# Smart Charging Model Design with ACO Algorithm for Determining Current Charging Pattern

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**Abstract**
The electric car battery-charging system significantly affects the quality of battery usage and charging time. Therefore, we need smart charging which can determine the optimal battery-charging pattern to produce a fast and controlled charging system. This study discusses the implementation of an Ant Colony Optimization (ACO) algorithm in a battery-charging system. The ACO algorithm determines charging current patterns, resulting in fast and controlled charging for each battery. The experimental results show that the system with the ACO algorithm can charge four lead-acid batteries quickly and in a controlled manner. This research also shows that the ACO algorithm setting system can charge the battery 8,413 minutes faster than the conventional CC-CV method.

**Keywords:** Ant Colony Optimization, Smart Charging, battery

## 1 Introduction

Fossil fuel reserves are dwindling because of the lots used in operational transportation. Using material burn fossils too wide can also increase CO2 gas emissions, which have dangerous implications for the environment, such as green-house gas emissions and global warming. One of the efforts to reduce the excessive consumption of petroleum fuels is the implementation of electric car technology. Electric vehicles replace petroleum-fueled vehicles or Internal Combustion Engines (ICEs), which are considered harmful to the environment because they produce greenhouse gas emissions. In Indonesia, electric cars are still built and used on a limited basis, and research on electric vehicles is still ongoing with efforts to increase the quality and quantity of electric cars used to achieve specified targets[1] [2].

Charging technology is also needed, which has various advantages such as shortening the charging duration. The amount of charging current used dramatically influences the battery charging duration; the greater the current, the shorter is the duration. However, the current can also affect battery health; if the charging current is too large, it can cause damage to the battery. For this reason, various battery-charging methods have been used, such as Constant-Voltage (CV). Method that are safe to use and increase capacity up to 20%, but this method can reduce efficiency on battery up to 10% [3], Constant-Current ( CC ) is the method used for charging the battery more than one battery[4], and conventional charging namely Constant Current-Constant


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Voltage (CC-CV) is combination two method so that it sets the battery in two steps, namely the battery is filled with a constant current until the SOC of the battery reaches the limit (90%) then the charging system will supply a constant voltage until the current reaches the smallest value when the SOC of the battery reaches 100%, Method This rated possible charging without risk charging overcharging and suitable for various type of battery [5] [6]. However, pure CC-CV is considered less precise for fast battery charging. Therefore, a charging system is equipped with an algorithmic approach to adjust the current pattern according to the SOC level of each battery so that charging can be performed quickly and safely.

Ant Colony Optimization (ACO) is an intelligence algorithm inspired by ant colonies in choosing the fastest and shortest path from various paths from the nest to food based on pheromone substances left behind by other ants. Before, the ACO method is widely used in fast battery charging systems using lithium batteries for cellphone batteries with small energy capacities [7] [8]. In 2017, the ACO method was used in settings using solar panels [9] [7]. This paper presented an ACO algorithm to determine fast and controlled charging current patterns. The ACO algorithm control system controls the charging of the battery and also maintains damage to the battery owing to an imbalance in the amount of charge flowing in the storm, causing the battery's heat temperature to increase as a result of the charging process taking too long [8] [9].

To prove the feasibility of the ACO algorithm in the proposed electric car battery charging system, research results were provided to demonstrate the advantages of the charging system obtained. The charging system with the ACO algorithm can provide a faster charging duration compared with charging using the conventional CC-CV method. In addition, the ACO algorithm also prevents the charging system from overcharging**Sample Heading (Third Level). Only two levels of headings should be numbered. Lower level headings remain unnumbered; they are formatted as run-in headings.**

## 2 Related Work

This paper is connected to two main research categories, namely smart charging of EVs and ACO algorithm techniques, which are reviewed in the following subsections.

### 2.1 Smart Charging of Electric Vehicles

Many studies have been conducted on the adverse effects of uncontrolled battery charging, starting from increasing the battery temperature and reducing the battery cycle life. This indicates that fast charging without controlling the charging current on the battery causes a reduction in the State of Health (SOH) of the battery and fatal damage to the battery. Serhan et al.[5] have reviewed the effects of various charging methods, including constant current charging, two-step current charging, constant voltage charging, two-step method, pulsed Method, and reflex method. In this study, the charging methods were compared and simulated using MATLAB Simulink to analyze the effect of each method in terms of battery lifetime, charging temperature, state of charge, overcharging, undercharging, and charging duration. The results of this study show that the CC method has an effect on increasing the charging temperature, the CV method has an impact on reducing the battery life cycle due to the large current at the start of charging, the CC-CV method has an effect on overcharging, and the reflex method has an impact on raising the temperature. Because of these problems, smart charging is needed, which can control the charging process starting from SOC estimation, current patterns, duration of fast charging, and the effect on battery life.

Ali et al.[10] proposed an efficient and fast electric car lithium-ion battery charger based on fuzzy logic. In this study, undefined is used to regulate the amount of charging current flow and protect the battery from overvoltage and overheating. Apart from electric vehicle batteries, this research was also conducted on cell phones and notebook batteries. In this study, the system was processed in real-time using Arduino and MATLAB Simulink. This research results in charging the battery 9.76% faster than normal CC-CV, and charging the battery up to 99.26% without a significant decrease.

Moreover, Attia et al.[11] proposed a closed-loop optimization system for electric vehicle battery charging based on machine learning. Researchers argue that experiments to maximize battery life while charging require a very long time and a wide sampling of variable space. Therefore, this study developed a closed-loop machine learning method to determine current and voltage patterns that aim to maximize the life of the battery cycle with a short data acquisition time.

Furthermore, Ullah et al.[12] proposed smart charging capable of predicting the electric vehicle charging duration time using a combination of Ensemble Machine Learning (EML) algorithms. In this paper, the prediction of charging duration was obtained using four machine learning algorithms; Random Forest (RF), Extreme Gradient Boosting (XGBoost), Categorical Boosting (CatBoost), and Light Gradient Boosting Machine (LightGBM). This study uses 2 years of data charging from Japan's private and commercial vehicles. The results of this study show that XGBoost can predict charging time with the highest level of accuracy, with an RMSE of 2.29 for commercial EVs and 2.58 for private Evs.

Bonfitto et al.[13] proposed an ANN method to analyze the accuracy of state of charge (SOC) estimation of lithium electric vehicle batteries. The proposed algorithm is designed to meet the characteristics of smart charging in terms of SOC estimation, and the algorithm is trained using a real driving cycle profile to obtain computational costs. In this work, the SOC estimates obtained tend to converge to the expected value or remain constant when the error is lower than 4%. Meanwhile, estimates can deviate and go beyond range tolerance in issues where more mistakes are big. In addition, SOC estimation is not affected by problem noise during measurement, which is usually the most annoying signal in natural applications.

### 2.2 Ant Colony Optimization Algorithm Techniques

The use of the Ant Colony algorithm has been widely discussed to solve various cases, particularly in the field of electric vehicle charging. Mavrovouniotis et al. [14] use the Ant Colony System (ACS) algorithm to solve problems regarding electric vehicle charging scheduling that arises at battery charging stations using simple delivery rules, first come, first serve. In this study, ACS can minimize the maximum delay compared with other algorithms.

Moreover, Liu et al.[8] used the ACS algorithm to find the optimal charging current pattern in a battery-charging system. This study was conducted on lithium-ion batteries for mobile phones and laptop computers. The work showed a comparison of the results of charging with and without the algorithm, namely the CC-CV method. In this study, it was found that a charging system with an AC S algorithm is capable of filling in the power battery up to 70% capacity with a time of 30 min and provides 25% more cycle life than the normal charging CC-CV.

Furthermore, Phonrattanasak et al.[15] proposed Multi-Objective Ant Colony Optimization (MOACO) in the fast-charging station planning process to minimize the total cost of installation and losses to the distribution system while maintaining system security in residential areas. The MOACO algorithm was tested in three cases of fast-charging stations, namely 60, 80, and 100 kW, in a residential area of the Tianjin Development Zone. The numerical results show that fast-charging stations in optimal locations have minimum total cost and power loss. This study also shows that the MOACO algorithm is effective in finding the best fast-charging station locations in residential area distribution systems.

Leeprechanon et al.[16] Proposed a fast charging station (FCS) planning model based on the principle of coverage location by combining the ACO and bee algorithms. This research aims to maximize the cost and serviceability of fast charging by considering various issues, including the traffic service distance, waiting time limits, and power distribution system of each FCS. Other metaheuristic optimizations.

## 3 Ant Colony Optimization (ACO)

Marco Dorigo pioneered a study in 1992 regarding the Ant Colony System (ACS) algorithm in solving the Traveling Salesman Problem (TSP) [16] . Dorigo found a solution to the TSP problem based on indirect communication between a group of ants and a medium in the form of pheromones. Furthermore, in 2006, Dorigo refined his findings algorithm with the name *Ant Colony Optimization* (ACO) [17] , which utilizes ants as a computational intelligence technique. The principle of the ant colony optimization algorithm is inspired by the behavior of ant colonies when searching for food sources based on pheromones. Ants can find the shortest distance between a food source and their place of residence because each ant leaves a chemical called a pheromone on the path it has traveled; this pheromone becomes a signal for other ants. The shortest path will leave a stronger pheromone, so the other ants will choose that path. Pheromones are substances that come from the endocrine glands of ants and can be used to identify fellow colonies, remember the way home, and find the fastest way to food [18]. Over time, the pheromones on that path evaporate, but the best paths will often be traversed by ants, so that the pheromones on the best paths become bigger and the pheromones on other paths evaporate until they run out. This concept is widely applied to solve problems consisting of many variables.

In battery-charging systems, ACO is used to find fast and safe charging current patterns for each battery. The charging current is assumed to be the path that can be traversed by the ants, and the duration of charging is assumed to be the distance between the paths. Thus, the ACO was used to determine the charging current pattern based on the charging duration. The ACO termination process consisted of four stages:

1. Initialization. This stage is the preparation stage for ACO algorithm parameters, such as path or node variables and time, which can be assumed to be the distance between points i and j or $L\ (ij)$.
2. Random distribution of ants. At this stage, *m* ants are scattered to analyze each node so that they can leave the initial pheromone level $(\tau_{i,j})$ to be processed further.
3. Pheromone calculation. At this stage, addition and evaporation of pheromones also occur, resulting in a pheromone update process.

   Pheromone evaporation

   $$\Delta\tau_{ij(a)} = (1-\rho)\tau_{ij\,(a)} \tag{1}$$

   Then the update pheromone that is in that path is

   $$\tau_{ij(a+1)} = \tau_{ij(+)} + \Delta\tau_{ij(a)} \tag{2}$$

   $$\tau_{ij(+)} = n_{ij} \tag{3}$$

   Where:

   $\Delta\tau_{ij(a)}$ = Residual pheromone after evaporation
   $\tau_{ij}$ = Pheromones update each stage
   $\tau_{ij(+)}$ = Additional pheromones after new ants pass
   $\rho$ = Pheromone evaporation coefficient
   $n_{ij}$ = the ability of ants to release pheromones $(1/L_{ij})$

   The coefficient value, ρ, must be below 1 because the pheromone evaporates only partially and not completely.

4. The path selection process is based on the principle of probability, such that a path with a higher pheromone level will have a greater probability. This path selection process is repeated until the best or fastest path is found

   $$P_{ij} = \frac{(\tau_{ij}^{\alpha})\,\eta_{ij}^{\beta}}{\Sigma(\tau_{ij}^{\alpha})\,(\eta_{ij}^{\beta})} \tag{4}$$

   Where:

   $P_{ij}$ = probability value of path selection
   $\alpha$ = degree of importance of pheromone
   $\beta$ = degree of importance of visibility
   $n_{ij}$ = the ability of ants to release pheromones $(1/L_{ij})$

5. Termination of the best path. Path termination is obtained when almost all ants choose one path, and that path is determined as the fastest path.

# 4 Charging with ACO Algorithm

## 4.1 *Charging Pattern Based On ACO Algorithm*

The ability of the ACO algorithm to find the best and fastest paths is implemented in an electric car battery charging system so that the algorithm can find charging current patterns and produce fast and controlled charging processes. A good charging system must have a short charging duration and safe for the battery. This research was conducted on 4 12V 30AH lead acid batteries. The initial stage of this research is to search for current patterns based on the ACO algorithm; these current patterns are divided into 5 stages which represent the battery voltage; the possibility of charging current can be seen in Table 1.

**Table 1.** Possibility of Charging Current

| Stages | Battery SOC (%) | Possible Current Patterns (A) | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | 0-50 | 15 | 14 | 13 | 12 | 11 | 10 |
| 2 | 50-70 | 5 | 4 | 3 | 2 | | |
| 3 | 70-90 | 3 | 2 | 1 | | | |
| 4 | 90-99 | 2 | 1 | | | | |
| 5 | 100 | 0 | | | | | |

Table 1 lists the possible current used for charging the battery. The battery charging process is divided into five stages: stage 1 is the initial stage when the battery voltage is around 10-12V; at this stage, there are six possible charging currents based on the fast and safe charging current for the initial SOC of the battery, which is approximately 0.5-0.3 of capacity. In stage 2, when the battery voltage is around 12-13V, then there are five possible currents: in stage 3, when the battery voltage is 13-14.05, there are only two possible currents, and these possibilities are the two smallest currents, this refers to the prevention of overcharging the battery. Thus, a small current is necessary when the SOC of the battery is almost full, and stage 4 is the final stage, that is, when the battery is fully charged (SOC 100%) the charging current at this stage must be 0A. Also at this stage, the charging process stops automatically.

The possible current paths are shown in Fig. 1. These paths are nodes that the ants can traverse to find the best current pattern. There are 144 possible combinations of the current patterns. Table 2 lists the final results of the charging current patterns obtained from the ACO algorithm.

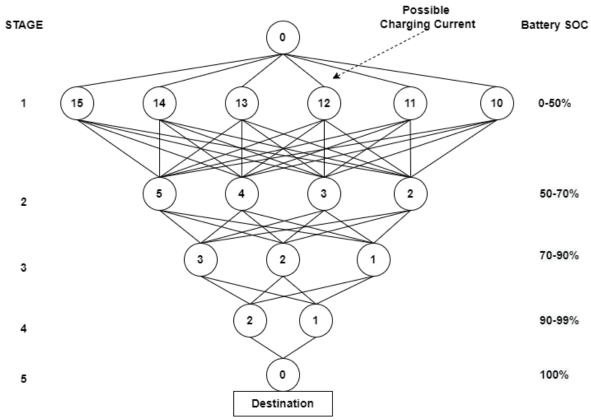



**Fig 1.** Pattern paths that can be traversed by ants

The steps in finding the best current pattern based on the ACO algorithm include:

The Initialization stage begins with modeling the problem in the Ant Colony algorithm, can be seen in fig 1. The Ant Colony algorithm model consists of pathways with variable current magnitudes. In this modeling, it is divided into 5 stages, where each stage contains several possible current variables to be analyzed using the Ant Colony algorithm in order to obtain a safe and controlled charging current pattern. in this ACO model there are 16 nodes and 50 paths, that has distance between point i and point j or L_ij. The calculation formula for L_ij;

$$L\_ij=30/i+|i\text{-}j| \backslash \quad (5)$$

In the experiment of the algorithm, a total of m(50) ants are deployed to determine choices on each path using probability techniques, with the following conditions;

(α) Control parameter for the influence of $\tau$_ij = 1

(β) Control parameter for the influence of n_ij = 1

Visibility value calculation 〖 n〗 _ij, This parameter influences the probability-based pathfinding technique and the ability of ants to release pheromones

$$n\_ij = 1/L\_ij \quad (6)$$

The process of selecting paths using probabilistic techniques is carried out iteratively, followed by evaporation and the addition of pheromones, in order to update the pheromone values on each path, with the condition:

(ρ) Pheromone evaporation parameter = 0.5

so,

$$〚Δτ〛\_(ij(a))=0.5τ\_(ij\ (a)\ ) \tag{7}$$

The addition of the pheromone is n_ij, then the pheromone update:

$$τ\_(ij(a+1))=n\_ij\ +\ 〚Δτ〛\_(ij(a)) \tag{8}$$

Path selection is based on the highest probability level. Based on the concept of finding the best path in the Ant Colony algorithm, the chosen current path is in Table 2.

**Table 2.** Final Current Charging Pattern Based on ACO

| **Stage** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **Current Charging (A)** | 10 | 5 | 3 | 2 | 0 |

I *charging pattern* = [ $I_1$ $I_2$ $I_3$ $I_4$ $I_5$ ]
I *charging pattern* = [ 10 5 3 2 0 ]

## 4.2 Charging System

The charging pattern results obtained from the ACO algorithm were applied to a 12V 120-watt charging system. The charger was used to charge four 12V 30AH lead acid batteries simultaneously. The flowchart of the charging system is shown in Fig 2. The charging system is divided into five stages based on the results of the ACO algorithm. Each battery voltage in each channel is read to determine the SOC of battery and stage number of the battery in. Subsequently, the battery flows current according to the ACO algorithm. After the battery was fully charged, the charging device automatically cut off the charging current to prevent overcharging. The charging system flowchart is a flowchart for each channel. Therefore, the flowchart only applies to one charging channel.

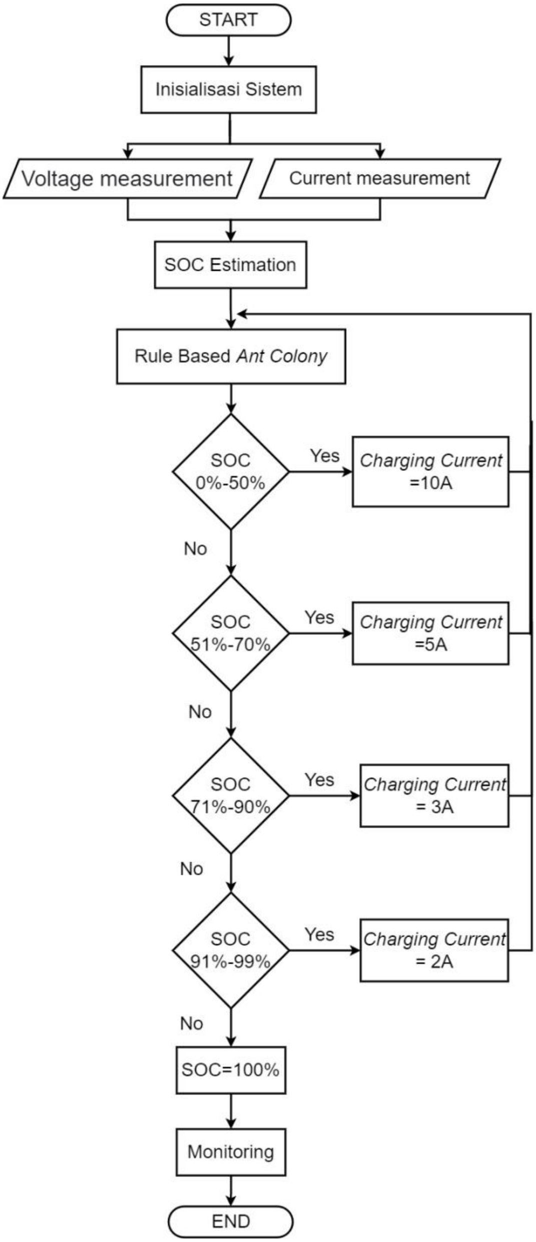



**Fig 2.** Flowchart Charging System

There are two components of this charging system, namely the 12V 10A charger and the ACO algorithm microcontroller. in this microcontroller section, the ACO algorithm program is embedded, and this section contains four outputs or channels that can be connected to the battery. An algorithmic microcontroller can display the battery status of each channel including the charging voltage, charging current, and battery SOC. In Fig 3. A schematic of the electronics of the proposed charging system is presented.

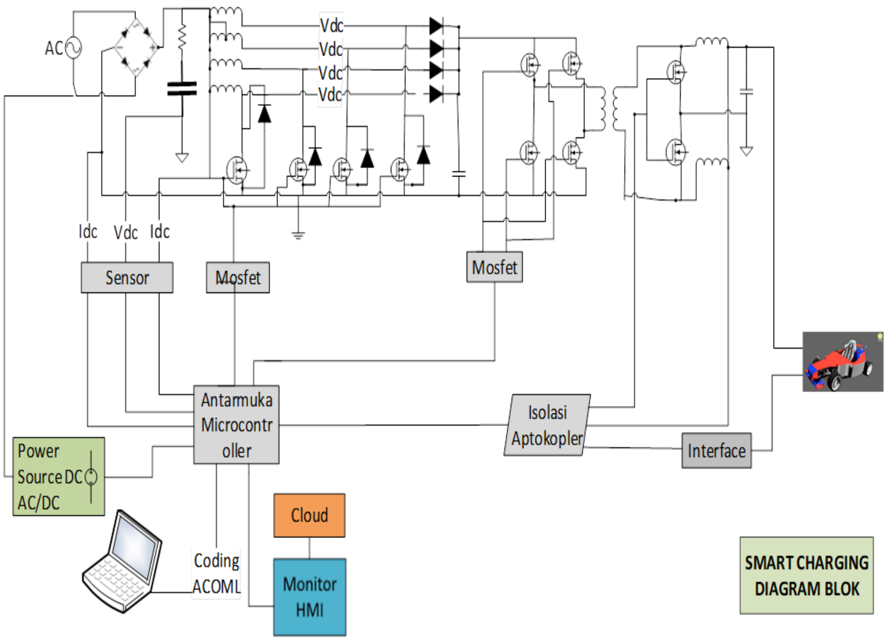



**Fig 3.** Electronics Schematic Charging System

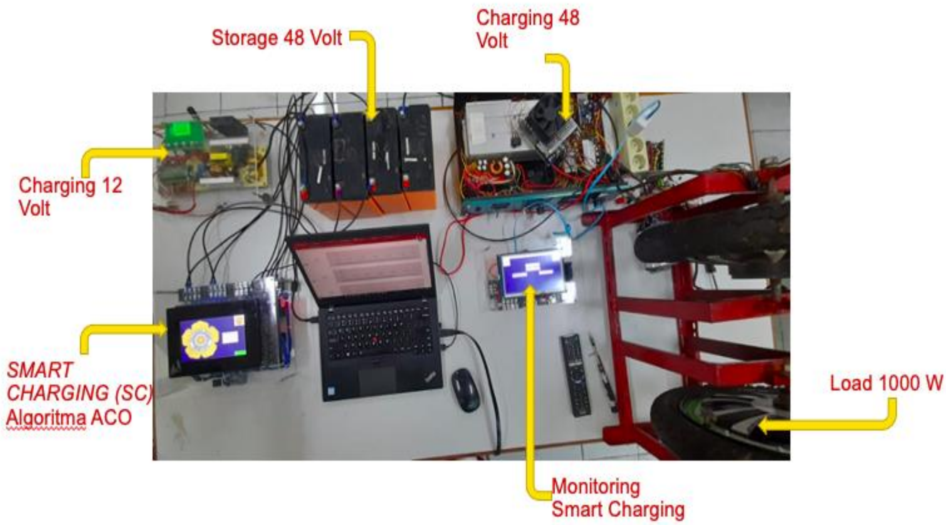
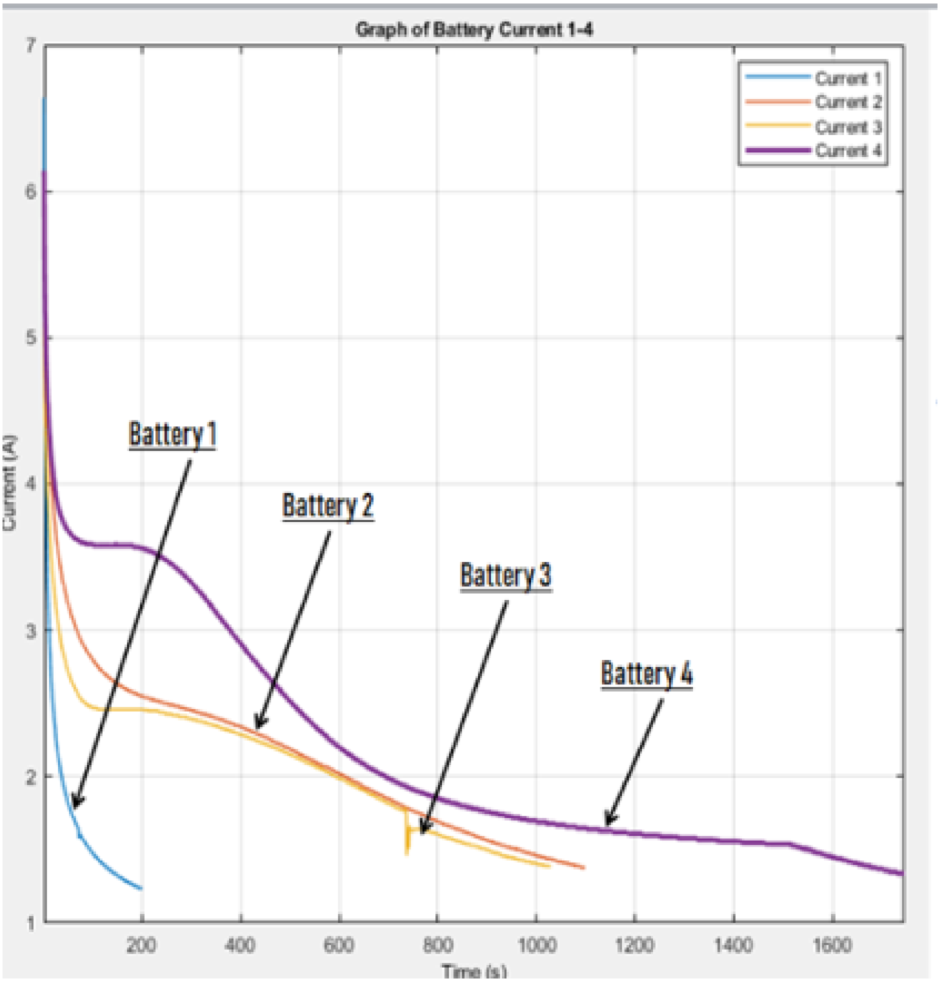


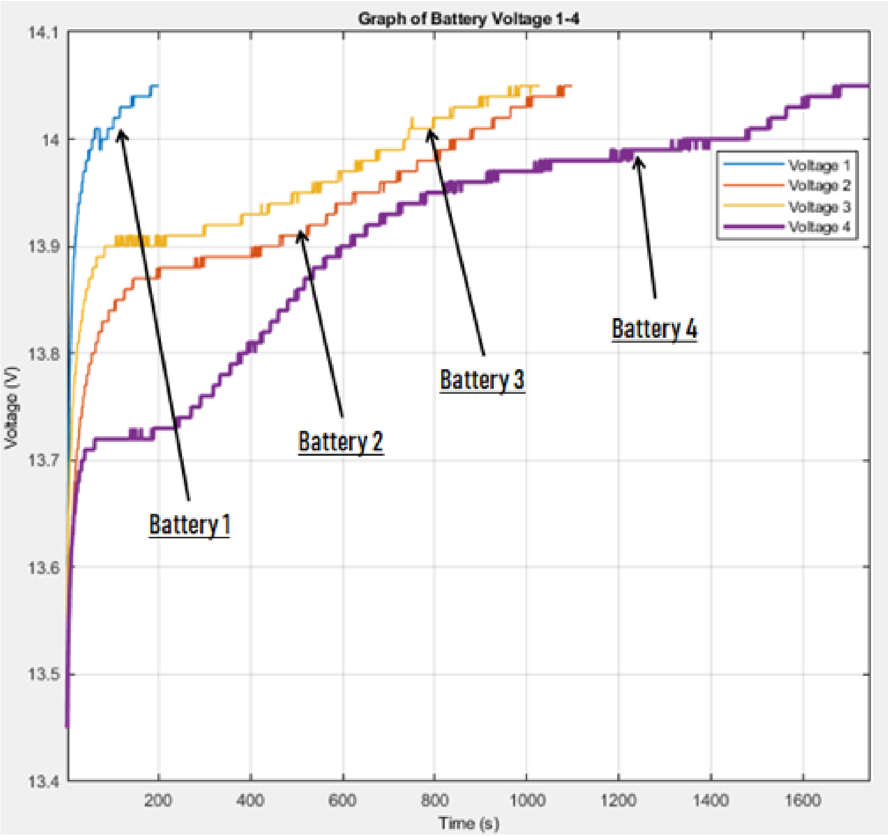

**Fig 4.** Charging Devices with ACO Algorithm

## 5 Experimental Result

The proposed algorithm was implemented in the charging system of the algorithm microcontroller. In Figure 4 shows the results of charging the four batteries. Fig 4 (a) shows the result of the charging voltage of the four batteries, resulting in different charging times for each battery up to 100% SOC because the initial SOC of each battery is different. The data and battery specifications in this experiment are shown in Table 3.




(a)




**(b)**

**Fig 5**. Graph Result of Charging (a) Battery Voltage Graph (b) Battery Current Graph

**Table 3.** Charging System Data

| Battery Number | Specifications | capacity | Initial SOC | SOC Finals | Charging Time (minutes) |
|---|---|---|---|---|---|
| 1 | Lead Acid | 12V 30A | 85 % | 100% | 3,067 |
| 2 | | | 80% | | 17.8 |
| 3 | | | 83% | | 16.28 |
| 4 | | | 80% | | 27.9 |

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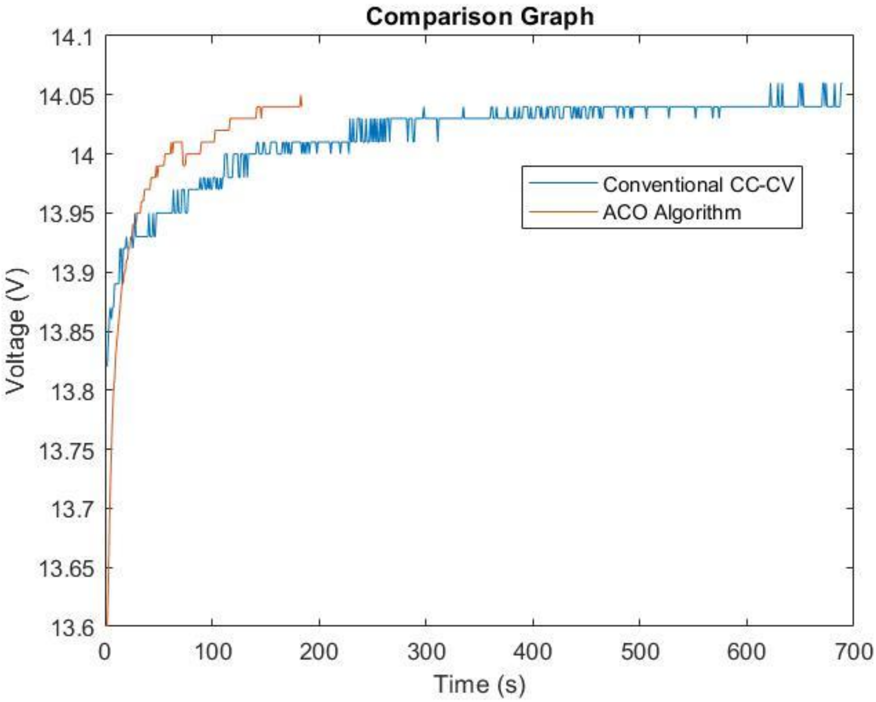


**Fig 6.** Comparison Graph of Proposed Algorithm

The charging system results obtained using the ACO algorithm were compared with the charging results obtained using the conventional CC-CV method. A comparison is shown in Fig. 5. Thus, the charging system with ACO can charge the battery 8,413 min faster than charging with the conventional CC-CV method. Following its purpose, the ACO algorithm aims to find filling patterns that are fast and controllable.

## 6 CONCLUSION

The main purpose of this research and experiment is to prove the feasibility of the ACO algorithm in determining the charging current pattern of electric car batteries so that the battery charging process can be carried out quickly and in control. The current used as the ACO algorithm variable was adjusted to the battery capacity. Therefore, charging process did not cause overcharging. In the ACO algorithm-based charging system, the authors integrated an algorithm for charging four lead-acid batteries. The test results show that ACO works quite well and can obtain an optimal solution so that ACO can find the appropriate charging current pattern for a 12V lead acid battery. The fast and controlled charging pattern obtained is able to charge faster than charging with the conventional CC-CV method to charge the battery from 85% to 100% SOC capacity, which is 8,413 minutes faster.

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