# Analysis of AIMD Algorithm for EV Charging

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## ABSTRACT

The Additive Increase and Multiplicative Decrease (AIMD) algorithm is the Internet's de-facto protocol for capacity sharing and congestion avoidance. We present an analysis of the AIMD algorithm here in EV charging problem in terms of its parameters and their impact on the average charging power. We show a closed-form expression for the average final share of AIMD, propose a counterpart algorithm for EV charging, and validate the expression by testing the algorithm under different varying parameters.

## CCS CONCEPTS

• **Hardware** → **Power networks**; **Smart grid**; **Power networks**; **Smart grid**; • **Networks** → *Network resources allocation*; *Network control algorithms.*

## KEYWORDS

AIMD, electric vehicles, smart grid, charging control, power distribution system, congestion

## 1 INTRODUCTION

With the integration of new end-nodes in today's electric grid such as distributed energy sources (DER) and electric vehicles (EV), the grid is transforming into a more dynamic nature. Especially, mass penetration of EVs into the distribution systems will cause adverse effects because of the overlap of peak loading hours and EVs' arrival times [2]. This necessitates the need for smart and attentive control and coordination of these end-nodes. This kind of demand side management of resources is a very popular engineering problem that was also heavily studied especially in the development of today's Internet [6]. The Additive Increase and Multiplicative Decrease (AIMD) algorithm [1] was proposed as a congestion avoidance solution and has been used as the Internert's de-facto control method.

The proven success of the AIMD algorithm in the Internet inspired many in the power area to adapt the algorithm to power network problems [4, 5, 7, 8]. A recent study [3] demonstrated that the local grid frequency can also be utilized in a decentralized AIMD algorithm to control grid-connected microgrids. An analysis is presented in [10] to show how AIMD operates in terms of fairness


*e-Energy'19, June 25-28, 2019, Phoenix, AZ, USA*

ACM ISBN 978-1-4503-9999-9/18/06…$15.00
https://doi.org/10.1145/1122445.1122456

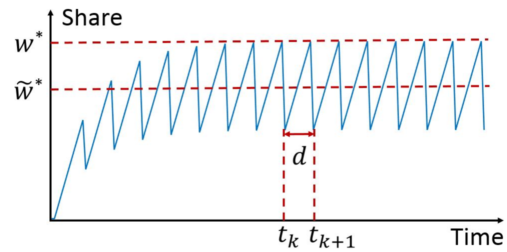


**Figure 1: Capacity share $w(n)$ vs. time w/ AIMD in action as $n$ tends to infinity.**

and voltage violations once the voltage thresholds are properly set. Further, in [9], a method is proposed on how to set these voltage thresholds dynamically by means of statistical analysis. Studies mostly implemented AIMD in a centralized manner. However, a communication network with a heavily centralized control scheme is a costly investment and not scalable. It is also highly vulnerable in terms of cyber security. To that end, a fully autonomous operation based on local measurements will be of great value since it will significantly reduce the cost and complexity of the system [9, 10].

In this paper, we propose an AIMD based EV charging algorithm and its decentralized congestion detection mechanism. Then, we present its parameters and investigate their impacts on the final user share. Finally, we evaluate the results and briefly discuss how we can utilize them to develop a better distributed control algorithm.

## 2 AIMD MODELING AND EV CHARGING

AIMD has two modes, namely additive increase (AI) and multiplicative decrease (MD). It linearly increases the user share ($w$) by $\alpha > 0$ in AI phase. When capacity is reached, $w$ is scaled down by $0 < \beta \leq 1$ for MD phase. This is formalized as follows:

$$w_i(t+1) = \begin{cases} w_i(t) + \alpha_i & \text{if there is no congestion} \\ w_i(t) \times \beta_i & \text{if congestion occurs} \end{cases} \quad (1)$$

After analytical derivation, the steady-state average value of user share $w_i$ is found as:

$$\widetilde{w}_i^* = \alpha_i \frac{(1+\beta_i)}{2(1-\beta_i)p_i} d \quad (2)$$

where $d$ is the average time between two successive capacity events and $p_i$ is the probability that agent $i$ decreases its share at the capacity event. This is demonstrated in Fig. 1. Any increase in the additive parameter will also increase the final share. $d$ is the period of congestion; thus, the final share also tends to increase as the time between two successive congestion events gets longer. On the other hand, the final share has a quadratic relationship with $\beta$ since it is inversely proportional to $(1 - \beta_i)$. As $\beta$ approaches one, the denominator gets smaller, and the final share increases. Finally, the probability of taking action in the MD phase also affects the final share. As this probability gets smaller, the agents will ignore the congestion events, and causes an increase in the final share.

The counterpart algorithm of AIMD for EV charging is shown in Alg. 1. The congestion is detected based on whether the local voltage $V_c(t)$ is greater than the threshold $V_{th}$ specific to each node. $V_{th}$ is calculated from voltage statistics and updated at every update period $T_u$, and its value corresponds to a chosen left tail quantile ($\delta$) of voltage distribution as depicted in Fig. 2.

Fig. 3 shows a typical waveform of voltage, current and voltage threshold when AIMD is in action. The algorithm checks the voltage at algorithm operation intervals ($T_a$), e.g., every 10 sec.

## 3 CASE STUDY

To validate (2), we tested a case scenario with different charging parameters ($\alpha, \beta, \delta, p$) on a simplified grid model. We used 15 EVs, and set the nominal values of the parameters as: $\alpha = 1$, $\beta = 0.5$, $p = 1$, $\delta = 0.25$, and EV arrival time mean = 17h53m. The overall average charging currents resulting from each parameter test (while others staying the same) are shown in Fig4.

We see that the increase parameter $\alpha$ greatly impacts the average charging current since it is directly proportional to the final share. The decrease parameter $\beta$ has a rather quadratic relationship since $\beta$ appears both in nominator as $(1+\beta)$ and also denominator as $(1-\beta)$ in (2). Choosing $\beta$ closer to 1 results in a more dramatic change and higher average charging current, however longer transient time since it directly determines the speed of convergence. $p$ parameter is inversely proportional to the final share as seen from its hyperbolic curve. The results clearly show that $\delta$ has also an inverse relationship with the average final share just as the decision probability $p$.

**Algorithm 1: Proposed AIMD algorithm.**

**Input:** Charger voltage and current: $V_c(t)$, $I_c(t)$
**Output:** Charger current command $I_c(t+1)$
**if** $V_c(t) > V_{th}(t)$ **then**
  $I_c(t+1) = I_c(t) + \alpha(t)$
**else**
  **if** $p \geq rand(1)$ **then**
    $I_c(t+1) = \beta(t) \times I_c(t)$
  **end if**
**end if**

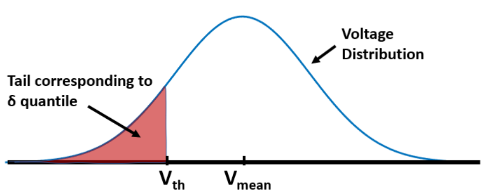


**Figure 2: Calculating the voltage threshold from the voltage distribution.**

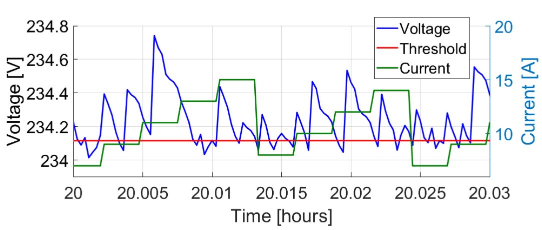


**Figure 3: Voltage, voltage threshold and charging current.**

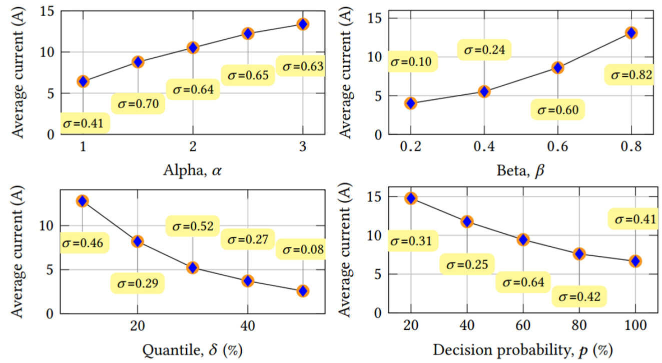


**Figure 4: Average charging current with changing $\alpha$, changing $\beta$, changing $\delta$, and changing $p$.**

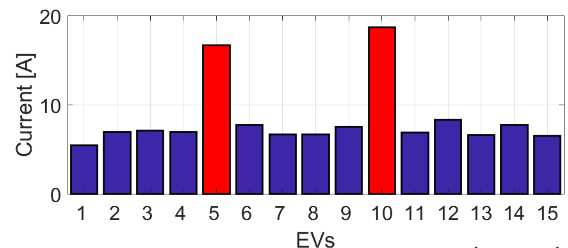


**Figure 5: Average charging currents when $\alpha = 4$ for $5^{th}$ and $10^{th}$ EVs and $\alpha = 1$ for others.**

## 4 DISCUSSION AND CONCLUSION

Our validation and analyses show that AIMD-based EV charging is promising and can be fine tuned for close-to-optimal decentralized operation. We showed that four of the AIMD algorithm parameters ($\alpha$, $\beta$ , $p$, and $\delta$) directly impact the average final share, and thus can be used for tuning the control algorithm. The system operator, for example, can adjust the AIMD parameters in favor of or against a user to reward or penalize it depending on a predefined policy. Fig. 5 demonstrates such a case where $5^{th}$ and $10^{th}$ EVs have a higher $\alpha$ value that resulted in higher average charging current compared to other vehicles.

This analysis showed us that our algorithm is parameter dependent. It learns an operating point for itself around the measured voltage level, and thus does not have any global information regarding the overall capacity. This is an expected behaviour from a decentralized control approach which is heavily dependent on local information. Our algorithm does not communicate at all with anywhere else, and is therefore, completely decentralized. This makes it inefficient in utilizing the available capacity, however it still serves as a straightforward, plug-and-play, baseline control framework that, when properly tuned, will converge to a stable operating point thanks to its AIMD-based structure.

## 5 FUTURE WORK

In future studies, we will look into hybrid solutions where we can combine the local knowledge with some global information to have a more dynamic and efficient control over grid-connected power electronics systems such as EVs and photo-voltaic (PV) cells.

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