Lithium Polymer Battery Modelling and Fault Detection Design

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Abstract— The accurate battery model and parameters identification are used to produce a reliable Battery Management System (BMS). In this research, the battery model using the equivalent circuit Thevenin model is proposed after considering its complexity, model accuracy, and robustness. Parameters identification is done by using pulse test data that contains current and Vd (the difference between Open Circuit Voltage (OCV) and terminal voltage) data that represent the battery characteristics. Recursive Least Square (RLS) algorithm is used to estimate the parameter recursively in order to lighten the computation process. The fault detection is also simulated using Matlab Simulink as a design of effective and efficient BMS to protect the battery from damage or failure. The results show that the battery modelling with the equivalent circuit Thevenin model can represent battery dynamic well. Parameters identification with the RLS algorithm shows accurate results with RMSE of 0,0021. The validation result also shows that the parameters obtained are accurate with the error of 0,0104%. The fault detection simulation also shows accurate detection toward any fault operation of the battery. It can detect faults in some parameters such as SOC fault, OCV fault, and overvoltage.

Keywords— battery modelling, fault detection, simulink

I. INTRODUCTION

A battery is a device that serves as an energy storage. It has been used in mobile phones, electronic equipment, computers, UPS even as an energy source driving the electric engine on the electric vehicle. The battery is a key source of energy in electric vehicle. If there is a failure in the battery, there will be a failure in the system as a whole. Therefore, we need an effective and efficient Battery Management System (BMS) so that the operation of the electric-powered vehicles can be successful. The battery performance when connected to a load or a source of current or voltage is based on a chemical reaction that occurs in the battery itself [1].

BMS is the main link between the motor as the driver, the battery as the energy providers, and the charger. BMS can optimize the operation of the car that is efficient and safe and can ensure the preservation of the lifetime of the batteries [1]. Its main function is to monitor the condition of a battery, such as the State of Charge (SOC) and the State of Health (SOH). However SOC and SOH are variables that cannot be measured directly. They are estimated based on the usual battery modeling [3]. Based on the modeling algorithm to obtain a battery made these variables. Thus it is expected the battery modeling produce accurate estimates. However, it should be noted regarding the modeling complexity and accuracy so that the model can be applied to the system and can be applied in real time.

Battery modelling is important to approach the nature and characteristics of the battery and has parameters that must be identified first performed using RLS algorithm. It will be a bridge between engineering with a battery so that it can produce an accurate estimate. It is the necessary modeling and identification parameters of the battery and accurately so as to produce a reliable BMS system. However, there may be a fault in the system modeling of the BMS battery that can be fatal. To minimize the impact of the failure of the system, hence fault detection is needed.

In this paper, modeling parameter identification fault detection in lithium polymer battery with Recursive Least Squares Algorithm is proposed. The algorithm is implemented using Matlab Simulink with the aim to optimize the work of BMS. It is necessary to keep the battery working well, effectively and efficiently. Fault detection works to determine the condition of the battery in the event of fault or does not go according to specification even in an emergency.

Fault detection is an important component in the management of a system operation automation system or operation of an appliance or in the operation of a tool that does not comply with the specifications which are not optimal [4], [5]. At one plant, causing no operation of a device can vary, such as tuning on the controller, errors in calibration sensor that is not optimal [6], [7]. Fault in this case is not only identified with the workings of a hardware failure [8].

There is the possibility of errors, especially in the BMS system which can be fatal in the system. To minimize the impact of the failure needed the fault detection system. So, Simulink modelling fitted battery fault detection to help optimize the work on the system.

II. FAULT DETECTION DESIGN

A. Battery Modelling

The battery is a non-linear system that difficult to model. Modelling the usual battery can be divided into two kinds of electrochemical models and equivalent circuit models [4]. The model usually can describe the electrochemical battery characteristics with mathematical equations to describe the reactions of the battery. However this model is still difficult to describe the dynamic behavior of the battery. An approach to the dynamic nature of the battery can also be modeled by equivalent circuits using resistors, capacitors and voltage source to shape the circuit [2].

This paper uses the Thevenin model of the first order RC circuit [5]. Based on the model of Fig. 1, the state space models can be derived as follows [3] :

$$\begin{bmatrix} \dot{x1} \\ \dot{x2} \end{bmatrix} = \begin{bmatrix} \frac{-1}{R_p C_p} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \end{bmatrix} + \begin{bmatrix} \frac{1}{C_p} \\ \eta \end{bmatrix} I \qquad (1)$$

Where the first state x1 is Up (voltage on a parallel RC circuit) and a second state x2 is s which is obtained from the formula SOC Coulomb Counting. Output which can be obtained from the state space models include SOC, OCV (Open Circuit Voltage), Vd (voltage difference between the terminal voltage and voltage OCV), and Up.

This paper uses the Thevenin model to identify the parameters. If the models and the parameters are accurate then it will obtain an engineered form that can represent the characteristics of the actual battery. Data collecting and battery testing are performed to estimate the characteristics of the battery. Data current and voltage are used for parameter identification with adaptive algorithms. If the identification and extraction of parameters are done, the next is the validation that is used as a reference for testing whether the modeling and parameter identification which are done are accurate or not [9], [10]. The general overview of the research conducted can be summarized in the block diagram as shown in Fig. 2. The identification method of conventional systems such as RLS does not always give good results to describe the dynamic system when compared to other methods such as Genetic Algorithms, Neural Networks, or the Kalman Filter [7].

However, with the modification and development, RLS method can also be useful and produce good estimates. Basic problems of the RLS algorithm is the phenomenon of saturation because the weakness of the covariance matrix envolve exponentially.

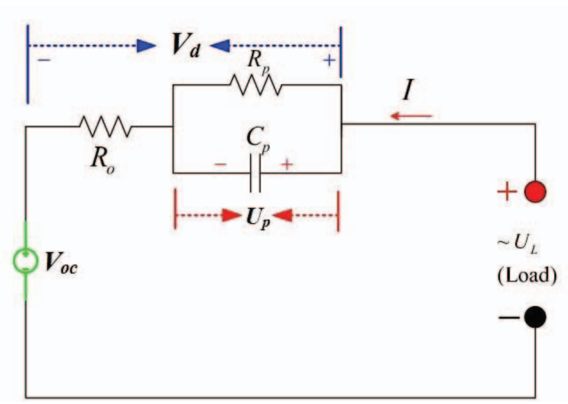

Fig. 1. Equivalent circuit Thevenin Model

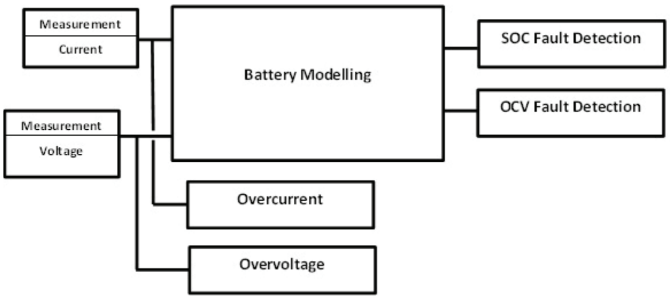

Fig. 2. Block diagram research

B. Design of Experiments

Fig. 3 shows the experimental system used. Battery testing to determine its characteristics to the conduct of charging, discharging, and open circuit with a switch by the circuit switching. Measuring and controlling part in this study using Arduino UNO32. Measurements were made of the amount of battery current and voltage then conducted computer-assisted data storage and data processing [12]. On the basis of these measurements, the magnitude of the measured current and voltage may be a reference so that it can be done programmatically by the computer so that the controller gives a signal to the switching circuit to switch charging, discharging / open circuit [13].

C. Parameter Estimation

To identify the parameters, in this study algorithms used to require data Vd voltage which is the difference between the terminal voltage OCV. Basically, the terminal voltage is the voltage on the battery when connected to the load, while the OCV is the battery voltage when connected open (disconnected by the load) [11]. Sensor voltage in the circuit is only able to measure the terminal voltage only [14].

The data used for parameter identification is the test data pulses in which the battery was disconnected and continued with a load of 2.2 A. When the battery is connected load battery OCV is not known because the measured sensor is a voltage terminal. Therefore it is necessary to estimate the OCV to know the Vd voltage. The OCV estimate is performed by linear regression footage in hopes estimated OCV. The OCV is generated closer to the effects of discharge of the battery when testing the pulse.

III. SIMULATION

Based on the Thevenin equivalent circuit models, the parameter value of Rp, Cp, and Ro is use to solve the state space modelling and with the input of current and voltage as well as the output in the form of SOC, OCV, Vd. Then each parameter gives parameter fault detection which gives the value of the

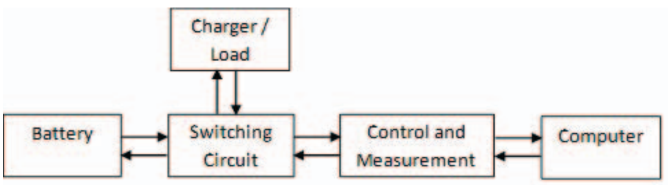

Fig. 3. The System General Overview

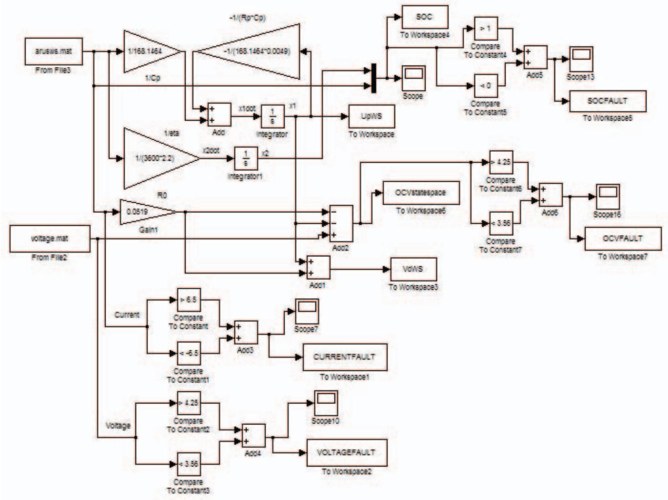

Fig. 4. Simulink battery modelling and fault detection

upper limit and lower limit with an output in the form of SOC system output fault, and OCV fault. It also adds detection for overvoltage and overcurrent faults. The Simulink modelling overall battery as shown in Fig. 4.

A. SOC Fault

SOC of this modelling uses Coulomb Counting method and determining the limits of SOC is to give the maximum voltage of 4.25 V or can be fault if it exceeds the voltage limit. In this case, a voltage of 4.25 V is SOC of 100% [15],[16]. And for a minimum threshold SOC is a voltage of 3.56 V or during SOC of 0%. If the value of the SOC exceeds the upper limit or lower limit of the SOC, it will become fault.

B. OCV Fault

OCV is the battery voltage when connected open. The OCV estimation by the modelling based estimation is done with the battery [17]. At this parameter, determined the limits of SOC is to give the maximum voltage of 4.25 V. The voltage of 4.25 V is an SOC of 100%. Then, for a minimum threshold SOC is 3.56 V or during an SOC of 0%. In this case, if the voltage exceeds or is less than the limit, it will become fault.

C. Overvoltage and Overcurrent

Current and voltage data is coming from the sensor readings directly on the battery. Current and voltage are the input from the battery to the simulink modelling. In the overall system, the current and voltage are used as well as the output which can be defined as a fault condition if the output overcurrent or overvoltage experience. The current in this paper has a maximum value of 6.5 Ampere where in this research used a battery which has a capacity of 6.5 Ampere. Therefore, the value becomes the maximum limit of the current work. If it exceeds the limit, it will become fault or overcurrent. As for the voltage has a maximum value of 4.2 V and a minimum value of 2 V. When the battery works more or less than these values, it will become fault or overvoltage.

IV. RESULT AND ANALYSIS

A. Parameter Identification

Parameter identification is carried out by Recursive Least Square method. With such a system input and output current is Vd. The general equation is as follows.

$$\mathrm{Vd}(n) + a_1 \mathrm{Vd}(n-1) = b_0 I(n) + b_1 I(n-1) \qquad (2)$$

From (2), the regressor is written

$$\varphi = [\mathrm{Vd}(n-1)\ I(n)\ I(n-1)]^T \qquad (3)$$

After the RLS algorithm is executed, obtained estimation weights a1, b0, and b1. From the weight gained can be done by using the parameter extraction (4), (5) and (6).

$$R_0 = \frac{b_0 - b_1}{1 + a_1} \qquad (4)$$

$$R_P = \frac{2(a_1 b_0 + b_1)}{1 - a_1^2} \qquad (5)$$

$$C_P = \frac{T_S(1 + a_1)^2}{4(a_1 b_0 + b_1)} \qquad (6)$$

Based on Fig. 5, it can be concluded that the parameters of the battery change over time and do not reach the point of convergence.

Table I shows the data error of iterations estimate optimal weights with RLS algorithm. Based on these data, it can be seen that the linear regression method has a smaller error. Small error values also indicate that the parameter estimation by RLS algorithm can produce an accurate estimate [11], [18].

B. Validation

Validation aims to find out whether the model and parameter identification are done correctly or approaching the truth.

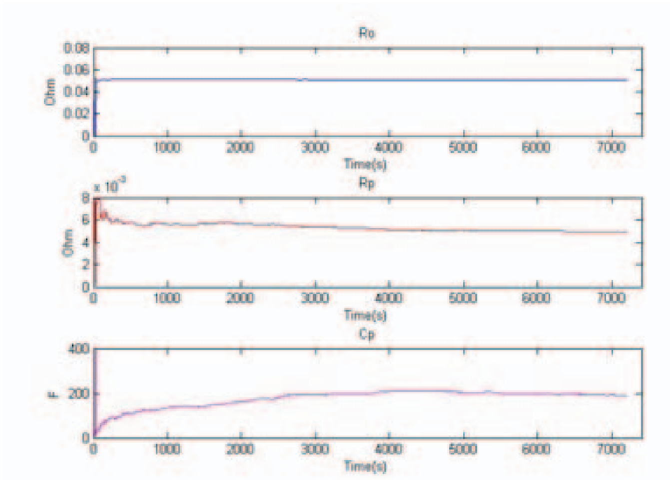

Fig. 5. Results of linear regression method parameter extraction

TABLE I. DATA ERROR RLS ALGORITHM

Method	MAE	MSE	RMSE
Linear Regression	0,0015	4,4 x 10^{-6}	0,0021

Validation is done with the state space models based on (1) by discretizing the equation is changed into forms such as

$$\begin{bmatrix} x_{1(k)} \\ x_{2(k)} \end{bmatrix} = \begin{bmatrix} \frac{-1}{R_p C_p}\Delta t + 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{1(k-1)} \\ x_{2(k-1)} \end{bmatrix} + \begin{bmatrix} \frac{\Delta t}{C_p} \\ \eta \Delta t \end{bmatrix} I \qquad (7)$$

The value of Rp and Cp is required to form (7), the value is obtained from the extraction of the parameters that have been done before. Input from the state space model of the flow of the test pulses are used for validation. While output that can be observed by the model is the State of Charge (SOC), OCV, Up, and Vd [19]. Validation parameters obtained Using linear regression method where Vd estimates made after the model and parameters are known. Fig. 6 shows the validation results for Vd in all test data pulse length. The blue line shows the Vd data obtained by linear regression method while the red line shows the estimated Vd [20].

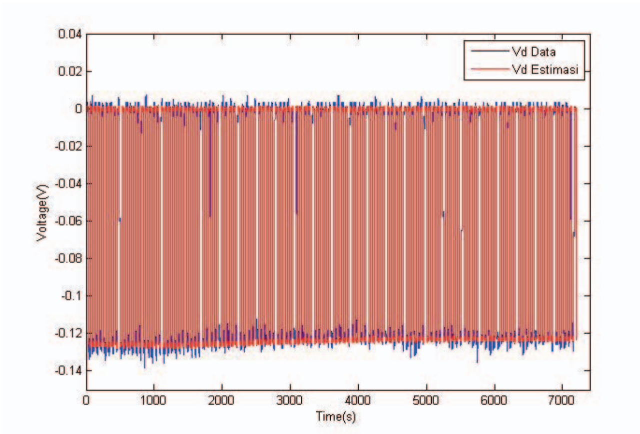

Fig. 6. Vd Linear Regression method

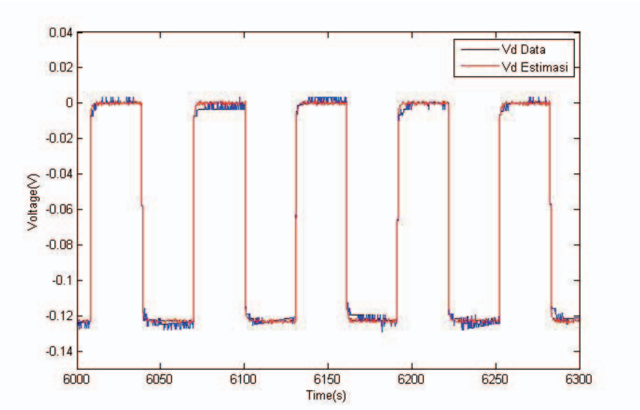

Fig. 7. Vd Validation using Linear Regression Method to-6000 until 6300

TABLE II. DATA VALIDATION ERROR OCV

Method	MAE	%Error	MSE	RMSE
Linear Regression	4,06 x 10-4	0,0104	2,6 x 10-7	5,1 x 10-4

Table II also shows the data validation error OCV for both methods. Obtained more accurate parameter identification method of linear regression indicated by the error value is smaller when compared to the reference method OCV footage.

C. *Result*

1) SOC Fault

The Fig. 8 shows the output in matlab on the parameters of SOC. We can observe that the SOC can be fault that is the value equal 1.

In Fig. 4, given the upper limit value is 1 and the lower limit is 0. From these values, if the output value is equal to 1, it has become fault and if the output is equal to 0, it has become safe. If the SOC has a value of 1.2 or -0.2, the SOC has become fault and occurs when the sampling time 7400.

2) OCV Fault

The Fig. 9 shows the output in matlab on the parameters OCV. We can observe that the OCV can be fault that the value equal 1.

In this case the same as the voltage, the OCV maximum value is 4.25 volts and the minimum value is 2.56 V. The OCV is obtained based on the experimental data on the battery before simulink modelling and fault detection on the battery. The point is to know the state of the battery safely making it easier to give especially in case if something goes fault.

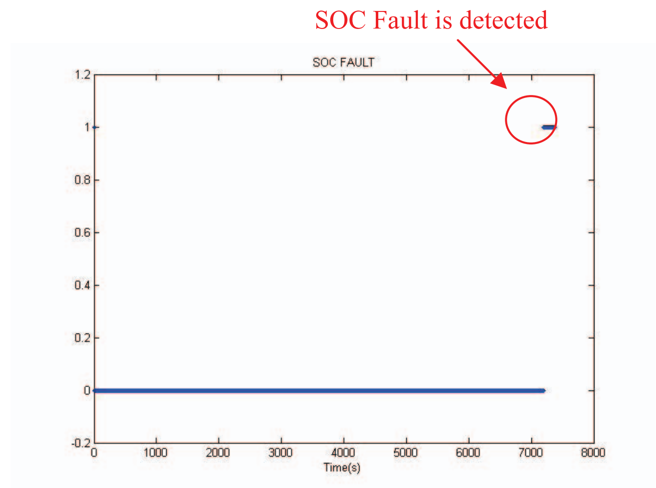

Fig. 8. SOC Fault

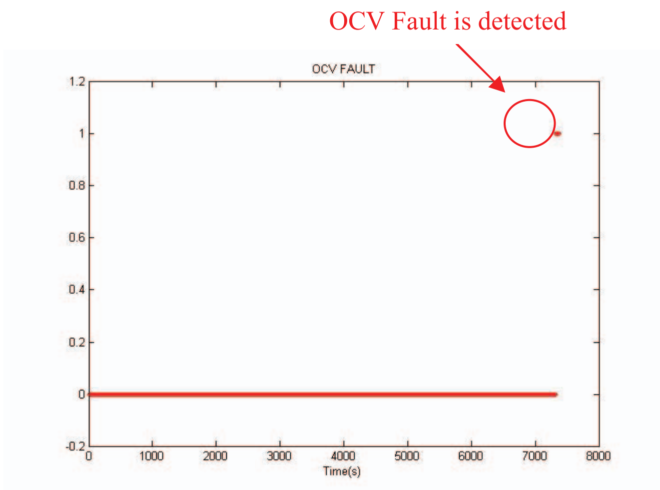

Fig. 9. OCV Fault

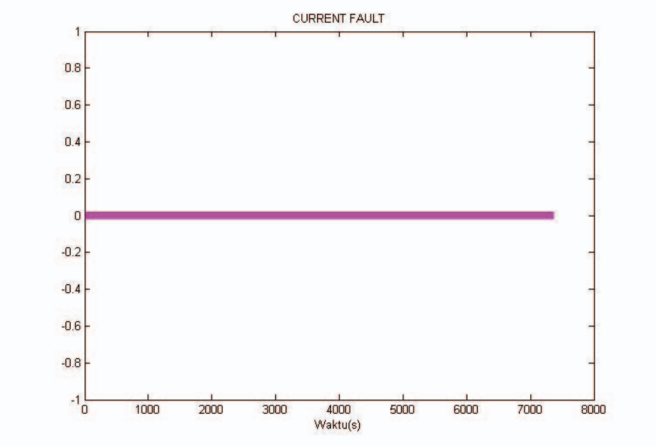

Fig. 10. Current Fault

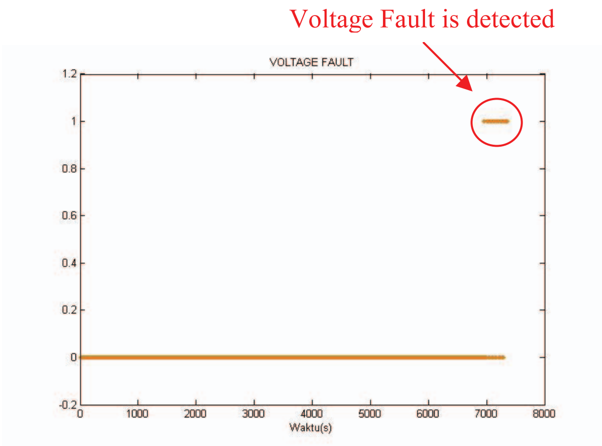

Fig. 11. Voltage Fault

3) Current Fault

The Fig. 10 shows the output in matlab on the current parameters. We can observe that the output current equals 0 and it is safe or not experiencing any fault because the condition has a value of 2.2 Ampere. In the current curve, it can be normal because it does not exceed the current maximum limit at 6.5 Ampere.

The values are as much as 7400 sampling time. When the values indicate a value more than 6.5 A or lower than -6.5 A, it will become overcurrent.

4) Voltage Fault

The Fig. 11 shows the output in matlab in the voltage parameter. We can observe that it will become fault if the value equals 1.

The voltage has a maximum value of 4.25 V and a minimum voltage of 2.56 V based on the experimental data. Then the figure above has occurred overvoltage because it exceeds the maximum voltage.

V. CONCLUSION

The identification of parameters which is performed using RLS algorithm shows a fairly accurate result. It is proven by the validation conducted showing 0.0104% error. The simulation results the equivalent circuit models of Lithium Polymer batteries into the model Matlab/Simulink to determine the limits of the battery work which can detect faults, such as SOC fault, OCV fault, overcurrent and overvoltage. The simulation results the equivalent circuit models of Lithium Polymer batteries into Matlab Simulink model to determine the limits of the battery can detect faults in some parameters such as :

- SOC fault, if the value of the SOC exceeds the upper limit or lower limit of the SOC will become fault.
- OCV fault, if the voltage exceeds or is less than the limit then will become fault.
- The value becomes the maximum limit of the current work. If it exceeds the limit, it will become fault or overcurrent. As for the voltage has a maximum value of 4.2 V and a minimum value of 2 V. When the battery work is more than or less than these values, it will become fault or overvoltage.

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