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METHODS
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A Fault Diagnosis Method for Lithium-Ion Battery Packs Using Improved RBF Neural Network

Jia Wang[1], Shenglong Zhang[1] and Xia Hu[2]*

[1]Department of Automotive Engineering, Changshu Institute of Technology, Changshu, China, [2]Department of Technology Center, Shanghai Automotive Industry Corp. Group, Shanghai, China

With the increasing demand for electric vehicles, the high voltage safety of electric vehicles has attracted significant attention. More than 30% of electric vehicle accidents are caused by the battery system; hence, it is vital to investigate the fault diagnosis method of lithium-ion battery packs. The fault types of lithium-ion battery packs for electric vehicles are complex, and the treatment is cumbersome. This paper presents a fault diagnosis method for the electric vehicle power battery using the improved radial basis function (RBF) neural network. First, the fault information of lithium-ion battery packs was collected using battery test equipment, and the fault levels were then determined. Subsequently, the improved RBF neural networks were employed to identify the fault of the lithium-ion battery pack system using the experimental data. The diagnosis test results showed that the improved RBF neural networks could effectively identify the fault diagnosis information of the lithium-ion battery packs, and the diagnosis accuracy was about 100%.

Keywords: fault diagnosis, lithium-ion battery packs, RBF, neural network, battery safety

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***Correspondence:**
Shenglong Zhang
suckersands88@163.com

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INTRODUCTION

With the increasing attractiveness of new energy vehicles, the safety of the electric vehicle battery is crucial. A total of 124 electric vehicle combustion accidents were reported in 2020, including 23% charging fire, 38% standing fire and 39% driving fire (Electric vehicle observer, 2020). These accidents are related to the car battery pack. Therefore, the correct diagnosis of the battery can effectively reduce the risks of battery thermal runaway and traffic accidents. To effective and accurate identification of failures for the battery, Schmid et al. (2021) developed a fault diagnosis method by using the fuzzy clustering algorithm. In this algorithm, the switches of reconfigurable battery system were used to isolate the fault of the electric vehicles. Tian et al. (2020) developed a sensor fault diagnosis algorithm using the equivalent models and particle filters. Then this diagnosis was employed to test the battery pack using the recursive least square algorithm. The results show that the algorithm proposed in this study can be used to identify the diagnosis of the battery pack. Schmid et al. (2020) developed a new data-driven method to identify the single cell voltages. The principal component analysis method was used first to estimate the fault information. Then a developed cross-cell monitoring algorithm was used to carry out the fault diagnosis. Jiang et al. (2021) proposed a new signal-based fault diagnosis model for lithium-ion batteries. Then this model was used to verify the data from the thermal runaway of electric vehicles. The results show that the method developed in their study can be used to diagnose the faults of the lithium-ion batteries. Development of the machine learning theory dramatically provides an effectively algorithm to diagnose and identify the fault information, like the neural network. The neural network method is a good algorithm to predict different data, since it can effectively study and train the different mathematical models. Therefore, it has been widely used to identify different engineering problems, especially for the vehicle engineering. Ardeshiri et al. (2020) summarized the main research methods for remaining service life and fault diagnosis using the machine learning algorithms. Li et al. (2020) used the Long Short-Term Memory (LSTM) neural network to diagnose the fault of the battery. Zhang et al. (2021) also used the LSTM neural network to diagnose the faults of the photovoltaic array problem. The results show that the method developed by Zhang et al. can be used to identify photovoltaic array faults. Kara (2021) developed a fault diagnosis method combing Convolutional Neural Networks (CNN), LSTM, and PSO algorithms to accurately capture nonlinear characteristics for lithium-ion battery prediction problem. Although the prediction results for the LSTM neural network is good for diagnosing the fault of the battery and photovoltaic array problem, the structure of this method is very complex and it has a low prediction efficiency. Yao et al. (2020) used the wavelet-neural to identify the lithium-ion batteries of the electric vehicles. To improve the safety and reliability of the vehicles, four parameters were selected as the variables, influencing the performance of the electric vehicles. The results show that voltage difference value has great influence on the diagnosis of the electric vehicles. Niri et al. (2020) used the Wavelet-Markov Load Analysis method to predict the power state of the lithium ion batteries for electric vehicles. Meng et al. (2017) used the BP neural network to diagnose the lithium battery using nine parameters. Yao et al. (2021) used the Support Vector Machine (SVM) method to identify the Lithium-ion batteries. For the SVM algorithm, the kernel function parameter and penalty factor was optimized by using the grid search method. The results show that the SVM-based fault diagnosis algorithm can effectively identify the fault information of the batteries. The training speed of BP, wavelet, and SVM neural network is slow and easy to fall into local solution, therefore, these methods are always optimized using the optimization algorithm (Cheng et al., 2014; Gao et al., 2021; Shi et al., 2021).

With the increase of the electric vehicles, the lithium iron phosphate battery pack has attracted significant attention since it has high security and a significant market share. However, not too much researches have been published to test and diagnose the lithium iron phosphate battery pack. Therefore, the lithium battery type was selected as the research objective in this study. As can be seen from above, the neural network has become the main method to identify and diagnose the battery. In the neural network algorithms, the RBF neural network is a good algorithm since it can accurately approximate any nonlinear function with the fast convergence speed. Hence, this paper presented a fault diagnosis method for lithium-ion battery packs using improved RBF neural networks. The rest of the paper can be summarized as follows. To obtain the sample data, the test equipment of the lithium iron phosphate battery pack is shown in details in *Data Preparing for Lithium-Ion Battery Packs*, as well as the fault levels and treatment methods. In the *Neural Networks*, the neural networks used in this study are listed including the General Regression Neural Network (GRNN) and the Probabilistic Neural Network (PNN) algorithms. Following this, the results of the fault diagnosis using the different methods are shown and discussed in the *Fault Diagnosis Results and Discussions*. Finally, the conclusions and the future work are present in the *Conclusions and Future Works*.

TABLE 1 | The fault levels and management techniques for the electric vehicles.

Fault levels	Management techniques
I	Alarming
II	Power reduction
III	Stopping the car
IV	Cutting off the high voltage

DATA PREPARING FOR LITHIUM-ION BATTERY PACKS

The acquisition module of the electric vehicle plays a critical role in enhancing car safety because it can real-time display the data of the battery system, such as voltage, current, and temperature. It is widely known that the main failures of the electric vehicle are influenced by voltage, current, and temperature for batteries. Therefore, these three parameters were selected as the input data to establish the fault diagnosis model.

If errors occur inside the batteries, the Controller Area Network (CAN) bus of the battery management system immediately sends the fault data (voltage, current, and temperature) to the central control module. Subsequently, the main control module divides the fault information from the CAN bus into different fault levels according to the fault type and severity. Based on the vehicle safety requirements, the battery system fault information is always divided into four levels, as shown in the **Table 1**.

In this study, a method of diagnosing the battery system of electric vehicles was developed using the neural networks. A pure electric passenger car was employed to collect the fault information of a lithium iron phosphate battery pack. The main parameters of the battery pack were 352 V/ 100 Ah battery pack. **Figure 1** shows the charging and discharging of the battery test equipment. The main experimental equipment consisted of the lithium iron phosphate battery pack, battery charge and discharge tester, CAN data analyzer, and laptop. **Figure 2** shows the connection mode of the test equipment. The functions of each experimental equipment are as follows:

1) The battery charging and discharging tester was a TECHPOW intelligent charging and discharging tester, which could analyze energy feedback during battery charging and discharging and simulate different vehicle conditions for evaluating the power battery performance. The direct-current voltage of this tester ranged from 0 to 1500 V, and its current ranged from 0 to 400 A.
2) The tested battery pack was a 352 V / 100 Ah battery pack divided into two boxes and used in series.

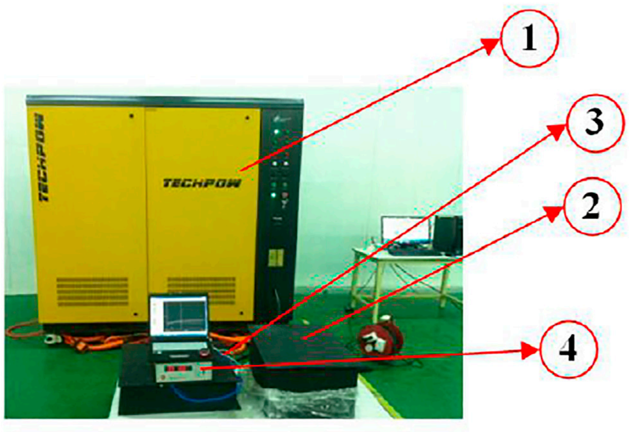

FIGURE 1 | The test equipment of the lithium iron phosphate battery pack.

3) A CAN data analyzer was used to collect the data from the internal sensor of the battery.
4) A stabilized voltage of 12 V was used to power the battery management system.
5) A laptop was used to collect and show the experimental data.

Six parameters of the battery were selected as the input data, the fault levels were set as the output data for the neural network. For discussing the voltage fault of battery pack, the voltage of battery pack and single battery should be discussed respectively. Due to the individual differences in the production and application of batteries, the total voltage of battery pack may be in a reasonable range, while the voltage of a single battery is abnormal. Therefore, the system should monitor the voltage of battery pack and single battery at the same time. The data collection method can be summarized as follows:

1) Single-voltage (L1 and L2).

The range of the charging voltage for lithium iron phosphate single-voltage is from 2.0 to 3.65 V. The charging voltage was set from 2.4 to 3.25 V. For the upper-limit voltage, the voltage for fault diagnosis was 3.7 V when the actual battery voltage collected using the sensor was 3.3 V. The fault level for this condition is denoted No. I. For the lower-limit voltage, the fault diagnosis voltage was 2.05 V, as the actual battery voltage collected using the sensor was 2.45 V. The fault level for this condition is denoted No. II. Because the voltage for Level IV was very high, the fault value was randomly selected to some extent.

2) Battery voltage (L3 and L4).

The battery pack voltage of lithium iron phosphate battery packs ranges from 275 to 401.5 V. Considering the safety during the experiments, a 315–361.5 V battery pack voltage was adopted. For the upper-limit voltage of the battery pack, the fault diagnosis voltage was 410 V when the actual voltage of the battery pack recorded by the sensor was 450 V. The fault level for this condition is denoted No. I. For the lower limit, the fault diagnosis voltage was 203 V when the actual voltage of the battery pack collected using the sensor was 243 V. The fault level for this condition is denoted No. III. The fault value was also selected randomly, as the voltage range for fault level III was broad.

3) Discharge current of battery pack (L5).

The test battery is a battery pack with consideration to both power and energy, so a discharge rate of up to 10 C (time less than 10 s) will not pose potential safety hazards. Values detected by the current sensor are measured values. Due to the wide range of current value in Grade IV faults, the fault value is randomly selected according to the range.

4) Temperature of battery pack (L6).

The tests were performed under the temperature of 298.15 K and the pressure of 101.325 kPa condition. The electric heating system inside the battery pack is utilized to works, so that the temperature sensor inside the battery pack detects the

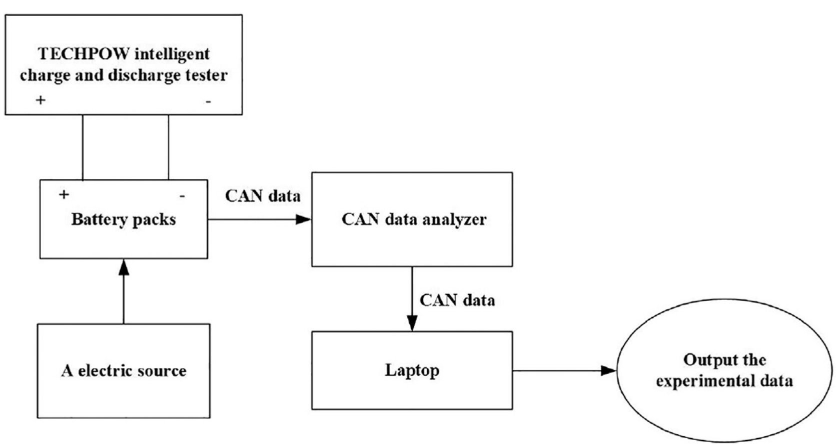

FIGURE 2 | The specific connection mode for the test equipment.

TABLE 2 | The fault levels and corresponding range of the different parameters.

Levels	Parameters	I	II	III	IV
L1	Maximum single-voltage (V)	(3.65, 3.75]	(3.75, 3.85]	(3.86, 3.95]	>3.95
L2	Minimum single-voltage (V)	[2.1,2.5)	[2.0, 2.1)	[1.9, 2.0)	<1.9
L3	Maximum voltage of battery pack (V)	(401.5, 412.5]	(412.6, 422.5]	(422.6, 432.5]	>432.5
L4	Minimum voltage of battery pack (V)	[231,275)	[215, 230)	[200, 215)	<200
L5	Discharge current of battery pack (A)	(700, 800]	(800, 900]	(900, 1,000]	>1,000
L6	Temperature of battery pack (°C)	(55, 60]	(60, 65]	(65, 70]	>70

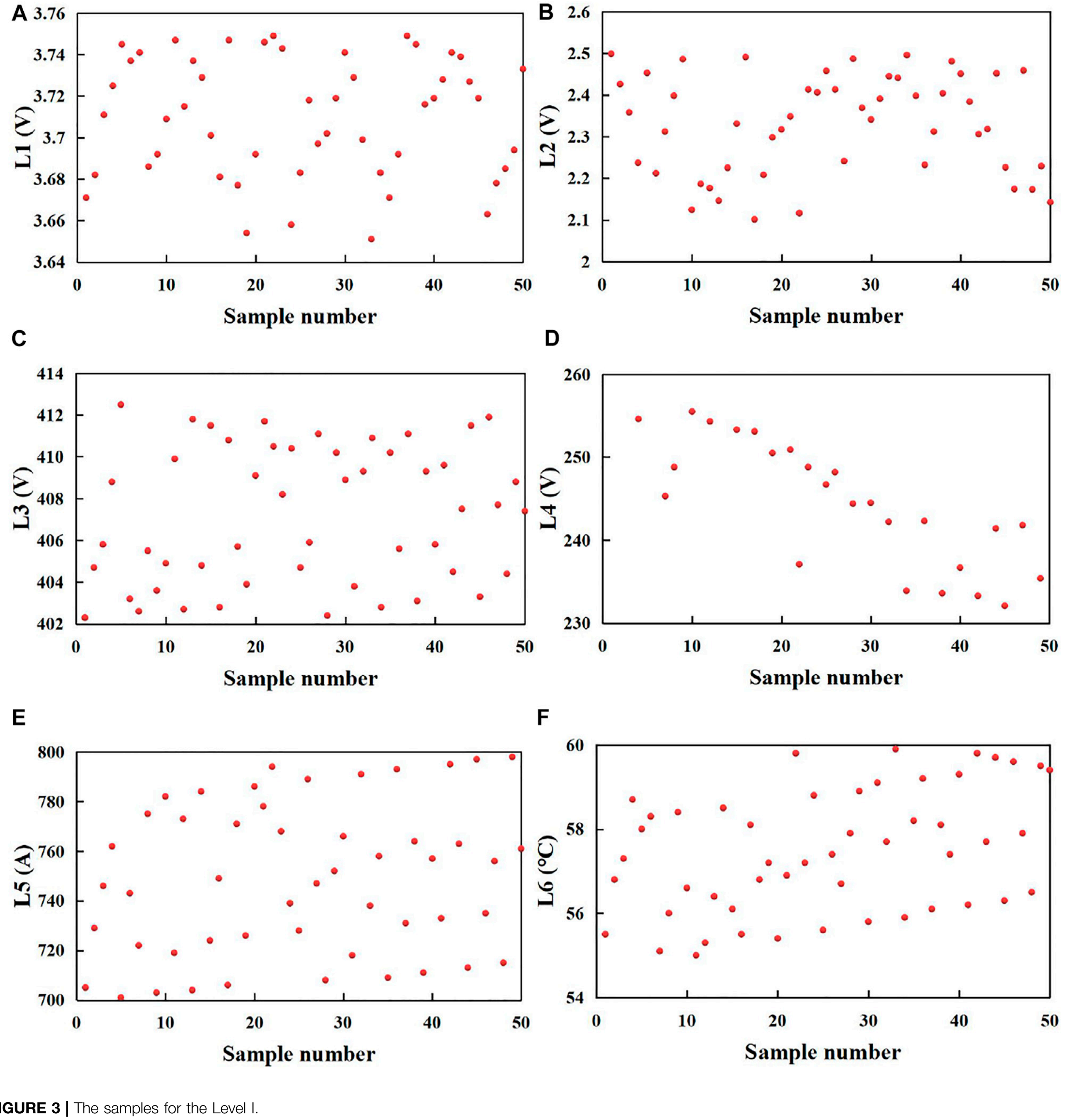

FIGURE 3 | The samples for the Level I.

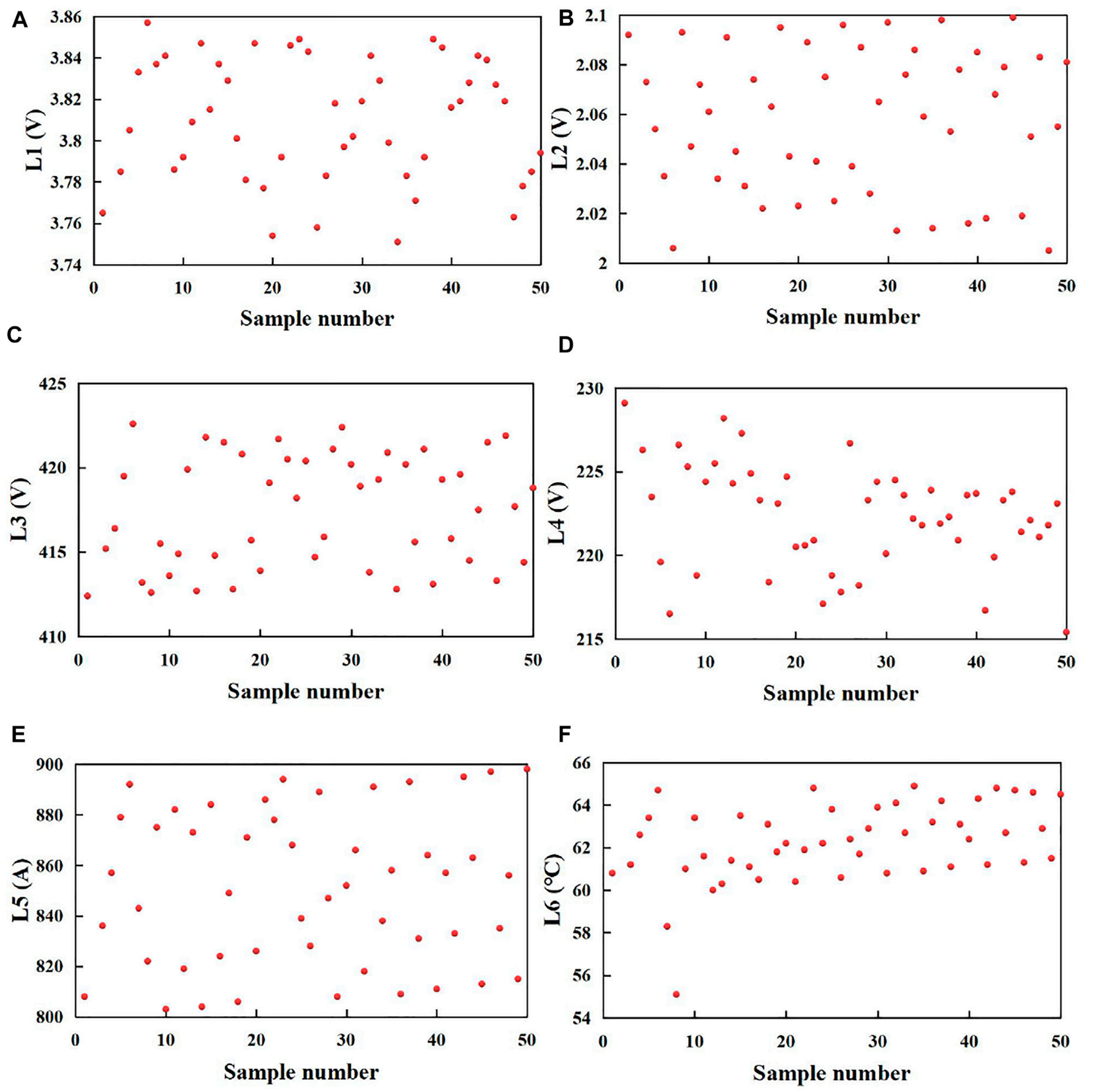

FIGURE 4 | The samples for the Level II.

temperature value reaching the fault levels. Because the temperature value range of Grade IV faults is large, the fault value is randomly selected according to the range.

Based on the design requirements of the electric vehicle and the performance of the lithium iron phosphate battery pack, the parameter ranges for all faults levels were determined, as shown in the **Table 2**. The maximum and minimum single-voltage values, L1 and L2, were used to control the charging and discharging processes, respectively. The charging and discharging processes were stopped when the voltage reached the maximum and minimum values. The maximum voltage of battery pack L3 was utilized to control battery pack charging, and the minimum voltage of battery pack L4 was used to regulate battery pack discharging. The discharge current of the battery pack was used to control the discharging current of the battery pack. The battery pack temperature was used to control the temperature value of the battery pack during charging and discharging. Fifty sample data were randomly selected at every time in the experiment. **Figures 3–6** show the test data obtained using the above experimental equipment for different fault levels.

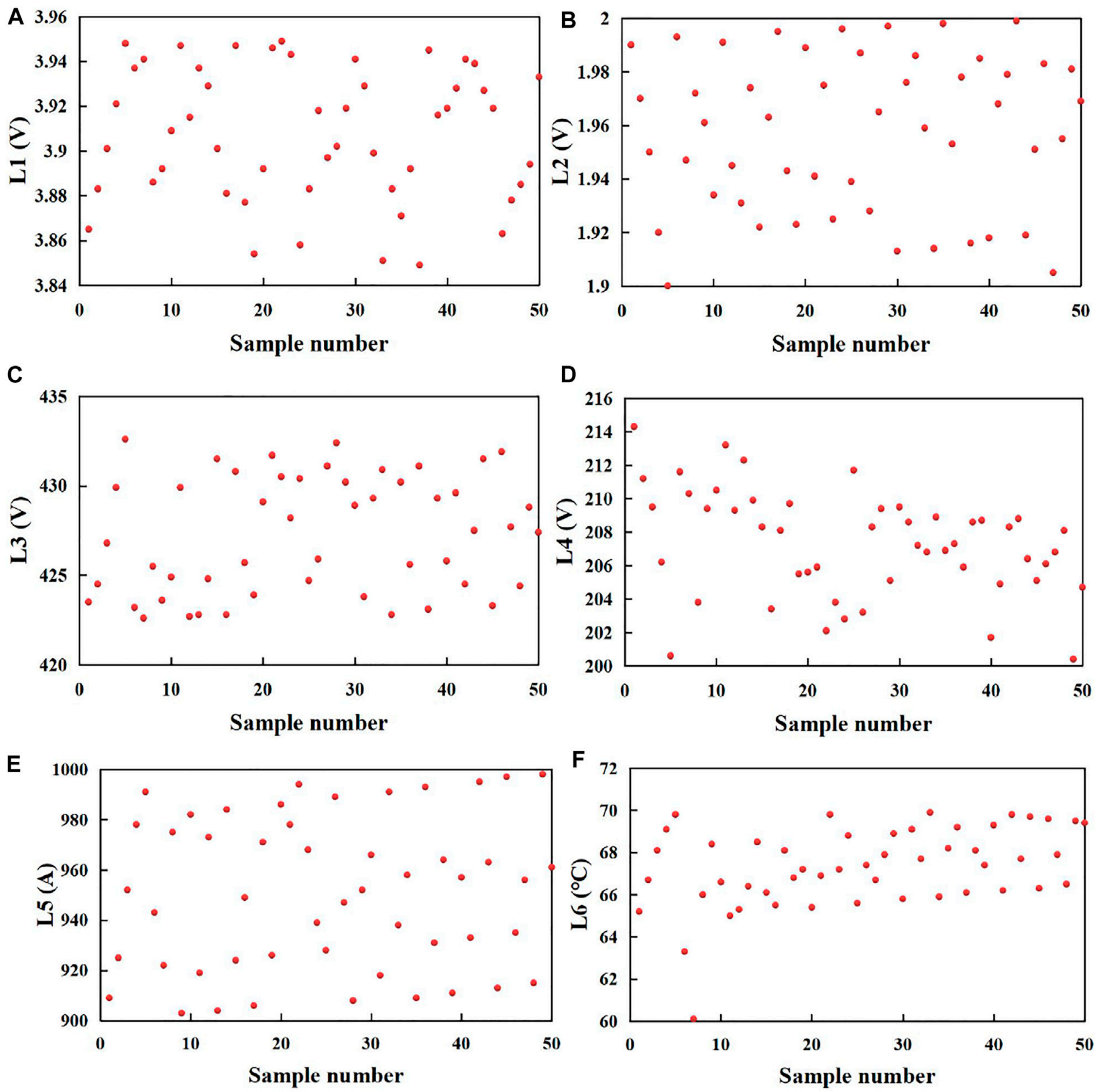

FIGURE 5 | The samples for the Level III.

NEURAL NETWORKS

The RBF neural network is a three-layer typical feedforward neural network developed by Powell in 1985. It is an effective algorithm to predict different data in different fields. With the rapid development of machine learning techniques, the improved RBF algorithm can improve the data prediction accuracy, like the GRNN and the PNN algorithms. In this study, these two algorithms were employed to diagnose the fault information for the lithium-ion battery packs.

The GRNN is an improved model of the RBF method developed by Specht (1991). It can obtain better solutions than the RBF neural network especially in the non-linearity mathematical problem using the less samples. The structure of the GRNN model can be found in the **Figure 7** with four layers. The Gaussian function is used to obtain the output value from the hidden layer (Zhang, 2019):

$$o_i = \exp\left(-\frac{(x-x_i)^T(x-x_i)}{2\delta^2}\right) \tag{1}$$

where $i = 1, 2, ..., m$. x is the input value and x_i is the center of the i^{th} neural. δ is the extended speed.

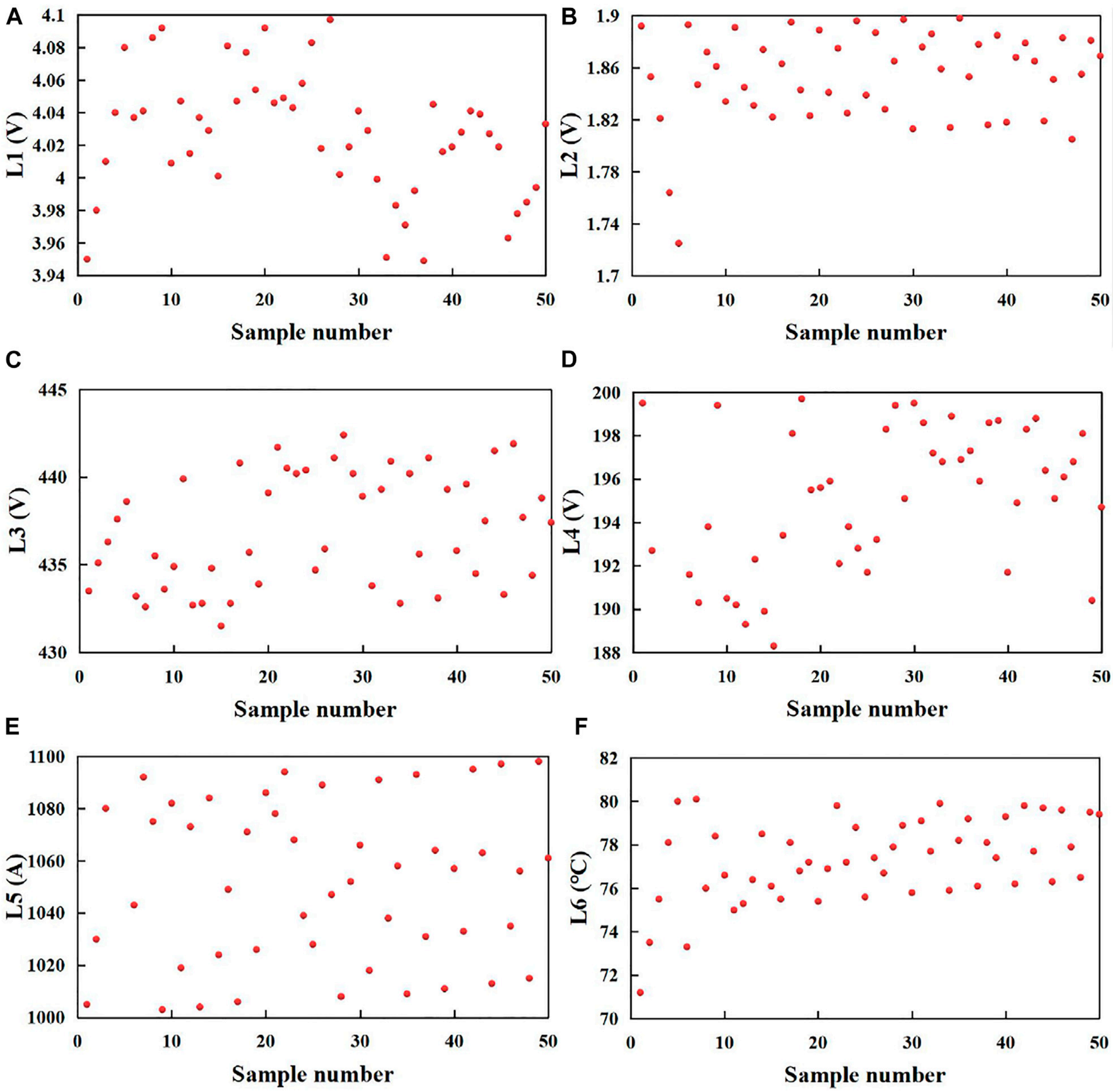

FIGURE 6 | The samples for the Level IV.

The PNN method used the density function estimation and Bayesian theory to approximate the output data (Song, 2020). It also includes an input, a pattern, a summation and an output layer, like the structure of the GRNN neural network in the **Figure 7**. The input and output in the pattern layer of the PNN algorithm can be expressed as (Ni, 2014):

$$\vartheta_{ij}(p) = \frac{1}{(2\pi)^{0.5d}\sigma^{d}} e^{-\frac{(p-p_{ij})^{T}(p-p_{ij})}{2\sigma^{2}}} \tag{2}$$

where $i = 1, 2, ..., n$. d is the dimension of sample space. σ is the smoothing factor.

FAULT DIAGNOSIS RESULTS AND DISCUSSIONS

For verifying the accuracy of the neural networks, the last five samples for each fault levels were selected as the test samples, and the first 45 samples were used as the training data in the **Figures 3–6** .

Parameter Setting for the Neural Networks

The parameters of the neural networks have great influence on the output results. To obtain the best results, the selection of the parameters becomes very important. For the GRNN and PNN algorithms, the spread value is one of the most important

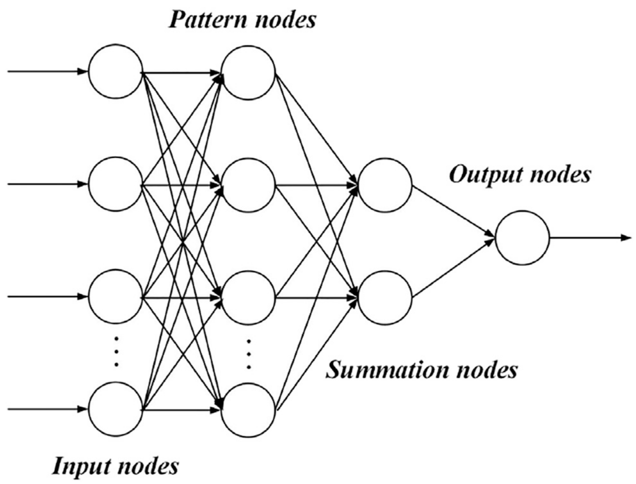

FIGURE 7 | The structure of the GRNN neural network (Specht, 1991; Ghritlahre and Prasad, 2018).

TABLE 3 | The fault diagnosis results for RBFNN algorithm using different spread value.

Spread	Diagnosis accuracy (%)	Number of errors
10	75	5
15	80	4
20	60	8

TABLE 4 | The fault diagnosis results for GRNN algorithm using different spread value.

Spread	Diagnosis accuracy (%)	Number of errors
10	85	3
15	85	3
20	90	2

parameters need to be determined. The results are too rough if the spread value is very big, and the results are not smooth enough if the spread value is very small (Wen et al., 2014). Therefore, different spread values have been selected and discussed for GRNN and PNN algorithms using the first 20 samples for each fault level. To compare the calculation accuracy for the improved RBFNN, a traditional RBF neural network is also employed in this study to diagnose the fault of the battery. The results can be found from the **Tables 3–5**. As can be seen from the **Tables 3–5**. The number of errors for the traditional RBF neural network is more than the other two algorithms. It can be conclusion that the GRNN and PNN algorithms are suitable for battery diagnosis problem. The diagnosis accuracy has been changed with the change of the spread value. The diagnosis accuracy is the best when the spread value is equal to 20 for GRNN and PNN algorithms. In addition, the PNN algorithm is superior to the GRNN algorithm for the identification of the fault information of the battery.

TABLE 5 | The fault diagnosis results for PNN algorithm using different spread value.

Spread	Diagnosis accuracy (%)	Number of errors
10	90	2
15	90	2
20	95	1

TABLE 6 | The fault diagnosis results for GRNN algorithm using different sample size.

Sample numbers	Diagnosis accuracy (%)	Number of errors
20	90	2
30	95	1
40	95	1
45	100	0

TABLE 7 | The fault diagnosis results for PNN algorithm using different sample size.

Sample numbers	Diagnosis accuracy (%)	Number of errors
20	95	1
30	100	0
40	100	0
45	100	0

The Selection of the Sample Size

The selection of the sample size also influences the output results of the neural networks. Therefore, different sample size has been used to diagnose the fault information of the lithium iron phosphate battery pack with the spread value of 20, as shown in the **Tables 6**, **7** As can be seen from the table, with the increase of the sample size, the diagnosis accuracy is increased. When the sample size is 45, the GRNN and PNN algorithms can both identify fault information of the battery. The diagnosis accuracy is about 100%. It can be inferred that the GRNN and PNN algorithms can be used to identify the fault information of the lithium iron phosphate battery pack with high accuracy. The PNN algorithm can obtain the better results using the less samples than the GRNN algorithm.

CONCLUSIONS AND FUTURE WORKS

This paper presented a fault diagnosis method for the electric vehicle power battery using the improved RBF neural networks. Six parameters of the lithium iron phosphate battery pack were selected as the variables, and the fault levels were selected as the target. The CAN bus was used to collect all the experimental data. Then the GRNN and the PNN algorithms were employed to identify the fault information of the battery. At the same time, the parameter and the sample size were also discussed and compared. The results show that the parameter and the sample size influence the output results of the neural networks, and the GRNN and PNN algorithms can be used to identify the fault information of the battery. To protect the battery effectively and precisely, further studies will introduce the state of health (SOH) parameter, and the new fault diagnosis method will be employed to verify the accuracy and feasibility.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

JW is responsible for the full-paper design and experimental data analysis, SZ is responsible for the compilation of the algorithm, and XH is responsible for obtaining the experimental data.

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Conflict of Interest: Author XH was employed by the company Shanghai Automotive Industry Corp. Group.

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