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SMART CHARGING PROCESS DEVELOPMENT BASED ON ANT COLONY OPTIMIZATION MACHINE LEARNING FOR CONTROLLING LEAD-ACID BATTERY CHARGING CAPACITY

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The Indonesian government has targeted 2.1 million two-wheeled electric vehicles and 2,200 four-wheeled electric vehicles (EV) by 2025. This is hampered by limited electricity supply and EV charging, which takes long time. Multi device interleaved DC-DC bidirectional converter has been applied and assessed as the most suitable method for battery EV and plug-in hybrid EV because it produces high power >10 kW. For power below 10 kW, it is recommended to use a sinusoidal, Z-Source, and boost amplifier type converter. The smart charging (SC) system will be applied to electric vehicles, which only require a minimum charging power of around 169 W for four lead acid batteries. This paper focuses on an SC system that is capable of charging the battery quickly while still paying attention to the state of health (SoH) of the battery. The SC developed uses a DC-DC boost converter to increase the voltage produced by the switch mode power supply (SMPS). Estimated charging time is less than 30 minutes and still pay attention to the battery SoH. SC will also use pulse width modulation (PWM) as a duty power cycle regulator. This research applies a multi-layer perceptron (MLP) classifier to a neural network (NN). The results of the research show that smart charging can charge up to 600 W with an estimated charging time of around 11 minutes. The charging condition is above 60 % and the power duty cycle setting is 100 %. The power estimation results processed using the ant colony optimization (ACO) based neural network method show a root mean square deviation value of 0.010013430 for charging four lead acid batteries. These results are useful to help solve the problem of capacity requirements and battery charging speed for EVs, with good SoH

***Keywords:** smart charging, ant colony optimization, machine learning, lead acid battery*

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1. Introduction

The energy crisis and low energy efficiency of conventional vehicles is an opportunity to develop electric vehicles [1–3]. Electric vehicles (EV) are vehicles that have no emissions and can make a good contribution to reducing environmental problems [2]. Based on the energy source, vehicles are divided into four main categories, namely conventional vehicles, hybrid electric vehicles (HEV), fuel cell tank electric vehicles (FCEV), and battery electric vehicles (BEV). This category also shows the direction of increasing electrification. The energy source for conventional vehicles and HEVs is gasoline or diesel, which are the main contributors to carbon radiation in the environment. However, when compared with conventional vehicles, the level of carbon emissions from HEVs is lower, because HEVs also use batteries as an energy source. HEV fuel efficiency increases, fuel consumption costs are reduced, refueling is easy, and energy recovery occurs when braking [4, 5]. However, the initial cost of HEV is higher due to the need to procure batteries, while CO_2 emissions also still occur.

The third and fourth types of vehicles are known as zero-emission vehicles, which depend on hydrogen fuel cells and batteries respectively [6]. FCEVs are very high energy, with higher efficiency than conventional vehicles and HEVs [7]. This type also could regenerate power through the braking process. Completely free from petroleum-based fuels. The disadvantages are high initial capital, the need to pay attention to hydrogen generation issues, and security of onboard storage. FCEV vehicles are still in the development stage and mass production scalability has not yet been achieved.

BEV vehicles are purely battery-powered. Having the same advantages as HEV and FCEV types, pure BEVs are free of toxic emissions and noise, have lower maintenance and operational costs, are easier to mass produce, with energy supplies that can be localized in most areas of the earth [7, 8]. However, battery procurement is expensive, the weight of the battery is a burden on the vehicle, the battery charging time is relatively long, and new infrastructure is still needed.

With the issue of depleting petroleum-based energy, it appears that EVs are the vehicle choice of the future. In this case, the battery is the most important part of the EV. Batteries convert chemical energy into electrical energy.

There are two types of batteries, namely primary batteries and secondary batteries [9, 10]. Primary batteries cannot be recharged, while secondary batteries can be recharged [11]. Lead acid, nickel-cadmium, nickel-metal hydride (Ni-MH), lithium-ion (Li-Ion) and polymer lithium-ion are commonly used rechargeable batteries [12]. This type of lead-acid battery is easy to get and has an affordable price. This type of battery is a major factor in use in EVs [13–16]. For lead-acid batteries, the required voltage is between 13.2–14.7 V, while for general batteries it is 12 V. There are several methods for charging batteries, including constant voltage (CV), constant current (CC), and constant current-constant voltage (CC-CV). Filling lead acid using CC-CV is considered more appropriate than other methods because this method is a combination of the two previous methods. CC-CV is considered capable of reducing charging time and increasing capacity faster by up to 20 %, with minimal overcharging [17, 18]. However, research developments in this field generally refer to world EV developer standards [19], which began in 2009 for fast charging technology. Research areas include inlet connector design innovation, max voltage (500–1000 volts), max current (250–631 A), max power (185–400 kW), max market power (125–350 kW), communication protocol, and vehicle to everything (V2X) function technology [20]. The latest research starting in 2020 was carried out in ChaoJi standards for different electrical configurations, namely 1500 V, 600 A and 900 kW. This research is still in the development stage, so market power is not yet available. By referring to previously developed technology, it is possible that the resulting max market power could be equal to 900 kW. In this case, the communication protocol used is controller area network (CAN). It appears that the problem of battery charging is still a concern and requires development. This shows that the topic discussed in this research is still relevant.

2. Literature review and problem statement

The papers [21–23] mentioned that during the charging process, the voltage on the battery will increase to the maximum voltage. The battery charger voltage must be at least 1 volt higher than the voltage of the battery to be charged. In [21], the battery charging process runs CC-CV using Atmega16 microcontroller control. This is done to avoid complex mathematics-based designs. The paper [22] specializes in charging designs for 72 volt voltage to accommodate the scarcity of 72 volt chargers in Indonesia. However, this research is directed at 2-wheeled vehicles. The target of 2-wheeled vehicles is also the research focus of [23] who designed a boost converter. This refers to the conditions in Indonesian society in particular, which are starting to use electric bicycles a lot. In the case of lead-acid batteries, lead (Pb) is used on both electrodes as the active material. In a charged condition, the positive electrode on lead acid consists of lead dioxide (PbO_2) while the negative electrode consists of pure lead (Pb). The charging process occurs when the battery is supplied with an electric source whose voltage value has been adjusted to the battery specifications. The charging process in [21–23] suits with this kind of battery.

The papers [16, 18, 19] discussed the constant voltage (CV) charging method, which is the most common method of charging lead-acid batteries. This method can reduce the estimated battery charge and capacity by up to 20 % but can reduce battery efficiency by around 10 %. In this method, the voltage is kept constant during the charging process. The current will increase during the initial charging process or when the battery is empty, then will gradually decrease after there is a charge from the charger because there is an increase in reverse current. The CV charging method allows for fast charging and is feasible for lead-acid battery types but is not suitable for Ni-MH or Li-Ion types. The paper [16] focused on online monitoring of battery SoC and SoH to follow developments in the use of IoT technology, which was starting to develop at that time. They seem to be trying to make it easier for users to monitor the charging process. This trend, including the advantages of using certain batteries, can be seen in the results of the review in references [18, 19].

The paper [24] mentioned that constant current (CC) charging is rarely implemented in lead-acid batteries. In the CC charging method, batteries are arranged in series to form groups, where each group is charged from a DC source loaded by a rheostat (variable electrical resistance). During the charging period, the current will remain constant by reducing the resistance in the circuit as the battery voltage rises. To avoid excessive heat (overheating), the charging process is carried out in two stages. In the beginning, the current supplied is higher and as it approaches final charging it decreases. In this method, the charging current is set at around one-eighth or 10 % of the current in the battery. The CC charging process requires a longer estimated time and is dangerous if overcharging occurs. The papers [16, 19] proved that this charging method is suitable for Ni-MH types. Thus, handling charging for lead acid batteries safely is a research challenge that can still be developed. It will be the potency of research novelty.

Referring to [16, 25], it can be said that the CC-CV method is a very popular method recently. CC-CV is a combination of two methods that have been discussed previously. The paper [18] also discussed that the CC-CV method allows for fast charging without the risk of overcharging and is suitable for various types of batteries. However, different methods will produce different results. Choosing the right charging process control method and system is the key to the successful implementation of electric vehicles.

The papers [4, 16] then notified that fast charger is a CC-CV charging model, even though the slow battery charging process is a type of charging that is highly recommended because it can extend battery life and is safe for the battery. Slow charging is usually referred to as normal charging, and is no longer the standard for EV charging, although it is still used in some countries. On the other hand, fast charging needs to be avoided unless due to limited time available. Fast charging can reduce battery life. However, renewable chargers are able to overcome the bad effects resulting from fast charging by adding a control system or smart charger. Smart chargers can monitor the state of charge (SoC) during charging, temperature and time during the charging process. The purpose of using a smart charger is to determine the charging current and stop charging. For the smart charging classification, there is level 3, which is implemented for AC and DC. Level 3 AC voltage produces power between 22–43.5 kW with an estimated charging time of 10–30 minutes. AC voltage level 3 chargers have been implemented in China. Currently, the papers [24, 26] mentioned that the lead-acid battery charging process needs to be developed by taking into account charging estimation and battery state of health (SoH). These studies emphasize the need for safe fast charging methods to support the implementation of electric vehicles. The SoH parameter will be one of the important parameters that must be considered.

In [27], it can be found that research in the development of smart charging (EVSC) is currently being carried out. The areas studied include the benefits and challenges of EVSC procedures from various points of view, the role of EV aggregators in EVSC, charging methods and objectives, and the infrastructure required to implement EVSC. These studies also discuss additional services provided by EVSCs and EV load forecasting approaches. EV load forecasting is an interesting area of research related to EVSC design. Estimating EV loads is important to obtain optimal operating conditions while meeting grid requirements. Although it is impossible to predict the load of each EV due to differences in travel patterns, the paper [28] discussed that load forecasting techniques can be carried out using time series models, support vector machines, and machine learning. Machine learning has been applied in various sectors, for various purposes. Recent research in [29] utilizes machine learning combined with blockchain technology to meet smart grid needs. The advantages of machine learning, which allows scheduling of energy use with a large database, have been developed by [30] for the latest smart grid research in terms of detecting incorrect data injection. The paper [31] introduced a time variation-based energy system operating framework, while [32] worked on modeling the identification and detection of cyber attacks, the paper [33] focused on electricity theft detection algorithm, and [34] researched on demand response capacity-based energy management system. In this case, it appears that machine learning optimization using the ant colony optimization machine learning (ACO-ML) control system has not yet appeared in the latest research. ACO-based optimization technique has also not been found in a search of recent publications for the energy or EV sector. All this allows us to assert that it is expedient to conduct a study on smart charging process based on ant colony optimization machine learning for controlling lead-acid battery charging capacity.

3. The aim and objectives of the study

The aim of the study is to develop a smart charging process for controlling lead acid battery charging capacity, using a DC-DC boost converter system in a smart charging system, with the duty power cycle regulation using pulse width modulation and ant colony optimization machine learning (ACO-ML). This will allow the potency of charging model development for lead acid battery in EV vehicles.

To achieve this aim, the following objectives are accomplished:

– to get the parameter validation with the best root mean square error (RMSE) value of smart charging;

– to determine the accuracy and performance level of the network model based on parameters obtained in the best RMSE.

4. Materials and methods

The object of the research is smart charging model. The smart charging modeling circuit diagram for charging lead acid batteries for electric vehicles is shown in Fig. 1, 2. The lead battery was chosen because the charging model studied was applied to an electric car model owned by the university. The choice of voltage value is also based on the needs of that model of electric car.

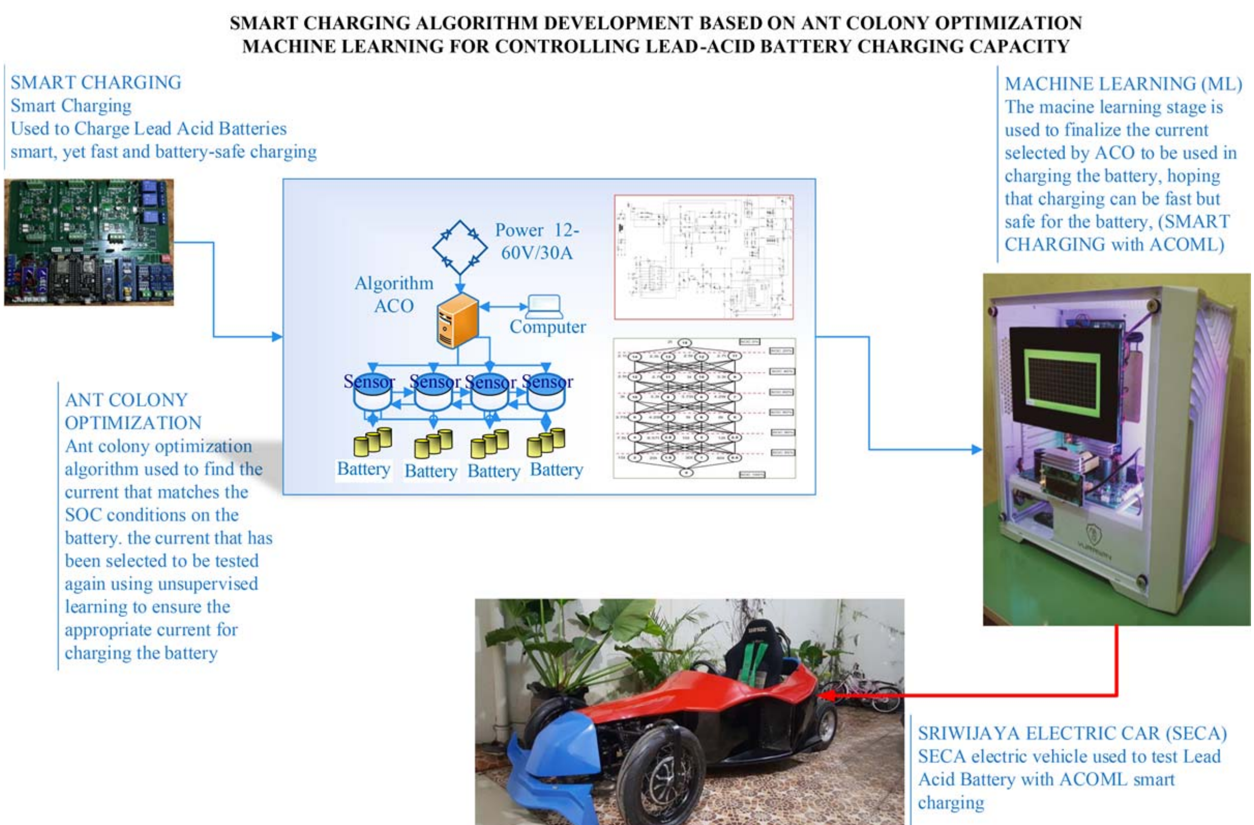
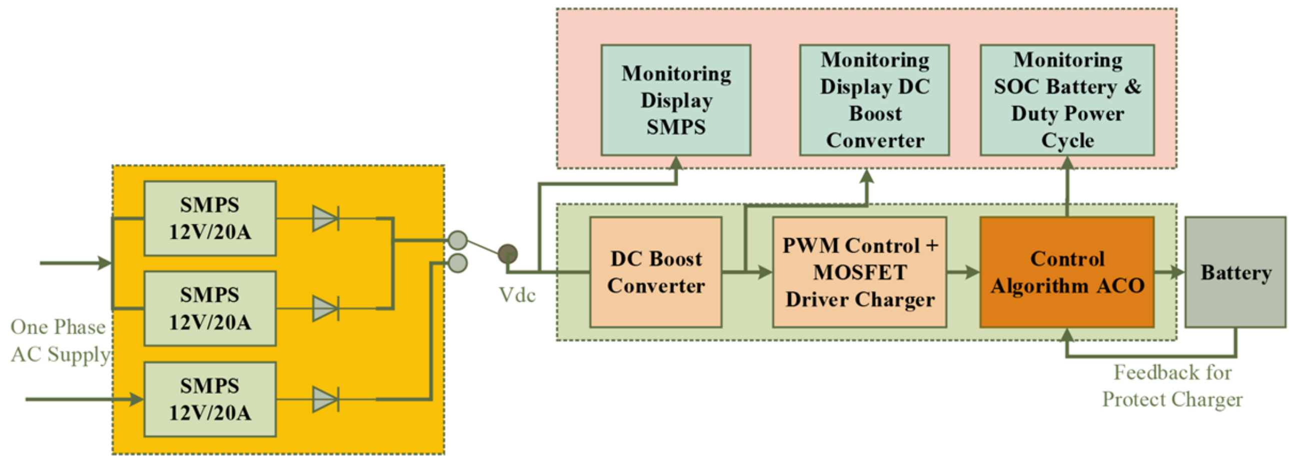
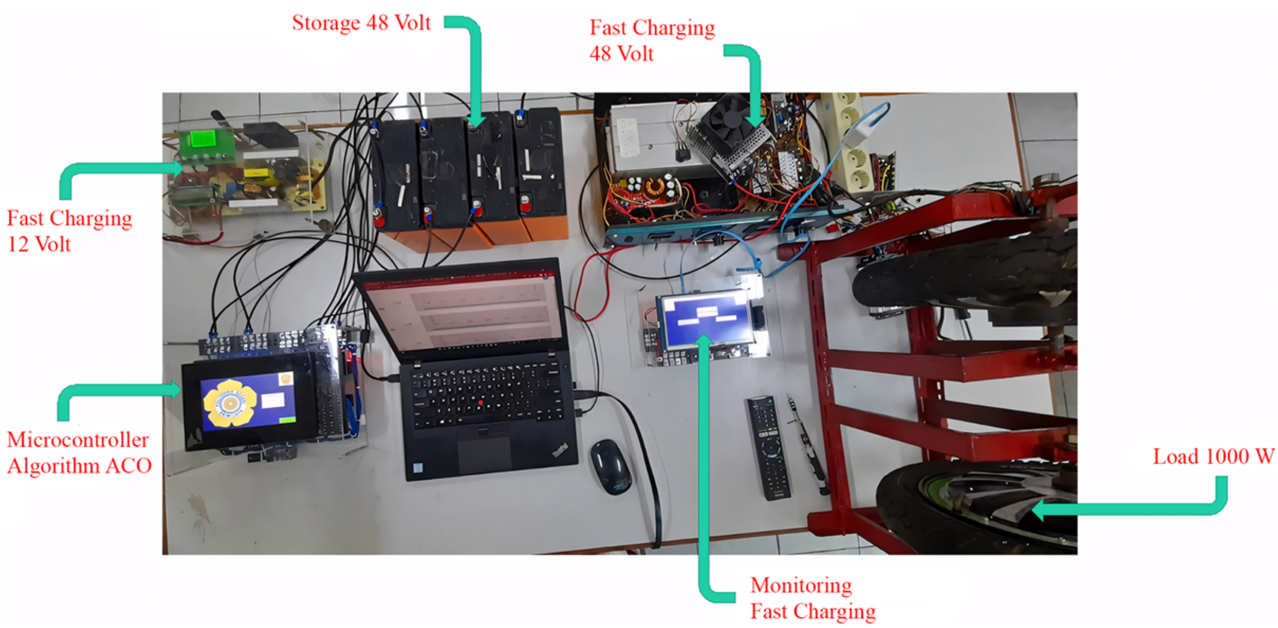


Fig. 1. Block diagram of smart charging model: research framework



a



b

Fig. 2. Block diagram of smart charging model:
a — schematic; *b* — design result

The overall design of smart charging consists of a switched mode power supply (SMPS), DC Boost Converter, and PWM DC Speed Controller. In this smart charging system designed, the voltage will be generated by the SMPS and increased by the DC Boost Converter according to the voltage required when charging. Furthermore, the PWM DC Speed Controller has a function as a duty power cycle regulator during the charging process. How the designed smart charging system works is shown in Fig. 3.

The battery charging process begins by connecting the battery to smart charging, then charging with constant current. The battery voltage will increase until it reaches the required voltage. Smart charging is also connected to the ACS712 voltage and current sensor module, where this electronic module can measure voltage as well as current in a circuit. Next, the voltage and current data from the sensor will be processed on a programmed microcontroller so that the voltage and current data will appear in the serial monitor and the SOC on the battery will appear on the PZEM-015 module. Data that has been processed by the microcontroller will also be recorded on the serial monitor screen record. The data was then transferred into the Microsoft Excel program. This data collection process is summarized in the diagram in Fig. 4.

Data obtained from the monitoring system during filling will be processed using the Microsoft Excel and RapidMiner Studio applications. From the literature review and methods design, it is hypothesized that with ant colony optimization modeling, smart charging will give better characteristics of SoH.

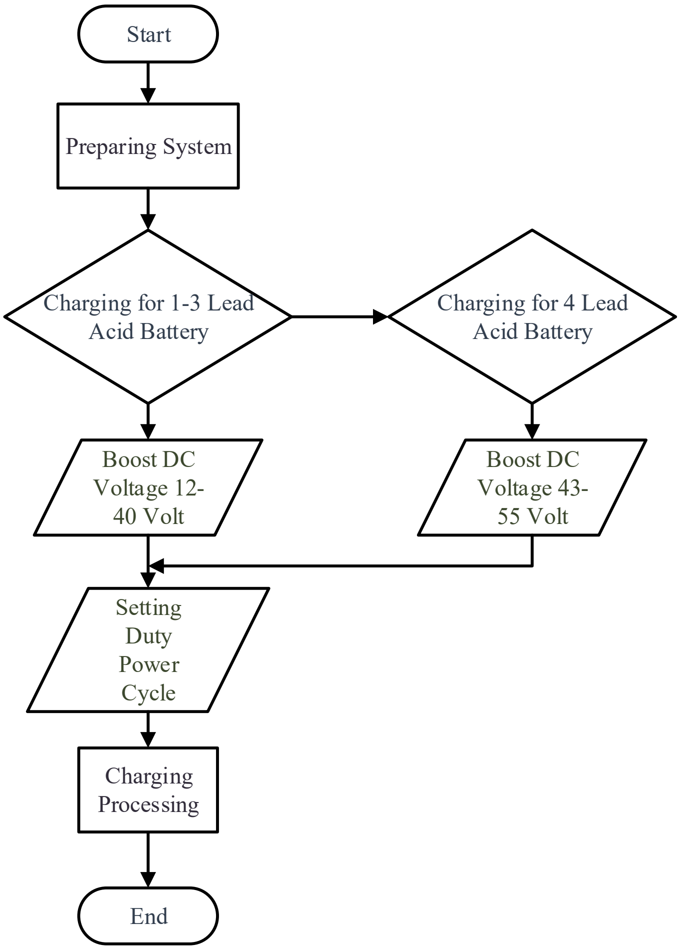


Fig. 3. Flow diagram of how smart charging works

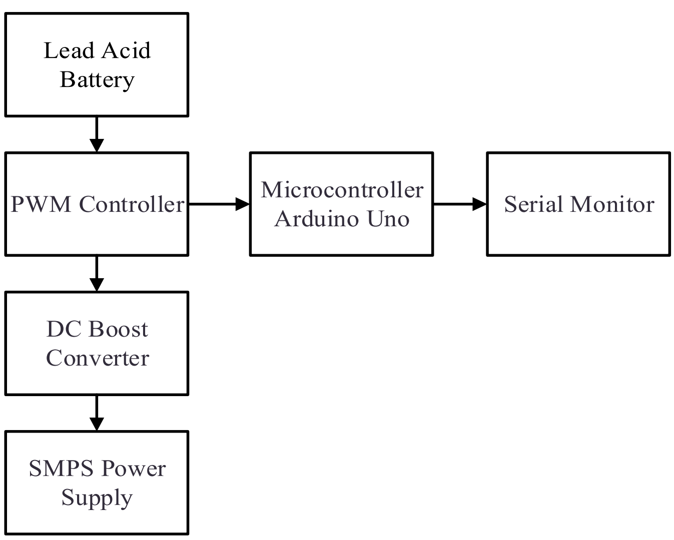


Fig. 4. Block diagram of the data retrieval process when charging

5. Results of the development of a control system with ant colony optimization modeling

5. 1. Parameter validation with the best root mean square error value

The results of data processing in the RapidMiner application are actual power values and estimated power. Both data are then returned to the Microsoft Excel application. The power estimation process in the RapidMiner application can be seen in Fig. 5.

The first step in implementing a neural network for processing current and voltage measurement data is to read Excel in the operator menu. This operator is useful for reading processed Excel data from raw data. The result of the data processing process in the Excel application is data normalization. Normalized data is used for power estimation. Voltage and current data are network input, while power data is network output. To provide a difference between input data and output data, the data used for the output data has its attributes changed to labels.

The next step is to split the data. Neural network data algorithms are usually divided into 3, namely training data, test data and validation data. This data division can only be used for large data, while for small data it is enough to just use training data and test data. In this research, the data will be divided into 2, namely training data and test data. The comparison of training data and test data is 80 %:20 % or 0.8:0.2.

After splitting the data, cross validation is carried out, which is a method used to evaluate a model or algorithm. The appearance of the application is shown in Fig. 6. This method is used if the amount of data used is limited. The data is separated into two learning subsets and validated by a validation subset. After the overall data is divided by the split data operator, cross validation will be carried out on the training data by dividing the training data again randomly and evenly into k-sub parts. The parameter value in cross validation is the K value.

According to research, the value K=10 is the best K value to use. This value is used to obtain the most optimal level of accuracy. This process is called the training process, where the results are used to test the network model. In the testing process, the training network model will be tested for its level of accuracy using test data so that the performance of the network model can be seen on the training data and test data. This research uses 2 neurons in the input layer, 4 hidden layer neurons, and 1 neuron in the output layer (Fig. 7).

The performance test is then used to evaluate network performance. In this research, performance regression is used to determine the performance of the network model. Regression is a technique used to predict numerical values and is a statistical measure used to determine the strength of the relationship between a dependent variable (label attribute) and several other attributes called independent variables (regular attributes). In this performance, the output produced is in the form of label attributes and prediction attributes. The label attribute stores the actual power value while the prediction attribute stores the label value predicted by the neural network. The calculation method used is root mean square error (RMSE). The smallest RMSE was found as 0.010013430, is chosen so that the target power value is close to the actual power. The parameters used during the training process simulation to obtain the smallest RMSE value are shown in Table 1.

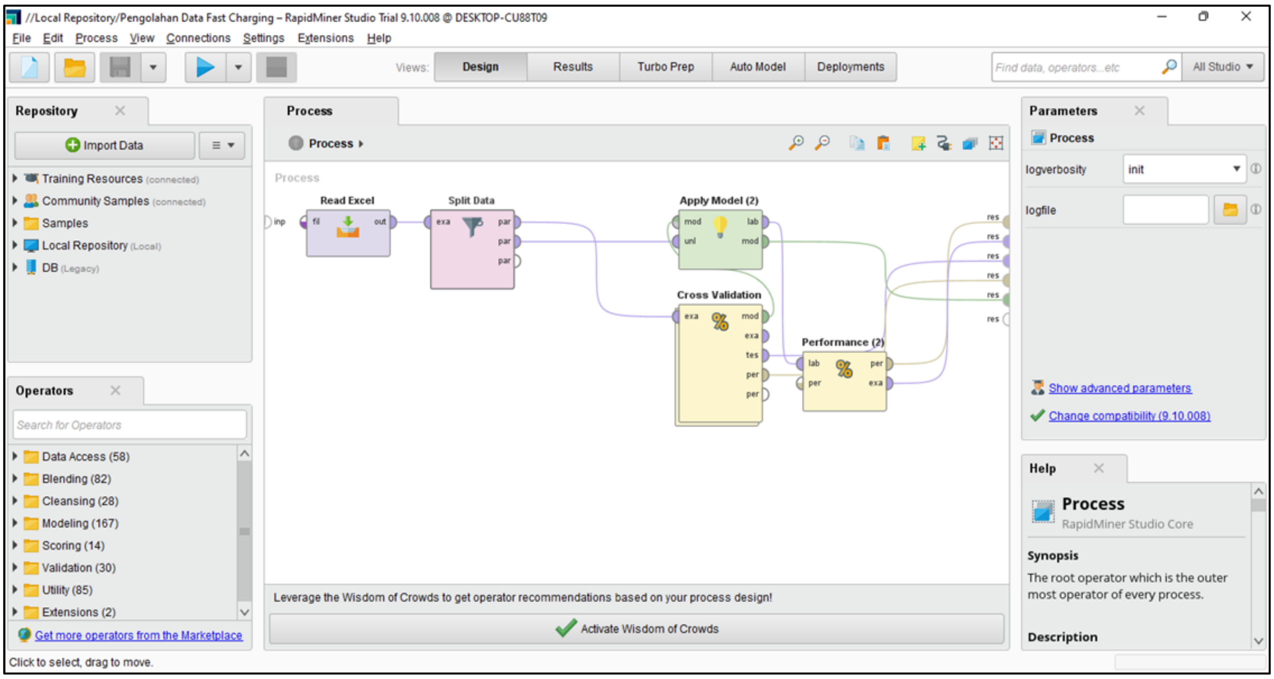


Fig. 5. Neural network scheme for the power estimation process in RapidMiner

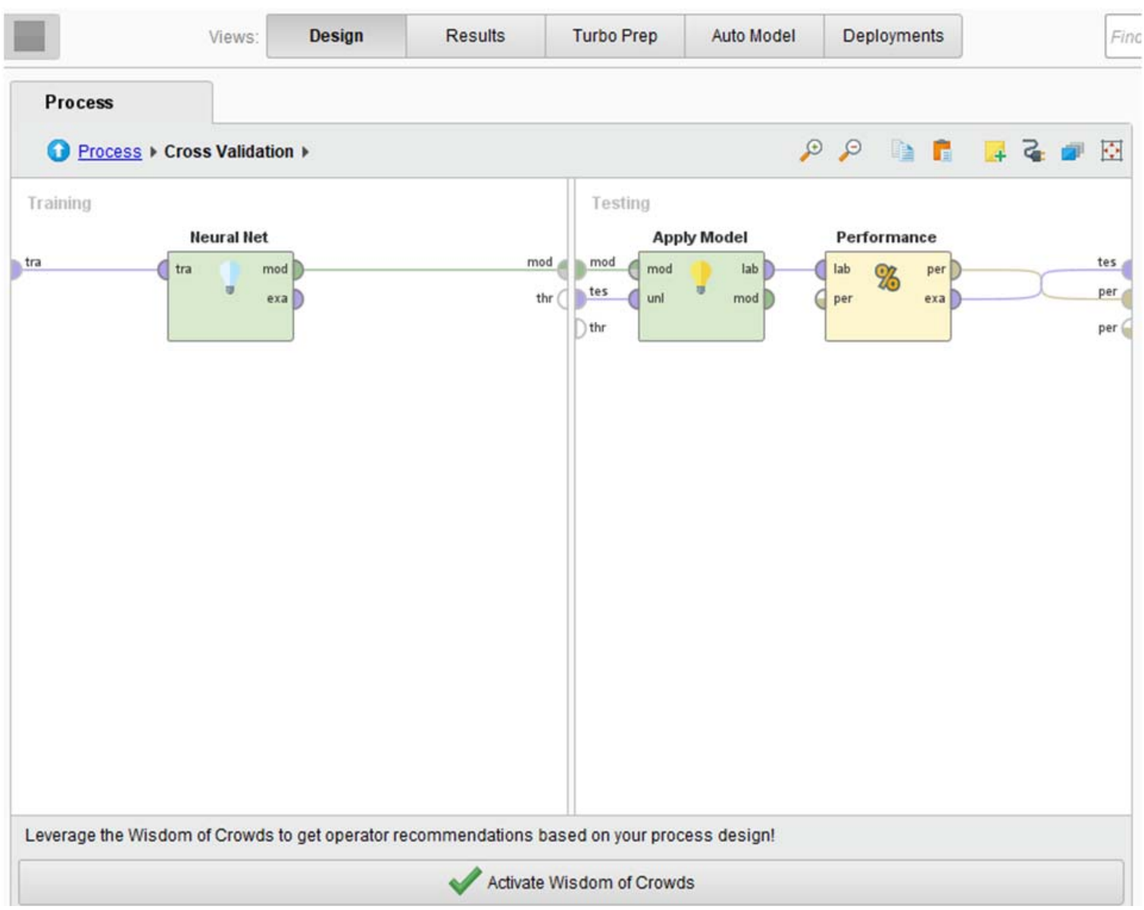


Fig. 6. Cross validation process

The parameters in Table 1 are the parameters that will be used in the charging system optimization process. These parameters are parameters that are thought to provide the best results in the charging process using ACO modeling.

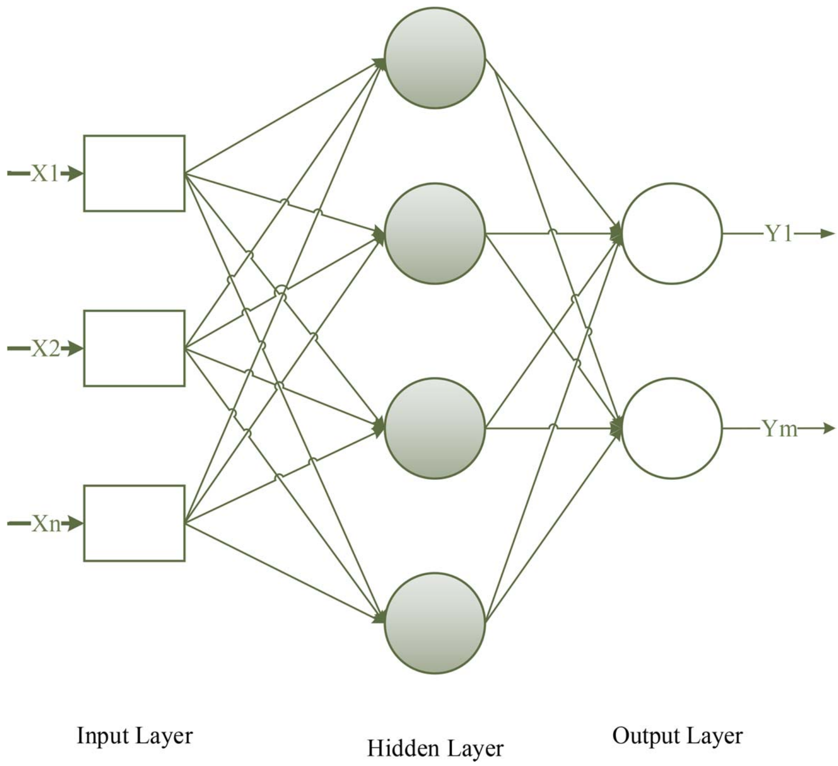


Fig. 7. Network model display based on test data results

Table 1

Neural network training parameters

Parameter	Count	Notes
Input neuron	2	Voltage and Current Value
Hidden neuron	3	–
Epoch	Trial-error	250, 500, 750, and 1,000
Learning rate	Trial-error	0.1–0.5
Momentum	Trial-error	0.1–0.5
Output neuron	1	Power Estimation Value

5. 2. The accuracy and performance level of the network model

After getting the smallest RMSE value in the training process, the network model is then used to be tested using test data. This aims to determine the level of accuracy and performance of the network model that has been trained.

The research method process flow is used to collect data on the battery charging process at 4 different voltages, namely for charging 12, 24, 36 and 48 V batteries. The charging process for 12 V batteries is carried out with the following conditions:

– total charging time: 6 minutes;
– average charge current: 4.5 A;
– data retrieval interval: 2 seconds;
– initial battery SOC: 62 %.

Examples of data obtained from the battery charging process are shown in Table 2.

When charging a lead acid battery, the initial voltage measured is 12.08 V so the voltage needs to be increased. When the initial SOC is around 62 %, the measured voltage is 12.19 V and the current is 5.5 A. When the initial SOC shows 100 %, which indicates the lead acid battery is fully charged, the measured battery voltage is 13.2 V and the current is 3.1 A with an estimated charging time of 6 minutes. So to charge four batteries with a SOC of around 60 % separately will take an estimated time of 36 minutes.

In the same way, the charging process for 24 V batteries (2x12 V) is carried out with a total charging time of 6 minutes, an average charge current of 5.38 A, a data collection interval of 2 seconds, and an initial battery SOC of 67 %. When charging two lead acid batteries, the initial measured voltage is 25.1 V so the voltage needs to be increased from 12 V to 25.2 V. The initial SOC measured when charging the battery is around 67 % for a voltage of 25.2 V and a current of 8.5 A. When the initial SOC shows 100 %, the measured battery voltage is 27.2 V and the current is 3.1 A with an estimated charging time of 6 minutes. When charging two batteries simultaneously, the batteries are arranged in series, so it is estimated that charging two batteries in stages with an SOC of 67 % takes around 12 minutes.

The charging process for 36 V batteries (3×12 V) is carried out with a total charging time of 8 minutes, an average charge current of 5.36 A, a data collection interval of 2 seconds, and an initial battery SOC of 59 %. When charging three lead acid batteries arranged in series, the measured voltage is 36.2 volts so the charging voltage needs to be increased from 12 volts to 37.3 volts. The initial SOC measured when the battery is about 59 % charged is a voltage of 36.2 V and a current of 8.5 A. When the initial SOC shows 100 %, the measured battery voltage is 41.3 V and a current of 3.1 A with an estimated charging time of 8 minutes. Charging three batteries simultaneously with SOC 59 % takes an estimated time of 8 minutes.

Table 2

12 Volt battery charging results

Data No.	Time (s)	Voltage SMPS (V)	Voltage DC Boost (V)	Current (A)	Power (W)	SOC (%)	PWM (%)
1	2	11.5	12.197	5.565	67.876	62	100
2	4	11.5	12.203	5.765	70.350	62	100
3	6	11.5	12.209	5.675	69.286	62	100
4	8	11.5	12.215	5.555	67.854	63	100
5	10	11.5	12.221	5.465	66.788	63	100
6	12	11.5	12.227	5.765	70.489	63	100
7	14	11.5	12.233	5.876	71.881	63	100
8	16	11.5	12.239	5.768	70.595	63	100
9	18	11.5	12.245	5.657	69.270	64	100
10	20	11.5	12.251	5.565	68.177	64	100
Until							
174	348	11.8	13.235	3.07	40.631	100	99
175	350	11.8	13.241	3.071	40.663	100	99
176	352	11.8	13.247	3.068	40.642	100	99

The charging process for 48 V batteries (4×12 V) is carried out with a total charging time of 10 minutes, an average charge current of 5.60 A, a data collection interval of 2 seconds, and an initial battery SOC of 48 %. When charging four lead acid batteries arranged in series the measured voltage is 46.7 V so the voltage needs to be increased to 47.8 V. The initial SOC measured when the battery is charged at around 48 % is a voltage of 47.8 V and a current of 10.5 A. When the initial SOC shows 100 % the measured battery voltage is 54.3 V and current 3.1 A with an estimated charging time of 10 minutes. Charging four batteries simultaneously takes an estimated time of 10 minutes.

The data that has been previously obtained is used for the system training process. The resulting training parameters can be seen in Table 3.

Table 3

Resulting training parameters

Battery (V)	Epoch	Learning Rate	Momentum	RSME
12	1000	0.4	0.5	0.004652485
24	1000	0.1	0.5	0.0049304
36	1000	0.1	0.5	0.0048831
48	1000	0.5	0.5	0.0043168

By using the parameters in Table 3, the charging training results graph for the 4 battery categories mentioned above can be seen in Fig. 8–11.

It can be seen that the training process gives almost identical results for predictive power and yield power, except at certain points (note the graph insert). With the above results, the network is tested with test data randomly selected by the system. Testing was carried out to determine network performance in the battery power estimation process. The testing process uses test data of 20 % of the total amount of data. The test results graph can be seen in Fig. 12–15.

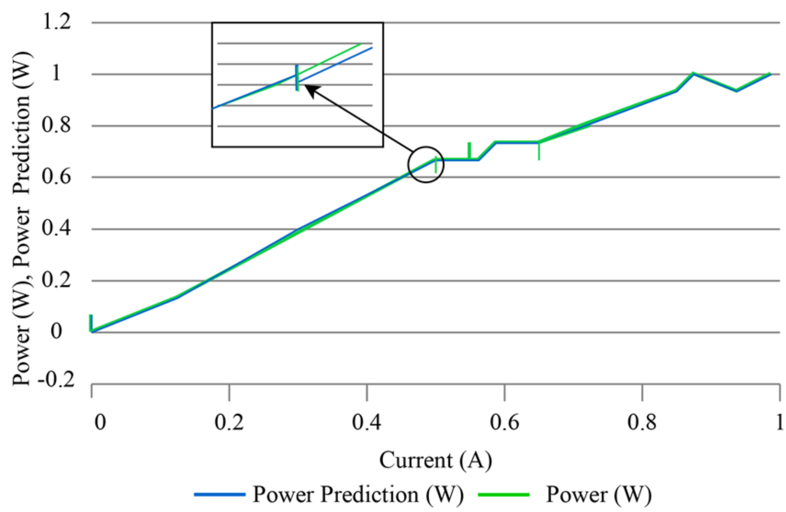


Fig. 8. Curve of 12 Volt charging training data

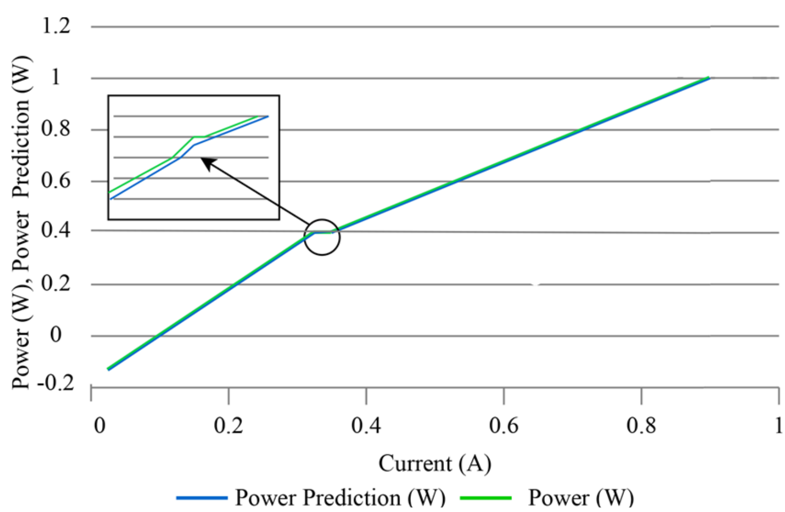


Fig. 9. Curve of 24 Volt charging training data

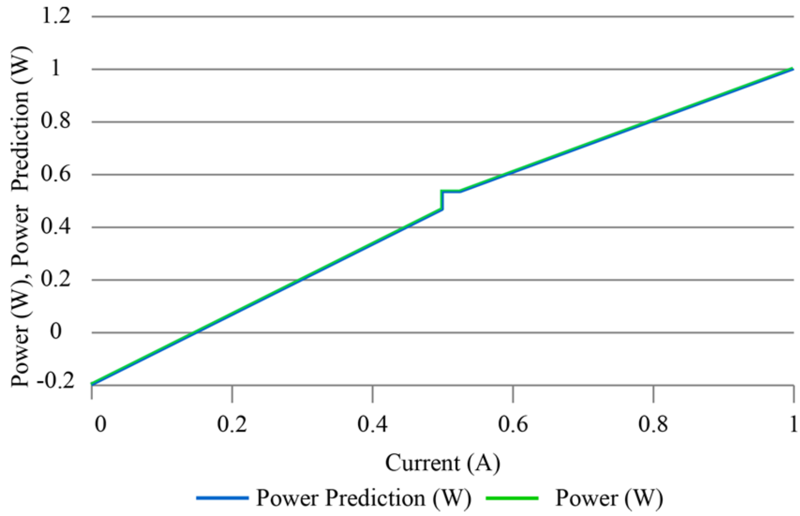


Fig. 10. Curve of 36 Volt charging training data

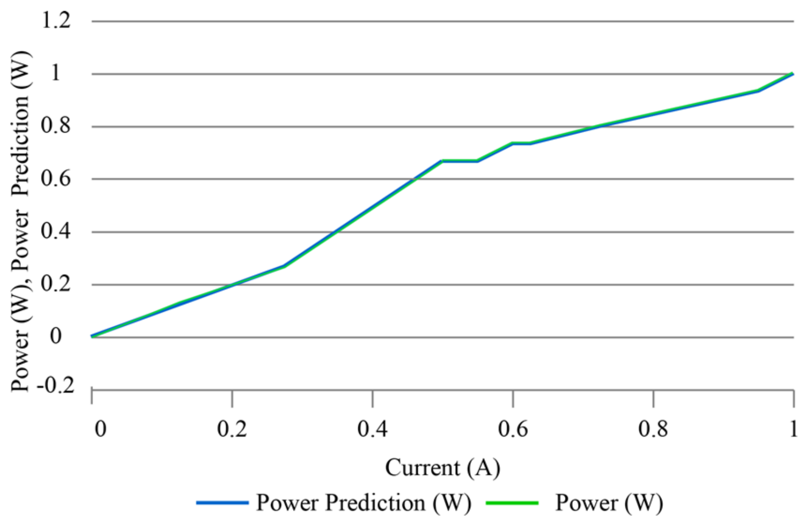


Fig. 11. Curve of 48 Volt charging training data

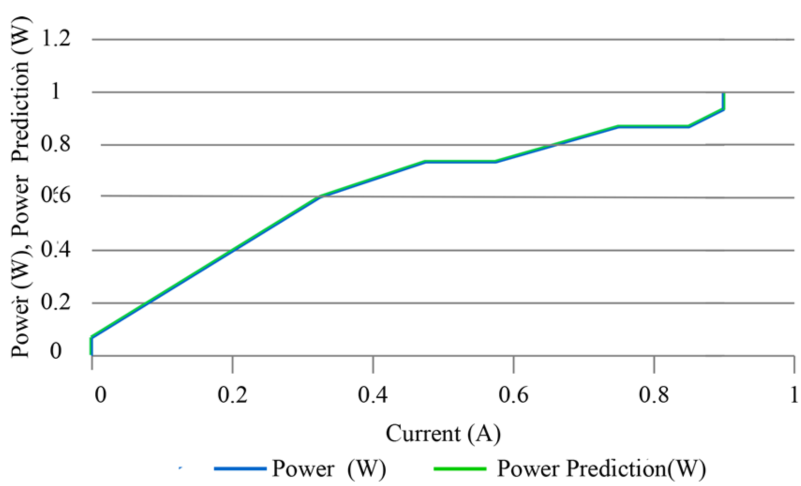


Fig. 12. Result of 12 Volt battery charging test

The model performance testing process still produces slight deviations when compared with the system training results. However, the filling process pattern is identical.

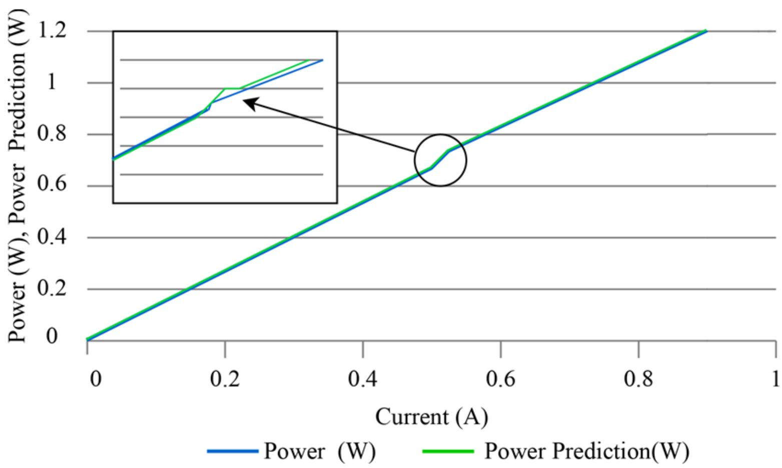


Fig. 13. Result of 24 Volt battery charging test

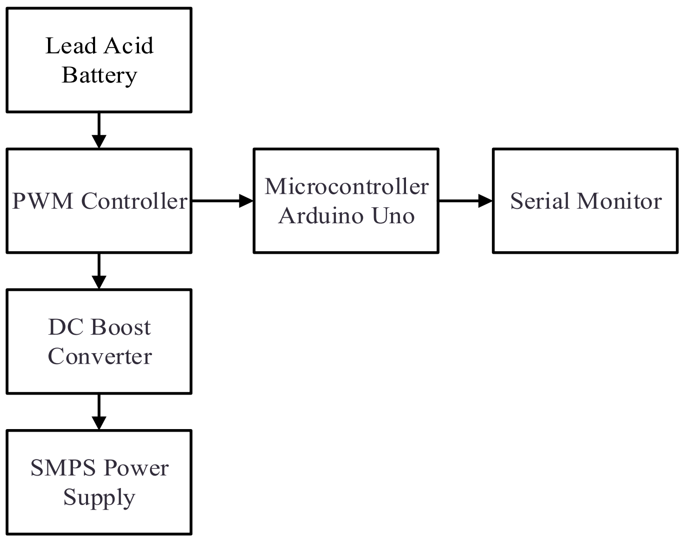


Fig. 14. Result of 36 Volt battery charging test

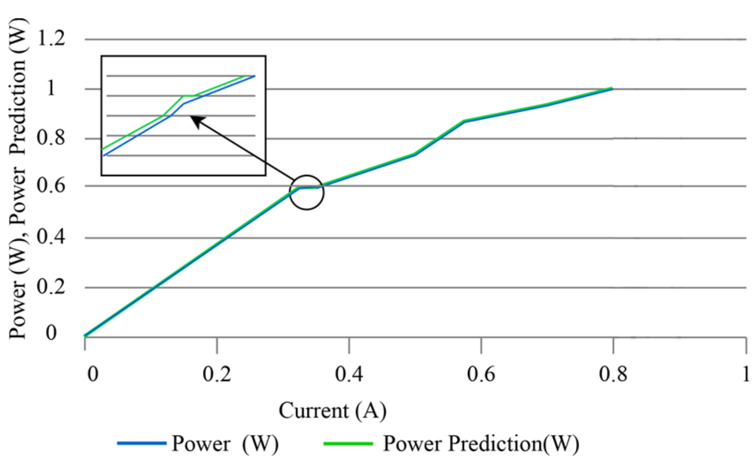


Fig. 15. Result of 48 Volt battery charging test

6. Discussion of the ACO modeling performance

The training and testing process to determine power estimates is carried out by the neural network method using the RapidMiner application. The RapidMiner application is freeware. Using freeware applications does not require software licensing fees to be used. The choice of this application as a training tool is also based on the program operators provided, so that it can be used according to the user's needs. This application does not require any special programs to be added for the operating process. The training process on battery charging data obtained the best parameter results as shown in Table 3. If observed, the difference in results between each parameter does not have a significant difference, however to estimate power a high level of accuracy is needed so the parameter that produces the smallest RMSE is selected. The neural network architecture model that is designed divides the training data and test data by 80 %:20 %. This neural network architecture model has 3 layers with 2 neurons in the input layer, 4 neurons in the hidden layer and 1 neuron in the output layer.

The level of accuracy of a neural network depends on the architectural model created, namely the number of iterations, learning rate and momentum. These parameters are related to each other and have their respective roles. In this study, there were two charging conditions, namely 24 volts and 36 volts (Fig. 8–11), which used the same number of iterations and learning rate, namely 1000 iterations and a learning rate of 0.1. These two parameters play an important role in producing a network that has optimal performance. The number of iterations shows the network's effort to learn data to produce input values that are close to the target. The greater the number of iterations, the more the network learns the data. To avoid the network losing learning patterns, an appropriate learning rate is given. Learning rate shows the rate of learning at each iteration. However, it should be noted that the number of iterations and learning rate affect the time required by the network to produce the appropriate output value.

The number of neurons in the hidden layer also plays an important role (Fig. 7). There is no specific theory that states the ideal number of neurons in the hidden layer. This number of neurons was obtained from the experimental process during the simulation. According to several previous studies, the use of one hidden layer is sufficient to produce a high level of accuracy.

After carrying out the training process and obtaining the correct parameters for estimating charging power, the testing process on the performance of the architectural model resulting from the training process obtained an RMSE value of 0.008001879 for 12 volt battery charging data, RMSE 0.005887915 for 24 volt battery charging data, RMSE 0.005970755 for 36 volt battery charging data, and RMSE 0.010013430 for 48 volt charging data. The results of this test are not too different from the training results, so it can be said that the neural network architectural model designed to determine power estimates in smart charging systems is very good. The fast charging SoC value is usually less than 80 % of the nominal battery capacity. The DC fast charging (DCFC) condition is capable of providing 50 kW or more, while the ultra-fast charging category is usually capable of providing 150 kW or more. Mega charging conditions are referred to refs [35–37], in the context of charging up to 80 % SoC within 10 minutes, at a speed of 6–9E, or greater than 300 kW.

The neural network architecture model to obtain the best RMSE is based on the ACO method, which was perfected by Dorigo [38] in 2006. ACO is an optimization that imitates ant behavior as a computational intelligence technique. The principle of the ant colony optimization algorithm is inspired by the behavior of ant colonies in searching for food sources based on pheromones. Pheromones are substances originating from the endocrine glands of ants, which can be used to identify fellow colonies, remember the way home, and find the quickest path to food [39]. Ants always look for the fastest route between home and food sources. The shortest path is marked by the number of pheromones left by the ants that pass through it. As more ants favor a path, its pheromone trail strengthens, while pheromones on other paths evaporate. This concept is widely applied to solve problems that consist of many variables. In this research, the shortest path is used to obtain the smallest RMSE, which indicates the smallest difference between training parameters and test parameters in Fig. 12–15.

In a battery charging system, ACO is used to find a fast and safe current charging pattern for each battery. The amount of charging current is assumed to be a path that can be traversed by ants and the charging duration is assumed to be the distance between paths, so that ACO is used to find charging current patterns based on charging duration. The ACO termination process consists of 4 stages, namely:

1) initialization, which 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 2 points;

2) random distribution of ants. At this stage, as many as K ants are distributed to analyze each node, so that the ants can leave the initial pheromone level, which will be processed further;

3) pheromone calculation, where the addition and evaporation of pheromones occurs, which continues to be updated during the process;

4) the path selection process based on the principle of probability, where the path that has a higher pheromone level will have a greater probability.

This path selection process is carried out repeatedly until the best or fastest path (smallest RMSE) is obtained. This is in accordance with the application of ACO by its inventor in 1992 for the Traveling Salesman Problem [40].

Although this research shows optimum results for the fast charging process on lead acid batteries safely, it does not make comparisons with other types of batteries. Research on the lead acid charging process still needs a lot of development, but a comparison of ACO modeling performance on other types of batteries will further strengthen the validity of the findings. This weakness is also a potential for developing research for the fast charging process, including developing methods to increase battery life that can meet the power usage requirements for electric cars, matching the capabilities of fossil-based fuels.

7. Conclusions

1. The training process produces the smallest RMSE value as 0.010013430. These findings ensure that the target power value is close to the actual power. Then, it can be concluded that DC Boost Converter can be used as a voltage increaser from 12 volts to 60 volts, adjusting to the number of batteries and the voltage required when charging the battery. PWM to regulate the duty cycle does not have a significant influence but is set to use a 100 % duty cycle setting. If a duty cycle use is below 100 %, there will be a voltage drop of around 2 volts during the OFF condition, this affects the battery charging condition, which results in a slower charging estimate.

2. The neural network model can be applied to estimate the state of charge of lead acid batteries using the parameters in RMSE value. The parameters used have obtained output results that are close to the target using the ACO method.

The resulting neural network architecture design consists of 3 layers, which include 2 neurons in the input layer, 4 neurons in the hidden layer, and 1 neuron in the output layer. This architecture was successfully used in four conditions, namely 12 volt, 24 volt, 36 volt and 48 volt charging.

Conflict of interest

The authors declare that they have no conflict of interest.

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The study was performed without financial support.

Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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References

1. Sun, X., Li, Z., Wang, X., Li, C. (2019). Technology Development of Electric Vehicles: A Review. Energies, 13 (1), 90. https://doi.org/10.3390/en13010090
2. Li, Z., Khajepour, A., Song, J. (2019). A comprehensive review of the key technologies for pure electric vehicles. Energy, 182, 824–839. https://doi.org/10.1016/j.energy.2019.06.077
3. Utami, M. W. D., Yuniaristanto, Y., Sutopo, W. (2020). Adoption Intention Model of Electric Vehicle in Indonesia. Jurnal Optimasi Sistem Industri, 19 (1), 70–81. https://doi.org/10.25077/josi.v19.n1.p70-81.2020
4. Bozhkov, S. (2021). Structure of the Model of Hybrid Electric Vehicle Energy Efficiency. Trans Motauto World, 6 (3), 76–79. https://stumejournals.com/journals/tm/2021/3/76
5. Ehsani, M., Singh, K. V., Bansal, H. O., Mehrjardi, R. T. (2021). State of the Art and Trends in Electric and Hybrid Electric Vehicles. Proceedings of the IEEE, 109 (6), 967–984. https://doi.org/10.1109/jproc.2021.3072788
6. Arif, S. M., Lie, T. T., Seet, B. C., Ayyadi, S., Jensen, K. (2021). Review of Electric Vehicle Technologies, Charging Methods, Standards and Optimization Techniques. Electronics, 10 (16), 1910. https://doi.org/10.3390/electronics10161910
7. Mohamed, N., Aymen, F., Ali, Z. M., Zobaa, A. F., Abdel Aleem, S. H. E. (2021). Efficient Power Management Strategy of Electric Vehicles Based Hybrid Renewable Energy. Sustainability, 13 (13), 7351. https://doi.org/10.3390/su13137351
8. Nieuwenhuis, P., Cipcigan, L., Berkem Sonder, H. (2020). The Electric Vehicle Revolution. Future Energy, 227–243. https://doi.org/10.1016/b978-0-08-102886-5.00011-6
9. Muslimin, S., Maulidda, R., Nawawi, M., Rahman, A., Kurnia, P. M. (2023). The Method of Constant Current - Constant Voltage (CC – CV) for SECA Electric Car Battery Charging with Fuzzy Logic Controller. Atlantis Highlights in Engineering, 14–23. https://doi.org/10.2991/978-94-6463-118-0_3
10. Carter, R., Cruden, A., Hall, P. J., Zaher, A. S. (2012). An Improved Lead–Acid Battery Pack Model for Use in Power Simulations of Electric Vehicles. IEEE Transactions on Energy Conversion, 27 (1), 21–28. https://doi.org/10.1109/tec.2011.2170574
11. B (2015). Dictionary of Energy, 41–81. https://doi.org/10.1016/b978-0-08-096811-7.50002-0
12. Bergveld, H. J., Kruijt, W. S., Notten, P. H. L. (2002). Battery Management Systems. Springer Netherlands. https://doi.org/10.1007/978-94-017-0843-2
13. Adityawan, A. P., Cahya, D. D., Sulistijono, L., Madyono (2013). Sistem Pengisian Batteray Lead Acid Secara Adaptive. PENS-ITS Sukolilo, 5 (1).
14. Achaibou, N., Haddadi, M., Malek, A. (2008). Lead acid batteries simulation including experimental validation. Journal of Power Sources, 185 (2), 1484–1491. https://doi.org/10.1016/j.jpowsour.2008.06.059
15. Setiaji, B., Dwiono, W., Tamam, M. T. (2020). Rancang Bangun Pengisi Baterai Lead Acid Dan Li-Ion Secara Otomatis Menggunakan Mikrokontroler PIC 16F877A Bersumber Energi Matahari Dengan Pengendali PI. Jurnal Riset Rekayasa Elektro, 1 (2). https://doi.org/10.30595/jrre.v1i2.5187
16. Shahriari, M., Farrokhi, M. (2013). Online State-of-Health Estimation of VRLA Batteries Using State of Charge. IEEE Transactions on Industrial Electronics, 60 (1), 191–202. https://doi.org/10.1109/tie.2012.2186771
17. Baterai Asam-Timbal. Dede Hendriono. Available at: https://henduino.github.io/library/ototronik/leadacid/
18. Thowil Afif, M., Ayu Putri Pratiwi, I. (2015). Analisis Perbandingan Baterai Lithium-Ion, Lithium-Polymer, Lead Acid dan Nickel-Metal Hydride pada Penggunaan Mobil Listrik - Review. Jurnal Rekayasa Mesin, 6 (2), 95–99. https://doi.org/10.21776/ub.jrm.2015.006.02.1
19. Wang, L., Qin, Z., Slangen, T., Bauer, P., van Wijk, T. (2021). Grid Impact of Electric Vehicle Fast Charging Stations: Trends, Standards, Issues and Mitigation Measures - An Overview. IEEE Open Journal of Power Electronics, 2, 56–74. https://doi.org/10.1109/ojpel.2021.3054601
20. Town, G., Taghizadeh, S., Deilami, S. (2022). Review of Fast Charging for Electrified Transport: Demand, Technology, Systems, and Planning. Energies, 15 (4), 1276. https://doi.org/10.3390/en15041276

21. Sidiq, R. K. (2015). Rancang Bangun Sistem Pengisi Baterai Mobil Listrik Berbasis Mikrokontroller Atmega16. Universitas Jember. Available at: https://repository.unej.ac.id/bitstream/handle/123456789/73490/111910201039--ROHMAT%20KHOIRUL%20SIDIQ-1-56.pdf?sequence=1&isAllowed=y
22. Yusuf Margowadi, R. A. N., Samodra, B., Dawam, M. D. N. (2021). Pengembangan Pengisi Baterai Cepat 72 Volt Untuk Charging Station Kendaraan Listrik Roda Dua. Seminar Teknologi Bahan Dan Barang Teknik 2020, 49–54.
23. Prianto, E., Yuniarti, N., Nugroho, D. C. (2020). Boost-converter sebagai alat pengisian baterai pada sepeda listrik secara otomatis. Jurnal Edukasi Elektro, 4 (1). https://doi.org/10.21831/jee.v4i1.32632
24. Camacho, O. M. F., Mihet-Popa, L. (2016). Tests de recharge rapide et intelligente de batteries pour voitures électriques utilisant des énergies renouvelables. Oil and Gas Science and Technology, 71 (1).
25. Syafii, Mayura, Y., El Gazaly, A. (2019). Characteristics of Lead-Acid Battery Charging and Discharging Against Residential Load in Tropical Area. 2019 16th International Conference on Quality in Research (QIR): International Symposium on Electrical and Computer Engineering. https://doi.org/10.1109/qir.2019.8898277
26. Catherino, H. A., Burgel, J. F., Rusek, A., Feres, F. (1999). Modelling and simulation of lead-acid battery charging. Journal of Power Sources, 80 (1-2), 17–20. https://doi.org/10.1016/s0378-7753(98)00248-1
27. Sadeghian, O., Oshnoei, A., Mohammadi-ivatloo, B., Vahidinasab, V., Anvari-Moghaddam, A. (2022). A comprehensive review on electric vehicles smart charging: Solutions, strategies, technologies, and challenges. Journal of Energy Storage, 54, 105241. https://doi.org/10.1016/j.est.2022.105241
28. Xing, Y., Li, F., Sun, K., Wang, D., Chen, T., Zhang, Z. (2022). Multi-type electric vehicle load prediction based on Monte Carlo simulation. Energy Reports, 8, 966–972. https://doi.org/10.1016/j.egyr.2022.05.264
29. Mololoth, V. K., Saguna, S., Åhlund, C. (2023). Blockchain and Machine Learning for Future Smart Grids: A Review. Energies, 16 (1), 528. https://doi.org/10.3390/en16010528
30. Esmalifalak, M., Liu, L., Nguyen, N., Zheng, R., Han, Z. (2017). Detecting Stealthy False Data Injection Using Machine Learning in Smart Grid. IEEE Systems Journal, 11 (3), 1644–1652. https://doi.org/10.1109/jsyst.2014.2341597
31. Teichgraeber, H., Brandt, A. R. (2019). Clustering methods to find representative periods for the optimization of energy systems: An initial framework and comparison. Applied Energy, 239, 1283–1293. https://doi.org/10.1016/j.apenergy.2019.02.012
32. Sakhnini, J., Karimipour, H., Dehghantanha, A., Parizi, R. M. (2021). Physical layer attack identification and localization in cyber–physical grid: An ensemble deep learning based approach. Physical Communication, 47, 101394. https://doi.org/10.1016/j.phycom.2021.101394
33. Javaid, N., Jan, N., Javed, M. U. (2021). An adaptive synthesis to handle imbalanced big data with deep siamese network for electricity theft detection in smart grids. Journal of Parallel and Distributed Computing, 153, 44–52. https://doi.org/10.1016/j.jpdc.2021.03.002
34. Pallonetto, F., De Rosa, M., Milano, F., Finn, D. P. (2019). Demand response algorithms for smart-grid ready residential buildings using machine learning models. Applied Energy, 239, 1265–1282. https://doi.org/10.1016/j.apenergy.2019.02.020
35. Srdic, S., Lukic, S. (2019). Toward Extreme Fast Charging: Challenges and Opportunities in Directly Connecting to Medium-Voltage Line. IEEE Electrification Magazine, 7 (1), 22–31. https://doi.org/10.1109/mele.2018.2889547
36. Ronanki, D., Kelkar, A., Williamson, S. S. (2019). Extreme Fast Charging Technology—Prospects to Enhance Sustainable Electric Transportation. Energies, 12 (19), 3721. https://doi.org/10.3390/en12193721
37. Tu, H., Feng, H., Srdic, S., Lukic, S. (2019). Extreme Fast Charging of Electric Vehicles: A Technology Overview. IEEE Transactions on Transportation Electrification, 5 (4), 861–878. https://doi.org/10.1109/tte.2019.2958709
38. Ant colony optimization (2007). Handbook of Approximation Algorithms and Metaheuristics. Available at: https://www.taylorfrancis.com/chapters/mono/10.1201/9781420010749-33/ant-colony-optimization-teofilo-gonzalez?context=ubx&refId=21abeb5d-2476-4646-acdf-25c398f93e16
39. Kao, Y., Cheng, K. (2006). An ACO-Based Clustering Algorithm. Lecture Notes in Computer Science, 340–347. https://doi.org/10.1007/11839088_31
40. Dorigo, M., Gambardella, L. M. (1997). Ant colony system: a cooperative learning approach to the traveling salesman problem. IEEE Transactions on Evolutionary Computation, 1 (1), 53–66. https://doi.org/10.1109/4235.585892