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# Decentralized Additive Increase and Multiplicative Decrease-Based Electric Vehicle Charging

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***Abstract*—Electric vehicle (EV) transition and low-cost renewable energy generation are putting power grid under a challenging transformation. Number of power electronics actuators connected to the grid is increasing, and the legacy control methods employed on the grid are not responsive to this growing demand. Thus, the grid integration of EVs and their charging management requires a system-wide solution that is scalable, autonomous, and stable. In this article, we investigate two very complex networks: *Internet* and *power grid* in the context of controlling mass-scale EV charging problem. We adapt the well-known additive increase-multiplicative decrease (AIMD) algorithm used in the Internet congestion control to EV charging in a distributed fashion. We develop an adaptation of the Internet's congestion control method for power grid considering the unique grid constraints using a decentralized concept. The advantage of the proposed method lies in its low-cost (memory-less) congestion detection mechanism based on only local voltage measurements. Results show that decentralized AIMD can successfully help flatten the peak loading caused by high EV penetration. To test the algorithm, a distribution grid model is designed based on IEEE 37-node test feeder with realistic load modeling. Finally, the results are presented in comparison with two other control architectures.**

***Index Terms*—Additive increase-multiplicative decrease (AIMD), decentralized control, electric vehicles (EV), grid integration, peak shaving, smart charging.**

## NOMENCLATURE

| | |
|---|---|
| AIMD | Additive increase multiplicative decrease. |
| SOC | State of charge [%]. |
| E2E | End-to-end. |
| TCP | Transmission control protocol. |
| RTT | Round-trip time [s]. |
| RTO | Re-transmission timeout [s]. |
| EWMA | Exponentially weighted moving average. |
| $R(t)$ | Sending rate. |
| $\alpha$ | Additive increase parameter. |
| $\beta$ | Multiplicative decrease parameter. |
| AvgRTT | Mean of RTT [s]. |
| StdRTT | Standard deviation of RTT [s]. |
| $\lambda$ | EWMA parameter. |
| $\omega$ | EWMA parameter. |
| $I_C$ | Charging current [A]. |
| $V(t)$ | End node voltage [V]. |
| AvgV | Mean of voltage [V]. |
| StdV | Standard deviation of voltage [V]. |
| $V_{\text{th}}$ | Voltage threshold [V]. |
| $p$ | Decision probability. |

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## I. INTRODUCTION

ELECTRIC vehicle (EV) transformation can be an important turning point for the utility grid toward more flexible and customer-oriented operation. With decreasing prices, EVs are anticipated to increase in sales by 2025 [2]. However, conventional electric utility grid operation is still not prepared for such a change. This potential mass EV penetration brings new problems in the distribution grid such as extreme voltage drops, frequent and increased peak loading, thermal overheating, and failure of equipment [3]–[10].

The EV charging solutions proposed in the literature to this oncoming problem can be split into three categories. These are direct, indirect, and autonomous methods [11]. In direct and indirect methods, extensive amount of data carrying information such as State of charge (SOC), grid congestion signals, price tariffs, vehicle arrival, and departure times need to be continuously exchanged between EV and the grid. Such signals are necessary to detect and control the charging of an EV. Ma *et al.* [12] proposes a decentralized charging control algorithm aiming to minimize the charging cost. The authors use the game theory and claim that the Nash equilibrium converges to a valley-filling strategy for large population of EVs. They assume that price and non-EV demand information are broadcast to EVs, and each EV determines their own charging rate based on this information. This information exchange still requires a dedicated communication network, which may not be available. Amini *et al.* [13] also focuses on reducing the charging cost for EVs. They formulate the EV charging problem as a linear programming price-based optimization. They use the Dantzig–Wolfe decomposition to decompose the problem into small subproblems. Their solution also requires the electricity price to be communicated to all EVs. The above methods require deployments of expensive networking and communication infrastructure at end-nodes. It is conventionally thought as more reasonable to use these methods when integrating EVs to the grid, however, they are not cost-effective and practical solutions, especially at massive scales. To that end, such centralized solutions are considered to be more demanding to realize than distributed ones in terms of the investment cost and inherent limitations (e.g., latency, data loss, and connection problems) of its communication network.

The internet's backbone data carrying traffic also had congestion problems in the past similar to the EV charging network. At the number of endpoints of the Internet drastically increased, the congestion management with scalable and easy deployment became a critical problem [14]. Solutions that ensure network stability by avoiding congestion [15], maximizing E2E throughput and guaranteeing the fair and efficient use of network capacity became necessary after the "congestion collapse" [16], [17] was practically observed. The multiprovider structure of the Internet and the scalability of the problem made it more convenient for the solution to be best implemented at smart end-points that operate end-to-end with completely local measurements. This decentralized E2E congestion management approach [18] was adopted by the mainstream transmission control protocol (TCP). Despite all the efforts exerted for centralized [19] and network-supported [20] control of congestion aiming at more efficient and fairer network capacity usage, many of these solutions were only implemented at network edges and unable to span multiple providers due to its limited deployment. As massive scales, decentralized structures operating at smart end-points with local/E2E measurements have become the most successful in terms of practicality and solving the congestion (or data traffic rate) control problem.

The Internet's existing TCP uses the additive increase-multiplicative decrease (AIMD) algorithm [15] for congestion avoidance. AIMD takes actions every time it is triggered by congestion events taking place on the network. The level of the congestion is measured by how long it takes to get the acknowledgement of a transmitted data packet from its destionation, a.k.a round-trip-time (RTT). Such a decentralized learning architecture yields some partial knowledge of the congestion that might be present in the shared network channels/links. Low and Lapsley proved that this straightforward solution can provide stable operation and proportional fairness among users [21]. As far as allocating a limited source among competing participants in a distributed fashion is concerned, AIMD shines out as a strong candidate. It can be adapted into many diverse fields with similar problems. Corless *et al.* provides a detailed mathematical analysis and modeling for AIMD and also discusses possible areas of applications [22].

The success of the AIMD algorithm in handling the Internet's backbone traffic due to congestion has been the main source of motivation for this article to adapt it for EV charging problem. Power system and Internet both have multi-input multi-output, complex, and very dynamic operation systems as illustrated in Fig. 1. When investigated carefully, one can observe multiple one-to-one parameter analogies between Internet operation versus EV charging as summarized in Table I.

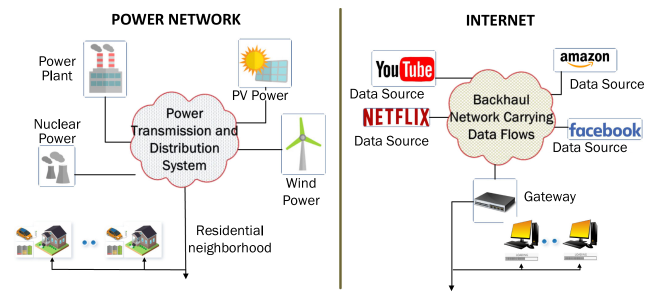


Fig. 1. Analogy between EV charging over the power grid and the downloads over the Internet.

TABLE I
EV CHARGING AND INTERNET OPERATION: ONE-TO-ONE COMPARISON

| | EV Charging | Internet Operation |
|---|---|---|
| Transfer parameter | Power | Data |
| | Power congestion | Network congestion |
| | Cost of charging power | Cost of data transfer |
| | Charging rate | Download rate |
| | Node voltage | Round-trip-time (RTT) |
| Time scale | Minutes to hours | milliseconds to seconds |
| Performance | State of charge (SoC) | Quality of service (QoS) |
| Fairness | No policy yet | Proportional fair |
| Control | Various [7], [10], [11], [23]; none scaled up yet | AIMD |

The key contributions of this article are as follows.

1) Developing a power distribution system level solution for the EV charging problem inspired by the Internet's proven, stable, and autonomous architecture.
2) Adaptation of the AIMD algorithm's congestion detection mechanism for grid congestion via local voltage information.
3) Large-scale simulation of the proposed decentralized AIMD algorithm on a distribution grid with 416 customers.

The organization of this article is as follows: Section II provides the background literature primarily on AIMD-based EV charging control algorithms. Section III introduces the basics of the AIMD algorithm as implemented on computer networks and proposes a counterpart of the algorithm for EV charging. Section IV presents the distribution grid and dynamic load model used to benchmark the algorithm. Section V discusses the simulation scenarios and results. Finally, Section VI concludes this article.

## II. RELATED WORK

Due to the similarity of the two systems, some research work studied the adoption of the AIMD algorithm for EV charging [24]–[26]. The authors in [27] improved this idea by considering the power system constraints. Beil and Hiskens investigated the impacts of an AIMD-based charging algorithm on the system dynamics of a distribution grid system [28]. Liu *et al.* compared two AIMD-based charging algorithms with an ideal centralized solution to assess the performance on low voltage (LV) distribution grid [29]. Crisostomi *et al.* studied the allocation problems of power generation for distributed energy sources in microgrids by proposing an AIMD approach [30]. However, they do not provide any detail on how the congestion signals are produced, transmitted, and implemented in the field but assume that users are notified of this information. Xia *et al.* uses historical voltage measurements to calculate a voltage threshold for triggering the AIMD algorithm [31]. However, this may cause a flexibility problem when it comes to adapting to the change of dynamics of the grid, i.e., EVs or photovoltaic systems. Power flow analysis is suggested in [32] to find and set voltage thresholds. However, this solution requires an offline computation, thus it cannot respond to new real-time conditions. Charging fairness, another important concept for charge management, is not analyzed in the aforementioned studies.

The congestion level on a distribution network can be mapped to the voltage drop [33]. The decentralized version of an AIMD-based charging algorithm utilizes the local voltage measurements and maps those to threshold voltage values, and it is triggered by voltage drops. We previously presented an analysis to extract the relationship between the voltage drop and the electrical distance to substation in a simplified radial distribution grid model [34]. The result of this analysis proved that avoiding voltage violations and providing charging fairness can be simultaneously archived *if the right voltage thresholds values are found based on each node's location in the grid*. Therefore, in the follow-up studies, the effect of such a congestion resulting from EV integration on different levels were explored on a low-voltage distribution grid by means of statistical analysis [35]. In [36], we used historical data of voltage measurements to extract these statistics and assign threshold values, which could be more expensive to implement due to its memory requirements. In this article, however, rather than collecting statistical voltage data which takes up to a week, we propose a very similar method used in the original AIMD control to determine the threshold values real-time using EWMA and Chebyshev's outlier estimation method. We further verify the fairness among EV owners in establishing proportional fairness among users based on their distance to the substation. The main objective is controlling each individual EV's charging based on their local voltage measurements that indirectly carry information regarding the grid status. Thus, the potential grid problems (e.g., voltage drops, congestion, etc.) can be linked to voltage and avoided by means of this autonomous decentralized solution, which also provides a fair distribution of the aggregated capacity among the users. This article provides an extended version of the preliminary paper [1]. We extended the previous study via providing 1) a more detailed explanation of the proposed algorithm on how it detects congestion in the grid, 2) more simulation results and analysis that highlight the contributions, and 3) a comparison study with two other algorithms in the literature.

## III. Distributed AIMD Algorithm for On-Board EV Charging

### A. Basic AIMD Operation

The AIMD is implemented as a congestion control and avoidance algorithm in TCP/IP protocol stack. It runs at every

**Algorithm 1:** AIMD Algorithm for the Internet End-Points.

**Input:** Previous sending rate: $R(t)$
**Output:** New sending rate: $R(t+1)$
**Parameter:** Additive increase parameter: $\alpha(t) > 0$
**Parameter:** Multiplicative decrease parameter: $0 < \beta(t) < 1$

```
if Network congestion NOT detected then
    R(t+1) = R(t) + α(t)
else
    R(t+1) = β(t) × R(t)
end if
```

end-point rather than network routers, which makes it an easily scalable and distributed algorithm when the network is further extended. When adding new end-points, it is required that only these end-points implement the AIMD operation without any updates to the routers. This approach relies on fate-sharing which is the assumption that nobody wants the network to fail. Therefore, every end-user implicitly agrees to take action when congestion occurs even tough every user is greedy by nature. The goal of such an agreement is to establish a stable, fair, and efficient system. The AIMD algorithm accomplishes the goal by adjusting the sending rate either by additive increase (AI) or multiplicative decrease (MD) depending on the network congestion. Algorithm 1 describes the implementation of AIMD.

To look for any indication of congestion, TCP/IP [18] measures the change in the network capacity by looking at the end-to-end network throughput, and *probes* the network by constantly doing AI on the sending rate as long as it does not observe any congestion. The throughput here refers to the rate of successful packet delivery over the network. This rate tends to increase as a result of the AI phase until a point at which the capacity of the network is reached. Such an event occurs due to long packet queues on the routers, and this causes slow network traffic (congested network), which eventually causes delays and packet losses. Loss or delay in packets result in lower throughput, and therefore, sending rate should be decreased when the network is congested. This is the point, where the MD is implemented. In this phase, end-users reduce their sending rates, and thus free up the network resource for further distribution. The reduction is done by each user individually via rescaling their sending rate by a factor less than one, which is the multiplication decrease. AI and MD phases keep following one another as the users are competing for the resource. The desired operation region, termed as *"knee,"* defines the set of points on the throughput versus rate curve right before the roll-off, where the capacity is reached and congestion collapse occurs (see Fig. 2).

One important feature of TCP/IP is its ability to detect the congestion autonomously without the need of a central command [14]. This is achieved through local RTT measurements. When data packets arrive at their final destination, an acknowledgment (ACK) is sent back to indicate that the packets have been delivered. RTT refers to the total time it takes for the data packets to get to the destination and their ACKs to be received back by the sender. The measured RTTs vary very much depending on the packet destination and the dynamic nature of

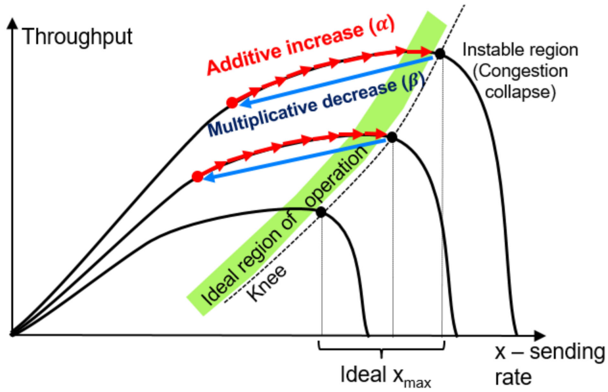


Fig. 2. TCP's congestion control management: As end users keep increasing their sending rate, throughput first increases but then saturates and sharply reduces.

**Algorithm 2:** AIMD Algorithm for EV Charging Network.

**Input:** Previous charging current: $I_c(t)$
**Output:** New charging current: $I_c(t+1)$
**Parameter:** Additive increase parameter: $\alpha(t) > 0$
**Parameter:** Multiplicative decrease parameter: $0 < \beta(t) < 1$
**Parameter:** Decision probability: $0 < p \leq 1$

1: **if** Grid congestion NOT detected **then**
2: **else**
3:   **if** $p \geq rand(1)$ **then**
4:     $I_c(t+1) = \beta(t) \times I_c(t)$
5:   **end if**
6: **end if**

the background traffic load on the network. Thus, AvgRTT and StdRTT are used as metrics to assess if a congestion may be happening in the middle of the network. The EWMA is used to estimate AvgRTT and StdRTT values as follows:

$$\text{AvgRTT}_{(i+1)} = \lambda \cdot \text{RTT}_{(i)} + (1-\lambda) \cdot \text{AvgRTT}_{(i)}. \tag{1}$$

$$\text{StdRTT}_{(i+1)} = \omega \cdot (\text{AvgRTT}_{(i)} - \text{RTT}_{(i)}) + (1-\omega) \cdot \text{StdRTT}_{(i)}. \tag{2}$$

where $\lambda$ and $\omega$ are the coefficients that determine the contribution of the recent measurements to the average values and thereby, the response time of the system.

Average RTT increases as the network starts being congested due to the background traffic. A congestion event is said to be detected if RTT exceeds a certain threshold, that is *re-transmission timeout (RTO)*. RTO is a very important parameter as it is used in self congestion detection, and it is dynamically updated at regular intervals to adapt to constantly changing network conditions. In essence, RTO is calculated as an outlier of the estimated average RTT value based on *Chebyshev's outlier estimation*. Chebyshev's Inequality [37] states for any probability distribution that

$$P(X \notin |\mu \pm k\sigma|) = \frac{1}{k^2}. \tag{3}$$

This means that $100 \times (1 - \frac{1}{k^2})$ percent of the measured $X$ values are to be between $\mu - k\sigma$ and $\mu + k\sigma$. For TCP/IP protocol, $k$ value is chosen to be 4, that is, around 93% of the time the true average of RTT must be within the measured RTTs. Then, the 7% should correspond to the outliers, which can be used as RTO as follows:

$$\text{RTO}_{(i+1)} = \text{AvgRTT}_{(i+1)} + 4 \cdot \text{StdRTT}_{(i+1)}. \tag{4}$$

Equations (1), (2), and (4) have the subscripts $i$ and $i+1$ to denote the $i$th and $(i+1)$th update intervals, respectively. In steady state, the difference between any two consecutive intervals $i$ and $(i+1)$ is equal to $\text{AvgRTT}_{(i)}$. This means that a lightly utilized/congested network is pushed to its limits by executing the AI phase at relatively shorter intervals to quickly reach the network capacity. As the capacity utilization increases, update intervals get longer (due to high RTTs) and the increase rate slows down contributing to the stability of the system.

### B. *Counterpart Algorithm for EV Charging*

There are major differences between the operation of Internet and power grid such as time-scale of the events, severity of failure, and digital versus analog operation. These cannot be ignored and should be managed with respect to specific operation conditions. However, the problem in the EV charging case is very similar to that of the Internet end-points' sending rate control. Furthermore, the electrical energy needs to be distributed among EVs in a fair, efficient (high utilization factor), and stable way taking the system capacity constraints into account. The solution should respond to the dynamic changes in the grid on time and result in the best utilization of the power capacity. The very similarity of the two problems gives us the courage to safely adapt the AIMD algorithm for EV charging [36].

The sending rate $R(t)$ in the Internet implementation can be modified as charging current $I_c(t)$, and the counterpart algorithm for EV charging can then be written as in Algorithm 2. The key part of implementing this algorithm, as in the Internet case, is the detection of the congestion. The voltage of the node to which the EV is connected can be used for congestion monitoring as a counterpart of RTT. Grid voltage carries significant information regarding the loading level of the grid, and it is responsive to changes due to highly dynamic loads such as EVs, or sources such as intermittent renewable energy generation. As AIMD is concerned, increasing the charging current in the AI phase will lead to voltage drops. If the voltage $V(t)$ drops below a certain threshold voltage value, $V_{\text{th}}$, the grid can be regarded as congested, and the MD phase activates and reduces the current. Additionally, as an extra control nub, we introduced another parameter, namely "decision probability," $p$ in the counterpart algorithm. This is the probability that the user decreases its current at the congestion event. When $p$ is set to one, the user will always respond to every congestion detection and activates MD phase. Any value of $p$ less than one will make it more likely for the user to ignore the congestion and result in an increase in the average charging power. Along with $\alpha$, we can also use $p$ to converge to a desired operation point.

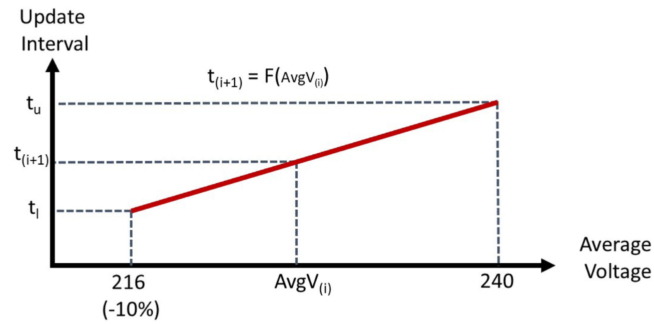


Fig. 3. Update interval calculation for the EV charging algorithm.

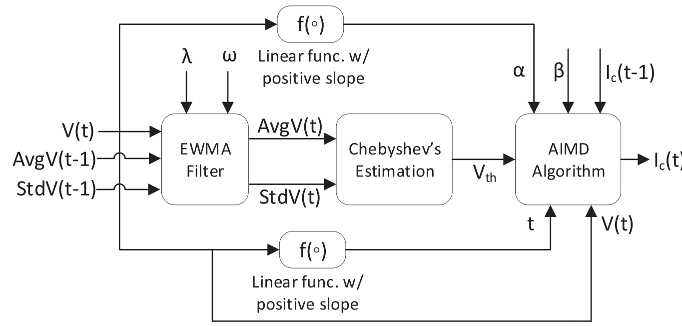


Fig. 4. Schematic overview of the proposed methodology.

The critical voltage threshold value is similar to RTO and can be calculated using AvgV and StdV of the measured voltage. If EWMA is applied again, then the following equations are obtained:

$$\mathrm{AvgV}_{(i+1)} = \lambda \cdot V_{(i)} + (1-\lambda) \cdot \mathrm{AvgV}_{(i)}. \tag{5}$$

$$\mathrm{StdV}_{(i+1)} = \omega \cdot (\mathrm{AvgV}_{(i)} - V_{(i)}) + (1-\omega) \cdot \mathrm{StdV}_{(i)}. \tag{6}$$

Unlike RTO, $V_{\text{th}}$ should be inversely proportional to the congestion level, since it decreases as the congestion increases. Therefore, a voltage outlier below the average voltage should be chosen as the voltage threshold value $V_{\text{th}}$, i.e.,

$$V_{\text{th}(i+1)} = \mathrm{AvgV}_{(i+1)} - 4 \cdot \mathrm{StdV}_{(i+1)}. \tag{7}$$

In the Internet case, the length of the update interval $|t_{(i+1)} - t_{(i)}|$ was set to be $\mathrm{AvgRTT}_{(i)}$, since both are time quantities. As for the EV charging case, $\mathrm{AvgV}_{(i)}$ must be mapped to a time value through a function. This function can be intuitively assumed to be a positive-sloped line with the following equation and illustrated in Fig. 3:

$$t_{(i+1)} = \frac{\mathrm{AvgV}_{(i)} - 240 \cdot (1-10\%)}{240 - 240 \cdot (1-10\%)} \cdot (t_u - t_l) + t_l. \tag{8}$$

where $t_u$ and $t_l$ denote the upper and lower possible values for the update interval, respectively. 216 V corresponds to the minimum utilization voltage level (-10%) allowed by the distribution grid standards [38].

In order for the algorithm to respond to capacity changes, it should further be modified. Capacity can be monitored by voltage [39]. Therefore, the difference between the operating point and the minimum utilization voltage can be used as a capacity indicator, and the increase parameter $\alpha(t)$ is adjusted through a simple linear function as follows:

$$\alpha_{(i+1)} = \frac{V_{(i)} - 240 \cdot (1-10\%)}{240 - 240 \cdot (1-10\%)} \cdot (\alpha_{\min} - \alpha_{\max}) + \alpha_{\min}. \tag{9}$$

The same adjustment can also be made for the decision probability $p$. By relating it to the voltage through a simple linear function, we can further force the algorithm to adapt itself to the available system capacity

$$p = 1 - \frac{\mathrm{AvgV}_{(i)} - 240 \cdot (1-10\%)}{240 - 240 \cdot (1-10\%)}. \tag{10}$$

For this article, the following parameters are used: $\lambda = 0.7$, $\omega = 0.2$, $\alpha_{\text{min}} = 1$, $\alpha_{\text{max}} = 5$, $t_u = 60$ s, $t_l = 5$ s and $\beta = 0.5$. We chose these values based on the practices of the TCP implementation. The schematic overview of the presented methodology is illustrated in Fig. 4.

## IV. System Description for the Distribution Grid Test Case

This section covers the description of the test system in which the proposed algorithm will be implemented. The testing scenarios and their results will be given in the next section together with a discussion analyzing the results.

EV charging network is essentially a LV distribution grid with a substation being the source and grid-connected EVs being the consumers. Grid topology describes how the sources and loads are interconnected through distribution lines. Similar to the Internet case, the topology gets more complicated as new end-users (EVs) get connected to it. Usually, the grid topology is also unknown to grid operators, as already is to end-users. Therefore, having decentralized algorithms running independent of the topology is surely of significant importance. A distribution grid with a nonregular topology would serve as a good testing medium to get more consistent results compared to testing on specific topologies such as the single line, radial types. Such a complex distribution grid model will be presented in the next section. In addition to this, a more realistic distribution grid model does not only have EVs, but also other dynamic loads such as households and commercial buildings whose power consumptions fluctuate over time. Accurately modeling these type of loads based on real data will also contribute to the fidelity of the results as well as the quality of the analysis.

### *A. Distribution Grid Model*

For our test benchmark, the distribution grid model with primary and secondary networks presented in [40] is used. This test feeder is modeled according to the IEEE 37-node test system, which operates at a nominal voltage of 4.8 kV and a peak power of 1.5 MW. We designed the primary and secondary networks in

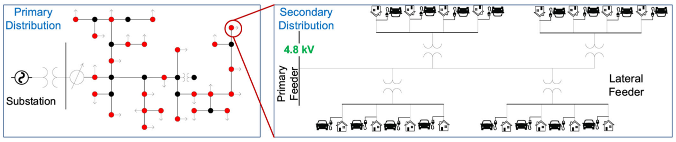


Fig. 5. Primary and secondary distribution network implemented in the MATLAB model.

MATLAB Simulink as shown in Fig. 5. Each red node in Fig. 5 represents a neighborhood that is connected to a primary feeder bus. There are a total of 26 neighborhoods located at different points of the grid.

We model each neighborhood as a secondary network as shown in Fig. 5. The secondary network is developed following a similar procedure and the data described in [40]. It contains four inner nodes, and at each node a pole-mounted transformer of 25 kVA is located. Each transformer steps down the primary feeder voltage of 4.8 kV to a secondary split-phase voltage level of 120/240 V and supplies power to four houses. In total, there are 416 residential customers in the model. The overall distribution grid operates slightly over 350 kW at peak hours without any charging event.

### B. EV Load Model

In order to model EV charging load on the distribution grid, we focused on their critical parameters. We derived their arrival and departures times from a Gaussian distribution with mean and standard deviation of (17 h 30,1 h 00) and (07 h 47, 0 h 23), respectively. The load model generates (SOC) values for each EV at the time of grid connection based on a Gaussian daily trip distribution with mean and standard deviation of (40.0 mi, 5.0 mi). Each EV is assumed to have a 70 kWh battery pack with an on-board charger of 10 kW corresponding to around 41 A RMS ac current for a rated voltage of 240 V. Finally, the battery charging takes place at a 90% efficiency for all vehicles. The battery SOC is computed by the following equation:

$$\mathrm{SOC}(t) = \frac{Q_0 + \int i_{bt}(t)dt}{Q_n} \times 100 \tag{11}$$

where $Q_0$ is the initial battery charge, $Q_n$ is the nominal charge capacity of the battery, and $i_{\mathrm{bt}}$ is the battery charging current.

The reason all the EVs are modeled with the same configuration type is to prevent possible confusions that might arise in the discussion of addressing fairness performance of the algorithm. We wanted to make sure the EVs' rates of charge do not interfere with the charging control algorithm's capability of attaining a fair charging scheme. Designing a charging control algorithm that can attain fairness across heterogeneous EVs with different capabilities is a future direction this article can be taken to.

### C. Residential Load Model

We designed a random consumption data generator for residential houses. This generator uses 16 days of real residential power consumption data downloaded from E-gauge [41] (see Fig. 6). These data are used to create a statistical distribution of the load model in 1-min resolution assuming a normal distribution. The developed power consumption probability distribution function is then used to populate a load profile in 1-min resolution for each house in the grid model. Each house is assumed to operate at 0.9 power factor lagging to include reactive power consumption into study as well.

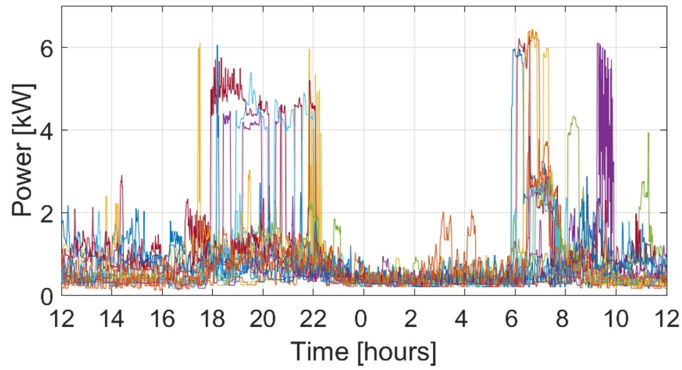


Fig. 6. Sixteen days (shown in different colors) of power consumption data of a household.

### D. Performance Comparison Benchmark Studies

In order to analyze the proposed algorithm on the distribution test grid, we first need a reference case to compare our results with. This case covers the scenario, where the EV penetration is set 100% (full-load). For the full-load case, the charging is assumed to be done at the rated power of 10 kW for all vehicles (no control). The time interval for the simulations is chosen to be between 16:00 and 24:00 when almost all of the charging events take place.

Besides, we run the test scenario with one fully decentralized [42] and one centralized [24] algorithm to evaluate and compare the performances. Studli *et al.* proposes a centralized, AIMD-based charging control assuming that the capacity congestion event is notified to each user over a unidirectional communication link [24]. This algorithm is the ideal implementation of the AIMD algorithm and, therefore, will serve as a benchmark. $\alpha$ and $\beta$ parameters presented in Algorithm 1 are set to 1 and 0.5, respectively. These values are chosen specifically based on their domain set ($\alpha > 0$ and $0 < \beta < 1$). An increment current of 1 A rms in each AI phase is assumed. Geth *et al.* proposes to use droop control, where the power-voltage droop functions are predefined [42]. In this article, we adapt the LM2 type droop function presented in [42] for the nominal charging power of 10 kW. The algorithm cuts off the charging power when the voltage goes below 0.9 p.u. (216 V). Charging power is linearly changed with voltage when the voltage is between 0.9–1.0 p.u. When the voltage is above 1.0 p.u., the EVs will be charged at the maximum rated power of 10 kW.

We refer the algorithms as follows: *D-AIMD* for the proposed distributed AIMD algorithm, *C-AIMD* for the ideal centralized AIMD algorithm [24], *Droop* for the droop control algorithm [42], and *No-Control* for the rated charging power for all EVs.

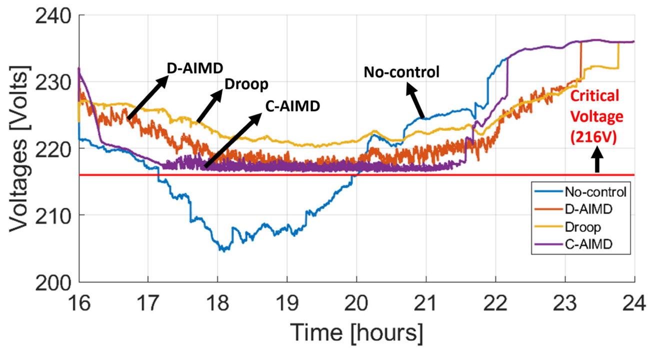


Fig. 7. Voltage profiles of 416 households for 100% EV penetration under different control algorithms.

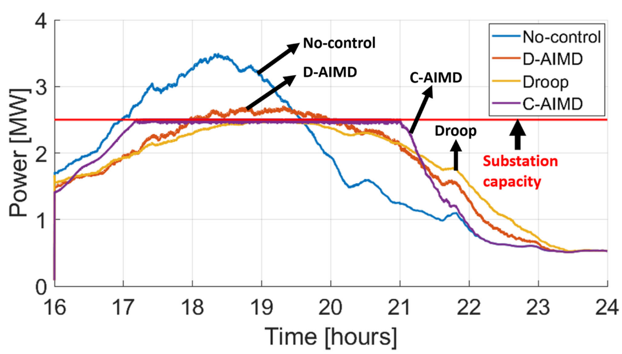


Fig. 8. Total power consumption of the distribution grid under different control algorithms.

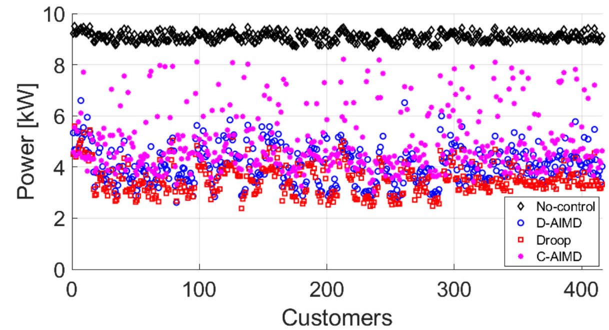


Fig. 9. Average charging powers for 100% EV penetration under different control methods (blue circle: D-AIMD; red square: Droop; magenta star: C-AIMD; black diomand: No-control.

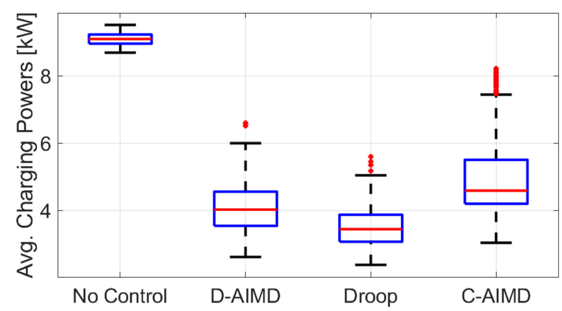


Fig. 10. Voltage profiles of 416 households for 100% EV penetration with AIMD charging.

## V. Results, Analysis, and Discussion

Minimum of all the household voltages in the grid across the simulation time of 8 h for all four scenarios are shown in Fig. 7. The minimum allowed utilization voltage is also shown in red. The baseline case clearly shows that the minimum voltage in the grid drops far below the minimum critical level (216 V) when No-control action is taken. This result strongly suggests that the EV charging should be controlled to mitigate the impact.

All three algorithms successfully managed to keep the lowest voltage above the critical level of 216 V. Droop is operating well above this voltage level, since all vehicles simultaneously decrease most of their charging power as their voltage gets close to 216 V. This naturally results in lower capacity utilization, lower average charging power, and longer charging time, which will be discussed later. C-AIMD marks the benchmark points for our decentralized AIMD algorithm. It is also programmed to decrease the current by half as the voltage hits the minimum (or when overloading of substation transformer occurs). C-AIMD is operating right at 216 V and D-AIMD operates closely above C-AIMD minimum voltage levels. This suggests that D-AIMD finds itself a place between the ideal (C-AIMD) and static droop operation in terms of voltage control.

Fig. 8 shows the overall substation transformer loading in MW for all three cases. As seen, the substation capacity is overloaded (highly congested feeder) and the peak power rises as vehicles arrive home when there is no control over charging vehicles. All algorithms manage to stay below/around the rated capacity, whereas Droop is slightly under the capacity making it deliver the same energy in a longer time. C-AIMD operates right at the capacity, since it already receives the congestion information. We see that the D-AIMD is also able to operate close to the capacity limit *without needing an explicit capacity information*. Compared to the *no control* case, D-AIMD handles the congestion by shifting the peak load of the system toward the midnight, and thus performs an autonomous demand-response management.

Fig. 9 presents the average charging powers of each customer in ascending order of electrical distance to substation for all control methods. The average charging powers among all EVs for D-AIMD, Droop, and C-AIMD algorithms are calculated as 4.07, 3.50, and 5.00 kW, respectively. This can also be better observed as boxplots of average charging powers in Fig. 10. The red lines inside each box represent the median value of the average charging powers for each algorithm, whereas the height of the boxes show how big the variations among the charging powers are. C-AIMD has the highest average charging power overall but shows a lot of variations among them. Droop has lower variations, however, it provides less average charging power that results in longer charging times. D-AIMD again locates itself in between these two cases having less variations compared to C-AIMD and higher charging power compared to Droop.

Fig. 11 shows typical charging current waveforms of a randomly chosen vehicle for all presented cases. Droop presents a continuous current trend as its control action is defined to be

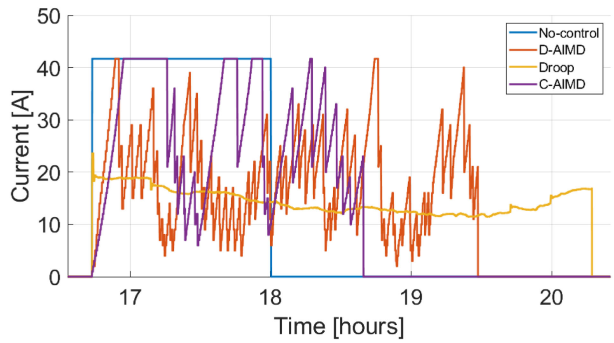


Fig. 11. Charging current in the AIMD control for a random vehicle.

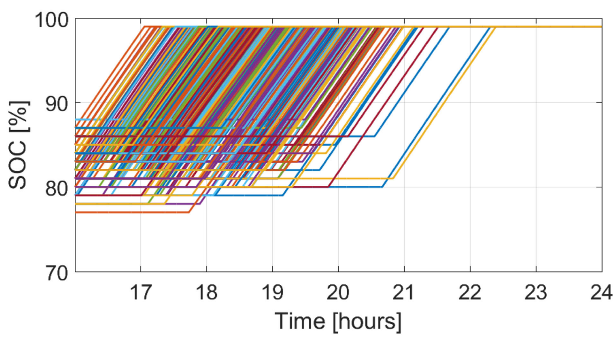


Fig. 12. SOCs of all vehicles for 100% EV penetration for No-control.

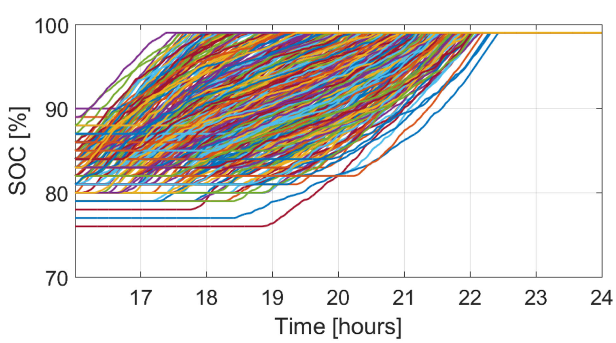


Fig. 13. SOCs of all vehicles for 100% EV penetration with D-AIMD.

a linear function over a small voltage range and takes longer time to complete charging. D-AIMD and C-AIMD exhibit a very dynamic behavior because these algorithms are constantly probing and monitoring the network and take control actions accordingly. However, note that the algorithm does not diverge into instability as expected by the stability proof provided by [15]. As a consequence of this service, the charging durations are expected to be longer compared to the no control case. Figs. 12 and 13 show the SOC changes of all vehicles under 100% penetration for uncontrolled and controlled (D-AIMD) EV charging, respectively. As seen, the charging takes longer times on average in the controlled case because of the managed charging powers. All the EVs are fully charged, up to 98%, leaving a protection margin for battery safety.

The distribution system used in this article is not completely balanced. If one phase is significantly more loaded than the others, its voltage will drop more. This will trigger the AIMD algorithm more often causing it to enter the MD phase more. Reducing the charging rate will also reduce the stress on the particular phase under discussion and help avoid a possible congestion in that phase. Therefore, it is fair to say that the algorithm operates independent of whether the network phases are balanced or not.

## VI. Conclusion

This article presented the well-known AIMD algorithm used for Internet congestion management and adapts a revised version of it for the EV charging problem. We observed the following key findings: First, the algorithm can respond to grid congestion events in a decentralized way without causing instability via observing changes in the end-node voltage. Second, a *proportionally fair* capacity allocation is established while operating fully decentralized without any central information or command. Third, peak-shifting of the load on the distribution grid is successfully accomplished without any need for a centralized controller. The comparison in the article showed that the proposed algorithm (D-AIMD) has an overall performance between the ideal AIMD case (C-AIMD) and the static decentralized operation (Droop).

The future work will include improvements for the proposed algorithm for more dynamic conditions. It will be worthy to explore better tuning of AIMD's various parameters adopted for EV charging. For instance, the update interval calculation based on average local voltage measurements could be done in a more or less aggressive way than a linear model. Further, the increase and decrease parameters of AIMD can be tuned for better probing the available grid network capacity and/or stronger guarantees for stable operation. These explorations will enable better understanding of the tradeoff between stability and efficiency of purely decentralized EV charging with AIMD. We will also explore battery lifetime/aging implications of the AIMD-type dynamic charging profiles as opposed to Droop-like steady-state controllers. This can provide an insight to better tune AIMD controller parameters.

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