THE STUDY ON IMPROVED BATTERY MODEL AND CHARACTERISTICS OF ELECTRIC BUS

Man $YU^{1,2}$, Longlong Wei¹, Lang Wei¹ and Xuan Zhao¹

¹School of Automobile Chang'an University Middle-section of Nan'er Huan Road, Xi'an 710064, P. R. China { 364896557; 2606853176 }@qq.com; weilang09@163.com; zhaoxuan@chd.edu.cn

> ²Xi'an Automobile Maintenance Industry Management Office No. 111, Jianshe West Road, Xi'an 710054, P. R. China

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ABSTRACT. The effects of discharging current and temperature are neglected in traditional battery model. Besides, adaptability of the model is also poor. However, the working condition of electric bus is complex and volatile, and the discharging current is often very large. This indicates that traditional battery model can hardly describe the battery characteristics precisely. An improved battery model based on battery discharging experiment is built in this paper. Discharging current, ambient temperature and SOC are taken into consideration in the model. Elman neural network is used to calculate parameters of the battery. By comparison of real vehicle test and simulations based on improved battery model and Thevenin battery model at the speed of 40km/h, driving range of improved battery model is consistent with the test of real vehicle. This indicates that the accuracy and adaptability of improved battery model are better than traditional battery model. The improved battery model can stand for the characteristics of real battery. **Keywords:** Transportation, Battery model, Electric bus, Neural network

1. Introduction. Battery is a key component that affects the dynamic performance and economic performance of electric vehicle. However, the characteristics of the battery are affected by many factors, such as the cycle index, charge and discharge current, polarization resistance, cell voltage, ambient temperature, and connection mode [1]. In the research of EV battery model, an enhanced dynamic storage battery model based on pspice is proposed [2,3]. However, the battery model is too complex to consider the practical application of the project. The authors give an EV battery model based on a controllable voltage source [4]. It requires a high model order, so it is difficult to implement. The neural network model was put forward, which took the weights of neurons into account instead of the state variables [5,6]. However, the accuracy and calculation burden of the model were influenced by the choices and quantity of input variables of the neural network. Therefore, establishing an accurate battery model is not only the key point for electric vehicle study but also the fundamental guarantee of vehicle test and simulation. At present, SOC (State of Charge) is the only parameter considered to build battery model [7]. Although the method is simple, the influences of discharge rate and ambient temperature on the battery are neglected, and the error of the simulation process for electric vehicle battery is large [8]. In this paper, a battery model taking full account of the current, ambient temperature and SOC is established. The model parameters are predicted by neural network to realize the accurate modeling of battery for electric bus.

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2. Improved Thevenin Battery Model. The Thevenin battery model is a kind of commonly used battery capacity model [9]. It can clearly reflect the characteristics of the battery; however, the parameters are fixed. So accurate battery model can hardly be established under various conditions [6]. The battery internal resistance R_r is the key to the accuracy of the model. Considering that the battery internal resistance R_r is affected by SOC, charge and discharge current and ambient temperature, the improved battery model is established, as is shown in Figure 1.



FIGURE 1. Improved Thevenin battery model

The function can be described as (1)

$$R_{rc}(SOC, I_b, T) = f_1(SOC, I_b, T)R_{rd}(SOC, I_b, T) = f_2(SOC, I_b, T)$$
(1)

where R_{rc} is the battery charge resistance, and R_{rd} is the battery discharge resistance, which can change with the SOC, ambient temperature, charge and discharge current.

The improved battery model is based on the simple model and can fully reflect the non-linear characteristics of the battery. The battery characteristics can be described accurately [7]. Compared with the traditional battery model, the advantages are as follows. (1) Electric vehicle battery often works in conditions with large current for a long time, so the battery discharge rate has a great effect on the parameters of battery. The battery performance decreasing at large discharge rate fails to be reflected in traditional model since constant resistance is adopted, while battery characteristics can be described accurately in the improved battery model due to the fact that discharge rate is considered as a factor that can affect internal resistance. (2) The ambient temperature has an important impact on the battery characteristics. The battery characteristics will change as the ambient temperature of electric bus battery changes in a great range. The internal resistance in the improved battery model is related with the ambient temperature.

The charge and discharge processes of improved battery can be described as:

$$E_0 - I_b R_0 - I_r R_{rx} - U_b = 0$$

$$\frac{dU_{cr}}{dt} = \frac{I_b - I_r}{C_r}$$
(2)

In the formula, during the charge process, $R_{rx} = R_{rc}$, while during the discharge process, $R_{rx} = R_{rd}$.

3. The Study on Battery Characteristics. In this paper, Mingtai 3D-240 6V/240Ah lead-acid battery is used in battery charge and discharge test, and high-current discharge instrument, integrated tester and high-low temperature test chamber are adopted. The tests are carried out at the temperature of 0°C, 10°C, 20°C and 30°C with the discharge rate of 0.25C, 0.35C, 0.45C, 0.55C, 0.65C, 0.75C, 0.85C and 1.00C. Each group of test is repeated 10 times. Battery discharge characteristics at different temperature and discharge rate are obtained.



FIGURE 2. Terminal voltage at different discharging current



FIGURE 3. Terminal voltage at different ambient temperature

When the ambient temperature is 30° C, the battery voltage U_b at different discharge rates is shown in Figure 2. At the discharge rate of 0.55C, the battery voltage U_b at different ambient temperatures is shown in Figure 3. The data in Figure 2 and Figure 3 show that the ambient temperature T and discharge rate have a great impact on the battery characteristics. Figure 2 shows that at 30° C, if the discharge rate is 0.25C, the capacity of battery is 270Ah, while if the discharge rate is 1.00C, the capacity of battery is 160Ah. Figure 3 shows that at the discharge rate of 0.55C, the battery capacity changes little at 20°C-30°C, while the battery capacity decreases significantly with the ambient temperature decreasing if the temperature is lower than 20°C. The battery capacity changes as the battery internal resistance changes. Therefore, the ambient temperature, charge and discharge rate and SOC are the main factors that affect the battery resistance. According to the characteristics of battery model, the battery internal resistance R_r is non-linear related with the ambient temperature T, the discharge rate and SOC. As a result, higher order function fitting is feasible. Research showed that third-order polynomial fitting can be used [8-10]; however, the complexity of the model and the difficulty of simulation also increased due to the increasing of order. Therefore, Elman network is adopted to predict battery internal resistance.

4. Parameters Prediction and Modeling of Improved Battery Model. As the traditional battery model can hardly describe the characteristics of real battery, the improved battery model is established in the study. The internal resistance R_r of the model

is nonlinear correlated with ambient temperature T, discharge rate and SOC [11,12]. Considering the acquisition of model parameters, the Elman neural network model is used to predict the parameters.

4.1. Model parameter prediction based on Elman neural network. Neural network is similar to brain synaptic connection structure, and information processing can be realized through neural network. The Elman neural network is a two-layer back-propagation feedback neural network. The memory and stability of it are much better compared with the traditional neural network.

According to analysis, SOC, ambient temperature T and discharge current I_b of the battery are the main factors that affect the internal resistance R_r of the battery for the improved battery model. Therefore, SOC, the ambient temperature T, and the discharge current I_b are considered as the input of Elman neural network, and the battery internal resistance R_r is the output. As is shown in Figure 4, the number of Elman neural network implicit layers is 2 and the topological structure of Elman neural network is $3 \times 6 \times 5 \times 1$ [5]. In the neural network parameter prediction process, the Levenberg-Marquardt back propagation algorithm is used as the training function, and the logsig function is used as the implicit layer transfer function.



FIGURE 4. Network topology of neural network

The Elman neural network is trained by the battery discharge test data. The discharge test data at the temperature of 0°C, 10°C, 20°C and 30°C with the discharge rate of 0.25C, 0.35C, 0.45C, 0.55C, 0.65C, 0.75C, 0.85C and 1.00C are selected as training data. 20 data were chosen between 5.3V and 6.3V at equal interval in each group. Therefore, 720 training data are obtained. Finally, 677 valid data are used for training since 43 data with large error are removed.

According to SOC, ambient temperature T and discharge current I_b , battery internal resistance at certain ambient temperature and discharge rate can be predicted by neural network in real time. Accordingly, the accurate battery terminal voltage U_b at this moment can also be obtained. Compared with the traditional battery model, higher accuracy and adaptability can be achieved through the improved model.

4.2. The establishment of improved battery model. The improved battery simulation model established with Matlab software is shown in Figure 5. The model includes charge state calculation module (SOC_Caculator), static open-circuit voltage calculation module (E_Caculator), internal resistance current calculation module (Ir_Caculator), internal resistance neural network module (NN_Model) and voltage calculation module (Ub_Caculator). Apart from the neural network prediction sub-module, normalization and anti-normalization sub-module should also be considered to normalize the input and output data.

When the ambient temperature is 30°C, the simulation results of the battery terminal voltage U_b , the charge state SOC and the discharge current I_b are shown in Figure 6.



FIGURE 5. Simulation model of improved battery model



FIGURE 6. Simulation results of battery model

The traditional model only focuses on prediction of the battery output parameters. The inside parameters are neglected. Therefore, it is unfavorable for the research of battery since much significant information is lost. An improved battery model is built on the basis of Elman network in the study. Elman network is used to predict battery internal resistance. Therefore, battery internal resistance, static open circuit voltage, internal capacitance are considered and necessary data are provided for further study.

5. Modeling and Testing of Electric Bus. Since the traditional battery model can hardly describe the characteristics of electric vehicle batteries, and the error in the vehicle modeling and simulation is relatively large, the improved battery model based on the characteristics of the electric bus driving process is built. Therefore, the accuracy of improved battery model is discussed in this paper.

The electric bus model is established with Matlab software, and the model is simulated at constant speed according to GB/T18386-2005. the simulation results and vehicle test results are compared to verify the accuracy of the battery model. Considering that the electric bus is operated in city cycle conditions generally, and the difficulty in simulation process due to the use of Matlab ode15s non-rigid solver, the simulation is carried out at UDDS based on Cruise.

5.1. Modeling and simulation of electric bus. The electric bus model includes motor module (motor), motor controller module (Motor_Controller), power converter module (Power_Converter), battery module (Battery_Model), load module (Load), power train module (Power_Train), wheel module (Wheels) and driver module (Driver). The model established with Mablab/Simulink is shown in Figure 7.



FIGURE 7. Electric bus model

Parameters	Symbol	Value	Parameters	Symbol	Value
Mass of vehicle (kg)	m_a	4700	Rated current (A)	I_n	200
Complete vehicle kerb mass (kg)	m_0	3750	Rated speed (r/min)	N_n	3000
Tire radius (m)	r	0.363	Rated power (kW)	P_n	40
Windward area (m^2)	$C_D A$	3.48	Max power (kW)	P_{\max}	60
Rotational mass conversion factor	δ	1.05	Max voltage (V)	$U_{\rm max}$	288

6.17

214

 i_a

 U_n

TABLE 1. Parameters of electric bus and motor

In order to meet the simulation requirements of electric bus and the actual control rules of the test vehicle, a double closed-loop control strategy is used for permanent magnet DC motor control module. The strategy includes a speed feedback loop and an armature current feedback loop. The bus can be well operated in a variety of conditions and strong anti-interference ability can be realized.

Max speed (r/min)

Max torque (Nm)

 $N_{\rm max}$

 $T_{\rm max}$

4000

300

According to the parameters of Chang'an University medium electric bus, the vehicle parameters and motor parameters selected in vehicle model are shown in Table 1.

In order to verify the performance of the improved battery model, the model is simulated at variable working condition. When the simulation time is 5s, the speed and current of the electric bus decrease when the accelerator pedal position changes from 80% to 30%. Battery internal resistance and terminal voltage are shown in Figure 8 and Figure 9.

According to the simulation results in Figure 8 and Figure 9 with the decreasing of electric bus load, the battery current and the internal resistance of improved battery model decrease correspondingly while the voltage increases. It indicates that the battery parameters can change with driving conditions of electric bus.

5.2. Experimental research on electric bus. Driving range test is an important test to reflect the performance of electric bus battery, and actual capacity of electric bus battery can be obtained through the driving range test. The accuracy of battery model can be verified by comparison among the driving range of real vehicle, improved battery model and Thevenin battery model.

According to GB/T18386-2005, driving range experiment at constant speed of 40km/h is adopted to electric bus to test the battery performance [2]. The initial SOC is set to 1 and the lower limit is set to 0.2 in order to protect the battery. Test result is shown in Table 2. It can be seen that driving range of electric bus is 163km.

Ratio of final drive

Rated voltage (V)



FIGURE 8. Changing curve of battery internal resistance



FIGURE 9. Changing curve of battery terminal voltage

TABLE 2. Test result of 40km/h equal speed driving range

Time (min)	Distance (km)	Number of parking	Interval of parking	Average speed
241	163	0	0	40.58

5.3. Comparison of simulation results and vehicle test results. According to the requirements of electric bus test, the model is simulated at the speed of 40km/h. The initial SOC is set to 1 and the simulation will be stopped when the SOC decreases to 0.2. Simulation result of driving range is 166.43km if the improved battery model is used. In the same condition, the driving range is 183.91km if Thevenin battery model is used.

When the electric bus runs at the speed of 40km/h, the driving range of real vehicle, improved battery model and Thevenin battery model are compared in Figure 10.

It can be seen that driving range of real vehicle and improved battery model are basically the same while the error between real vehicle and Thevenin battery model is relatively large. It demonstrates that improved battery model is more accurate and adaptable. Therefore, the improved battery model can describe the characteristics of battery for electric vehicle.

5.4. Simulation study of electric bus based on Cruise in UDDS cycle condition. UDDS (Urban Dynamometer Driving Schedule) is obtained with the statistics of driving characteristics in urban area. Due to the limitation of driving range, electric bus is



FIGURE 10. Driving range of the electric bus



FIGURE 11. UDDS cycle run

generally used in city conditions. So the simulation results at UDDS can reflect the performance of electric bus. The speed fluctuation in UDDS is shown in Figure 11.

The electric bus model is complex, and the model is non-rigid, so ode15s solver can be used in the simulation. However, it is difficult to do so and the simulation time is too long. Therefore, Cruise is adopted in this paper. UDDS is preset in Cruise to make the simulation easier. Cruise can be connected with Matlab and the joint simulation can be carried out conveniently. The speed, acceleration, mileage and other parameters of electric bus can be acquired from the simulation, and the simulation results are shown in Figure 12.

The SOC of electric bus in UDDS is shown in Figure 13, and driving range is shown in Figure 14. It can be seen from Figure 13 and Figure 14 that when the SOC is reduced from 1.0 to 0.2 in the UDDS, the driving time is about 4.2h and the range is about 134km.

The simulation results of electric bus model show that the driving distance of electric bus is closer to the test results when the improved battery model is used to describe the characteristics of the electric vehicle battery. The characteristics of battery for electric bus can be described more accurately through the improved model. The simulation results show that the improved battery model can reflect the economic and dynamic performance indexes of electric vehicle precisely.

6. **Conclusion.** Characteristics of discharging current and ambient temperature are neglected in traditional battery model and the adaptability is poor. However, the working condition of electric bus is complex and volatile, and discharging current of battery for electric bus is often large. This indicates that traditional battery model can hardly describe characteristics of batteries of electric bus accurately. An improved battery model



FIGURE 12. (color online) Curve of velocity, acceleration and mileages in UDDS



FIGURE 13. Curve of SOC in electric bus

based on battery discharging test was built. Discharging current, ambient temperature and state of charge calculated through Elman neural network are taken into consideration. Based on the electric bus, real vehicle range test, the range simulation of improved battery model and Thevenin battery modelare are carried out at the speed of 40km/h. The result shows that the driving range of real bus is 163km, the driving range of improved battery model is 166.43km and the driving range of Thevenin battery model is 183.91km. It indicates that driving range of improved battery model is consistent with the result of real vehicle test, and the accuracy and adaptability of improved battery model are better than traditional battery model. The characteristics of battery can be described accurately through improved battery model. Finally, the electric bus is simulated in UDDS by Cruise. The simulation result shows that the driving range of electric bus is 134km, and the driving time is 4.2h. The research of this paper is applicable to the modeling and



FIGURE 14. Curve of driving range in electric bus

simulation of lead-acid batteries for electric buses, and further research will be carried on other types of batteries such as lithium-ion batteries.

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