed and connected to the same five different buses, i.e. 3, 4, 7, 8 and 12. Then, we compare two scenarios, as follows.

S1: all PEVs at any s'th bus have the same objective function:

$$f_s(p_{i,s}) = -\frac{p_{i,s}^3}{3 \cdot p_{\max}}, \tag{8}$$

where $p_{i,s}$ is the power load of the i'th PEV plugged at bus s, and $p_{\max}$ is the maximum charge rate (i.e., 3.3 kW, as described in Section IV-A).

S2: all PEVs that are connected at buses 3, 4 and 7 have the following utility function f_{s_1}, while PEVs connected at buses 8 and 12 have utility function f_{s_2}:

$$f_{s_1}(p_{i,s}) = -\frac{p_{i,s}^3}{3 \cdot p_{\max}}, \tag{9}$$

$$f_{s_2}(p_{i,s}) = -\frac{p_{i,s}^4}{4 \cdot p_{\max}^2}. \tag{10}$$

In both scenarios, up to $88 \cdot 10^3$ PEVs connect for charging at each bus. The AIMD parameters are $\alpha = 0.34$ W, $\beta = 0.99$, $p_s^{\max} = 180$ MW, and $\Gamma = -1$.

Fig. 5 summarizes our results for Scenario S1 (above) and Scenario S2 (below). The effect of the different objective functions can be noticed by comparing Fig. 5(a), where the algorithm fairly manages to complete charging at all buses at about the same time, and Fig. 5(c), where the vehicles associated with a steeper utility function (prioritized vehicles) finish earlier than the vehicles of other buses. Hence, results confirm qualitatively our expectations; in particular, to better appreciate the effect of the prioritization in a quantitative way, we compare the 5 buses characteristics also in Table I.

TABLE I
UNSYNCHRONIZED CONTROL PERFORMANCE WITH PRIORITIES

Bus #	Mean power rate	Global charge duration
3	1.537 kW	4 hours, 18 minutes
4	1.531 kW	4 hours, 19 minutes
7	1.53 kW	4 hours, 19 minutes
8	1.702 kW	3 hours, 53 minutes
12	1.727 kW	3 hours, 49 minutes

In addition, Figs. 5(b) and 5(d) show that the frequency always lies in a safe range $[0.998, 1.001]$ pu. These results show that by designing steeper, or less steeper utility functions, it is possible to prioritize some vehicles, if desired, as an alternative to a fair approach.

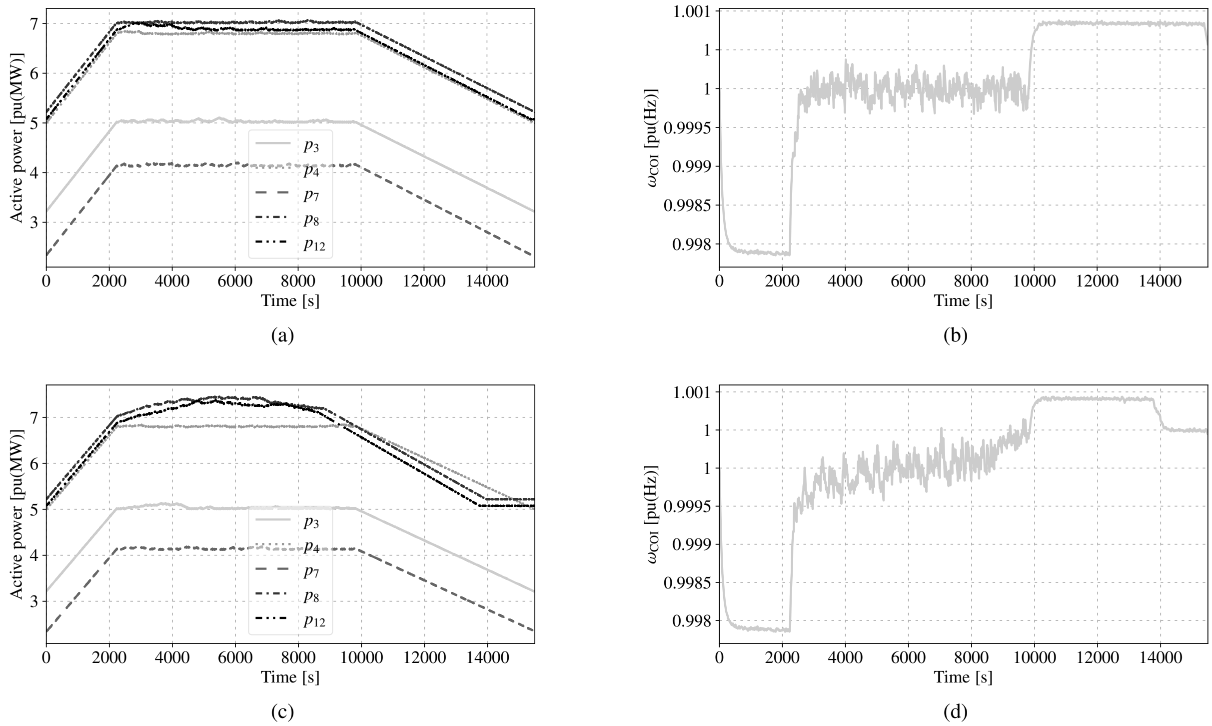

Fig. 5. Unsynchronized AIMD results; (a) active powers of loads at buses 3, 4, 7, 8 and 12 (where PEVs are), decentralized controller with no priorities; (b) ω_{COI}, decentralized controller with no priorities; (c) active powers of loads at buses 3, 4, 7, 8 and 12 (where PEVs are), decentralized controller with priorities; (d) ω_{COI}, decentralized controller with priorities.

F. Different Priorities Within the Same Bus

The previous example assumes that all PEVs connected to the same bus have the same utility functions. While this is convenient to illustrate the proposed control strategy, in practice, PEVs connected to the same bus may have different utility functions. In this section, we consider that PEVs are equally distributed and connected to buses 3 and 4. At each bus, half of the PEVs have the utility function f_{s_1} (see (9)), and the other half have utility function f_{s_2} (see (10)). Fig. 6 shows the system behaviour in terms of the power loads at buses 3-4. The control strategy is effective, as with the same number of PEVs, the power grid would have collapsed in an uncontrolled scenario. Moreover, PEVs with prioritized charging end earlier than those without priority, independently from the bus at which they are connected.

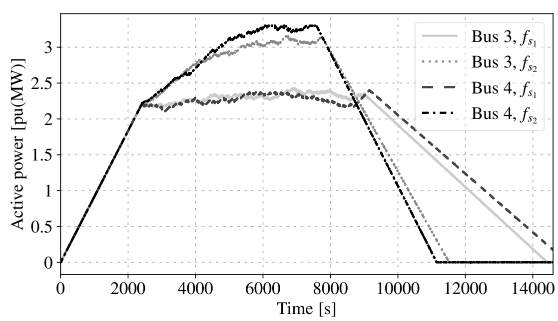

Fig. 6. Active powers of PEVs subgroups at buses 3 and 4: prioritized vehicles (i.e., with utility function f_{s_2}) finish charging earlier than non-prioritized vehicles (with utility function f_{s_1}), independently from the bus at which they are connected.

V. Conclusions

The paper proposes a decentralized AIMD algorithm for charging PEVs without affecting the system stability, by dynamically allocating the available power in an optimized way. A first interesting result of our work, is that automatic frequency-based, or voltage-based control strategies fail to preserve the stability of the network. On the other side, power-based control strategies can be used to automatically and seamlessly adjust charging rates of PEVs to optimize a desired cost function of interest.

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