Research on prediction method of SOC of bus battery based on FNN

**Yanxia wu ,Zhouyu Gao#,Xu Wang,Yazhang Han ,Yan Fu\* and Wei Li**

College of Computer Science and Technology, Harbin Engineering University,

Harbin 150001, China

\*Corresponding author: Yan Fu

[e-mail: fuyan@hrbeu.edu.cn.]

Abstract

In recent years, with the development of new energy technology, pure electric bus plays an increasingly important role in public transportation. However, the SOC of bus battery can not be measured directly, which results in low prediction accuracy of SOC. In order to solve this problem, firstly this paper analyzes the factors affecting the prediction of battery SOC which uses the subtractive clustering optimization method to build the FCM algorithm, known as ANFIS model. Secondly, the objective function and clustering center of FCM algorithm are optimized by using the weight sample den-sity function to reduce the sensitivity outliers of FCM algorithm. Then the simulated annealing genetic algorithm is used to optimize the FCM algorithm. Finally, the PSO algorithm based on particle distribution to adjust the inertia weight was used to optimize ANFIS parameters, which dynamically balanced the global and local search capabilities of PSO algorithm, thus improving the prediction accuracy of ANFIS model. The experimental results show that the im-proved ANFIS model effectively reduces the prediction error of bus power battery SOC.

Keywords: SOC, ANFIS , FCM, PSO, Adjust inertia weight

1. Introduction

Since the Paris agreement in 2016, some countries have made some efforts in energy conservation and emission reduction, but in recent years, the problems of environmental degradation and energy shortage have become increasingly serious on a global scale. Accelerating the development and promotion of new energy technologies has become a global consensus and is one of the main directions of the development of the vehicle industry. The power source of new energy vehicles is green and pollution-free, so the popularization of new energy technology in the vehi-cle industry is an important way to deal with the increasing shortage of global oil resources and envi-ronmental warming. However, the key of new energy technology lies in the development of safe, efficient and low-cost power battery. Currently, lithium iron phosphate battery has gradually become one of the main battery types used as the power source of new energy vehicles due to its advantages of good thermal stability, high energy ratio and long service time [1][2].

Battery management system is an indispensable part in electric vehicles [3]. The responsibility of this system is to ensure the safe use of power batteries and monitor the use of batteries so as to ensure the safe running of electric vehicles [4]. However, the SOC of the battery is an important state parameter in BMS [5], which is as important as the fuel gauge in the fuel vehicle. A more accurate SOC can guide the charging and discharging strategies. Much of the oth-er functionality of BMS is also SOC dependent. In addition, accurate SOC estimation can also assist the driver in determining the time to charge the bus. However, in the application scenario, SOC cannot be directly measured; it can only be determined accord-ing to other parameters such as operating voltage and operating current of the battery[6]. Moreover, the relationship between SOC and various factors cannot be represented linearly under the requirement of high precision [7], and various factors will also affect each other in the battery operation.

With the development of science and technology, the ways to predict battery SOC can be mainly divid-ed into two categories: one is to predict SOC by us-ing traditional approaches, and the other is to predict SOC by using artificial intelligence methods [8]. The commonly used traditional prediction methods are :(1) ampere time integration method; (2) open-circuit voltage method; (3) impedance analysis; (4) discharge test method; The commonly used intelli-gent prediction methods are :(1) kalman filtering; (2) fuzzy logic method; (3) neural network method; (4) support vector basis; (5) extreme learning machine; (6) fuzzy neural network; Because of its simplicity and effectiveness, the ampere-integral method has been more widely applied to the prediction of battery SOC [9] . In this method, SOC is defined as the inte-gral of current, so this method is a direct and effec-tive way to measure SOC. However, this method simply records the charge or discharge of electricity, neither consider the effect of self-discharge reaction, operating temperature and charge/discharge ratio on rated capacity, nor the effect of current sensor preci-sion and intermittent use of battery on initial SOC. Open circuit voltage method is often used as a means of SOC calibration due to its long measurement time [10]. Although this method is simple and accurate, the conditions for using it are too strict. Kalman fil-ter is a method of SOC prediction based on the estab-lished equivalent circuit. KF is a linear filtering method proposed by Rudolf e. Kalman in the 1960s. The advantage of using kalman filter to predict SOC is that it is suitable for the environment with severe current fluctuation, but the error of SOC estimated by this algorithm is closely related to the battery equiva-lent model used. Moreover, the algorithm assumes that the system noise is gaussian noise, but in prac-tice, these assumptions may not be true，and the standard KF algorithm cannot effectively and rapidly calculate due to its own characteristics [11].

Due to its ability to learn knowledge from samples, fuzzy neural network greatly reduces the dependence on expert knowledge when establishing fuzzy rules, and can optimize its own parameters through training. Compared with fuzzy logic, fuzzy neural network has become a research hotspot in recent years. Zhang mei established a 4-layer fuzzy neural network to estimate the SOC of nickel hydride batteries, and the maxi-mum estimation error did not exceed 2.5% [12]. Un-der the condition of constant resistance load test, Li I H et al. compared the SOC estimation model of BP network and fuzzy neural network, and the results showed that the fuzzy neural network was good, but the working environment of the battery was relatively single [13]. Dai H et al. combined the kalman filter with the ANFIS model and established a model with high accuracy considering the single battery in the battery pack of electric vehicles [14].Yin andong et al. established ANFIS model in the laboratory to predict SOC of LiFePO4 battery, and the maximum error was less than 1% when 3 input was used in the model [15].

At present, most of the research focuses on the combination of two or more methods, which can make up for each other's shortcomings and improve the accuracy of prediction of SOC. The ANFIS mod-el used in this paper belongs to the fuzzy neural net-work which combines the neural network and fuzzy logic. It has a high prediction accuracy in the predic-tion method of battery SOC, and is suitable for the application scenario of bus battery which requires high prediction accuracy.

The purpose of this paper is to study the method of SOC prediction of bus power battery. The main research content is divided into the following three parts:

(1)Firstly, this paper analyzes the factors affecting the battery SOC, and finally determines the voltage, current, average temperature and maximum voltage difference of the battery input as the model.

(2) Secondly, this paper establishes ANFIS based on the improved FCM algorithm of meshing method and subtractive clustering method, and trains the model on the data set with hybrid learning method. Experiments show that the clustering algorithm has better performance than the meshing method, but the maximum error of the prediction model is large and the model training efficiency is low.

(3)Finally, this paper first uses sample weighting method to reduce the sensitivity of FCM algorithm to outliers, and then uses simulated annealing genetic algorithm to find the optimal clustering center to solve the problem of large maximum error. Sample weighting can reduce the influence of outliers on cluster center iterative computation, while simulated annealing genetic algorithm can reduce the depend-ence of FCM algorithm on initial cluster center. To solve the problem of low training efficiency of the model, particle swarm optimization (PSO) is adopted to adjust the inertia weight according to the particle distribution.

2. Research

Common battery models include electrochemical model such as Nernst model, equivalent circuit mod-el such as Thevenin model and mathematical model such as neural network model. ANFIS is a mathemat-ical model. This chapter analyzes the relationship between battery SOC and different factors and com-pletes the selection of input parameters. Then, the meshing method for generating initial FIS [15] and an FCM method based on subtractive clustering op-timization [16] are introduced respectively. Secondly, the data set used in this paper is introduced. Finally, a hybrid learning algorithm is used for model training and SOC prediction.

2.1. Battery SOC influencing factors and model input selection

SOC is only directly related to the rated battery power and the remaining battery power, but it is not easy to measure them directly in usage scenarios. Therefore, factors indirectly related to the battery SOC should be considered as the input of the model when establishing the mathematical model. There are many factors indirectly related to the car battery SOC, such as working voltage, working current, working temperature, internal resistance and so on. It has a big impact on the bus battery, the number of battery life cycles, the self-discharge response and so on. So the increase over time makes it difficult to accurately estimate the battery SOC.

These factors include voltage, current, temperature, battery aging, internal resistance, self-discharge re-sponse, and the unbalanced state of the battery pack. These factors also affect each other. To SOC estima-tion model is set up, the first to determine the input parameters of the model, based on the parameters of SOC contribution and the change of parameters in a data set, the selection of battery voltage, current, av-erage maximum temperature and battery voltage dif-ference for input, battery SOC as output, establish an ANFIS model of 4 input 1 output.

2.2. ANFIS initial FIS selection

After the input variables of the ANFIS model are determined, the structure and training method of the initial Fuzzy Inference System (FIS) of the model shall be determined in an appropriate way.

2.2.1. Meshing method

Meshing method is a method of linear division of training data. The complexity of the initial FIS gen-erated by meshing is exponentially related to the number of fuzzy subsets. Grid partitioning USES a custom number of membership functions to divide input variables into a finite number of fuzzy areas. These regions form the network structure. The sample space is divided into several subregions by meshwork, and the membership relation between different attrib-utes of input vector and each subspace is calculated, and fuzzy rules are obtained to build the model.

2.2.2. FCM method based on subtractive clustering

Subtractive Clustering Method (SCM) is a hard Clustering Method based on density proposed by Chiu [17]. FCM clustering algorithm can be used to establish the uncertainty description of the category of samples[18] .This method is based on mountain clustering and has some optimization. In the subtrac-tive clustering method, the clustering center is select-ed from the samples.

The complexity of ANFIS model mainly depends on the number of fuzzy rules and the number of parti-tion regions of input variables. In order to reduce the number of fuzzy rules generated by meshing and re-duce the complexity of the model, clustering method can be introduced. Different from the meshing meth-od, the number of fuzzy rules generated by the AN-FIS network structure generated by the clustering algorithm is only related to the number of clusters, so the system complexity will be greatly reduced.

In this paper, the samples are grouped into 10 clas-ses, and the gaussian function is used as the member-ship function. The initial parameters of the member-ship function are calculated from the input attributes of each dimension, the clustering center and the membership degree. The structure of the initial FIS is shown in Figure 1.Compared with meshing method, the number of rules and model complexity obtained by SubFCM method are greatly reduced, but it is still necessary to determine which way to choose to build ANFIS model by predicting SOC errors.

The FCM algorithm based on subtractive cluster-ing is denoted as SubFCM.

ANFIS structure diagram based on subtractive clustering is shown in Fig. 1.

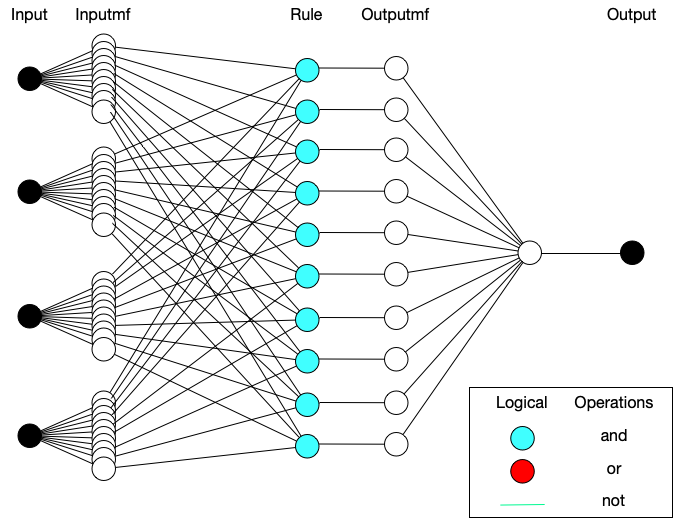


Fig.1.Schematic diagram of ANFIS structure based on subtractive clustering

Table 1 shows the proportion of the number of sam-ples whose SOC absolute error value is greater than 5% predicted by the SubFCM-ANFIS model in Test1 in different ranges of SOC values.

Table 1 the proportion of sample quantity whose absolute value of error in different SOC ranges is greater than 5%

|  |  |
| --- | --- |
| **Scope of SOC** | **Proportion** |
|  |  |
| [0.148,0.4) | 5.1% |
| [0.4, 0.6) | 3.3% |
| [0.6, 0.8) | 4.7% |
| [0.8,1] | 5.81% |

Since there is no phenomenon that the bus runs out of power, no data samples with SOC lower than 0.148 are included in the data set. Set sample clustering center of the maximum membership degree as samples as that category, then found by calculation, it is found that the sample with large prediction error is far away from its cluster center compared with other samples with small prediction error in the same category, that is to say, the biggest reason of error is the use of the effect of the clustering method is affected by the outlier is higher. To solve this problem, firstly, these isolated sample points should be weighted to reduce their impact on the iterative calculation clustering center; secondly, the method of generating FCM initial clustering center should be improved to reduce the impact of outliers on the results of SCM algorithm. In addition, in the process of model training, the trend of error decline is relatively gentle and may fall into local optimization, which is also the characteristic of BP algorithm.

2.3. Sample weighting and annealing genetic algorithm were used to obtain IFCM

In FCM, it is considered that all samples are equally valid, lacking consideration for samples far away from most samples in the same category. How-ever, in the complex scenario of bus operation, the distribution of samples is uncertain and there are in-evitably some isolated points in the data set.

This paper introduces the Cosine Similarity (CS) to European distance weighting. CS uses the Cosine value of two vectors as the evaluation of the differ-ence between them. Cosine similarity is calculated by (1).

 (1)

In (1), X and Y are n-dimensional vectors, and is the Angle between X and Y. The modified Euclidean distance calculation is shown in (2).

 (2)

The subtractive clustering point density calculation based on cosine similarity is shown in (3).

 (3)

After obtaining the density index of all samples according to (3), it is necessary to normalize the index of all samples. The result of normalization is the weight of each corresponding sample, so as to reduce the negative impact of samples far away from most samples on FCM algorithm. The sample weight is calculated as shown in (4).

 (4)

Where, *n* is the number of samples. The higher the density index is, the greater the weight will be. However, for samples with a small number of samples in the neighborhood space, a small weight value will be obtained, which reduces its influence on FCM results. The calculation of the objective function of the weighted sample FCM algorithm is shown in (5).

 (5)

By using the Lagrange multiplier method, the calculation of ci and *uij* in the weighted sample FCM algorithm is shown in (6) and (7) respectively.

 (6)

 (7)

In the process of iteration, FCM clustering algorithm is prone to local minimization due to its dependence on the initial clustering center. In this paper, simulated annealing genetic algorithm is used to improve the FCM algorithm.

The application of simulated annealing genetic algorithm to sample weighted FCM can prevent FCM from being trapped in local optimality when iteratively calculating the clustering center, so that FCM can find the optimal clustering result, and the improved algorithm is denoted as IFCM.

2.4. Parameter optimization of ANFIS based on improved particle swarm optimization algorithm

The selection of optimization methods in training is very important for ANFIS to obtain effective training results [19]. Particle swarm optimization improves the performance of ANFIS [20]. However, the performance of PSO algorithm depends largely on the choice of its Settings [21]. In the PSO algorithm, the position with the highest fitness is *pbesti*, and *gbest* is the position with the highest fitness of all particles in the process of changing positions. The velocity attribute vector *Vi*=(*vi1, vi2… vim*), then f(*Xi*) represents the fitness value of particle I at the position of *Xi*. After initializing the particle and *gbest* and *pbesti*, the calculation of the particle updating its velocity and position is shown in (8) and (9), respectively.

 (8)

 (9)

In (8),  is the inertia weight and is non-negative value. *c1* and *c2* are learning factors, indicating the tendency of the particle to move to the optimal position of the individual and the optimal position of the group. *r1* and *r2* are represented as random Numbers between 0 and 1 in order to make certain differences between different particles.

In (8), the right-hand side of the equation can be divided into three parts. Part 1 represents the particle's ability to maintain past velocity. The larger the value of this part, the stronger the particle's global search ability; on the contrary, the better the local search ability. Part 2 is usually referred to as the self-cognition term of the particle, which represents the learning ability of the particle to its own experience, and reflects the orientation of the particle to the optimal position of the individual. The third part is the group cognition term, which represents the learning ability of the particle to the group experience, and reflects the tendency of the particle to the optimal position of the group.

The IFCM method was used to establish the initial FIS. Then the ANFIS model's ANFIS parameter set and ANFIS parameter set are obtained. These parameters determine the dimensions of particles in the PSO algorithm. The fitness value used in PSO is inversely proportional to the mean square error of the battery SOC prediction model based on ANFIS.

In practical application, in (8) often uses dynamics according to the linear decreasing weight strategy, so that the algorithm can focus on different search capabilities in different operation periods. At this time, the calculation of  is shown in (10).

 (10)

In (10), a *Gk* is the maximum iteration number of the algorithm,*ini*is the initial value, usually set to 0.9, *end* is the last optimization of PSO algorithm, usually set to 0.4, g is the current iteration number. However, this linear diminishing weight strategy is often unable to deal with nonlinear changes, which often makes PSO iteration take a long time when the problem is more complex. In addition, with the operation of PSO algorithm under this strategy, due to the decline of w, the algorithm often lacks the global optimization ability in the later stage of operation, resulting in the algorithm falling into the local optimal solution.

In view of this phenomenon, this paper proposes a method to adjust  according to the distribution of particles in particle swarm optimization, so that in the process of algorithm iteration, can be adjusted according to the spacing between particles to determine whether the search ability of PSO algorithm focuses on global or local optimization. Firstly, the average distance of particle I relative to other particles in set M jointly constituted by the current position of each particle and *gbest* are calculated, as shown in (11).

 (11)

In f (11), n is the number of elements in set M. Then  is calculated according to the average distance of *gbest*, *dg*, and the maximum and minimum average distances in the current particle. After is limited to the closed interval [0.4,0.9] where more is used, its calculation is shown in (12).

 (12)

In (12), *dmax* is the maximum average distance of particles in set M, and *dmin* is the minimum average distance of particles in set M. When *dg* is large, is also large, which makes other particles far away from the optimal position jump out of the local optimal position where they may fall into and approach to the optimal position. When *dg* is small, is also small, so that more particles can approach the optimal position with a small change in position.

In addition, the acceleration constant *c2* has been modified to dynamically adjust, and its calculation is shown in (13).

 (13)

In (13), *g* is the number of times the particle position has been updated; *Gk* is the maximum number of updates to the set location; *c2ini* is the initial value of the learning factor *c2*.

The specific steps to optimize the ANFIS model with the improved PSO are as follows:

Step 1: determine the network topology of ANFIS, determine the number of parameters m, and the initial parameter set *P*=(*p1,p2... , pM*). Set the number of particle swarm n and the maximum number of iterations *Gk*. If n population particles are randomly initialized, the position vector of the ith particle is *Xi*=(*xi1,xi2... xim*), the velocity vector is *Vi=(vi1,vi2... ,vim)*, where 1≤ i ≤n, set global best position *gbest*=P, iteration count g=0, maximum speed *Vmax=(v1,v2... , vm)*;

Step 2: determine the reciprocal of the RMSE indicator of the ANFIS model, the fitness value of the ith particle is F(*Xi*), and the best position of the particle *pbesti = Xi*;

Step 3: calculate the average distance between particles and other particles (the *gbest* position is also considered as one of the particles), update the inertia weight according to equation (12), and update the learning factor *c2* according to equation (13) and set *g=g*+1;

Step 4: calculate the velocity *V* of each particle according to formula (8), and compare each dimension of V and Vmax of each particle. If *vij>v*j, make *vij=vj*;

Step 5: calculate the position of each particle according to formula (9), and then update the historical best position *pbesti* and the best position *gbest* of each particle. If F(*Xi*)>, F(*pbesti*), then let *pbesti=Xi*, if F(*Xi*)>F(*gbest*), then let *gbest= Xi*;

Step 6: judge the termination condition of the algorithm. If it is satisfied, it will be terminated. Otherwise, go to step 3.

3 result

In this paper, the battery discharge data of 9 buses of the same model are selected from two bus operation lines. After preprocessing the data of 6 buses of the same line, 115267 groups of data are obtained. 80% of the data are training sets, the remaining data are test set test1, and then 27000 groups of data are randomly selected from the data of the other 3 buses as test set test2. Each one-dimensional attribute of the test set sample should be between the maximum and minimum values of the corresponding attributes of the training set, otherwise the results of the sample will not be included in the model results.

3.1. Evaluation criteria

(1) mean variance, which is used to reflect the prediction accuracy of the model as a whole, is calculated by (14).

 (14)

In formula (14), *ti* is the true value of SOC, *fi* is the estimated value of the model, and N is the number of samples of the test set.

(2) the maximum error, which is used to reflect the stability of the model, is calculated by (15).

 (15)

(3) average training time, calculated by (16).

 (16)

In (16), is *timeend* and *timebegin* are the time to reach the training termination state and the time to start the training, and T is the number of experiments.

Owing to the high frequency of data collection and the same bus between adjacent samples on most of the time difference is small, and considering the bus power battery drops faster at the beginning of the discharge voltage, therefore in the process of single vehicle single discharge, when the battery SOC is greater than 50%, samples are taken every 5 seconds. When the battery SOC is greater than 50%, samples are taken every 10 seconds. After screening, a total of 115,267 sets of data were obtained. This is because bus driving usually does not reduce the SOC to a very low level. It includes only the data of line A. Then the data is processed to obtain the required model input variables. Wherein, the calculation of the average temperature of the battery pack temperature acquisition node in the model input variable is expressed by (17).

 (17)

In (17), n is the number of temperature acquisition nodes in the battery pack, and tempi is the temperature acquired by the ith acquisition node.

The maximum voltage difference of a single battery is calculated by (18).

 (18)

In (18), *volti* is the voltage value of the ith single battery, and N is the number of single batteries.

In order to speed up the convergence rate of the model and to avoid the distribution of different input variables on the result of training, We need to select the battery discharge voltage v, battery discharge current I, the average temperature of the battery temperature acquisition node, maximum differential pressure between monomer battery normalized processing, and map it to [1, 1] range. Due to the SOC values on the closed interval [0, 1], we do not normalized processing. An example of standardized data is shown in table 2 .



Table 2. examples of normalized data

|  |  |  |
| --- | --- | --- |
| Name | Not normalized | The normalized |
|  |  |  |
| Terminal voltage value | 629.3 | 0.0485 |
| Current value | 101.4 | -0.4173 |
| The average temperature | 26.2 | 0.3083 |
| Maximum monomer pressure difference | 3.7 | 0.7209 |

After preprocessing the data set in data belong to the lines of A selected time serial data, 115267 group. Then 80% of the data is randomly selected as the training set, and the rest as the test set test1, which is used to directly test the accuracy of the model. Then, three vehicles are randomly selected from line B, and 27000 groups of battery discharge data are randomly selected from the driving data of these three vehicles as test set test2. Its function is to verify the robustness of the model for different vehicle operating environments. Each dimension attribute of the test set sample should be between the maximum and minimum value of the corresponding attribute of the training set, otherwise the result of the sample is not included in the model result.

The experimental results confirm that the number of clusters is 10. Various static parameters of the improved ANFIS model are shown in table 3.

Table 3. static parameter setting table

|  |  |
| --- | --- |
| populations | 100 |
| **Maximum evolutionary algebra** | 100 |
| **Crossover probability** | 0.7 |
| **Mutation probability** | 0.01 |
| **Initial annealing temperature** | 100 |
| **End of annealing temperature** | 1 |
| **Annealing coefficient** | 0.8 |
| **The fuzzy exponential** | 2 |
| **Clustering number** | 10 |
| **Number of particle swarm iterations** | 600 |

The learning factor *c2* in the particle swarm optimization algorithm increased with the number of iterations, with the initial value of 0.8 and the final value of 1.8. The inertia weight changes adaptively according to (13).

There are two aspects to optimize the algorithm. On the one hand, the density index improved by cosine similarity is introduced to weight the samples, so as to reduce the negative impact of outliers on FCM. Then, SAGA-FCM algorithm is used to obtain the optimal clustering center and membership matrix, so as to obtain a better and more stable initial FIS structure, and give the initial value of *gbest* to the particle swarm optimization algorithm of subsequent training model; On the other hand, ANFIS is trained by PSO algorithm which adjusts the weight according to the particle distribution. The improved model reflects a better ability to predict battery SOC, reduces the maximum error, and improves the prediction accuracy. Table 4 shows the comparison of SOC prediction effects of all models before and after the improvement.

Table 4. comparison of model effects before and after improvement

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| The model name | RMSETest1 (%) | RMSETest2 (%) | maxETest1 (%) | maxETest2 (%) |
|  |  |  |  |  |
| Meshing method -ANFIS | 2.56 | 2.78 | 17.98 | 18.84 |
| SubFCM-ANFIS | 2.69 | 2.94 | 12.14 | 13.76 |
| IFCM-PSOANFIS | 2.42 | 2.64 | 9.03 | 9.44 |
| Lm-bp neural network | 2.67 | 2.87 | 18.03 | 18.94 |

As is shown in Table 4, IFCM-PSOANFIS model is superior to the original model in both indicators. In the longitudinal comparison model of IFCM-PSOANFIS model, the maximum error of SubFCM-ANFIS decreases by 4.09% and 5.26% respectively in test set 1 and test set 2, and the mean square deviation decreases by 0.25% and 0.49% respectively. In addition, compared with the SubFCM-ANFIS model, the convergence speed of IFCM-PSANFIS model is reduced in the single iteration time, while the overall time is slightly improved. The experimental results show that PSO algorithm and IFCM algorithm with adaptive dynamic inertia weight can effectively improve the prediction accuracy of the model, not only effectively reducing the maximum error of model prediction SOC, but also reducing the mean square deviation of model prediction SOC to a certain extent, and improving the performance of the model as a whole. The results of IFCM-PSOANFIS model to Test2 also prove the robustness of the model. In addition, according to Table 4, a horizontal comparison between the LM-BP neural network model and the IFCM-PSOANFIS model also reflects the superiority of the IFCM-PSOANFIS model.

In addition, statistics show that in Test1, the number proportion of samples whose SOC error absolute value predicted by the IFCM-PSOANFIS model is greater than 5% decreases in different ranges of SOC values, as shown in table 5.

Table 5. the absolute value of errors in different SOC ranges before and after the improvement is greater than the proportion of 5%

|  |  |  |
| --- | --- | --- |
| Scope of SOC | The proportion in SubFCM-ANFIS | The proportion in IFCM-PSOANFIS |
|  |  |  |
| [0.148,0.4) | 5.1% | 3.65% |
| [0.4, 0.6) | 3.3% | 2.26% |
| [0.6, 0.8) | 4.7% | 3.37% |
| [0.8,1] | 5.81% | 4.32% |

It can be concluded from table 5 that the improved model effectively improves the prediction accuracy of SOC on the whole, not only reduces the maximum prediction error of SOC, but also reduces the sample proportion with the absolute value of prediction error greater than 5%.

4. Conclusion

In this paper, the influence factors of battery SOC are studied and analyzed. According to the application scenarios of bus batteries, the influence of unbalanced state in the battery pack is taken into account. Finally, the input parameters of the model are determined as voltage, current, average temperature and maximum voltage difference in the battery pack. Then the ANFIS model is generated by using the grid division method and the fuzzy c-means algorithm based on subtractive clustering, and the training and testing are carried out on the data set. By considering the mean square error, maximum error and training time, a better clustering algorithm is selected as the way to generate ANFIS model. However, the maximum error of the model is large and the training efficiency is low.

Secondly, to solve the problem of large maximum error, the sensitivity of FCM algorithm to outliers is reduced by means of sample weighting, and then the optimal clustering center is found by means of simulated annealing genetic algorithm. Aiming at the problem of low training efficiency, the particle swarm optimization (PSO) algorithm based on adaptive inertia weight is used to optimize the model parameters. In the concrete implementation, the sample weighting is to introduce the cosine similarity into the density function in the subtractive clustering, considering not only the absolute distance between samples, but also the difference in sample direction, and finally normalizing the density obtained as the weight of the sample. The simulated annealing genetic algorithm finds the minimum value of the weighted FCM objective function of the samples with the specified number of clusters. The adaptive inertia weight PSO algorithm determines the value of inertia weight by the position relation between the global optimal particle and the ith generation particle, so as to select the global search ability or local search ability of the algorithm.

Finally, the improved algorithm has been trained and tested on the data set, and the experimental results show that the improved ANFIS model improve the estimation accuracy, and decrease the mean square error and the maximum error.

References

1. Julien C, Mauger A, Zaghib K, et al. Comparative issues of cathode materials for Li-ion batteries[J]. Inorganics, 2014, 2(1): 132-154.
2. Li Y, Wang C, Gong J. A wavelet transform-adaptive unscented Kalman filter approach for state of charge estimation of LiFePo4 battery[J]. International Journal of Energy Research, 2018, 42(2): 587-600.
3. Hua Zhoufa, LI Jing. Overview of power battery SOC estimation methods for electric vehicles [J]. Power Supply Technology, 2013, 37(9): 1686-1689.
4. Li Tian-feng, YI Ying-ping, SHI Wei. Design of 48V battery management system for new energy vehicles [J]. Electronic Measurement Technology, 2019, 42(8): 6-11.
5. Liu Qian, SUN Hong. Design of battery management System and Estimation of charged state [J]. Power Supply Technology, 2014, 38(5): 897-899+905.
6. Kong Qing, WANG Dong, ZHANG Zhiguo. Research review on power battery SOC estimation of electric vehicles [J]. Electric Age, 2012 (10): 30-32.
7. Luo Ling, SONG Wen-ji, Lin Sh-li, et al. Influence of working temperature on SOC of lithium iron phosphate batteries and research Progress [J]. New Energy Progress, 2015, 3(1): 59-69.
8. Zhang zhijian, Chen hang. Overview of prediction methods of lithium battery SOC [J]. Power supply technology,2016,40(06):1318-1320+1333.
9. Meng J, Ricco M, Luo G, et al. An overview and comparison of online implementable SOC estimation methods for lithium-ion battery[J]. IEEE Transactions on Industry Applications, 2017, 54(2): 1583-1591.
10. Huang C, Wang L. Gaussian process regression-based modelling of lithium-ion battery temperature-dependent open-circuit-voltage[J]. Electronics Letters, 2017, 53(17): 1214-1216.
11. Xiao Ma, Danfeng Qiu, Qing Tao, et al. State of Charge Estimation of a Lithium Ion Battery Based on Adaptive Kalman Filter Method for an Equivalent Circuit Model. 2019, 9(13)
12. Zhang Mei. Prediction of charged state of MH/Ni batteries based on Fuzzy Neural network [J]. Power Supply Technology, 2012, 36(9): 1316-1318.
13. Li I H, Wang W Y, Su S F, et al. A merged fuzzy neural network and its applications in battery state-of-charge estimation[J]. IEEE Transactions on Energy Conversion, 2007, 22(3): 697-708.
14. Dai H, Guo P, Wei X, et al. ANFIS (adaptive neuro-fuzzy inference system) based online SOC (State of Charge) correction considering cell divergence for the EV (electric vehicle) traction batteries[J]. Energy, 2015, 80: 350-360.
15. Yin An Dong, Zhou Bin, JIANG Hao, et al. Prediction of LiFePO4 battery SOC of adaptive neural fuzzy system [J]. Journal of Electronic Measurement and Instrumentation, 2014, 28(1): 84-90.
16. Cui Yuesheng, HU Xi. Research on lightning Activity Prediction based on IFCM-TS [J]. Foreign Electronic Measurement Technology, 2019, 38(7): 12-16.
17. Chiu S L. Fuzzy model identification based on cluster estimation[J]. Journal of Intelligent & fuzzy systems, 1994, 2(3): 267-278.
18. Huang Sheng, CAO Yu. Improvement of FCM algorithm and Simulation Experiment Research [J]. Computer Age,2020(08):75-78.
19. Dervis Karaboga, Ebubekir Kaya. Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey. 2019, 52(4):2263-2293.
20. Mashallah Rezakazemi, Amir Dashti, Morteza Asghari, et al. H 2 -selective mixed matrix membranes modeling using ANFIS, PSO-ANFIS, GA-ANFIS. 2017, 42(22):15211-15225.
21. Marco S. Nobile, Paolo Cazzaniga, Daniela Besozzi, et al. Fuzzy Self-Tuning PSO: A settings-free algorithm for global optimization. 2018, 39:70-85.

WU Yanxia was born in 1979. She received the B.S., M.S. and Ph.D. degrees from Harbin Engineering University, Harbin, China. Now she is an associate professor in the College of Computer Science and Technology in Harbin Engineering University. Her current research interests include compiler technology and computer architecture.

(Email: wuyanxia@hrbeu.edu.cn)

GAO Zhouyu was born in 1999. He received the B.S degree in computer technology. He is currently pursuing the M.S. degree majoring in software engineering. His research interests include computer vision, image processing, machine learning and deep learning.

(Email: 977829178@qq.com)

WANG Xu was born in 1996. He received the B.S degree in computer technology from Harbin Engineering University，Harbin, China. He is currently pursuing the M.S. degree majoring in software engineering. His research interests include computer vision, image processing, machine learning and deep learning.

(Email: 2750250486@qq.com)

HAN Yazhang was born in 1995. He received the M.S degree in software engineering from Harbin Engineering University, Harbin, China, in 2020. His research interests include computer vision, image processing, machine learning and deep learning.

(Email: 654662230@qq.com)

LI Wei was born in 1996. He received the B.S degree in computer technology from Harbin Engineering University, Harbin, China. He is currently pursuing the M.S. degree majoring in computer science and technology. His research interests include computer vision, image processing, machine learning and deep learning.

(Email: liwei188@hrbeu.edu.cn)

FU Yan was born in 1978. She received the M.S. degrees from Harbin Engineering University, Harbin, China. Now she is currently a lecturer in Harbin Engineering University.Her current research interests include

compilation technology、computational Intelligence.

(Email：fuyan@hrbeu.edu.cn)