Acta Technica 62 (2017), No. 7A, 1033–1042

Performance evaluation of engineering project management by modern management methods

Zhijian Luo[1], Jianping Peng[2]

Abstract. Traditional evaluation of performance of engineering project management mainly adopts the method of single linear analysis. This method is simple and easy to use, whereas it fails to reflect the complex non-linear correlation between evaluation indexes. In this regard, a modern evaluation of performance of engineering project management method based on Evolutionary Morphology Neural Network (EMNN) is proposed. First and foremost, the system to evaluate the performance of engineering project management based on modern management methods is established, and its utility function index is established, and its utility function is established to confirm the indexes of this system. Secondly, the concept of Evolutionary Morphology Neural Network is proposed. In this paper, we give the calculation method of the error energy function of the EMNN on the non-continuous partial derivative of the connection weight value. The adjustment and calculation formulas of network connection weight are given. On that basis, a new learning algorithm is proposed for EMNN, and the optimal value of parameter learning rate is obtained by genetic algorithm. Eventually, the proposed method is verified effective through the application of the performance evaluation for engineering project management example on the basis of modern management methods.

Key words. Modern management, Engineering project, Performance appraisal, Evolutionary Morphology Neural Network (EMNN).

1. Introduction

Currently, China has ushered into an era of rapid developed in the construction of metro. The various hazards of engineering projects determine that metro construction is a high-risk, large-scale construction project. In the process of engineering construction, a series of problems occur, such as quality difficulty, difficulty

[1]School of Management, Xinhua College of Sun Yat-sen University, Guangzhou City Guangdong Province, 510520, China

[2]Business School, Sun Yat-Sen University, Guangzhou City Guangdong Province, 510275, China

in cost control and frequent safety accidents, etc., which are urgently guided by the scientific theory and method of project management, as to elevate the performance of managing the engineering project.

Many scholars have conducted some analysis on how to improve the level of engineering project management. There are three main types of engineering project management research: the theoretical research of metro project management theory; single target control of metro project management; Research on management performance of metro project. The research of theory and target control has achieved considerable performance and formed a relatively mature system. The research on the performance evaluation of project management is mainly limited to the qualitative analysis of general management rather than the quantitative analysis. The study of quantitative project management performance evaluation is an urgent need to improve the comprehensive management level of engineering projects.

This paper evaluates the performance of integrated management of engineering projects. Based on the project management knowledge system, this paper establishes an evaluation index system, covering integration, scope, schedule, cost, quality, human resources, security risks, communication and procurement. Because engineering project management is a special land of grey system, the entropy value method and the multi-level grey evaluation method are used for comprehensive evaluation, as to make project management performance evaluation more scientific and reasonable.

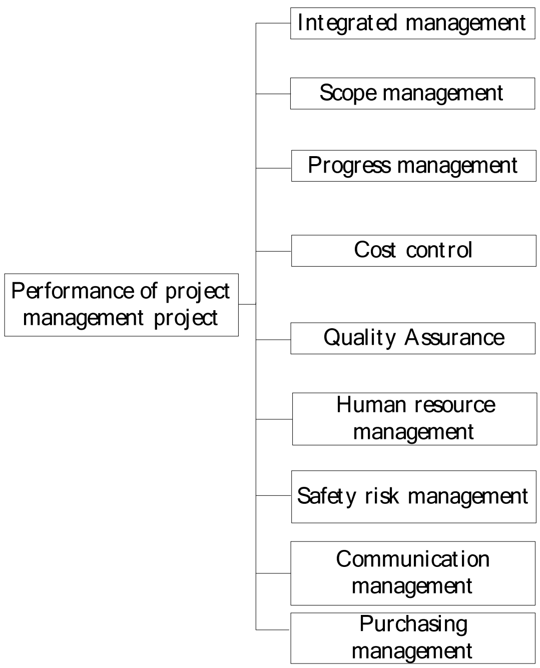

Fig. 1. Evaluation index system for project management performance

2. Evaluation index system for project management performance

2.1. Establishing index system

According to the nine aspects of the knowledge domain of project management knowledge and the factors involved in the management of engineering projects, and based on the characteristics of project management, this paper analyzes the important links of various aspects of project management performance. The evaluation index system covering 9 main factors and 29 subordinate elements indicators is established, as shown in Fig. 1.

2.2. Establishing index system for evaluating project management performance and the utility function of this system

Factors affecting the management performance of engineering projects can be summarized as progress, cost, quality, and safety.

Progress indicates the speed of construction production. The effect of progress control on project performance can be represented by the period advance rate.

(The cost control can be indicated by the deviation between the actual cost of the project and the budgeted cost.

The quality can be denoted by the sum of primary qualification rates of distributing and sub-divisional project qualities.

Safety control mainly depends on the effectiveness of the establishment and implementation of the safety management system, which can be scored by the experts. If accident occurs in a project, such project is not qualified to be evaluated.

In order to solve the incommensurability of project schedule, cost, quality, safety and other evaluation indexes, according to the actual situation and index characteristics of project management performance evaluation, through using nonlinear transform function, the original data of the evaluation index is converted into the utility evaluation value of the range $[-1, 1]$. The function of defining the utility of each single item is:

$$E_i = \frac{1 - e^{-ky}}{1 + e^{-ky}} \,. \tag{1}$$

Where y is the relative specific value between actual value of the evaluation index d_i and planned value s_i, thus:

$$x = \frac{S_i - d_i}{S_i} \,. \tag{2}$$

2.3. Confirmation of index weight

In view of the importance of indicators in the performance evaluation system of engineering project management, through investigation, the decision data is obtained, and decision matrix is constructed as $R = \{r_{ij}\}_{m\times n}$. Additionally, standardized matrix can be attained through calculating the decision-making matrix as:

$$\dot{R} = \{\dot{r}_{ij}\}_{m\times n} \,. \tag{3}$$

In formula, $\dot{r}_{ij} = r_{ij} \Big/ \sum\limits_{i=1}^{m} r_{ij}$

Where $\dot{r}_{ij} = r_{ij} \Big/ \sum\limits_{i=1}^{m} r_{ij}$. In line with the information entropy of decision-making index C_{ij}:

$$E_i = -\frac{1}{\ln n}\sum_{j=1}^{n} \dot{r}_{ij} \ln \dot{r}_{ij}, i = 1, 2, \cdots, m\,. \tag{4}$$

Eventually, the weight vector of various factor indexes C_{ij} is calculated:

$$\omega = (\omega_1, \omega_2, \cdots, \omega_n) \,. \tag{5}$$

Where $\omega_i = \frac{1-E_i}{\sum_{k=1}^{n}(1-E_k)}$. According to this model, the index weight of each factor of the project management performance indicator system can be obtained.

3. Mathematical foundation of EMNN

Matrix operators based on lattice algebras are widely applied to engineering science. In these applications, the traditional matrix addition and multiplication operators are replaced by the corresponding lattice algebraic operators. By introducing lattice algebra into matrix operators, a class of completely different nonlinear transformation is generated. MNN formed on the basis of the matrix operator of lattice algebra was originally proposed by Ritter and Davidson et al. [6-8]. The EMNN and the multi-layer MNN calculation foundation are roughly the same, which are briefly introduced in this section.

In the general artificial neural network, the input and output relationship of node j on the m layer is defined as

$$x_j(m+1) = f\left(\sum_{i=1}^{n} x_i(m)\cdot w_{ij} - \theta_j\right) \,. \tag{6}$$

In the EMNN, the addition and multiplication of the (1) method will be replaced by the addition and the acquisition of maximum and minimum. The input and output relationships of nodes in neural networks are modified to non-linear calculations. The topology of the EMNN is shown in figure 2. It can be attained that the EMNN is a multiplayer feed-forward neural network with multi-inputs and single output.

The i-th input training sample of the network is given as $x_i = \{x_{i1}, x_{i2}, \cdots, x_{iN}\}$, $(i = 1, 2, \cdots, K)$. The output of j-th neural cell on hidden layer is given as $u_j(t)(j = 1, 2, \cdots, H)$. K indicates the amount of training samples, N is the dimension of each training sample, and H is the number of neurons in the implicit layer. N depends on the size of the structure element (such as the selected structure element of the 9

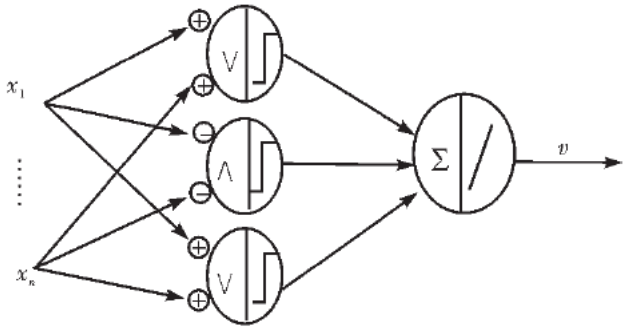

Fig. 2. Topological structure of EMNN

neighborhood domains in this paper, and N=9), whereas the number of hidden layer neurons is freely selected. The output of the entire network is $v(t)$. Wi_{ij} represents the connection weight of the i-th node of the input layer to the j-th neuron of the implicit layer. Wo_j represents the connection weight of the JTH neuron to the output layer of the hidden layer. Their relationship is denoted as:

$$u_j(t) = f_j\left(\vee_{i=1}^{n}\left(x_i(t) + Wi_{ij}\right)\right) \text{ or } u_j(t) = f_j\left(\wedge_{i=1}^{n}\left(x_i(t) + Wi_{ij}\right)\right). \tag{7}$$

Where $\vee$ and $\wedge$ represent the computation to acquire maxima and minima, N is the number of input neurons (dimensions of input training sample).

The output layer is composed of one node, and the entire network output v(t) is defined as:

$$v(t) = f\left(\sum_{j=1}^{H} Wo_j \cdot u_j(t)\right). \tag{8}$$

In the foregoing formula (2) and (3), the activation function of hidden layer is defined as $u_j(t) = f(z) = {}^{1}\!/\!_{(1+e^{-z})}$, where $z = \vee_{i=1}^{n}\left(x_i(t) + Wi_{ij}\right)$; the activation function of output layer is defined as $f(z) = z$, i.e. $v = f(z) = z$, where $z = \sum_{j=1}^{H} Wo_j \cdot u_j(t)$.

4. Training of EMNN

Before the EMNN is used for image restoration, we need to train EMNN's connection weights Wo and Wi. Assume the dimension of each input training sample is N (the corresponding number of neurons in the input layer of the network), and the training sample number is L.

In the whole image restoration, the training of the network is a supervised learning process, i.e. EMNN shall be trained to minimize both the expected output and the actual network output. The adopted MSE guiding function E is defined as:

$$E\left(Wi_{ij}, Wo_j\right) = \frac{1}{2N}\sum_{i=1}^{N}\left(d_i - y_i\right)^2. \tag{9}$$

Where d_i and y_i respectively denote the actual output and expected output of the network corresponding to the i-th input training sample, i.e. the composite function of actual output y_i is defined as:

$$y_i = v(t) = f(z_1), z_1 = \sum_{j=1}^{H} Wo_j \cdot u_j(t), u_j(t) = f(z_2) = \frac{1}{1+e^{-z_2}},$$
$$z_2 = \vee_{i=1}^{n}\left(z_3(i)\right), z_3(i) = x_i(t) + Wi_{ij}.$$

A conjugate gradient algorithm based on genetic algorithm is used to train network connection weights Wi_{ij}, Wo_j. At each step of the iteration, the genetic algorithm is used to obtain the optimal value of the learning constant η. The adjustment formula of its network connection weight value is presented as follows. η is the learning constant, α is the momentum factor.

$$Wi_{ij}(t+1) = Wi_{ij}(t) - \eta \cdot \frac{\partial E}{\partial Wi_{ij}(t)} + \alpha \cdot \left[Wi_{ij}(t) - Wi_{ij}(t-1)\right]. \tag{10}$$

$$Wo_j(t+1) = Wo_j(t) - \eta \cdot \frac{\partial E}{\partial Wo_j(t)} + \alpha \cdot \left[Wo_j(t) - Wo_j(t-1)\right]. \tag{11}$$

Where $\frac{\partial E}{\partial Wi_{ij}(t)}$ and $\frac{\partial E}{\partial Wo_j(t)}$ refer to the gradient vector of two connection weights of Error guidance function E. following the chained derivation regulation of the partial derivative of composite function, the calculation shall be conducted as:

$$\begin{aligned}\frac{\partial E}{\partial Wi_{ij}(t)} &= \frac{\partial E}{\partial y_i}\cdot\frac{\partial y_i}{\partial z_1}\cdot\frac{\partial z_1}{\partial u_j(t)}\cdot\frac{\partial u_j(t)}{\partial z_2}\cdot\frac{\partial z_2}{\partial Wi_{ij}(t)} \\ &= -(d_i - y_i)\cdot Wo_j(t)\cdot u_j(t)\cdot(1-u_j(t))\cdot\frac{\partial z_2}{\partial Wi_{ij}(t)}\end{aligned} \tag{12}$$

$$\frac{\partial E}{\partial Wo_j(t)} = \frac{\partial E}{\partial y_i}\cdot\frac{\partial y_i}{\partial z_1}\cdot\frac{\partial z_1}{\partial Wo_j(t)} = -(d_i - y_i)\cdot 1\cdot u_j(t). \tag{13}$$

Where $\frac{\partial z_2}{\partial Wi_{ij}(t)}$ is not constant at $x_i(t) = Wi_{ij}$. As enlightened by literature [13, 14], the partial derivative $\frac{\partial z_2}{\partial Wi_{ij}(t)}$ is defined as:

$$\begin{aligned}\frac{\partial z_2}{\partial Wi_{ij}(t)} &= \frac{\partial \vee_{i=1}^{n}\left(x_i(t)+Wi_{ij}\right)}{\partial\left(x_i(t)+Wi_{ij}\right)}\cdot\frac{\partial\left(x_i(t)+Wi_{ij}\right)}{\partial Wi_{ij}} \\ &= \frac{\partial \vee_{i=1}^{n}\left(x_i(t)+Wi_{ij}\right)}{\partial\left(x_i(t)+Wi_{ij}\right)} \\ &= \frac{\partial \vee_{i=1}^{n}\left\{x_s(t)+Wi_{sj},\bigvee_{i\neq s}\left[x_i(t)+Wi_{ij}\right]\right\}}{\partial\left(x_i(t)+Wi_{ij}\right)} \\ &= \begin{cases} 1,\ \ if\ x_s(t)+Wi_{sj} > \bigvee_{i\neq s}\left[x_i(t)+Wi_{ij}\right], \\ 0.5,\ \ if\ x_s(t)+Wi_{sj} = \bigvee_{i\neq s}\left[x_i(t)+Wi_{ij}\right], \\ 0,\ \ else\ \ x_s(t)+Wi_{sj} < \bigvee_{i\neq s}\left[x_i(t)+Wi_{ij}\right]. \end{cases}\end{aligned} \tag{14}$$

Algorithm 1 Conjugate gradient algorithm based on genetic algorithm

Step 1 Initialization: the training pattern $< x, d >$ is given for the learning algorithm, where X is the input vector of the network, d is the expected vector of the network, and y is the actual output of the network. Setting the upper limit of error $\varepsilon > 0$. The maximum iteration is MaxTime. Assume the iteration time as t=1, and the connection weights Wi and Wo are randomly initialized.

Step 2 Train the network for the first time, and calculate the E of error function.

Step 3 WHILE ($E < \varepsilon$? and t<MaxTime) Do

The two gradient vectors of the error function E are calculated according to (7)-(8) formulas

The optimal value of η is obtained by genetic algorithm:

$$\eta[t] = \max\left\{\eta > 0 | E\left(Wi(t)+\lambda\cdot\frac{\partial E}{\partial Wi}\right),\ \text{among}\ \lambda\in(0,\eta)\ \text{decline}\right\}.$$

According to (5)- (6), the two connection weights of the network, Wi and Wo, shall be calculated, where η is the learning constant, and α is the momentum factor

(4) t=t+1.

Calculate the error function of the i-th training sample input network $E\left(Wi_{ij}, Wo_j\right) = \frac{1}{2N}\sum_{i=1}^{N}\left(d_i-y_i\right)^2$

ENDWHILE

Step 4 Save weight vector Wi and Wo for image restoration.

Genetic algorithm GA is used to obtain the optimal learning constant in the above algorithm, and the main process is defined as:

(1) Encoding. Approximately represent each learning rate η as a fixed length of binary number. Each binary string represents a possible solution, and all possible solutions together make up the space.

(2) Initialization. The total number of individuals in the evolution process is n.

We randomly select n points $\lambda(0,j)(j=1,2,\cdots,n)$ from the solution space to form the initial population $P(0)=\{\lambda(0,1),\cdots,\lambda(0,n)\}$, and Set iteration times t=0 and Max_gen= 50.

(3) Calculation fitness. Randomly select $\lambda(t,j)\in P(t)$ to calculate $G(\lambda(t,j))$, where $P(t)$ represents the population in t-th generation.

(4) Genetic selection. Through using the bet wheel selection mechanism, the individual $\lambda(t,j)$ survival probability is $P_j=G(\lambda(t,j))/\sum_{j=1}^{n}G(\lambda(t,j'))$.

(5) Genetic operators. Pairwise individuals $(\lambda(t,j_1),\lambda(t,j_2))$ were randomly selected from population P(t). Set C_r as the crossover operator, where the crossover probability is denoted as P_c.

The mutation operator will change the value of certain genes in the binary string. The variation probability shall select the smaller value, such as 0.005.

(6) Terminal condition. Repeat the above (3)-(5) step until a satisfactory solution is found or the maximum number of steps is reached.

5. Experimental analysis

A company has completed a number of projects recently: its basic data is shown in table 1: the management performance of the project is evaluated as follows:

Table 1. Basic data of project

No. of project	Area of structure/ m^2	*d progress control*		cost control/ 10 thousand Yuan		Quality control/ point		Security control	
		Planned value	Actual value	Planned value	Actual value	Planned value	Actual value	Planned value	Actual value
1	21357	359	391	2077	2192	79	85	3‰	0
2	13765	256	274	1019	991	84	79	3‰	1‰
3	5198	127	112	372	345	74	71	3‰	1‰

5.1. Calculation of utility value of guideposts

The utility values of each index are calculated based on the data in table 1, which are listed in table 2.

Table 2. Result of influence exerted by various indexes on the project management performance

No.	Progress	Cost	Quality	Security
1	-0.0886	-0.0796	0.0563	0.2448
2	-0.0782	0.0213	-0.0443	0.1653
3	0.1165	0.0536	-0.0325	0.1658

5.2. *establishing of training sample*

Establish a training sample for project management performance evaluation: the evaluated value of performance is regulated as [-1, 1], as indicated in Fig. 3.

Table 3. Sample setting

sample	Control type				Target value
	progress	cost	quality	security	
1	1	1	1	1	1
2	0	0	0	0	0
3	-1	-1	-1	-1	-1
4	-0.2173	-0.0934	0.0706	0.3722	0.0336
5	0.1512	0.0993	-0.0215	0.1239	0.0892
6	0.0113	0.0352	-0.0624	0.1247	-0.0752
7	0.1823	-0.0112	0.0356	0.3326	0.1614

5.3. *Calculation of evaluation value of project management performance*

According to three projects in table 1 from the trained neural network, the evaluation is carried out. The network output is $A_1 = -0.0256$, $A_2 = -0.0963$ and $A_3 = 0.0287$. As A equals to 0, The actual value is not deviated from the planned value, and the performance of the project management is considered normal. When A is less than 5, the performance of this project is deemed not effectively managed. When A outstrips 0, the performance of this project is deemed effectively managed.

6. Conclusion

In this paper, a method to evaluate the performance of engineering project management based on the EMNN is proposed. The project management performance evaluation system based on modern management method is established, and the utility function index of this system is established. The index is confirmed, and the concept of the evolutionary morphological neural network is proposed. The optimal value of parameter learning rate is obtained by genetic algorithm. Eventually, the proposed method is verified effective through the application of the performance evaluation for engineering project management example on the basis of modern management methods. Through the evolution of neural network, the complex nonlinear relationship between project duration, quality, cost, safety and project performance is uncovered. Accordingly, the evaluation shall be more objective in terms of the performance of project management.

Acknowledge

This research is supported, in part, by a grant [Grant Number 71572196] from the National Natural Science Foundation of China.

References

[1] D. S. Abdelhamid, Y. Y. Zhang, D. R. Lewis, P. V. Moghe, W J. Welsh, and K E. Uhrich: *Tartaric Acid-based Amphiphilic Macromolecules with Ether Linkages Exhibit Enhanced Repression of Oxidized Low Density Lipoprotein Uptake*, Biomaterials, *53* (2015), 32–39.

[2] N. Arunkumar, K. Ramkumar, S. Hema, A. Nithya, P. Prakash, V. Kirthika: *Fuzzy Lyapunov exponent based onset detection of the epileptic seizures*, 2013 IEEE Conference on Information and Communication Technologies, ICT 2013, (2013), art. No. 6558185, 701–706.

[3] J. J. Faig, A. Moretti, L. B. Joseph, Y. Y. Zhang, M. J. Nova, K. Smith, and K. E. Uhrich: *Biodegradable Kojic Acid-Based Polymers: Controlled Delivery of Bioactives for Melanogenesis Inhibition*, Biomacromolecules, *18* (2017), No. 2, 363–373.

[4] Z. Lv, A. Halawani, S. Feng, H. Li, S. U. Réhma,: *Multimodal hand and foot gesture interaction for handheld devices.* ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), *11* (2014), No. 1s, 10.

[5] Y. Z. Chen, F. J. Tang, Y. Bao, Y. Tang, G. D. Chen: *A Fe-C coated long period fiber grating sensor for corrosion induced mass loss measurement.* Optics letters, *41* (2016), 2306–2309.

[6] N. Arunkumar, S. Jayalalitha, S. Dinesh, A. Venugopal, D. Sekar: *Sample entropy based ayurvedic pulse diagnosis for diabetics*, IEEE-International Conference on Advances in Engineering, Science and Management, ICAESM-2012, (2012), art. No. 6215973, 61–62.

[7] J. W. Chan, Y. Y. Zhang, and K. E.Uhrich: *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry, *26* (2015), No. 7, 1359–1369.

[8] M. P. Malarkodi, N. Arunkumar, V. Venkataraman: *Gabor wavelet based approach for face recognition*, International Journal of Applied Engineering Research, *8* (2013), No. 15, 1831–1840.

[9] L. R. Stephygraph, N. Arunkumar: *Brain-actuated wireless mobile robot control through an adaptive human-machine interface*, Advances in Intelligent Systems and Computing, *397* (2016), 537–549.

[10] N. Arunkumar, V. Venkataraman, T. Lavanya: *A moving window approximate entropy based neural network for detecting the onset of epileptic seizures*, International Journal of Applied Engineering Research, *8* (2013), No. 15, 1841–1847.

[11] J. W. Chan, Y. Y. Zhang, and K. E. Uhrich: *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry, *26* (2015), No. 7, 1359–1369.

[12] Y. J. Zhao, L. Wang, H. J. Wang, and C. J. Liu: *Minimum Rate Sampling and Spectrum Blind Reconstruction in Random Equivalent Sampling.* Circuits Systems and Signal Processing, 2015; *34* (2015), No. 8, 2667–2680.

[13] N. Arunkumar, K. Ramkumar, V. Venkatraman, E. Abdulhay, S. L. Fernandes, S. Kadry, S. Segal: *Classification of focal and non focal EEG using entropies.* Pattern Recognition Letters, *94* (2017), 112–117.

Received May 7, 2017