A Study on Prediction of Equipment Asset Life Cycle Cost Based on BP Neural Network

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Abstract. Equipment asset has a great value and use value, the management for it should be focused on the important consideration of the life cycle cost, making the disturbance of equipment asset value always permeates the overall process of equipment asset management, so as to provide scientific and reasonable baseline for decision-making related to equipment asset management. Using the methods of BP neural network, in this paper I provide a new angle of analysis for the equipment asset life cycle cost prediction through function approximation, making the prediction more operational.

1.Introduction

Equipment asset has a great value and useful value, the management should emphasize particularly on the whole equipment related value movement state, covering a series of asset life cycle process of purchase, use, maintenance, and disposal. In other words, equipment asset has a great value and use value, the management for it should be focused on the important consideration of the life cycle cost, making the disturbance of equipment asset value always permeates the overall process of equipment asset management, so as to provide scientific and reasonable baseline for decision-making related to equipment asset management.

Using the methods of BP neural network, in this paper I provide a new angle of analysis for the equipment asset life cycle cost prediction through function approximation, making the prediction more operational.

Once you have the equipment asset, you will have the use value and value of the equipment. Its use value appears as the equipment asset with the ability to work， while the value go as the cost of the equipment asset consumption, namely the life cycle cost.

With the continuous improvement of equipment performance, the equipment asset life cycle cost keep on rising. From procurement and use to retirement and disposal, however，equipment asset often take more than a decade or even longer. From the practical experience, the cost of use and support accounting for a large part will only be visible after asset have gone into service.While compared with the cost of use and support as recurrent input, the purchasing cost as a one-time investment cost being very high tend to create an illusion to people that the value of equipment asset is judged mainly by the purchasing cost one-time invested. This could be lead to a trying situation that the equipment asset "can be affordable but can't afford to use". As result, once having equipment asset we should go out of the misunderstanding of the pursuit of minimum purchase cost, matching of purchasing cost one-time invested in the moment with the cost of use and support as recurrent input in the future. Not only attending the purchasing cost ensuring "can be affordable", but also emphasizing the cost of use and support ensuring "can afford to use "and "used properly", so as to ensure that the force, with a certain amount of equipment asset and coming to a certain level, can form and release some ability of support, realizing a virtuous cycle in the management of equipment asset. In other words, in the early stages of the purchasing of equipment asset do we require its well-predicted life cycle cost, "knowing fairly well", and on the basis of meeting the support requirement consider fully life cycle cost of equipment asset, improving the cost-effectiveness of limited funds as efficient as possible, achieving maximum efficiency with the least amount of resource consumption, getting rid of the huge life cycle cost, and bringing about real change from "buying then considering" to "considering then buying".

2.Method Introduction

2.1 Traditional method of prediction.

From a lot of literatures by the author reading, it is observed that commonly used methods include engineering approach, analogy method, parameter method, experience method, and expert analytical approach in the prediction of equipment asset life cycle cost. Practice shows that the traditional forecasting methods in equipment asset life cycle cost have its own application conditions and the applicable scope; therefore there are some shortcomings for the process of actual prediction. Although the use of these methods improve the speed and precision of the equipment asset life cycle cost prediction to a greater or lesser degree, but still exist deficiencies and disadvantages. If engineering method is used to predict equipment asset life cycle cost, it cost more money and time, the inspection and audit is more complex, and before there is not enough details it cannot conduct effectively cost prediction；Analogy method does not apply to the equipment of large technical change span and low similarity ；As for parametric method, the precision of prediction depends on similarity between similar equipments, the quantity of statistical sample, the selection of parameter and the form of regression model on the cost influence, and more dependent upon the understanding of equipment by the analysts and their modeling skills and experience；In the case of experience method，it is common for relying extensively on the forecasters experience and subjective consciousness；Although expert analysis method can translate the qualitative decision problem into combining qualitative and quantitative decision, but has the feature of duality, on the one hand, the opinions of the experts can often mean people's knowledge on a particular system, particularly the cumulative results of different experts more can greatly reflect the state of a system in an all-round way, on the other hand, there is a certain subjectivity in the expert analysis method.

2.2 BP method of neural network.

BP (back propagation) neural network is the multilayer feedforward artificial neural network applying back propagation learning algorithm, with distributed storage of information, high fault tolerance, parallel processing of information, self-learning and nonlinear mapping approximation ability and other characteristics. However, the most popular application has been the three-layer BP network structure consisting of input, hidden and output layer that are most applicable to the approximation relation of analog input and output. There are two steps in its information processing: feedforward propagation and feedback learning, in which network learning is a kind of process that error is feedback-propagated and value-corrected from the output layer to input layer, and the purpose of learning is to make the real output of network approximation of a given desired output.

With the very strong learning association and fault tolerance, BP neural network is able to carry out large-scale parallel information processing, and has a high simulation ability of nonlinear system which can effectively deal with forecasting and decision-making and other related issues.

And, indeed, the process of equipment asset life cycle cost prediction is a kind of system engineering, there are certain interaction relations and the structure associated benefit among various factors affecting equipment asset life cycle cost, and there is nonlinear relationship between these factors and equipment asset life cycle cost. At the same time, the problem of equipment asset life cycle cost prediction can be thought of as a problem of multiple objective input and single objective output. And compared with the traditional method of life cycle cost prediction, a decision by the method of BP neural network, without precise evaluation index weights (influencing factors), do not have to know the exact checking rules, require only self-analyzing and self-learning over the representative samples of the input in advance, and make reasonable evaluation for the forecasting equipment asset life cycle cost. It can be said that the application of BP neural network method will provide a new angle for the equipment life cycle cost prediction, making the prediction more objective, more scientific, and more controllable.

3.Model Construction

The prediction model of equipment asset life cycle cost, based on the BP neural network, is set up usually following the following steps, all of which can be realized with the help of Matlab software.

3.1 Construction of the BP artificial neural network.

Through the above analysis, we know that the work of equipment asset life cycle cost prediction can be done with an effort to analyze the interaction relations and the structure associated benefit among various factors affecting equipment asset life cycle cost and the nonlinear relationship between these factors and equipment asset life cycle cost. We can set up a three-layer BP neural network, in which we take the various factors affecting equipment asset life cycle cost as the neurons of input layer, Determine the neurons of middle layer applying the trial and error method, And take the equipment asset life cycle cost as the output layer.

3.2 Import data from input and output layer.

By selecting a number of existing equipment, we can take the determinated index data greatly affected on the equipment asset life cycle cost as the input samples, Taking the index data of equipment asset life cycle cost as the output samples. It is important to note that the data of input and output layer should be carried out normalization processing. Process input/output data, in order to limit the network input and output data to [0, 1] or [1, 1] range. That is because, on the one hand, the network's input data tend to have different physical significance and various dimensions, the data processing make all component in [0, 1] or [1, 1], with the ability to ensure that the BP neural network from training start gives the input data equally important position；On the other hand, there are tangent S function between hidden layer and output layer, capable of prevent the neuron output becoming saturation due to the absolute value of the input data being too large, which make the adjustment weights into the flat area of error surface. At the same time, the output of tangent S function is between [1, 1], if we don't adjust the output data, it will affect the accuracy of the network operation.

3.3 Training the networks.

Set μ for input sample, $I_k^\mu (k = 1,2,3,4,5)$ for input layer unit state, $H_j^\mu (j = 1,2,3)$ for relevant output layer unit state, $O_i^\mu (i = 1,2)$ for relevant hidden layer unit state, W_{ij} for weight from hidden layer to output layer, W_{jk} for weight from input layer to hidden layer.

Assume the state function of BP artificial neuron as $g(h) = \dfrac{1}{1 + e^{-2\beta h}}$, for sample μ, the input of hidden layer unit as

$$h_j^\mu = \sum_{k=1}^{5} W_{jk} I_k^\mu$$

The output of hidden layer as

$$H_j^\mu = g(h_j^u) = g(\sum_{k=1}^{5} W_{jk} I_k^\mu)$$

The input of output layer unit i as

$$h_i^\mu = \sum_{j=1}^{3} W_{ij} H_j^\mu = \sum_{j=1}^{3} W_{ij} g\left(\sum_{k=1}^{5} W_{jk} I_k^\mu \right)$$

The network's final output as

$$O_i^u = g(h_i^\mu) = g\left(\sum_{j=1}^{3} W_{ij} H_j^\mu \right) = g\left(\sum_{j=1}^{3} W_{ij} g\left(\sum_{k=1}^{5} W_{jk} I_k^\mu \right) \right)$$

Set the ideal output of sample μ for $\{T_i^\mu\}$, then the error function as

$$E(W)=\frac{1}{4}\sum_{\mu j}\left(T_i^{\mu}-O_i^{u}\right)^2=\frac{1}{4}\sum_{\mu j}\left[T_i^{u}-g\left(\sum_{j=1}^{3}W_{ij}\,g\left(\sum_{k=1}^{5}W_{jk}I_k^{\mu}\right)\right)\right]$$

If the steepest descent method is adopted to improve the connection weight correction, then the weight of W_{ij} and the correction of W_{jk} are expressed respectively as

$$\Delta W_{ij}=-\eta\frac{\partial E}{\partial W_{ij}}=\eta\sum_{\mu}\left(T_i^{\mu}-O_i^{\mu}\right)g'\left(h_i^{u}\right)H_j^{\mu}=\eta\sum_{\mu}\delta_i^{\mu}H_j^{\mu}$$

$$\Delta W_{ij}=-\eta\frac{\partial E}{\partial W_{ij}}=-\eta\frac{\partial E}{\partial H_j^{\mu}}\frac{\partial H_j^{\mu}}{\partial W_{jk}}=\eta\sum_{\mu j}\left(T_i^{\mu}-H_i^{\mu}\right)g'(h_i^{\mu})W_{ij}\,g'(h_j^{\mu})I_k^{\mu}$$

$$=\eta\sum_{\mu j}\delta_i^{u}W_{ij}\,g'(h_j^{\mu})I_k^{\mu}=\eta\sum_{\mu}\delta_j^{\mu}I_k^{\mu}$$

Among them, $\delta_i^{\mu}=\left(T_i^{\mu}-O_i^{\mu}\right)g'\left(h_i^{\mu}\right)$; $\delta_j^{\mu}=g'\left(h_j^{\mu}\right)\sum_j W_{ij}\delta_i^{\mu}$, η for learning efficiency, the best value of η can be determined by making the objective function of $\min E\left(W^{(n)}+\eta\Delta W^{(n)}\right)=E\left(W^{(n)}\right)+\eta^{(n)}\Delta W^{(n)}$ minimal. $\eta^{(n)}$ for the optimal step length of $\eta^{(n)}$ reiteration n , by one-dimensional search method to calculate.

3.4 Using the network.

Import the predicted data of equipment asset life cycle cost which demand to predict into the well-trained BP neural network, by the software Matlab's operation to get the output results .

4.Empircal Analysis

Assume for a equipment asset X to conduct life cycle cost prediction. On the basis of detailed analysis of the existing equipment asset, we select 16 kind of equipment close (similar) with X , and select 6 important factors affecting equipment asset life cycle cost, expressed as, $\gamma_1,\gamma_2,\cdots,\gamma_6$, respectively, as the input variables; And select equipment asset life cycle cost as the output variable. Namely, the nodality (node number) of input layer is 6, the one of output layer is 1.The normalized data of input and output layer list as follows:

Table 1 The Normalized Data of Input and Output Layer

	Input variable						t output
	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	y
A	0.0035	0.4476	0.3953	0.1004	0.0343	0.0190	0.2437
B	0.0002	0.7059	0.2076	0.0078	0.0001	0.0784	0.5229
C	0.0014	0.4423	0.1676	0.2886	0.0685	0.0316	0.4213
D	0.0005	0.5099	0.1475	0.2540	0.0603	0.0278	0.4821
E	0.0008	0.4511	0.1681	0.0792	0.2902	0.0105	0.2225
F	0.0033	0.4508	0.1260	0.0594	0.3527	0.0079	0.2479
G	0.0020	0.5222	0.1459	0.0688	0.2519	0.0091	0.2871
H	0.0056	0.5415	0.1514	0.0713	0.2207	0.0095	0.2978
I	0.0008	0.3516	0.2241	0.1158	0.2923	0.0154	0.2637
J	0.0013	0.4785	0.1783	0.0866	0.2441	0.0112	0.2552
K	0.0010	0.4444	0.1911	0.0901	0.2615	0.0120	0.2734
L	0.0009	0.5309	0.1979	0.0933	0.1646	0.0124	0.2831
M	0.0012	0.4108	0.2794	0.1443	0.1452	0.0192	0.3177
N	0.0001	0.7154	0.1223	0.1252	0.0209	0.0161	0.5800
O	0.0001	0.7015	0.1306	0.1184	0.0279	0.0215	0.4590
P	0.0022	0.4994	0.4315	0.0082	0.0235	0.0353	0.5287

Construct BP neural network model. There are six components in the input layer of the network model, and 1 component in the output layer, first taking $a=1$, then $y=4$. $y=4$ as the initial values of trial and error, use MATLAB to train the different values of y to determine the optimal nodality of hidden layer. Through the training, when y=6, the trained network meets the requirements. Therefore, $y=6$ is feasible.

Take the data of the input and output layer in table 1 as the training sample, using the Matlab software to train the network.

For X , the input data of six important factors influencing the life cycle cost, respectively, are: $\gamma_1=0.0184$, $\gamma_2=0.4134$, $\gamma_3=0.3411$, $\gamma_4=0.0156$, $\gamma_5=0.0278$, $\gamma_6=0.1837$. Input the input layer into the well-trained neural network model to make calculation, and get the output:

0.4635.

Restore the output back to the life cycle cost of the equipment asset, and then the life cycle cost of the equipment asset is 463500 Yuan.

5.Summary

Life cycle cost of equipment asset is an important index of measuring equipment asset value. Owing to the life cycle cost of equipment asset with a certain unpredictability and fuzziness, we should select the appropriate method to conduct scientific prediction for the life cycle cost in the initial stage of purchasing equipment asset. Although the conventional prediction method of life cycle cost improve the speed and precision of the equipment asset life cycle cost prediction to a greater or lesser degree, but still exist deficiencies and disadvantages. In this paper I introduce the BP neural network method, with the aid of Matlab software, to predict life cycle cost of equipment asset, which shows the convenience and accuracy of the method in the aspect of equipment asset life cycle cost prediction, has changed the limitations and subjectivity of traditional forecasting methods, is a set of more scientific, more effective and applicable prediction method of equipment asset life cycle cost, and will play an important role in the field of equipment asset management.

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