Assessment of vehicle comprehensive maintenance capability based on RBF neural network

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Abstract. To solve the problems of experience-based and subjective-based methods of capability assessment on vehicle maintenance, a RBF neural network model is established, which takes the 7 key factors of vehicle maintenance capability as input, and takes the comprehensive maintenance capability as output. The self-organization learning method and least-squares method are used to determine the weight parameters of RBF neural network, based on which the comprehensive maintenance capability method of vehicle is designed. Simulation results show that the final error of the trained RBF neural network is 0.0073, and the percentage errors of neural network calculated based on test samples are less than 5%, which indicates that the established RBF neural network could assess the comprehensive maintenance capability method of vehicle effectively, which means the neural network is more practical.

1. Introduction
To make a long term development scheme, vehicle maintenance facility should learn and study the innovative development tendency of vehicle market more deeply and detailedly, based on which, a peculiar and explicit planning of comprehensive capability construction should be provided to point out the key development direction, and enhance the comprehensive maintenance support capability of facility roundly, and increase the overall maintenance capability on workshop repairment, road rapid repairment, and assistance repairment. Under this circumstance, the comprehensive capability assessment of facility on vehicle maintenance should be applied to find out the deficiency and inadequacy of vehicle maintenance facility.

Nowadays, the assessment methods of vehicle maintenance capability used widely by facility are based on experiences and investigations, which could only provide a sketchy and qualitative assessment on vehicle maintenance capability. The assessment methods designed by vehicle research institutions are mainly based on fuzzy algorithm\(^{[1,2]}\) and gray algorithm\(^{[3]}\), which bear simple principles and less calculation, but have strong subjectivity and the assessment results are easy influenced and altered by executor. Besides, other researchers also designed some assessment methods, such as generation-function-based method\(^{[5]}\) and set-pair-theory-based method\(^{[6]}\), however, the utilizations of neural network\(^{[7]}\) in this kind of assessment are rare and seldom. In this article, a vehicle maintenance capability model is designed based on RBF neural network, based on which the comprehensive assessment on maintenance capability is conducted.

2. Index System of Vehicle Maintenance Capability
The vehicle maintenance capability of facility refers to the level of capacity in completing the task of workshop repairment, road rapid repairment, or assistance repairment, and the matching degree of

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maintenance personnel, maintenance document, machines equipment, maintenance material, maintenance infrastructure, based on which the key indexes and sub-level factors of vehicle maintenance capability of facility could be determined.

The 7 key indexes of vehicle maintenance capability of facility, which are maintenance personnel, maintenance document, machines equipment, maintenance material, maintenance infrastructure, quality management, and process management, are specified in considering of the necessary segments and conditions of maintenance procedures. The 7 key indexes are shown in Fig.1.

![Fig.1 Construction and geometrical dimensions of specimens](image)

The overall vehicle maintenance capabilities of facility are discussed detailedly based on the 7 key indexes. Maintenance personnel key index mainly involves the arrangement states and ability conditions, and it includes arrangement state, position qualification, knowledge literacy, duty competence and management & usage 5 sub-level factors. Maintenance document key index mainly refers to the situations of arrangements and usages of the documents, and it includes basic status, laws & regulations, technology document, maintenance document and management & usage 5 sub-level factors. Machines equipment key index mainly contains the states of arrangements and usages of the equipment, and it includes arrangement state, matching accessory, technology state, measurement & calibration and management & usage 5 sub-level factors. Maintenance material key index mainly concerns the stations of material support, and it includes attrition standard, plan management, supply method, attrition record and management & usage 5 sub-level factors. Maintenance infrastructure key index mainly considers the fulfillment state of maintenance in using of the infrastructure, and it includes infrastructure composition, infrastructure placement, infrastructure requirement, matching infrastructure and management & usage 5 sub-level factors. Quality management key index mainly involves the conditions of the quality management system, and it includes quality system, management content, quality test and quality insurance 4 sub-level factors. Process management key index mainly contains the running conditions of the maintenance procedure management system, and it includes scheme management, organization scheduling, resource support, cost accounting, safety management and information management 6 sub-level factors.

3. Assessment Model of Vehicle Maintenance Capability

3.1. RBF Neural Network Model

RBF neural network, which is a forward network established based on function approximation theory, is a type of radial basic function, the training and learning of the RBF neural network equivalent to find a best fitting plane of the training data in multi-dimensional space. The RBF neural network is an efficient, versatile and flexible model, which could approximate any function with high accuracy as long as the hidden neurons provided sufficiently. The RBF neural network has already been used extensively in the fields of pattern recognition, artificial intelligence, automatic control and robot manipulator. In associating with the assessment of vehicle maintenance capability, rational and effective input layer, middle layer and output layer of RBF neural network should be constructed to design the key segments of the model.

RBF neural network is a 3-layer static forward network with strong mapping function between input and output, the structure of the network is shown in Fig.2. The RBF neural network contains input layer, hidden layer and output layer. Input layer composed directly by signal source node, which
transmits the input signal to hidden layer. Hidden layer composed by radial basic function, which is commonly realized and accomplished by gaussian functions. The mapping relationship between input layer and hidden layer is settled while the center point, which consisting of center vector and center width, of gaussian function is determined. The linear combination of the output of non-linear basic function of hidden layer is calculated in output layer.

\[
\phi(\|X - C_k\|) = \exp\left( -\frac{1}{2\sigma_k^2} \|X - C_k\|^2 \right) = \exp\left( -\frac{(X-C_k)^T(X-C_k)}{2\sigma_k^2} \right) \tag{1}
\]

where, \( X = [x_1 \ x_2 \ \cdots \ x_N] \) is the input of neural network, \( N \) is the total amount of input data, \( C_k = [c_{k1} \ c_{k2} \ \cdots \ c_{kN}] \) is the center vector of hidden node of number \( k \), \( \sigma_k \) is the center width of hidden node of number \( k \), \( k = 1, 2, \ldots, M \). \( M \) is the dimension of hidden layer of RBF neural network, \( M \) could be determined by 1.5 multiple of \( N \), and also could be determined by training the neural network with test samples in experimentations to acquire a more efficient dimension of hidden layer.

The output vector of RBF neural network is \( Y = [y_1 \ y_2 \ \cdots \ y_L] \), \( L \) is the total amount of output data. The output layer is the linear combination of hidden layer nodes, and then the output of RBF neural network of number \( j \) can be described as

\[
y_j = \sum_{k=1}^{M} w_{kj} \phi(\|X - C_k\|) + w_0 j \tag{2}
\]

where, \( w_{kj} \) is the weight coefficient between the hidden layer node of number \( k \) and the output layer of number \( j \), \( w_{0j} \) is the adjust coefficient of the output of number \( j \).

Considering of the assessment of vehicle maintenance capability, 7 key indexes are taken as RBF neural network inputs, then the dimension of input layer is \( N = 7 \), \( X = [x_1 \ x_2 \ \cdots \ x_7] \), and the hidden layer is \( M = 10 \). There is only one output, which is the vehicle maintenance capability, of RBF neural network, then \( L = 1 \). Thus, the output of RBF neural network can be described as

\[
y = \sum_{k=1}^{M} w_k \phi(\|X - C_k\|) + w_0 \tag{3}
\]

Then 4 sets of parameters of RBF neural network could be derived, which are center vector \( C_k \), center width \( \sigma_k \), output weight \( w_{kj} \) and output adjust coefficient \( w_{0j} \).

### 3.2 Self-organization Learning Method in Choosing Center

A most commonly used self-organization learning method, which is K-mean clustering algorism, is adopted to estimate the center vector and center width of radial basic function of neural network. K-
mean clustering algorithm classifies the data into several categories, and each category possesses the similar character and property. The center calculated with K-mean clustering algorithm is more effective and more typical\[9\].

The dimension of hidden layer of neural network in assessing the vehicle comprehensive maintenance capability of facility is 10, and the amount of clustering center could be assumed as 10. If the clustering center of number \(k\) in \(n\) times iteration is \(C_k(n)\), \(k = 1,2,\ldots,10\), then the learning process of clustering center could be shown as follow:

1. Initializing. 10 different samples are selected from the input training sample sets to use as initial clustering center \(C_k(0)\).
2. Sample importing. A training sample is selected randomly from the input training sample sets to use as input \(X_i\).
3. Matching. Calculating the distance between clustering centers and the selected input training sample, then ascribe it with the nearest clustering center into a same category. The calculation equation is

\[
\text{arg min}_k \|X_j - C_k(n)\|
\]

Then the corresponding category \(k\) is found, which means the selected training sample \(X_i\) belongs to category \(k\).

4. Clustering center updating. The clustering center of category \(k\) alters because of the adding of the selected training sample \(X_i\), and the new clustering center can be derived from

\[
C_k(n+1) = \begin{cases} 
C_k(n) + \eta [X_i - C_k(n)], & \text{if } k = k(X_i) \\
C_k(n), & \text{else}
\end{cases}
\]  

where, \(\eta\) is learning step length, \(0 < \eta < 1\). There is only one clustering center updated in one iteration process, and the others are remaining unchanged.

5. Estimating. Estimating the clustering centers, if they remain unchanged in every iteration process, the learning algorithm converges. A threshold value could be set in estimating the converging status, if the variations of clustering centers are less than the threshold value, then the algorithm is already converging, otherwise, turn to step 2 to keep iterating and calculating. When the learning algorithm converged, the final clustering centers \(C_k(n)\) could be used as the center vectors of radial basic functions of neural network.

The process of training and learning center vector of radial basic function of neural network with K-mean clustering algorithm is shown in Fig.3.

When the center vectors of radial basic function of neural network are determined, the center width of radial basic function of neural network could be calculated as

\[
\sigma_k^2 = \frac{1}{S_k} \sum_{X \in \theta_k} \|X - C_k\|^2
\]

where, \(\theta_k\) is the category of number \(k\) divided by K-mean clustering algorithm, \(S_k\) is the amount of training samples in category \(\theta_k\).

3.3. Least-squares method in determining weight

The quadrature least-squares method is applied to determine the output weight coefficients of radial basic function of neural network. Take the radial basic function as a special case of linear regression. If there are \(S\) training samples, then the output of neural network can be described as

\[
y(s) = \sum_{k=1}^{M} w_k \phi\left(\|X_s - C_k\|\right) + w_0 = \sum_{k=1}^{M} w_k P_k(s) + e(s)
\]

where, \(y(s)\) is the desired output of the model, \(e(s)\) is adjust coefficient and it could be taken as error of the neural network, \(e(s) = w_0\), \(P_k(s)\) is the regression factor of the model, and it is the responding variable of neural network with radial basic function.

Revise the output into matrix form.
To solve \( y = Pw + e \), quadrature triangular decomposition of \( P \) is conducted as

\[ P = U A \]

\( A \) is a upper-triangular matrix of \( I \times I \), and the elements in principal diagonal are 1, \( U \) is a matrix of \( K \times I \), and the columns of \( U \) are orthogonal, then

\[ U^T U = H \]

The elements of \( H \) in principal diagonal are \( h_i \), then we have

\[ y = Pw + e = UAw + e = Ug \]

Multiplying \( U^T \) on both sides of the above equation, then

\[ U^T y = U^T Ug = H g \]

Then

\[ g = H^{-1} U^T y \]

Also, if \( y = Pw + e \) is used as least-squares estimation, then \( Aw = g \), so \( w \) could be calculated. In summary, the steps of learning weight parameter with quadrature least-squares method are showed as follow:

1. Determining the amount of hidden layer nodes and the center of each node.
2. Educing regression matrix \( P \) with input training samples.
3. Quadrating the regression matrix to get matrix \( A \) and \( U \).
4. Calculating \( g \) based on matrix \( U \) and vector \( y \).
5. Calculating \( w \) according to \( Aw = g \).
4. Simulation Analyses

The 7 key indexes of vehicle maintenance of facility are taken as input and the vehicle comprehensive maintenance capability is taken as output to construct samples of RBF neural network. The samples are divided into 2 parts, training samples and test samples. There are 500 training samples are used to train the RBF neural network, and there are 10 test samples are used to verify the validity of the trained neural network. Some training samples and all test samples are showed in Table 1.

| Sample type | Sample sequence | Maintenance personnel | Maintenance document | Machine equipment | Maintenance material | Maintenance infrastructure | Quality management | Process management | Vehicle comprehensive maintenance capability |
|-------------|-----------------|-----------------------|---------------------|------------------|----------------------|--------------------------|-------------------|------------------|---------------------------------------------|
| Training sample | 1 | 1.121 | 1.02 | 0.691 | 0.701 | 0.275 | 0.792 | 0.117 | 0.66 |
| | 2 | 1.152 | 1.055 | 0.583 | 0.167 | 1.143 | 0.854 | 0.325 | 0.733 |
| | 3 | 0.741 | 1.049 | 0.678 | 0.825 | 0.345 | 0.102 | 0.447 | 0.63 |
| | 4 | 1.044 | 0.434 | 0.325 | 0.971 | 0.701 | 0.591 | 0.426 | 0.691 |
| | 5 | 0.37 | 0.793 | 0.798 | 1.003 | 0.833 | 0.576 | 0.439 | 0.717 |
| | 1 | 0.381 | 0.562 | 0.238 | 1.125 | 0.908 | 0.05 | 0.195 | 0.636 |
| | 2 | 0.296 | 0.164 | 0.927 | 0.158 | 0.964 | 1.009 | 0.226 | 0.647 |
| | 3 | 0.966 | 0.596 | 0.948 | 0.759 | 0.458 | 0.18 | 0.287 | 0.598 |
| | 4 | 1.19 | 1.164 | 0.011 | 0.669 | 0.975 | 0.242 | 0.161 | 0.648 |
| | 5 | 0.302 | 0.507 | 1.085 | 0.285 | 0.139 | 0.541 | 1.051 | 0.74 |
| | 6 | 1.014 | 0.675 | 0.812 | 1.019 | 0.165 | 0.166 | 0.914 | 0.762 |
| | 7 | 0.113 | 1.077 | 0.871 | 0.01 | 0.963 | 1.102 | 0.524 | 0.761 |
| | 8 | 1.04 | 0.988 | 1.092 | 0.389 | 0.444 | 0.79 | 0.221 | 0.657 |
| | 9 | 0.247 | 0.352 | 0.399 | 0.998 | 0.848 | 0.845 | 0.823 | 0.81 |
| | 10 | 0.795 | 0.78 | 1.009 | 1.147 | 0.143 | 0.475 | 0.52 | 0.7 |

The RBF neural network is training with MATLAB programming. After 200 times iterations, the training error of the neural network model fulfills the requirement of assessment, and the variation of error with iteration is showed in Fig. 4. The variation shows that the training error is decreasing gradually as the iteration time increasing, and the final training error of RBF neural network is 0.0073. The training error could be decreased further if keep iterating.
Comparing the expected output of test samples with the calculated output of RBF neural network model, the line chart of the comparison is showed in Fig. 5, and the comparison of errors are showed in Table 2. The results show that the absolute errors of RBF neural network are within a relative small range, and the percentage errors are less than 5%, which indicates that the established RBF neural network model is efficient and effective in assessing the vehicle comprehensive maintenance capability.

![Comparison of the expected output and the calculated output](image)

**Table 2 Comparison of errors of RBF neural network**

| Sample sequence | Expected output | Calculated output | Absolute error | Percentage error |
|-----------------|-----------------|-------------------|----------------|-----------------|
| 1               | 0.636           | 0.629             | 0.007          | 1.101%          |
| 2               | 0.647           | 0.647             | 0              | 0%              |
| 3               | 0.598           | 0.602             | 0.004          | 0.669%          |
| 4               | 0.648           | 0.625             | 0.023          | 3.549%          |
| 5               | 0.74            | 0.731             | 0.009          | 1.216%          |
| 6               | 0.762           | 0.74              | 0.022          | 2.887%          |
| 7               | 0.761           | 0.726             | 0.035          | 4.599%          |
| 8               | 0.657           | 0.668             | 0.011          | 1.674%          |
| 9               | 0.81            | 0.839             | 0.029          | 3.58%           |
| 10              | 0.7             | 0.688             | 0.012          | 1.714%          |

**5. Conclusion**

The key indexes of vehicle maintenance process studied detailedly to establish a RBF neural network with 7 inputs and 1 output, and 2 neural network parameters calculating methods, which are K-mean clustering algorism and least-squares method, are provided. The training and testing of RBF neural network are conducted in MATLAB environment, and the results showed that the errors between expected output and calculated output are all less than 5%, which manifests that the established RBF neural network model in assessing vehicle comprehensive maintenance capability is effective and rational, and the established model could provide data references for vehicle maintenance facility in maintenance capability assessment.

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