Investigation of AIMD Based Charging Strategies for EVs Connected to a Low-Voltage Distribution Network

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Abstract. In this paper we consider charging strategies that mitigate the impact of domestic charging of EVs on low-voltage distribution networks and which seek to reduce peak power by responding to time-of-day pricing. The strategies are based on the distributed Additive Increase and Multiplicative Decrease (AIMD) charging algorithms proposed in [5]. The strategies are evaluated using simulations conducted on a custom OpenDSS-Matlab platform for a typical low voltage residential feeder network. Results show that by using AIMD based smart charging 50% EV penetration can be accommodated on our test network, compared to only 10% with uncontrolled charging, without needing to reinforce existing network infrastructure.

Keywords: EV charging, AIMD, Smart Grid, Distributed algorithm.

1 Introduction

In the near future, with an increasing number of EVs plugging into the grid in residential areas it is likely that coincident uncontrolled charging will overload local distribution networks and substantially increase peak power requirements. It is therefore essential that careful consideration is given to developing smart grid infrastructure and charging strategies to mitigate the impact of the roll out of EVs on the grid. EV charging strategies have been the focus of considerable research effort in recent years [1]-[4]. Clement-Nyns et al. [4], propose a coordinated charging method is to minimize power losses and maximize the main grid load factor. In Richardson et al. [2] a technique based on linear programming to determine the optimal charging rate is developed in order to maximize the total power that can be delivered to EVs while meeting distribution network constraints. In [1] a coordinated charging algorithm using both quadratic and dynamic programming is employed to shift the EV loads to off-peak times while minimizing the power losses for both deterministic and stochastic data. In [6] a transportation micro-simulation is employed to secure power system operation using a multi-agent system (MAS) to coordinate EV charging behavior. In [8], to maximize a customer's own utility, a simple adaption strategy based on price

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feedback is effectively used to solve the distributed EV charging problem in the smart grid. Most recently, Stüdli et al. [5] propose charging strategies based on Additive Increase and Multiplicative Decrease (AIMD) algorithms that can be implemented in a decentralized fashion to maximize power utilization by EVs while achieving a fair allocation of power across customers. In this paper we investigate the performance of AIMD based charging strategies for EVs connected to a low-voltage distribution network with regard to mitigating the impact of EVs on the grid from the perspective of transformer loading levels and voltage profiles. In particular, we propose an extension of the AIMD charging strategy that seeks to reduce peak power by responding to time-of-day pricing. The strategies are evaluated using simulations conducted on a custom OpenDSS-Matlab platform for a typical low voltage residential feeder network.

2 Methodology

2.1 Assumptions

We make several assumptions in investigating the impact of EV charging on a LV distribution network, most of which are consistent with previous studies in [2], [3], [5] and [6]. The assumptions are as follows:(i) All EV batteries have a capacity of 20 kWh; (ii) Each EV charger is connected to a standard household outlet at 230V; (iii) The maximum power output from the EV home charger cannot exceed 3.7kW; (iv) Each EV has the ability to adapt its charge rate in real-time and continuously; (v) The initial state of charge (SOC) energy request for each EV ranges from 5kWh to 15kWh uniformly; and (vi) Power flow is unidirectional from grid to vehicle.

In order to implement smart charging strategies in practice, several specific assumptions are also required in relation to the communication and sensing capabilities of the smart grid infrastructure, namely:

1. Each EV charging point is equipped with a communication device and is able to receive broadcast signals from a local server.
2. Each EV charging point is able to detect its line voltage in real-time.
3. Each EV charging point is able to send the voltage signal back to the local server and regulate its own charge rate by commands from the server.
4. A centralized server is installed in the substation and is able to sense the available resource and broadcast signals to the local servers.

2.2 Distributed AIMD Algorithm

The basic idea of AIMD was originally applied in the context of decentralized congestion control in communication networks [7]. In [5] Stüdli et al. proposed applying AIMD to EV charging problems and investigated a number of practical scenarios. In this paper, the framework we assume is consistent with the domestic charging scenario demonstrated in [5]. The basic decentralized AIMD algorithm for EV charging is summarized as follows:

while *battery not charged* **do**
  if $P(k) < \overline{P}(k)$ **then**
    $c_i(k+1) = c_i(k) + \alpha.\varDelta T$
  else
    generate uniform random number, p **if** $p < p_i$ **then**
      $c_i(k+1) = \beta^{(1)}.c_i(k)$
    else
      $c_i(k+1) = \beta^{(2)}.c_i(k)$
    end
  end
end

Here, $c_i(k)$ is the charge rate of the ith EV, $P(k)$ is the total power demanded by all the EVs connected and $\overline{P}(k)$ maximum power available to charge EVs at the kth time instant. α is the additive constant value in kW/s, $\beta^{(1)}$, $\beta^{(2)}$ are the multiplicative constants, which are selected at random with probability p_i and $\varDelta T$ is the time interval between EV charge rate updates. During operation each active EV charge point additively increases its charge rate until a capacity event occurs at which point it applies a multiplicative decrease to the charge rate. A capacity event occurs when the power $P(k)$ demanded by the active EV charger points exceeds the maximum available power $\overline{P}(k)$. Here $P(k)$ is computed as:

$$P(k) = \sum_{i=1}^{N(k)} c_i(k), \tag{1}$$

where $N(k)$ is the number of active chargers at the kth time instant. The $P(k) < \overline{P}(k)$ capacity event condition is monitored by a central monitoring station (server) which broadcasts a message to the charge points when events occur. As disscussed in [5], this algorithm guarantees an equitable 'average' distribution of the power if each charge point chooses the same α, β and p, while requiring a minimum of communication infrastructure.

2.3 Formation of the Smart Charging Strategy

In this section a new charging strategy is formulated based on the decentralized AIMD method. The objective is to achieve benefits for both utilities and customers. In order to do this we incorporate power system constraints on voltages and load balance into the AIMD implementation so that all EVs can share the maximum amount of available power fairly while ensuring that the distribution network continues to operate within acceptable limits. In addition, we modulate the available power signal in response to a varying electricity price [11] to affect a shift in EV loads away from periods of high demand, thereby reducing peak-power capacity requirements and ultimately the cost to the consumer.

The infrastructure needed to support the proposed strategy consists of EV charging points, local monitoring stations at the distribution transformers and a central monitoring station at the main sub-substation. Each charge point must be capable of running the AIMD algorithm, measure its own socket voltage $V_i(k)$, and maintain bidirectional communication with the local monitoring station for its residential area. The role of each local monitoring station is to: (i) receive voltage capacity event signals from the EV chargers in its local residential area and generation capacity broadcasts from the central monitoring station; (ii) detect local infrastructure capacity events, and (iii) broadcast capacity event information to the charge points in its area. The role of the central monitoring station is to monitor available power in real-time and broadcast generation capacity events via the local monitoring stations to the charge points.

With this infrastructure in place the basic AIMD algorithm running on each charge point is modified to respond to all capacity events (voltage, infrastructure and generation) and to transmit a voltage event message to the local monitoring station when the voltage level drops below a minimum acceptable level, V_{min}. The pseudo code for the algorithm is as follows:

while *battery not charged* **do**
  if *capacity event* **then**
    generate uniform random number, p **if** $p < p_i$ **then**
      $c_i(k+1) = \beta^{(1)}.c_i(k)$
    else
      $c_i(k+1) = \beta^{(2)}.c_i(k)$
    end
  else
    $c_i(k+1) = c_i(k) + \alpha.\Delta T$
  end
  if $V_i(k) < V_{min}$ **then**
    transmit voltage event message
  end
end

The local monitoring station for a given residential area broadcasts a capacity event signal to the active EV charge points in its area if any of the following conditions are satisfied: (i) A generation capacity event is broadcast by the main substation; (ii) A voltage event message is transmitted by any of the charge points in its residential area; or (iii) A local infrastructure constraint violation is detected (e.g. transformer overload).

The central monitoring station is responsible for determining the power available and broadcasting a generation capacity event when this is exceeded. The total instantaneous power consumption is given by

$$P(k) = \sum_{j=1}^{N} h_j(k) + \sum_{i=1}^{N(k)} c_i(k), \tag{2}$$

where $h_j(k)$ represents the non-EV power consumption for the jth house on the distribution network at time k, $c_i(k)$ is the charge rate of the ith active EV charge point, N is the number of houses on the distribution network and $N(k)$ is the number of active charge points. The instantaneous available power is computed as

$$\overline{P}(k) = P_{rated} - \lambda - \Delta(k). \tag{3}$$

Here P_{rated} (kVA) is the maximum capacity that can be drawn from the substation and is the lesser of the available generation capacity or the substation rating. λ (kVA) is a constant 'safety margin' for secure operation. $\Delta(k)$ (kVA) is a time varying factor introduced to create an artificial reduction in available power at times of high electricity prices and is computed as

$$\Delta(k) = (E(k) - E_{min}).\xi. \tag{4}$$

In (4) ξ is a constant tuning parameter, $E(k)$ (cent/kWh) is the Time-of-Use(TOU) price [11] at time k and E_{min} is the minimum TOU price during the day.

In the AIMD EV charging study in [5] EV charging was considered independently of other household power consumption with $P(k)$ computed according to (1). This results in a significant communication overhead as the central substation cannot distinguish EV charge point power usage from other residential power consumption, hence this information must be communicated continuously to the central monitoring station by the active EV charge points. In our formulation $P(k)$ and $\overline{P}(k)$ are defined in terms of overall residential power consumption levels, hence $P(k)$ can be directly sensed at the central substation.

3 Simulation Platform

To evaluate the performance of the proposed AIMD charging strategy a test distribution network incorporating EVs is simulated based on a typical LV residential feeder layout. A simplified schematic diagram for the test network is given in Fig. 1. In our simulations, the voltage is set at 1.05pu at the source end of the external grid. A 2MVA distribution substation is connected to the external grid to bring the voltage level to 10kV. This substation feeds three distribution transformers serving residential areas. Each distribution transformer is connected by an unbalanced 336 MCM ACSR transmission line of different length (modeled as Pi-Equivalent circuits). Both household loads and EV charging loads are connected at the secondary side of each distribution transformer. As illustrated in Fig.1, the household loads with EV charging points are separated into three phases, and the number of houses connected to each phase is indicated in parenthesis. Non-EV charging loads are lumped together using balanced three phase modeling. The distance between each house connected to a given phase is randomly chosen between 10-50m. To simulate EV charging with this network a custom OpenDSS-Matlab platform was employed. OpenDSS [9], an open source electric power Distribution System Simulator, was used to simulate the test network and calculate its power flow distribution and voltage profiles at each sample instant. A master programme was developed in Matlab to simulate the operation of network over a period of time, with the following steps performed at each sample instant:

(a) simulate EVs connecting and disconnecting to charge points;
(b) compute the instantaneous charge rates according to the AIMD algorithm described in the previous section;
(c) generate updated OpenDSS simulation parameters;
(d) call the OpenDSS software to simulate the current state of the distribution network.

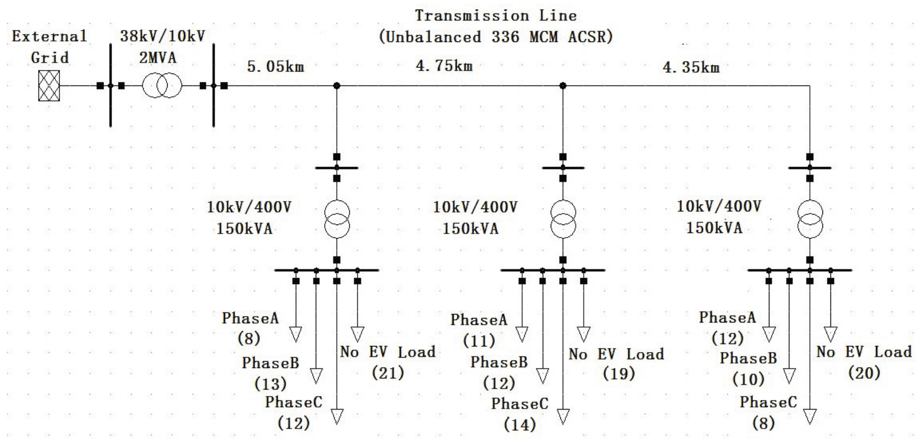

Fig. 1. Schematic diagram of the distribution network

4 Case Study

Utility companies hope that in the short to medium term (10-20 years) smart charging strategies will enable them to accommodate the extra loads represented by EV charging without needing to upgrade their distribution network infrastructure. To predict the impact of EV charging on the grid we assume a maximum penetration of EVs of 50% in the medium term and simulate the performance of both uncontrolled and smart charging under these circumstances for typical Irish winter grid loads. Residential power consumption winter profiles were generated based on residential customer smart meter electricity trial data provided by the *Commission for Energy Regulation* (CER) in Ireland [12].

For our AIMD algorithm implementation E_{min} and $E(k)$ are set in accordance with [11], ξ=12, P_{rated} is set to 450kVA and λ=50kVA. V_{min} is selected as 0.9pu, the minimum acceptable voltage level in Ireland, and the capacity limit of each of the distribution transformers is set to 150kVA. Charging is performed in accordance with the assumptions set out in Section 2.1. We also assume that each EV is automatically disconnected from the grid when it is fully charged. Updates are performed every 5 minutes (i.e. $\Delta T = 300$s).

From Irish traffic survey data [10] it can be concluded that the majority of commuters arrive home between 4pm-8pm each day. To capture this in our simulation we generate EV home arrival times from a normal distribution centered at 6 pm with a standard deviation of 1 hour. It should be noted that this falls within the period normally associated with peak-power on the Irish grid (5-7pm), hence unregulated EV charging has the potential to substantially increase peak-power on the grid. Fig. 2(a) shows the voltage profile of the minimum voltage level in the distribution network for three different scenarios: (i) no EVs on the grid; (ii) uncontrolled charging of EVs; and (iii) charging of EVs with our proposed AIMD smart charging algorithm. The corresponding power flows at the substation are plotted in Fig. 2(b). As expected the impact of uncontrolled EV charging is to increase the voltage drops significantly. The Minimum non-EV voltage on all buses was 0.92 pu during peak-periods, but with uncontrolled EV charging coinciding with peak-power, bus voltages drop to 0.87 pu, leading to voltage issues on the network. In addition, transformers are overloaded with demanded power exceeding the available power by 65%. Thus, for our test distribution network uncontrolled charging at 50% EV penetration cannot be supported. Simulations conducted for different EV penetration levels (not included) show that the maximum level that can be sustained under these conditions is 10%. In contrast, with AIMD smart charging voltage sags are substantially reduced (0.93pu compared to 0.87pu) and capacity and infrastructure constraints are maintained while making best use of available power.

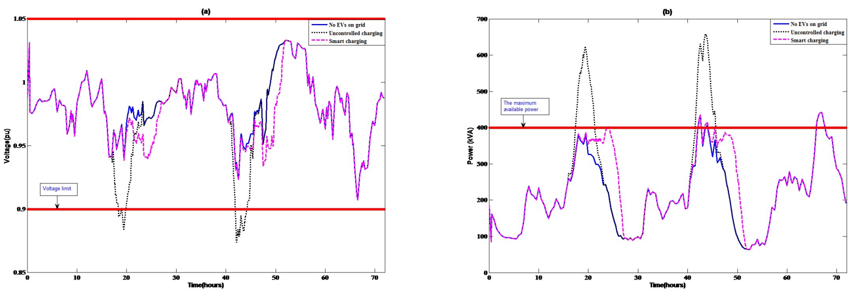

Fig. 2. Comparison of uncontrolled and AIMD smart charging of EVs for a typical LV network over a 72 hour period in mid-winter (0 = midnight): (a) Minimum voltage on the distribution network; (b) substation power flow

The daily price variation signal $E(k)$, set according to [11], is plotted in Fig. 3(a). The impact of the inclusion of this term to modulate the available power signal in the AIMD algorithm is clearly evident when comparing the voltage sags for uncontrolled and smart EV charging. In the latter the significant voltage sags have been postponed until after the peak-time (around 9 pm) reflecting a corresponding shift in the EV charging load. This is further highlighted in Fig. 3(b), which shows a comparison of the EV load profile obtained using AIMD with and without the inclusion of the price modulated available power term ($\Delta(k)$) in (3)).

Table 1 provides a summary comparison of the different charging strategies considered in the paper. From the table it can be seen that *SmartP* (i.e. price-adjusted AIMD) EV charging provides the best overall performance with the lowest line voltage drops, smallest maximum power requirements and the cheapest charging rate (40-50% less than with uncontrolled charging).

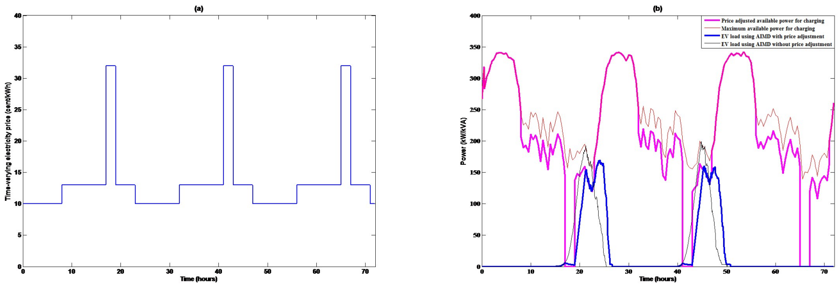

Fig. 3. (a) Plot of the TOU electricity price signal $E(k)$; (b) Comparison of EV loads obtained using AIMD smart charging with and without price adjusted available power.

Table 1. Comparison of all charging scenarios considered

Scenarios	*Mini Voltage(p.u)*	*Max Load[1] (%)*	*Energy[2] (kWh)*	*Cost(cents/kWh)*
NoEV	0.92	108	-	-
Unctrl	0.87	165	10.15	19.70
Smart[3]	0.91	118	10.15	12.69
SmartP[4]	0.92	109	10.15	10.90

5 Conclusions

In this paper, a novel distributed smart EV algorithm has been proposed for managing EV charging on a low-voltage residential distribution network. The algorithm, which is based on the AIMD EV charging algorithms proposed in [5], is designed to take account of capacity, infrastructure and voltage constraints on the network and encourage EV charging at off-peak times. Using a simulation of a representative low-voltage residential distribution network with 50% EV penetration the proposed algorithm has been benchmarked against uncontrolled charging and shown to effectively mitigate the impact of EV charging on the grid. Our results show that for the scenarios considered the proposed AIMD charging strategy is able to comfortably support up to 50% EV

[1] Maximum loading as a percentage of the sub-station rating (400kVA).
[2] Average energy per EV per day.
[3] AIMD smart charging without price adjustment.
[4] AIMD smart charging with price adjustment.

penetration without requiring strengthening of the distribution network infrastructure. Furthermore, by taking into account TOU pricing a significant reduction in the cost of EV charging can be achieved for the customer. Thus, the proposed AIMD based charging strategy has the potential to provide significant benefits to both EV owners and to utility companies.

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