Estimation of Residual Capacity of Lead Acid Battery using RBF Model

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ABSTRACT
Analytical models have been developed to diminish test procedures for product realization, but they have only been partially successful in consistently predicting the performance of battery systems. The complex set of interacting physical and chemical processes within battery systems have made the development of analytical models to be a significant challenge. Advanced simulation tools are needed to become more accurately model battery systems which will reduce the time and cost required for product realization. As an alternative approach, we have begun development of cell performance modeling using non-phenomenological models for battery systems based on Neural network which uses Matlab 7.6.0(R2008b). A Neural network based learning system method has been proposed for estimation of residual capacity of lead acid battery. RBF and regression network based technique are used for learning battery performance variation with time, temperature and load. Thus a precision model of Neural network has been evaluated. The correlation coefficient of this model is worth 0.99977 shows good results for the target and network output.

Keywords
Neural network, Radial basis function, Regression network, Lead acid battery, Residual capacity.

1. INTRODUCTION
The need to develop electric vehicles arises not only due to the high price of international petroleum but also for solving the worsening environment problems. Energy management is the major key technology of battery powered vehicle [1]. The increase of energy density and efficiency, and accurate measurement of the capacity are important research topics [2], [3]. Although many new electrochemical systems were studied for this application, the lead acid battery is still a leading candidate [4]. Measurement of the capacity of lead acid battery in battery powered vehicle was studied by electrochemical reaction [5]. The estimation of capacity of lead acid battery is a key point of energy management system in electric vehicle [6].

Many methods are used to improve the precision of battery capacity. Generally, the methods for measuring the capacity of the lead acid battery are: impedance method, conductance method or resistance method [7], [8].

The parametric fitting model method may not be accurate enough for the measurement of the capacity of the lead acid battery in the electric vehicle because the internal resistance of the battery is not constant [9]. These methods are only used for the batteries of the same model to be evaluated. This approach does not work anymore if the battery has some differences. The Coulometric method can measure the charge or discharge current of battery to solve the above disadvantages [10]. The Coulometric measurement method usually uses several correction factors added to minimize the errors and used together to determine the capacity.

The Ampere hours algorithm commonly estimate the battery capacity. The battery capacity is calculated by multiplying the current by time of discharge [11], [12]. Open circuit Voltage method is widely used in capacity estimation of the battery. The terminal Voltage of the battery is relevant to the capacity when the battery is under no load [13]. However, in the battery condition charge or discharge state is not open circuit, the capacity is inaccurate. Open circuit Voltage method and Ampere hours algorithm together to achieve the capacity for electric vehicle [14]. The open circuit method, loaded voltage method and the Coulometric measurement method can be combined together to measure the capacity of the battery in the battery powered vehicles [15].

Although the Coulometric method is convenient to use, it still has disadvantages. The measurement of the battery is based on the actual current and rated capacity while battery capacity depends on discharge current. The battery aging effect will also reduce the capacity, when it is not corrected, an error may occur. Modified Coulometric measurement method uses the Coulometric measurement method as the basis and consideres the current additive effect and the battery aging factor [16].

Neural network establishes a relationship between input and output data, which uses voltage, current, temperature as its input and the capacity as output. In order to train this artificial neural network based model, the data were collected after a series of the designed experiments carried out using the battery evaluation and testing system with the wide range of discharge current and temperature [17]-[19]. The virtue of the method is that it can be applied to the battery systems. In this paper, a new method for estimation of residual capacity of lead acid battery which uses Neural network is proposed and its based technique is also used for learning battery performance variation with time, temperature and load.

2. MATERIAL AND METHODS
2.1 Material
The material used in this work was a Lead acid battery type 46B24L produced by PT. GS Battery Indonesia.

2.2 Instruments

Mathematical Laboratory (Matlab) version R2008b (developed by MathWorks, Natick, Massachusetts) was employed to perform the simulation procedures and development of mathematical computing. All computational simulations were performed on a Window machine with Intel Dual Core 2GHz as the processors and 1 GB of RAM.

2.3 Overview of Radial Basis Function

The radial basis function requires more neurons than the feedforward network. This network will work better when it is given lots of input data. Radial basis function multiplies the distance between weight vector and input vector with weight bias. Radial basis function has a maximum value of 1 if the inputs receive zero. When the distance between weights vector and input vector decreases, the output of this function becomes larger. The RBF architecture used as a model of lead acid battery is shown in Figure 1. The activation function used in this network:

$$radbas(n) = e^{-n^2} \tag{1}$$

Radial Basis function is used to approximate the real value function $\{f(x)\colon x \in R^d\}$ of d variable by $\{S(x)\colon x \in R^d\}$ with scattered data position. If x_j a set of point in R^d and $f(x)$ is a function ($f(x)\colon R^d \rightarrow R$) such that $\{f(x_j)\colon j = 1,2,..n\}$ and

$$f(x_j) = e_j \tag{2}$$

then there is a interpolating function S such as

$$S(x_j) = f(x_j) \tag{3}$$

Now S has a form

$$S(x) = \sum_{j=1}^{n} \lambda_j \phi(\|x - x_j\|) \tag{4}$$

$$r = \|x - x_j\| \tag{5}$$

Whereas S is a linear combination of translates of a function ϕ. Function ϕ is called Radial Basis Function (RBF), which is a continuous spline depending upon the distances of data centers x ($x \in R^d$). As they are spherically symmetric about the centers, they are called radial. The norm is usually Euclidean. ϕ is a fixed function R^+ to R. λ_j is radial basis function coefficient. λ_j can be calculated with help of x_j and $f(x_j)$, as follows

$$f(x_k) = e_k \tag{6}$$

$$e_k = \sum_{j=1}^{n} \lambda_j \phi(\|x_k - x_j\|) \tag{7}$$

In matrix form (6) can be written as

$$A\lambda = E \tag{8}$$

Where λ, E are

$$\lambda = [\lambda_1\ \lambda_2\ \lambda_3\ \lambda_4 \ldots \lambda_j \ldots]^T \tag{9}$$

$$E = [e_1\ e_2\ e_3\ e_4 \ldots e_k \ldots]^T \tag{10}$$

Where A_{jk} is an element of A matrix

$$A_{jk} = \phi(\|x_k - x_j\|) \tag{11}$$

Radial basis function coefficients λ_j can be calculated by solving equation (8). It may be noted that the matrix A must be non singular to solve (8) for calculation of λ_j.

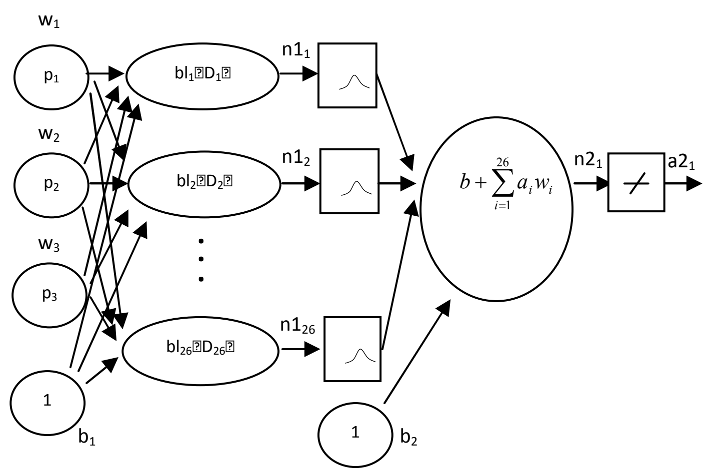

Fig. 1. RBF architecture used to model of lead acid battery (number of input variable 3, amount of data 26, single target)

2.4 Proposed Method

Coulometric method is one of the methods to measure capacity of Lead Acid Battery, in which the capacity is estimated by subtracting charge flow out of battery from the initial existing charge as described by (12).

$$Capacity = S_{initial} - Charge\ flow \tag{12}$$

$S_{initial}$ is a state of charge of battery (i.e. Before discharge takes place when battery is in a full charge $S_{initial}$=100).The capacity of battery is also a function of battery temperature. In this paper, a learning system has been proposed by using Radial Basis Function Interpolation method for learning battery characteristics with coulometric method. Therefore, it can be written as

$$Capacity = S_{initial} - \frac{1}{N_d}\int E(i,T)idt \qquad (13)$$

Equation (13) is written in integral form, N_d is a normalizing factor, so that capacity can be expressed in percentage form. Functional form of ε is not available in general but there is a need of correcting ε with the variation of battery performance for error free estimation. These two objectives are met by using Radial Basis Function. Its function is used to map E from discharge and temperature data. When battery performance is altered due to aging and other factors, the E automatically adapts itself and minimizes the errors in estimation of capacity. Radial Basis Function system must learn the initial nature of *E* from battery manufacturer data or by experiment at different temperature and discharge rate or through some empirical formula given to corresponding battery manufacturer. Therefore, the system is initialized by the knowledge of characteristics of a battery from a specific manufacturer and type.

The stages of algorithm to determine is the output capacity of the battery are as follows:

1. To determine the distance data-i with data-j, D_{ij}:

$$D_{ij} = \sqrt{\sum_{k=1}^{R}(p_{ik} - p_{jk})^2} \qquad (14)$$

2. To determine the activation distance data by radial functions multiplied by the bias:

$$a1_{ij} = e^{-(b1.D_{ij})^2} \qquad (15)$$

$$b1 = \frac{\sqrt{-\ln(0.5)}}{spread} \qquad (16)$$

3. To determine the weight of bias and weight of bias layer, $w2_k$ and $b2_k$, by solving linear equations with a least square method.

4. To determine the network output $a2_{ki}$, for each k = 1,2,..., s and i = 1,2,..., q, by the following:

$$a2_{ki} = a1_{i1}w2_{k1} + a1_{i2}w2_{k2} + ... + a1_{2R}w2_{kR} + b2_k$$

2.5 Learning

Learning vector set consists of current temperature and corresponding value of *E*. Current *i* and temperature *T* are the input variables to the RBF system and denoted through vector x_k (k=1, n) where $x_k = (i, T)^T$. RBF coefficients λ is calculated from learning vector set through (17). Equation (17) is generated from (8).

$$\lambda = A^{-1}E \qquad (17)$$

A matrix is calculated by (11). *E* is a column vector whose element e_k is the value of *E* for the vector x_k. Initial learning process is accomplished by battery information available from the data provided by manufacturer or through experiment. An incorrect prediction of capacity after a fill charge-discharge cycle calls for the modification of RBF system in order that the prediction will be correct in the next cycle. Therefore, modification of Radial Basis Function parameters λ are required. The Radial Basis Function parameter λ are recalculated with the current rate, temperature and error information.

In the previous paragraph the algorithm is described to find a new *E* when the discharge rate and temperature are limited to a single partition for most of time. In case, they are not limited to a single partition because it is difficult to evaluate the error in *E*. Hence, the problem is solved for two variables with a single equation, described by the (18). Here ΔQ, is the error in estimation of capacity.

$$Q + \Delta Q = \int (i_1(E + \Delta E_1) + i_2(E + \Delta E_2))dt \qquad (18)$$

If there is no error in *E* the equations will be a like (19)

$$Q = \int (i_1 E + i_2 E)dt \qquad (19)$$

This procedure can be extended for 'n' different discharge rate and temperature. Expressed in matrix form

$$\Delta Q = i\Delta E \qquad (20)$$

Equation (20) is solvable provided matrix *i* is not a singular.

3. RESULT AND DISCUSSION

Radial Basis Function coefficient initialize of battery discharge rate and temperature is required with error term ΔE. *E* is depended on the magnitude of discharge rate and temperature during discharge process and most likely *E* at this discharge rate and temperature has error. Input space partitioned in to n number of division for each variables is shown in Figure 2. The number of partitions may not be the same width for all input variables in general. Discharge current and temperature collected through each samplings is inspected for which partition it belongs. After completion of full discharge, an average is calculated for each partitions. Partition average of the maximum fired partition in temperature and discharge current may be taken as discharge current and temperature information for Radial Basis Function coefficient calculation.

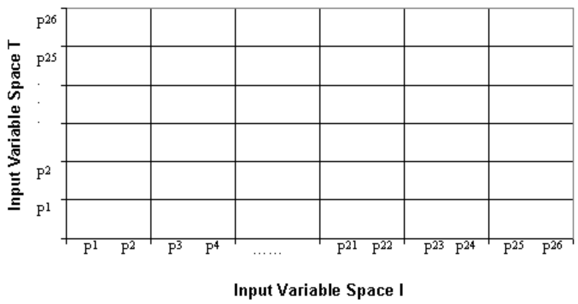

Fig. 2. Input variable I and T partition.

First Radial Basis Function system is initialized with current temperature and *E* data form (17).

$$E(i,T) = \frac{1}{(1 - k\log(\frac{i}{i_r})) + a(T - 298)} \quad (21)$$

Equation (21) is least square fitted with the experimental data of a 36Ah 12 V battery. i_r is reference current, E (i_r, 298K) equal to one, k and a are two parameters, k can be determined by least square fitting from second source information. Preliminary data until twenty-second data is used as a learning process. Initial *E* plot with current and temperature is shown in Figure 3. A number of experiments are carried out for validation of proposed method. In each experiment initial learning is given the perturbation to test the effectiveness of algorithm. First experiment has been done with 36 Ah 12V battery with load 5 ohm at room temperature. Before starting each experiments, the battery is in full Charge State. The twenty-third until the twenty sixth data is used as checking data. The plot after four data checks learning cycles is shown Figure 4. In this learning process, local correction is done for discharge rate only, and global correction for temperature. (i.e. correction is made for all temperature data) with the assumption that the temperature performance of battery altered very slowly in time while the discharge rate performance is most responsible for the error.

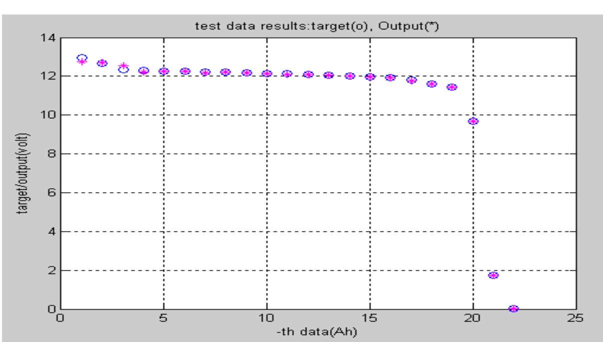

Fig. 3. Initial interpolated by RBF.

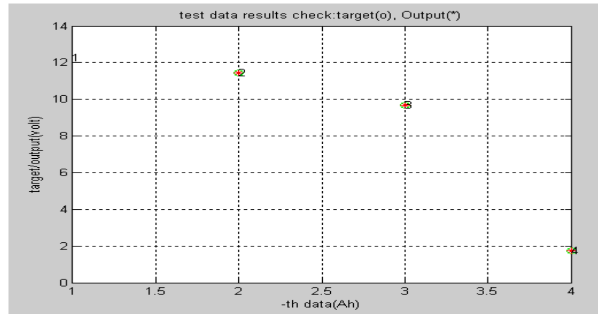

Fig. 4. The checking data interpolated by RBF.

While the training process with the regression neural network on the same data can be seen in Figure 5. From the graph shows that output and the target is almost the same. Likewise, the same test data appear similar, can be seen in Figure 6. Regression neural network model approach is used to perform this function. Hidden layer contains neurons equal to the number of input vectors. The output hidden layer with RBF activation results from the distance between input vector and weight of the input multiplied by the weight bias. This model was established using regression network spread value = 0.25.

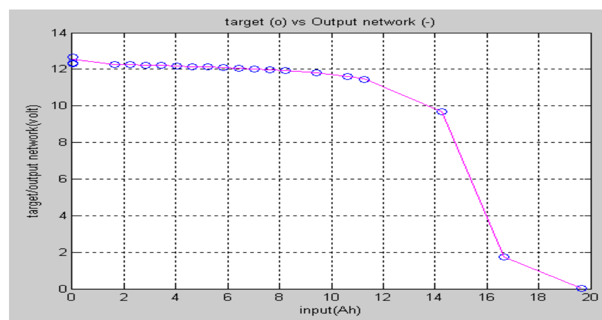

Fig. 5. Output regression networks with spread = 0.25.

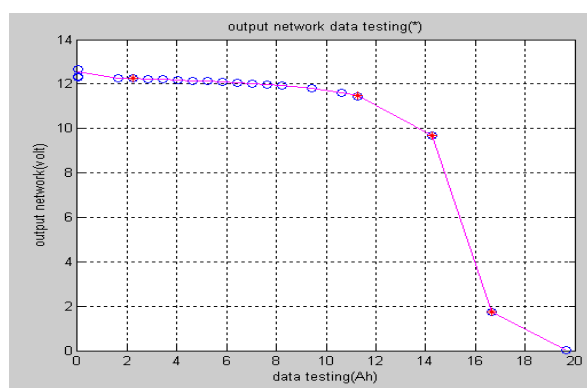

Fig. 6. The checking data interpolated by regression network.

The network output and target for the data were analyzed with linear regression. The linear regression for the target and network output in this model is shown in Figure 7. The equation for best fit in this model is:

$$Y = 1\,T + 0.0051$$

where Y: output network, T:target.

The correlation coefficient of this model is worth 0.99977 (close to 1) shows good results for the target and network output.

The network output and target for the data checking were analyzed with linear regression too. The linear regression for the target and network output in this model by using data checking is shown in Figure 8. The equation for best fit in this model is:

$$Y = 1\,T + 0.0029$$

where Y: output network, T:target.

The correlation coefficient at this model by using the data checking is worth 1 shows good results for the target and network output.

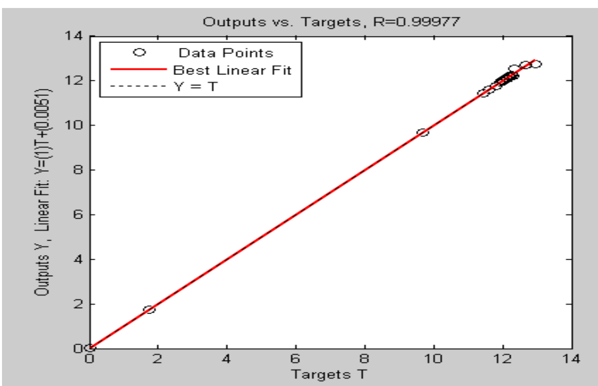

Figure 7. The linear regression for the target and network output.

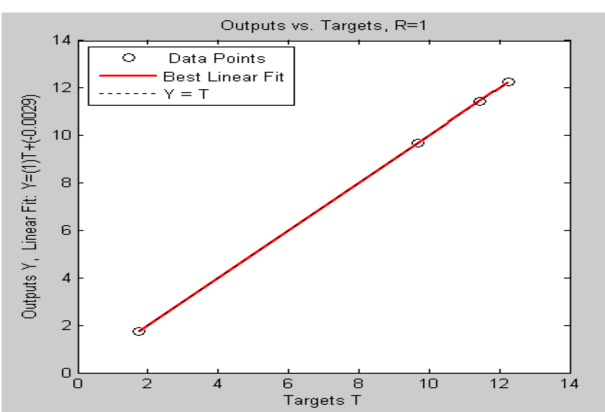

Figure 8. The linear regression for the target and network output by using the data checking.

There are two classes of uncertainty of issues that affect the specification and the use of RBF. First, because the RBF is a non-phenomenological model of system behavior, the map that is learned by an RBF cannot precisely replicate the map that of the source of its input/output exemplars. That is, the RBF is an uncertain representation of the source map. The training techniques used to identify the parameters of RBF are designed to minimize the error with its origin. In practice, there is always a fact that the input/output exemplars presented to an RBF during training, contains measurement noise. This precludes of the possibility exactly represent system behavior. This problem is mitigated by the fact that training procedures for RBF typically yield models that average through the measurement of noise yielding an average model of system input/ouput behavior. Second, there is uncertainty issue regarding the use of RBF. Under certain circumstances, the inputs to an RBF may be random variables or random processes. In this case, the inputs map to random output as they would with any deterministic map. The RBF can be used in the same way that a phenomenological model is used to establish the probability distribution of one or more random output given information on random inputs. In fact, because of its relative accuracy and computational efficiency, RBF are sometimes used as substitutes for phenomenological models where numerous model runs are required.

4. CONCLUSION

A new approach has been described to estimate the residual capacity of Lead Acid battery using neural network based RBF and regression network method. The proposed method considers battery non-linearity due to discharge rate, with temperature and corrects itself for aging and other variations of the battery characteristics to estimate capacity. Experimental results suggest that proposed method gives excellent prediction of residual capacity assuming that the initial charging state of battery is known and is able to learn performance variation. The proposed algorithm can further be extended to include factors such as incomplete charging and interrupted discharging.

Current efforts involve to complete a similar experiment with variable temperature under constant load conditions. When this information is available, both simulations the temperature and load are arbitrarily changed, can be performed. With additional experimental pulse data being generated, RBF architecture and regression network can be optimized to further increase the accuracy of the battery simulations. This will involve RBF and regression network training using experimental battery data where temperature and load are varied simultaneously. It is not clear that any simple rules or combination of rules will suffice to generate and accurate neural network simulations of real battery behavior. Additional tools like genetic algorithm and/or genetic programming may be used to establish more accurate transition rules. These initial efforts on battery modeling have proven to be very effective, and even more complex simulations of battery behavior that will be performed. With the advanced study of neural network modeling and further development of the parametric model, additional simulations can be performed using the hybrid model to help efficiently to design and optimize robust battery systems.

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