Journal of Theoretical and Applied Information Technology
15th July 2016. Vol.89. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

FORECASTING OF LEAD ACID BATTERY CAPACITY BASED ON LEVENBERG MARQUARDT NEURAL NETWORK

[1]B. S. KALOKO, [2]M. UDIN, [3]A. H. LOKA

[1]Department of Electrical Engineering, Faculty of Engineering, University of Jember, Jember, Indonesia

[2,3] Student of Electrical Engineering, Faculty of Engineering, University of Jember, Jember, Indonesia

E-mail: [1]bambangsrikaloko@yahoo.com, [2]udinmambak@gmail.com, [3]121910201061@students.unej.ac.id,

ABSTRACT

One of the discussion in the research of electric vehicle is the energy source or battery. Due to mature technology, environmental friendliness, and low cost, the lead acid battery has been widely accepted in electric vehicle. It is necessary to forecast battery capacity in electric car in order to know when the time to recharge the battery or replace it. The Levenberg Marquardt algorithm is chosen to adaptively optimize weights at each epoch so as to accommodate time-varying system conditions. In a state of nominal current of 1.2 A, battery discharge graph has 1.8617 Ah and 1.55 hours compared to simulation results 2 Ah and 1.38 hours thus 10.96 % of error is obtained. When the load is 8 W, showed 1.5 Ah of battery capacity and 3.1 hours with small error 1.58 % compared to the current load on the nominal load is equal to 20 W produced a greater error 27.27 % with 1.86 Ah and 0.8 hours. This means that the system made it would be better if used under a nominal load of the above nominal load. But it needs to design better system to maintain more accurate results of the battery capacity and the time.

Keywords: *Capacity of battery, Lead Acid Battery, Artificial Neural Network (ANN), Feedforward Backpropagation, Levenberg Marquardt.*

1. INTRODUCTION

The car is one means of transportation that is often used in daily life. Its use is practical and comfortable making the car to be excellent. Due to the higher world oil prices, making many people look for alternative-fuel cars, one of which is an electric vehicle [1]. Electric Vehicles are gaining more popularity due to the advantages such as high level efficiency, low level of environmental pollution, low rate of noise, multiple energy resources available, and regenerative [2].

One of the discussion in the research of electric vehicle is the energy source or battery. The capacity of the battery is the main parameter participating in a range of the battery electric vehicle (BEV) [3]. Many types of batteries can be selected as energy sources in electric vehicle. Nevertheless, recent development of electric vehicle batteries is mainly focused on the lead acid, nickel metal hydride (Ni-MH), and lithium ion (Li-ion), batteries. Due to mature technology, environmental friendliness, and low cost, the lead-acid battery has been widely accepted in electric vehicle [4]. Batteries in electric cars have limited capacity it must be done so that recharging of electric cars can go far. This situation if not solved immediately could cause the battery to depleted in the street. Of course this makes anxious and uncomfortable for users of electric vehicle. Therefore, it is necessary for forecasting of battery capacity in order to know when it's time to recharge the battery or replace it.

Artifical Neural network (ANN) is an inductive, or data based model for simulation of input/output mapping. ANN require training data to learn patterns of input/output behavior, and once trained, can be used to simulate system behavior within that training region. This can be done by interpolating specified inputs among the training inputs to yield outputs that are the interpolations of training outputs. The reason for using ANN to simulate system behavior is that it provide accurate approximations of system behavior and is typically much more computationally efficient than phenomenological models. This efficiency is very important in situations where multiple responses or prediction computations are required [5].

The Levenberg Marquardt algorithm is chosen to adaptively optimize weights at each epoch so as to accommodate time-varying system conditions [6]. This algorithm can be used to forecast battery capacity from several inputs and output as training

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

data. So that the time to recharge the battery from an electric car is able to known.

2. LITERATUR REVIEW

2.1 Lead Acid Battery

Currently the most common type of battery used for energy storage is the lead-acid battery. These batteries are most commonly used because it is cheaper compared to other battery types. The battery has a characteristic use of lead (Pb) in the second electrode as an active material. In the charged state, the positive electrode consists of lead dioxide (PbO_2) while the negative electrode consists of pure lead (Pb). A membrane attached to separate the two electrodes. Liquid sulfuric acid (H_2SO_4) is filled in the space between the two electrodes as the electrolyte. Lead-acid batteries are fully charged has a density of acid about 1.24 kg/liter at a temperature of 25 °C. The acid density fluctuations appropriate temperature and state of charge the battery.

All lead-acid batteries operate with the same basic reaction. When the batteries are discharged, the active material in the electrode reacts with the electrolyte to form lead sulfate ($PbSO_4$) and water (H_2O). When charging, lead sulfate turned back into lead dioxide on the positive electrode and the lead on the negative electrode, and sulfate ions (SO_4^{2-}) back into the electrolyte solution to form sulfuric acid. Here are the reactions that occur in a cell.

On the positive electrode

$$PbO_2 + 3H^+ + HSO_4^- + 2e^- \rightleftarrows PbSO_4 + 2H_2O \quad (1)$$

On the negative electrode

$$Pb + HSO_4^- \rightleftarrows PbSO_4 + H^+ + 2e^- \quad (2)$$

The overall reaction cell

$$PbO_2 + Pb + 2H_2SO_4 \rightleftarrows 2PbSO_4 + 2H_2O \quad (3)$$

The capacity that can be used in a battery depends on the current release of cargo. The greater the current release of the smaller cargo usable capacity and the battery voltage discharge will be more quickly achieved.

Age battery usage, such as number of cycles that can be done, will decrease with increasing temperature and deeper discharge. Recommended depth of discharge is 80%, while to a depth of discharge of 50% should be avoided. The behavior of the release or charging of a battery depends on several parameters. These parameters will be used for comparison battery. Several battery parameters, among others:

- Voltage
- Capacity Battery
- Battery State of Charge (BSOC)
- Internal Resistance
- Discharge Self (Self-Discharge)

SOC describe the energy available in the battery, the SOC can determine the total energy that can be used from a battery [7].

2.2 Capacity of Battery

The battery capacity is expressed in Ampere hours, Ah = strong currents (Ampere) x time (hour). It means that the battery can supply large amounts of current (Ampere) on average within a certain period, before each cell touching drop voltage that is equal to 1.75 V (each cell has a voltage of 2 V). For example, battery 12 V 6 Ah. In simple terms this means that the battery is able to deliver a powerful current of 6 Ampere in one hour, which means give an average power of 72 Watt and 72 Watt power supply for an hour or a power of 7.2 watts for 10 hours (Watts = Voltage x Ampere = 12 V x 6 A) [8].

2.3 Levenberg Marquardt

The Levenberg Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed forward networks), then the Hessian matrix can be approximated as

$$\mathbf{H} = \mathbf{J}^T \mathbf{J} \quad (4)$$

and the gradient can be computed as

$$\mathbf{g} = \mathbf{J}^T \mathbf{e} \quad (5)$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix.

The Levenberg Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

Journal of Theoretical and Applied Information Technology
15th July 2016. Vol.89. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \quad (6)$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quick as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm [9].

3. RESEARCH METHODOLOGY

In this section, determine several parameters of battery in simulation based on real battery. The type of battery that use is Yuasa YT7C (YB5L-B). Then, data parameters input and target are taken for designing ANN system. In the last, ANN system for battery capacity forecasting in simulink can be made.

3.1 Battery Parameter

Battery parameters that use in battery capacity forecasting simulation are shown in table 1.

Table 1: Battery Parameter

Manufacturer	Yuasa
Model	YT7C (YB5L-B)
Nominal Voltage	12 V
Capacity	6 Ah
Internal Resistance	0.02 ohm

3.2 Design of Neural Network

The feedforward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network.

In this paper, the backpropagation learning iterative algorithm has been used to control the weights in the feedforward network. The network consisted of three layers: input layer, hidden layer and output layer as shown in the ANN structure in Figure. 1 was designed using Matlab R2010b commercial neural network software.

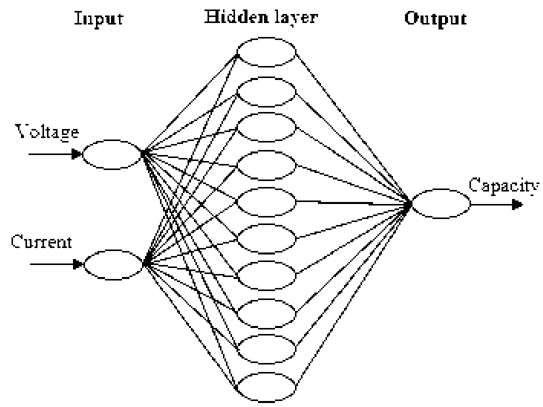


Figure 1. ANN Model

Input data for the system are load current and load voltage. Output data or called as target is battery capacity on certain nominal current. After getting input and target data, ANN structure can be built. The number of neurons in the hidden layer in the developed network, training and testing patterns and type of transfer functions applied in hidden layer and output layer activation functions are summarized in table 2.

Table 2: Network Parameters

Network type	Feed Forward Backpropagation
Training Function	Levenberg Marquardt backpropagation (TRAINLM)
Transfer Function	Log-Sigmoid (LogSig)
Performance	Mean Square Error (MSE)
Epoch	1000
Goal	10^{-6}
Neurons	10

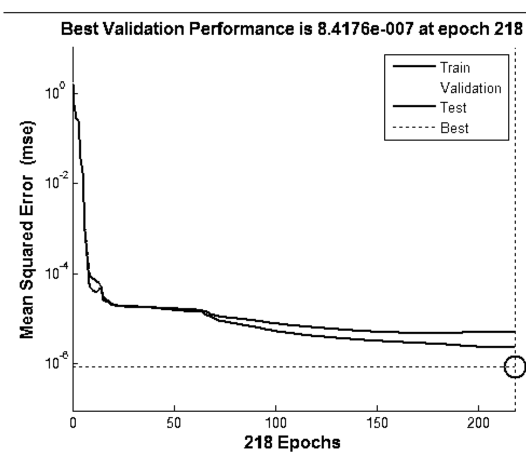


Figure 2. Mean Squared Error

The iteration is executed repeatedly until the difference between the real output of the network

Journal of Theoretical and Applied Information Technology
15th July 2016. Vol.89. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and the preferred output is equal to a negligible value, which signifies no additional advancement in the network was achieved. Figure 2 displays Mean Square Error (MSE) as a function of epochs.

It is clear from figure 2, MSE between the ANN predictions and test data were steadily minimized to 0.00000084176 at epoch 218, which signifies the finest validation effectiveness. Expanding the learning process could run to the ANN to memorize the training data sets and behaves in poor generalization capability of the ANN model. The ANN models have been completed.

3.3 Modelling in simulink matlab

The function of gensim are included in the m-file in the ANN will generate Simulink block of ANN systems that have been created. Thus, in making the modeling of these systems only need to be added and keeping the other Simulink blocks including battery, load, voltage and current measurement, and scope. ANN block is placed in the simulation with the input of current and voltage load on the circuit and the output of battery capacity. The following figure 3 shows the prediction capacity of the battery with ANN system in Matlab Simulink.

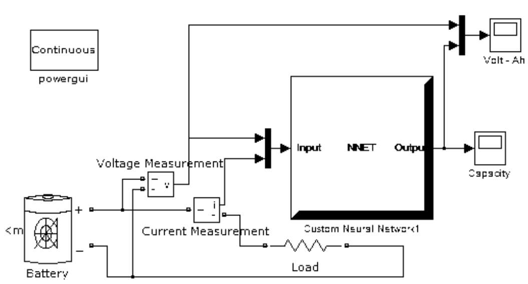


Figure 3. Modeling of Simulation

4. SIMULATION RESULTS AND DISCUSSIONS

In the simulation predictions of battery capacity can be known parameters of the battery discharge graph of figure 4 with a nominal current of 1.2 A. From the picture it can be seen that the nominal capacity that can be used is equal to 1.8617 Ah. This means that when used at nominal load with a nominal current of 1.2 A will be exhausted within 1.55 hours.

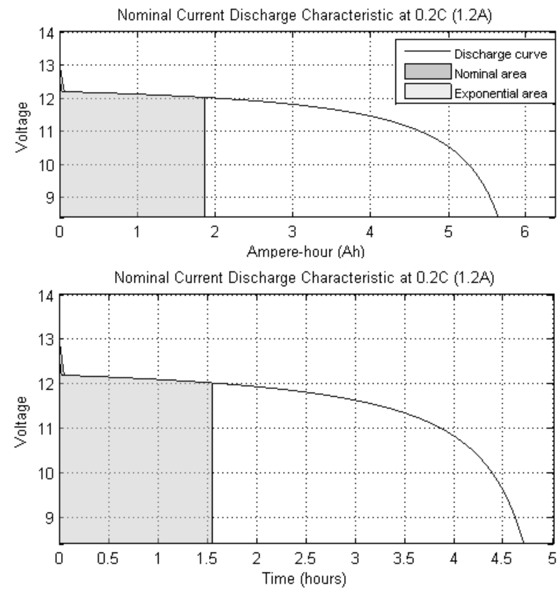


Figure 4. Characteristics of The Battery

While the results of the simulation predictions battery capacity at nominal load and nominal current of 14.2 W and 1.2 A in Figure 5 shows the results closer to the characteristics of the battery is depleted battery time of 1.38 hours with full capacity is 2 Ah and the highest voltage is 12.24 V.

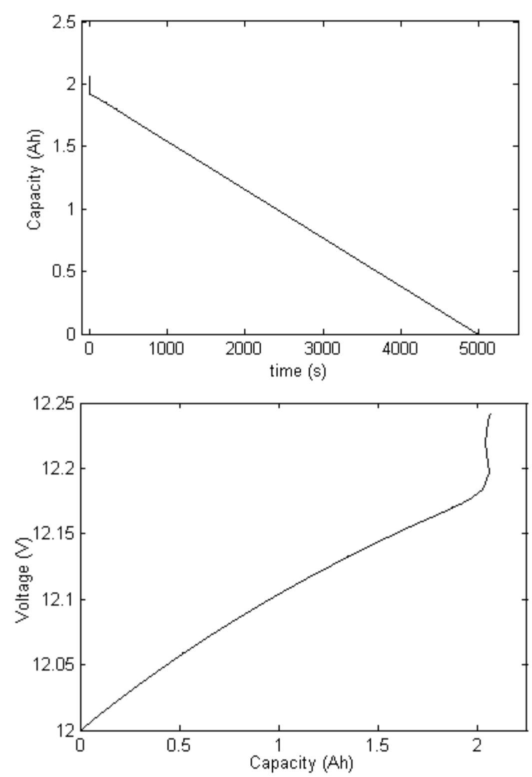


Figure 5. Result Prediction of Capacity Battery at Load 14.2 W

Journal of Theoretical and Applied Information Technology
15th July 2016. Vol.89. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Then the prediction system was tested with varying loads. In figure 6, when the load 8 W and a current is 0.59 A, resulting prediction depleted battery in 3.1 hours with a capacity of 1.5 Ah and the highest voltage is 12.25 V.

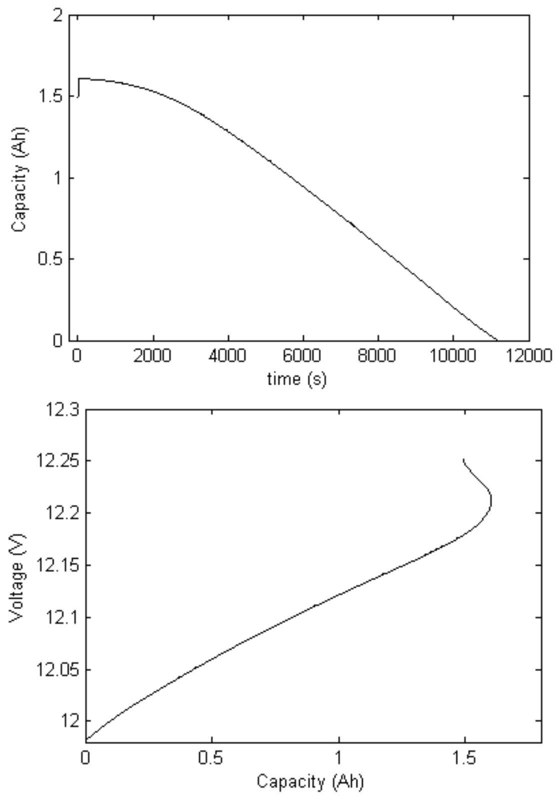
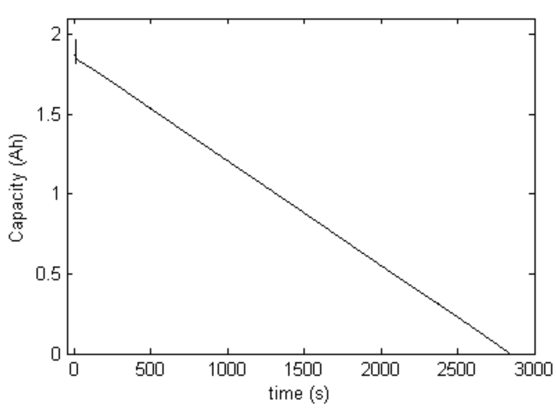


Figure 6. Result Prediction of Capacity Battery at Load 8 W

In testing the 20 W load voltage and capacity generated graphs in figure 7. In the 20 W load, resulting prediction depleted battery in 0.8 hours with a capacity is 1.86 Ah and the highest voltage is 12.23 V.



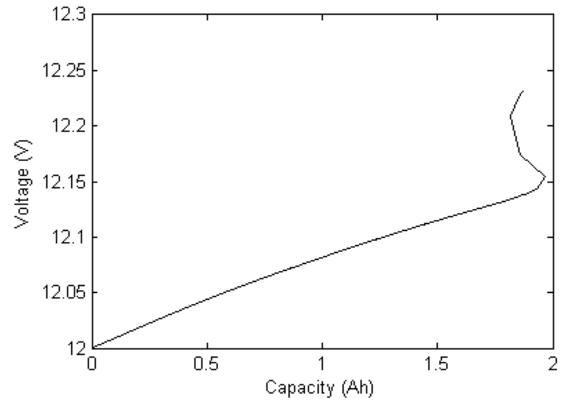


Figure 7. Result Prediction of Capacity Battery at Load 20 W

In table battery exhaustion can be seen that the smallest error occurs when the load 8 W is 1.58 %. And the greatest error is 27.27 %.

Table 3. Error Percent of The Time

Load (W)	Calculation (hour)	Simulation (hour)	Error (%)
8	3.15	3.1	1.58
14.2	1.55	1.38	10.96
20	1.10	0.8	27.27

5. CONCLUSION

A new approach has been described to forecasting of lead acid battery capacity based on levenberg marquardt using neural network. The experimental results suggest that proposed method gives excellent prediction of data simulation results compared with the characteristics of the battery. In a state of nominal current of 1.2 A, battery discharge graph has 1.8617 Ah and 1.55 hours compared to simulation results 2 Ah and 1.38 hours, so that it obtained error of 10.96%. Meanwhile, when the load is below the nominal load 8 W, showed 1.5 Ah of battery capacity and 3.1 hours with small error of 1.58%. Compared to the current load on the nominal load is equal to 20 W produced a greater error of 27.27% with 1.86 Ah and 0.8 hours. This means that the system made it would be better if used under a nominal load of the above nominal load. But it needs to design better system to maintain more accurate the battery capacity and the time

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

REFERENCES:

[1] B.S. Putra, Angga Rusdinar, and Ekki Kurniawan, "Desain dan Implementasi Sistem Monitoring dan Manajemen Baterai Mobil Listrik", *Eproc Journal*, No. 879, 2015.

[2] C.K. Wai, Y.Y. Rong, and Stella Morris, "Simulation of a Distance Estimator for Battery Electric Vehicle", *Alexandria Engineering Journal,* Vol. 54, 2015, pp. 359–371.

[3] Peter Cubon, Roman Radvan, and Vladimir Vavrus, "Optimization Source Structure of Electric Vehicle Using Calculation of Energy Consumption in Matlab GUI", *Mechatronics,* Vol. 13, No. 2, 2015, pp. 156-161.

[4] W.X. Shen, K.T. Chau, C.C. Chan, and Edward W.C.Lo, "Neural Network-Based Residual Capacity Indicator for Nickel-Metal Hydride Batteries in Electric Vehicles", *IEEE Transactions on Vehicular Technology*, Vol. 54, No. 5, 2005, pp. 1705–1712.

[5] N.A. Monfared, N. Gharib, H. Moqtaderi, M. Hejabi, M. Amiri, F. Torabi, and A. Mosahebi, "Prediction of state-of-charge effects on lead-acid battery characteristics using neural network parameter modifier", *Journal of Power Sources*, No. 158, 2006, pp. 932–935.

[6] Jie Liu, Abhinav Saxena, Kai Goebel, Bhaskar Saha, and Wilson Wang, "An Adaptive Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-ion Batteries", *Annual Conference of the Prognostics and Health Management Society*, 2010.

[7] Alief Prisma Bayu Segara, Dedet Candra Riawan, and Heri Suryoatmojo, "Monitoring Kinerja Baterai Berbasis Timbal untuk Sistem Photovoltaic", *JURNAL TEKNIK POMITS*, Vol. 1, No. 1, 2013, pp. 1-6.

[8] Paul Togan, "Perencanaan Sistem Penyimpanan Energi dengan Menggunakan Battery pada Pembangkit Listrik Tenaga Arus Laut (PLTAL) di Desa Ketapang, Kabupaten Lombok Timur, NTB", *Institut Teknologi Sepuluh November,* http://digilib.its.ac.id/public/ITS-Undergraduate-9448-2205100061-Paper.pdf

[9] MathWork documentation, http://www.mathworks.com/help/nnet/ref/trainlm.html