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Research on precise management and control technology of construction waste based on optimized PSO-ELM

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Abstract. The turbulence in the transportation of the muck truck and the aging of the sensor, make the data from muck truck sensors contain a lot of noise points. This has a serious impact on the management of construction waste which can lead to This has a serious impact on the management of construction waste which can lead to a great deal of time and money wasted by the regulators and transport drivers. To solve this problem, this paper firstly analyses the fault diagnosis results of vehicle sensors. Based on it, this paper then uses the fuzzy clustering method to creatively build a fault credit system of the muck truck. This fault credit system analyses the past performance of truck sensors and presents the results in a form of reliability. Combining the data with the reliability of the sensors is beneficial to reduce the influence of noise on the discrimination of electronic bills. Finally in the pattern recognition section, this paper improves PSO-ELM method to make the fault credit system of the muck truck can adjust the weight matrix and the offset matrix in the neural network. Therefore, the credit system can directly adjust the result of the electronic single discrimination without wasting extra computing power. The effectiveness and superiority of the method is verified in the dataset collected from real truck.

Keywords: Fault diagnosis, PSO-ELM, Fuzzy clustering method, Construction waste management.

1. Introduction

In recent years, with the rapid development of economy, society and urban construction, the emission of construction waste has increased explosively. The current construction waste supervision mode based on paper form can not meet the growing demand for construction waste supervision [1].

With the vigorous development of technologies such as Internet of Vehicles [2] and big data [3], new ideas are provided for the supervision of the whole process of construction waste. The whole process supervision mode of construction waste based on electronic bill emerges as the times require. Wang et al. [4] introduced the "BIM+GIS" technology into the field of construction waste supervision. Based on this technology, a platform of real-time monitoring and intelligent management for construction waste was established, so as to achieve precise management and control. Jiang [5] developed a smart city construction site sludge monitoring system and deployed the system to a cloud server. According to the real boundary of the construction site and the waste disposal yard, an electronic fence is virtual on the map to assist in judging whether muck trucks enter the waste disposal yard of construction site. When the muck trucks recognize the electronic fence, the stay time of muck trucks in electronic fence and status changes of in-vehicle equipment will be counted by the supervision system of muck trucks. When the muck trucks leave the electronic fence, the system will generate a record containing the statistical result information. By judging whether the muck trucks in the record have loading and unloading behaviors in the construction site and the disposal site, the starting point and end point of the muck trucks transportation can be identified. Finally the automatic identification and supervision of the construction waste generation and disposal positions can be realized, which makes every construction waste traceable. The records that can reflect the loading and unloading of construction waste in the electronic fence are called electronic bills, and the information generated by the muck truck passing through the electronic fence is called a node. The existing methods for judging the electronic bills are mainly based on the real-time recording of the transportation status and position of the muck truck by on-board sensors. When the vehicle arrives in the electronic fence of the construction site and has the behavior of loading soil, it is judged that the electronic bills start. Also, when the muck truck arrives at the disposal site and If there is unloading behavior, it is judged that the electronic bills is over. Finally a record including the whole process is an electronic bill. This discrimination method can maintain a certain accuracy in the early stage of operation. However, after a period of time when the transportation behavior occurs, the on-board equipment will occur error. So that the accuracy of this method to judge the electronic bills cannot be guaranteed, which greatly reduces the efficiency of construction waste supervision. In this context, it is of practical significance to improve the supervision level of construction waste by making full use of the data of the on-board equipment of the muck trucks with more noise and formulating a reasonable discriminant strategy for electronic bills.

The status of the truck will be recorded in the electronic bills [6], which can provide the basis for the management of the truck transportation by accurately judging the electronic bills. At present, the mainly research on the identification of electronic bills are manual and automatic methods. Manual method is to manually judge the electronic bills through various types of information recorded. However, in actual engineering, the recorded data is often massive, and the efficiency and accuracy of manual methods are difficult to satisfy. Therefore, people are becoming more and more enthusiastic about using automatic identification methods to discriminate electronic bills. Li et al. [7] used a mixed decision tree model to predict the delay of emergency vehicles. Su et al. [8] judged traffic events based on random forest and permutation importance method. Bi et al. [9] used the XGBoost model to judge the electronic bills, and finally compared with traditional machine learning algorithms such as decision trees and random forests, which fully prove its superiority. As a neural network with a typical perceptron structure, ELM has the advantages of simple structure, low time complexity and good recognition effect [10]. But the performance of ELM is sensitive to input weights and bias values, which are randomly generated in general ELM. In order to reduce the accuracy impact caused by the random selection of parameters, Feng et al. [11] used the Moore-Penrose inverse restricted Boltzmann strategy to recursively adjust the weights in the ELM. Lian et al. [12] used the whale optimization algorithm to optimize the extreme learning machine to improve the regression performance. Jian et al. [13] used the PSO algorithm to optimize the parameters in the ELM model and applied it to the color classification of sunglasses lenses, which achieved good results. The credit of the vehicle is not taken into account in the existing electronic bills identification method, but in practical engineering, the state of the vehicle sensor has a great influence on the collected data. Subhamita et al. [14] incorporated the prior knowledge into the neural network model and applied it to the phase transformation prediction of steel, and finally achieved good results. Wei et al. [15] used the fuzzy clustering method to divide the user's electricity consumption data into three regions: high, normal and low, and applied it to the study of abnormal electricity consumption. Inspired by this, this paper will first use the fuzzy clustering algorithm to classify the sensor status of the trucks, and based on this, each truck has a credit value. The better the data status of the sensor, the higher the credit we give to the truck, and the worse the data status of the sensor, the worse the credit we give to the truck. Then the data set is brought into the ELM, and the vehicle credit is used as the connection weight and offset supplement to participate in the ELM model training. Finally, the idea of PSO parameter optimization is used to find the optimal training parameters of the ELM model with the lowest ELM training error as the goal.

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The remainder of this article is arranged as follows: Section 1 introduces the problem background and main contributions in this study. Section 2 introduces the fuzzy cluster analysis and introduces several methods proposed in this paper. Section 3 introduces the data and data preparation and uses the method we proposed to solve the real problem. Traditional methods are also used to demonstrate the superiority of our method.

2. The proposed method

The discrimination algorithm of electronic bills is divided into two parts: sensor fault diagnosis and electronic bills discrimination. The specific steps can be summarized as follows:

Step 1: the on-board sensor data is used to diagnose the fault of the on-board sensor status of the muck truck, and use the fuzzy clustering method to construct a fault credit system for the muck truck.

Step 2: the improved extreme learning machine we proposed in this paper is used to discriminate the electronic bills.

2.1. Fuzzy Cluster Analysis

As a commonly used clustering analysis method, the biggest difference between fuzzy clustering analysis (FCA) [16] and ordinary K-means algorithm [17] is that K-means gives each sample a label to ensure that each sample is clustered into a certain class, which belongs to hard clustering class, while FCA provides more flexible clustering results. In most cases, the objects in the data set cannot be divided into distinct clusters. Therefore, a weight is assigned to each object and each cluster, to indicate how much the object belongs to the cluster. A piece of data in the data set may contain multiple types of wrong data. If this data is assigned to a certain category bluntly, it may adversely affect the discrimination accuracy of the electronic bills. In this case, the method of using fuzzy cluster analysis is obviously more secure than using the K-means algorithm. The algorithm flow is as follows:

Step1: Construct the objective function of fuzzy clustering model:

$$min\big(J(U,k)\big) = min\left(\sum_{i=1}^{k}\sum_{j=1}^{n} u_{ij}^{m}\left\|x_j - c_i\right\|^2\right)$$

$$s.t.\ \ \sum_{j=1}^{k} u_{pj} = 1\ ,p \subset [0,1]$$

Here, $c = \{c_1, c_2, \ldots, c_k\}$ represents k categories. $x = \{x_1, x_2, x_3, \ldots, x_n\}$ represents n samples.Urepresents the membership matrix. c_i represents the center point of the cluster. $m$is the fuzzy coefficient.

Step2: The objective function of the model is solved by the Lagrange multiplier method, and the equations for updating the cluster center point and the membership matrix are obtained.

$$u_q = \left(-\frac{\lambda_j}{m}\right)^{\frac{1}{m-1}}\left(\frac{1}{d_q^2}\right)^{\frac{1}{m-1}} = \frac{1}{\sum_{k=1}^{k}\left(\frac{d_q}{d_i}\right)^{\frac{2}{m-1}}}$$

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}}$$

Here, $c_i$is the equation for updating cluster center points. u_q is the equation to update the membership matrix. d_q is the distance to the qth classification point.

Step3: Repeat the above steps until c_i no longer changes or the initialization membership matrix changes very little.

2.2. ELM

In the real work scenarios, the system needs to output the electronic bills for this trip immediately after the muck truck arrives at the disposal site. This places great demands on the real-time and accuracy of the discrimination model of construction waste electronic bills. As a neural network with a typical perceptron structure, ELM has the advantages of simple structure, low time complexity, and good recognition effect. ELM as a single hidden layer feedforward neural network, like a general single layer neural network, maps data to a high-dimensional space through the hidden layer to mine its hidden features, and then an activation function is used to enhance the dispersion between features. The difference is that the last part assigns the output weight through the generalized inverse matrix algorithm with SVD as the core, and the output value does not feed back and change the hidden layer. Its formula can be summarized as follows:

$$f_L(x) = \sum_{i=1}^{L} \beta_i G(\omega_i \cdot x_i + b_i) = \sum_{i=1}^{L} \beta_i h(x_i)$$

Here, f_L is the classification result, L represents the sample size of the input, x is the input sample, ω_i is the vector in the hidden layer matrix,b is the offset matrix, G is the mapping relationship represented by the activation function, β is the output weight matrix.

From the principle of ELM, we can find that since ELM does not have a feedback structure, the values in its hidden layer cannot be changed, which leads to the fact that its algorithm training effect is completely restricted by the hidden layer. ELM defines the parameters of the hidden layer by randomly initializing the hidden layer. This method is fully uncertainly. This uncertainty directly leads to the fluctuation of the recognition accuracy of the model. At the same time, ELM maps the data to the high-dimensional space through the hidden layer to mine its hidden features, and then maps the data to the low-dimensional space through the activation function. This process can discover the hidden features in the data set, and can also bury the salient features in the data set. When there are a lot of bad data in the data set, we will get overfitted results when using ELM.

In order to solve the above problems, this paper proposes an improved PSO-ELM algorithm, which integrates the idea of data credibility and Particle Swarm optimization (PSO). This method we proposed firstly uses fuzzy clustering analysis method to classify the sensor states of vehicle-mounted equipment in the input data set and assigns a credit to each vehicle. Then the data set is brought into ELM, and the vehicle credit is used as the connection weight and offset supplement to participate in ELM model training. Finally, the idea of PSO parameter optimization is used to find the optimal training parameters of ELM model with the goal of minimizing ELM training error.

By introducing the idea of data credit and population stochastic optimization technology idea of particle swarm optimization, the improved single ELM formula proposed in this paper can be obtained as follows:

$$f_L(x) = \sum_{i=1}^{L} \beta_i G\big(m_i \cdot (\omega_i \cdot x_i + b_i)\big)$$

Here, m_i is the credit level of the muck truck.

Its optimization objective becomes:

$$min\|f_L - T\| = \|H(m \cdot x) - T\|$$

Here, T is the known sample label sequence.

The algorithm structure of PSO-ELM can be summarized as follows:

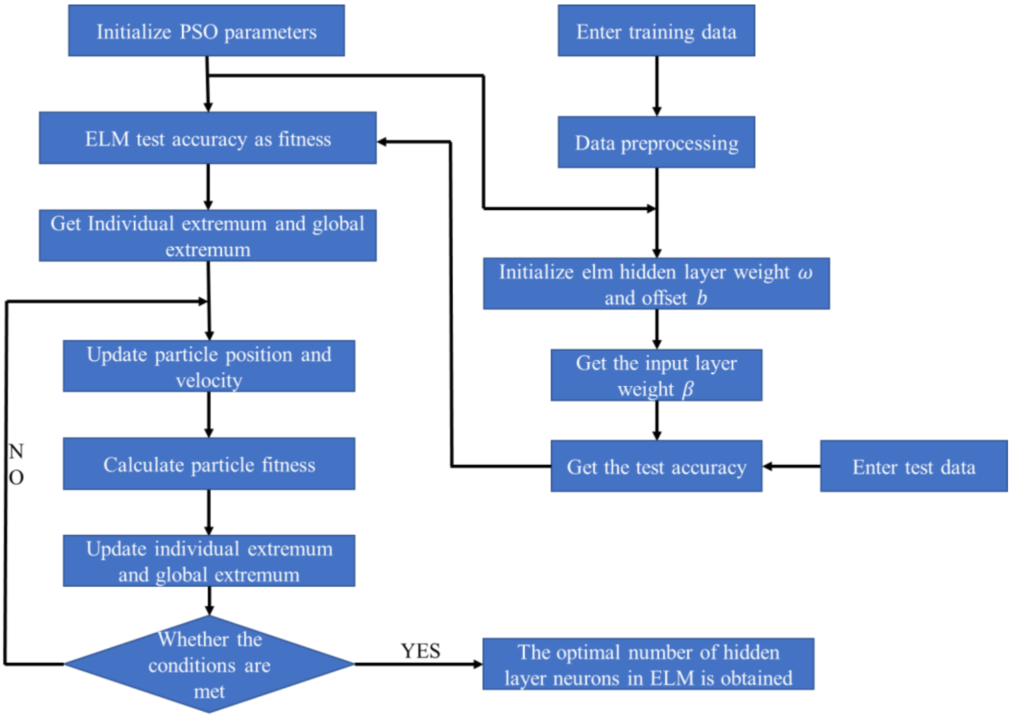

Figure 1. PSO-ELM algorithm structure diagram

3. Experimental verification

The data of this research comes from the real operation data of Shenzhen Construction Waste Smart Supervision System. The time span is from December 1, 2019 to December 10, 2019. A total of 11 construction sites with better quality were screened. The 10-day data for the designated site includes all the situations that the discriminant strategy can take into account, as well as all the common problem types. The laws and problems existing in the data of other construction sites in other time periods can find a solution in the 10-day data. These 10-day data are representative of the study of the electronic bill discrimination strategy.

The 10-day data mainly includes the trajectory data of the muck trucks, and the construction site ledger data. The ledger data contains information such as the license plate number, entry time and departure time of the vehicles on the construction site. The trajectory data of the muck truck includes vehicle license plate information, trajectory data, and real-time detection status of on-board equipment. About 70.46 million pieces of all vehicle trajectory data from December 1, 2019 to December 10, 2019 were intercepted, and the construction site ledger data selected a total of 16,447 pieces of muck truck loading and unloading data in the corresponding time period. By organizing experienced managers in the construction industry to participate in the symposium, 25 influencing factors that affect the accurate identification of the electronic bills are studied from six major perspectives such as the declaration status of the muck truck and the length of stay. These are used as the independent variable of the electronic bills discriminant model. The independent variables of the model are shown in Table 1. According to the model independent variables, the trajectory data and the construction site ledger data are matched and filtered to obtain a total of 83,742 node data.

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Table 1. Independent variable

Influence factor	Site strategy algorithm	Variable
Non-tube vehicle	Construction site not declared, Construction site not discharged, vehicle not declared	X_1
	Construction site declared, Construction site discharged, vehicle not declared	X_2
	Construction site declared, Construction site discharged, vehicle declared	X_3
	Construction site declared, Construction site discharged, vehicle not declared	X_4
Stay time	Stay time in the area - less than 1 minute	X_5
	Stay time in the area - 1 minute to 5 minutes	X_6
	Stay time in the area - 5 minutes to 30 minutes	X_7
	Stay time in the area - 30 minutes to 1440 minutes	X_8
	Stay time in the area - more than 1440 minute	X_9
Load status (Construction site judgment)	Not backfill construction site, empty vehicles in and empty out of the area	X_{10}
	Not backfill construction site, empty vehicles in and full out of the area	X_{11}
	Not backfill construction site, full vehicles in and empty out of the area	X_{12}
	Not backfill construction site, full vehicles in and full out of the area	X_{13}
	Backfill construction site, empty vehicles in and empty out of the area	X_{14}
	Backfill construction site, empty vehicles in and full out of the area	X_{15}
	Backfill construction site, full vehicles in and empty out of the area	X_{16}
	Backfill construction site, full vehicles in and full out of the area	X_{17}
Load state (Fence area judgment)	The proportion of heavy load is more than 95% in the area from empty to heavy and out of the fenced area after empty to heavy	X_{18}
	The proportion of heavy load is less than 95% in the area from empty to heavy and out of the fenced area after empty to heavy	X_{19}
	The proportion of heavy load is less than 95% in the area from heavy to empty and out of the fenced area after empty to heavy	X_{20}
Car body status	The car body status bit in the area is not open	X_{21}
	The car body status bit in the area is open	X_{22}
Speed status	There are points with speed of 0, 1-3 times	X_{23}
	There are points with speed of 0, more then3 times	X_{24}
	There are no points with speed of 0	X_{25}

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If the starting time period of the ledger and the time period of the node overlap, it is considered that they are matched, that is, the node is judged to be an electronic bills at this time. We use the license plate information of the muck truck in the ledger to screen all the nodes corresponding to the vehicle recorded in the ledger. In theory, there is only one electronic bills at most in the process of the muck truck transporting waste from the construction site to the disposal site. Then we use the time of the muck truck entering and leaving the construction site in the ledger to match the node where the electronic form is located and label it as a positive example, and other nodes of the vehicle during this time period are labeled as negative examples. The node labeling process is shown in Figure 2.

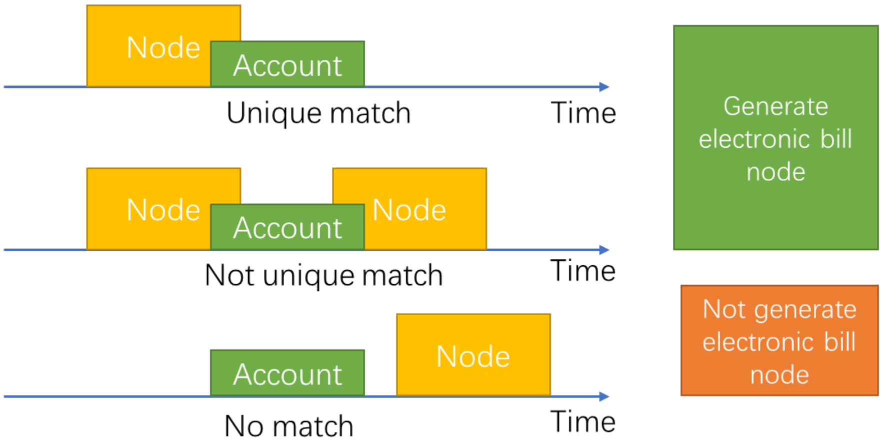

Figure 2. Node labeling process

3.1. Using Fuzzy Clustering to Construct Muck Truck Credit Standard

The research goal of this paper is to discriminate electronic bills in the case of inaccurate detection data of in-vehicle equipment. Firstly, the failure analysis of the on-board equipment of the muck truck is carried out to clarify the failure rate of the on-board equipment of the muck truck. It is assumed that the muck truck is in a fully loaded state during the recording time of the construction site ledger and the consumption yard ledger. During this time, the on-board lift sensor should be in a non-lifted state, the load sensor should be in a heavy-loaded state, and the compartment airtight sensor should be in airtight state. If the sensor does not record within the record time of the construction site log or there are a lot of warnings, we default that the sensor is damaged. By analyzing the sensor data and ledger data of the lifting, load and car body of the muck truck from December 1, 2019 to December 10, 2019, the failure rate of the muck truck is about 48%. The failure rate of each part of the muck truck is shown in Figure 3.

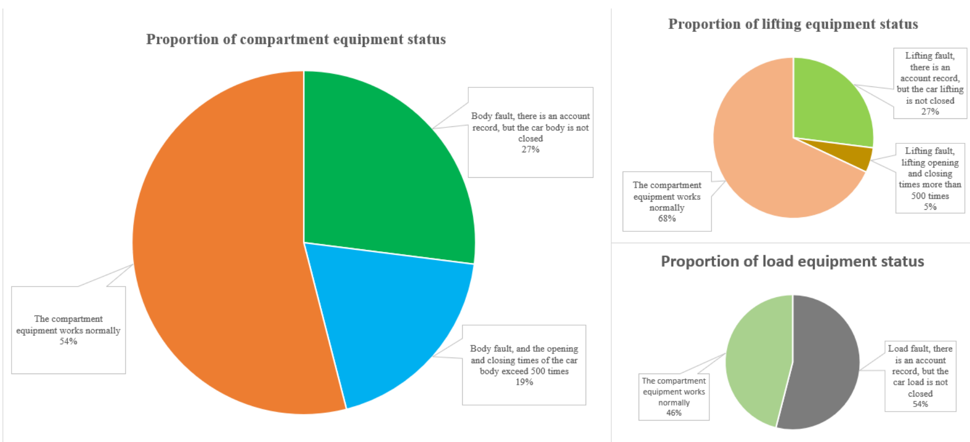

Figure 3. Muck truck breakdown analysis

In the past 10 days, about 4,478 muck trucks have been engaged in loading and unloading operations, of which about 2,328 muck trucks which on-board sensors are intact, about 91 muck trucks which on-board sensors are all damaged, and about 2,059 muck trucks have at least one damaged on-board sensor. We take the ratio of the state error data of each sensor to the total data in the corresponding trajectories of these 2059 muck trucks as input, and brought it into the fuzzy clustering model, and finally got about 1441 vehicles with mild faults, about 392 vehicles with moderate faults and about 226 vehicles are severely malfunctioning. In the process of electronic bills identification, the higher the accuracy of the status data of the on-board sensors, the easier it is to judge whether the muck truck has loading and unloading behavior. Therefore, the credit value is assigned to the muck truck from high to low according to the degree of failure. When training the ELM model, the corresponding data weights will be given according to the credit value of the muck truck. In order to better tap the potential features of the wrong data, the muck truck will be given corresponding weights according to the credit degree. Its information is shown in Table 2:

Table 2. Residue truck credit information

Sensor failure degree	Vehicle number	Vehicle credit rating	Model credit weight
No fault	2328	A	0.2
Minor fault	1441	B	0.4
Moderate fault	392	C	0.6
Severe fault	226	D	0.8
All faults	91	E	1

3.2. Using PSO-ELM for electronic bill discrimination

The dataset is divided into training set and test set according to the ratio of 7:3, and the credit of the muck truck is brought into the PSO-ELM model for training. In the test data, the results show that the recognition accuracy of the trained PSO-ELM is 96.8733% when the sin activation function is used and the number of neural nodes is 125. The model training iteration curve is shown in Figure 4.

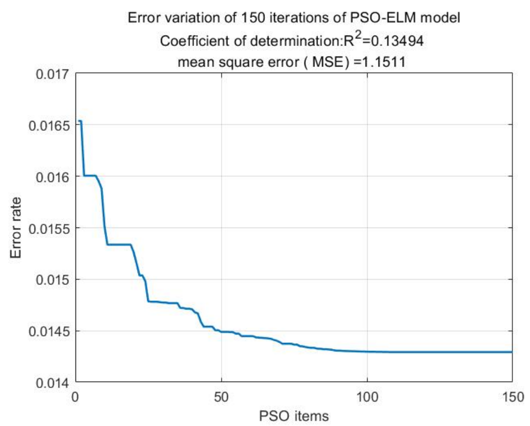

Figure 4. Training iteration curve of PSO-ELM model

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In order to further verify the significant effect of the PSO-ELM algorithm in improving the recognition accuracy and algorithm reliability, this paper also uses the original ELM and records the training results. The specific results are shown in Table 3. On the premise of using the credit value of the muck truck, compared with the training results of the original ELM algorithm, the PSO-ELM algorithm has a 2%-3% advantage in the recognition accuracy under the three activation functions. On the premise that the credit value of the muck truck is not used, compared with the training results of the original ELM algorithm, the PSO-ELM algorithm has a 3%-5% advantage in the recognition accuracy under the three activation functions. This fully demonstrates the superiority of our proposed method in terms of recognition accuracy and algorithm reliability.

Table 3. Comparison of results

	Type of network	The activation function	Neural nodes number	Recognition accuracy	Number of iterations
Add muck truck credit value	PSO-ELM	sigmoid	50	96.6595 %	86
			75	96.6701 %	69
			100	96.7572 %	84
			125	96.7073 %	99
		hardlim	50	96.6771 %	104
			75	96.6462 %	97
			100	96.8627 %	95
			125	96.8643%	116
		sin	50	96.5986 %	84
			75	96.6477 %	127
			100	96.7761 %	103
			125	96.8733 %	107
	ELM	sigmoid	50	94.4503 %	
			75	94.1839%	
			100	94.8691 %	
			125	94.6678 %	
		hardlim	50	93.6382 %	
			75	93.5601 %	
			100	94.0643 %	
			125	94.7574 %	
		sin	50	95.3417 %	
			75	94.9706 %	
			100	94.9422 %	
			125	94.3881 %	
No muck truck credit value	ELM	sigmod	50	91.7998 %	
			75	92.6198 %	
			100	91.8449 %	
			125	92.7183 %	
		hardlim	50	92.9167 %	
			75	93.0957 %	
			100	93.2307 %	
			125	92.8983 %	
		sin	50	93.0415 %	
			75	93.0858 %	
			100	92.9937 %	
			125	92.451 %	

4. Conclusions

This paper mainly studies electronic single discrimination with noise interference in construction waste management. Firstly, this paper based on the fuzzy clustering method builds fault credit system of the muck truck. This system gives a reliability value to the data obtained by each sensor to reduce the influence of noise points in electronic single discrimination. After that, the PSO-ELM is improved for efficiently utilize the system. The structural modification of PSO-ELM makes it more accurate in the identification of electronic single without increasing the running time. The fault credit system and improved PSO-ELM method is well adapted to the characteristics of truck sensor data noise. It does not roughly screen the features, but processes the features with fuzzy thought. This makes it efficiently solve the problem of the influence of noise points on the electronic single discrimination and gets the better accuracy. Finally, the feasibility and superiority of the proposed method are verified in dataset of real truck in 10 days.

However, due to the limitation of experimental conditions, the dataset in this paper contains only one route. Thus, further work is needed to improve the fault credit system to adapt to the more complex route.

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