MACHINE TOOL & HYDRAULICS Hydromechatronics Engineering
http://jdy.qks.cqut.edu.cn E-mail: jdygcyw@126.com
Citation format: Liang-hui HUANG, Shu-ping WANG, Cong-xiang WANG. Research on cost prediction of construction projects based on ant colony optimization and fuzzy Petri net[J]. MACHINE TOOL & HYDRAULICS,2018,46(24):68 –73.

Research on cost prediction of construction projects based on ant colony optimization and fuzzy Petri net

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Abstract: In order to effectively improve the accuracy of dynamic control of construction cost, the ant colony optimization algorithm and fuzzy Petri net theory are adopted to predict the construction cost. First, the sample project is selected by the rules of fuzzy production and the similarity between the projects is determined so as to establish the project cost forecasting model. The weights and thresholds are trained by BP neural network. Then, the parameters of the model are optimized by using ant colony optimization, so as to further improve the accuracy of project cost forecasting. The results of actual construction project show that compared with the traditional BP neural network prediction method, the proposed method has higher accuracy and can be effectively applied to the scientific management of construction cost.

Key words: Construction engineering, Engineering cost forecasting, Fuzzy Petri nets, Ant colony optimization
doi:10.3969/j.issn.1001-3881.2018.24.011 **Document code**: A **CLC number**: TP393

Cost savings for enterprise survival and development plays an important role [1]. In normal production conditions, effective cost reduction of production is equal to make a profit. Therefore, for each business, cost control is a very important task that needs to be taken seriously by all the departments in the enterprise. Engineering cost management including cost forecasting, cost planning, cost control, cost accounting and cost analysis. As a preliminary task in cost management, cost forecasting has been on the rise in cost management. At this stage, the modern engineering cost forecasting has become a scientific method to effectively improve the efficiency of enterprise engineering management.

In the whole process of cost management, accurate and effective cost forecasting is of great value for cost control [2]. At present, on the project cost forecasting, domestic and foreign experts and scholars have put forward a variety of engineering cost forecasting methods. In literature [4], a new method is proposed to predict the best time and economic cost for the completion of a project. In literature [5], it is proposed that using Markov chain to predict the cost of transmission line project, the algorithm requires fewer parameters, but the system implementation steps are relatively complex.

Petri nets have both strict mathematical expressions and intuitive graphical expressions, which are suitable

Received date: 2018-01-29
Foundation item: Guangdong Education Department, 2017 Guangdong Key Discipline - Management Science and Engineering, GJYH(2017) No. 1
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for accurate description of asynchronous and concurrent system models. Therefore, many researchers use Petri nets to predict system or equipment failure. In literature [6], the fuzzy fault Petri net is proposed to realize the motor fault analysis. However, the learning ability of the method is limited and the parameters are not optimized. Literature [7-8] proposed to apply fuzzy Petri nets to manufacturing cost management. This method improves the accuracy of cost management by effectively constructing fuzzy Petri nets. As we all know, ant colony optimization has good robustness and is easier to implement. It could search the global optimal parameter [9-10].

Therefore, this paper puts forward the application of the ant colony optimization algorithm and the fuzzy Petri net principle to the construction project cost prediction. This method uses ant colony optimization algorithm to adjust the weight, threshold and other parameters in the fuzzy Petri net model, so as to further improve the accuracy of construction cost forecasting. The results of practical construction example show that the proposed method of parameter optimization of fuzzy Petri nets has higher accuracy and verifies the feasibility and effectiveness of the proposed method.

1 Fuzzy Petri net definition

The fuzzy Petri Nets (FPN) adopted in this paper uses a single-layer single-point structure, which is defined as follows:

Definition 1 FPN is defined as a ten-tuple:

$$FPN = \{P,T,D,I,O,f,\alpha,\beta,S,W\} \qquad (1)$$

Where, $P=\{P_1,P_2,\cdots,P_m\}$, $m\geqslant 0$ is a limited set of places; $T=\{T_1,T_2,\cdots,T_n\}$, $n>0$ is the finite set of all transitions $t_i(i=1,2,\cdots,n)$, and the transition corresponds to the number of output sites one by one; $D=\{D_1,D_2,\cdots,D_M\}$ m is a finite set of propositions, and $|P|=|D|$, $P\cap T\cap D=\Phi$; I and O are the input function and the output function, respectively, reflecting the transition and the mapping between the places; $f:T\to[0,1]$ is the mapping of transition to its confidence μ; $\alpha:P\to[0,1]$ is the mapping relationship between the place and its token value $M(p_i)$; β: $P\to D$ is the mapping relationship between the place p and its proposition; $S:T\to[0,1]$ is the mapping of transition t_i to its threshold λ_i; $W=\{w_1,w_2,\cdots,w_m\}$ is the set of connection arcs corresponding to the input arc, which reflects the degree of dependence of the transition on the input place P.

2 Fuzzy Petri nets learning and training

2.1 Fuzzy production rules

The general form of a fuzzy production rule is a precondition-the rule conclusion (confidence), that is, the if-then (CF) pattern [5].

Definition 2 In the rule of fuzzy production, if there is "and", "or" in the preconditions or conclusion, we call this rule a composite rule. In this paper, the single-point FPO FPA rules type[5] is given by:

$$\text{IF}d_1 \text{ and } d_2 \text{ and } \cdots \text{ and } d_n$$
$$\text{THEN } d(CF=\mu_i)$$

Where, d is the result proposition.

2.2 Fuzzy reasoning algorithm

Set the variable x as given by:

$$x = \sum_{j=1}^{m}(M(P_{ij})\times w_{ij}),\ \forall p_{ij}\in I(t_i) \qquad (2)$$

Where, P_{ij} represents the j-th input repository corresponding to transition t_i, and P_{ij} represents the weight of the corresponding arc. When $x>S(t_i)$, the transition t_i triggers and can be ignited; when $x<S(t_i)$, the transition t_i does not meet the trigger conditions and can not be ignited.

Let function y as given by:

$$y(x) = \frac{1}{1+e^{b(x-S(t_i))}} \qquad (3)$$

Where, b is a negative constant with a sufficiently large absolute value and we set it to -100. Therefore, when $x>S(t_i)$, $y(x)=1$ means that the transition ignites. When $x<S(t_i)$, $y(x)=0$ indicates that the transition does not ignite. The transition trigger function is:

$$z(x) = y(x)\times f(t_i)\times x \qquad (4)$$

When $x>S(t_i)$, $z(x)>0$ represents the token value of the place after the transition t_i is ignited, and when $x<S(t_i)$, $z(x)=0$ means that the transition ignition fails and the token value remains in the initial state.

By using formula (4), one could ignite each transition in turn.

2.3 Parameter training

Parameters such as weights, thresholds and reliability in fuzzy reasoning rules need to be found by establishing models. BP artificial neural network is used to train the parameters to get the weight, threshold and other parameters of fuzzy neural Petri. However, these values are not accurate enough. Therefore, this paper uses ant colony optimization algorithm, based on the initial parameters to optimize its adjustment to the true value of continuous approximation.

3 Construction cost forecasting modeling

In the prediction of construction cost, this paper selects floors number, floors height, structure, foundation type, foundation treatment and the type of doors and windows as the characteristic index. Therefore, these feature indexes are used as the input place. The resulting construction cost forecast model structure is shown in Fig. 1. The rules of fuzzy production adopted are consistent with literature[7].

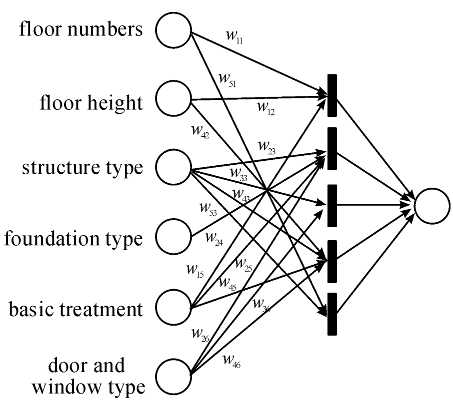

Fig. 1 Construction project cost forecasting model

3. 1 Parameter selection of the initial value

According to expert experience, the threshold $\lambda_1 - \lambda_5$ are set to 0.45, and the confidence $\mu_1 - \mu_5$ are set to 0.7. In addition, the initial value of the arc weight [7,9] is set as shown in Table 1.

Table 1 The initial weight value on FPN arc

arc	weight	arc	weight
w_{11}	0.3	w_{36}	0.65
w_{12}	0.5	w_{42}	0.3
w_{15}	0.2	w_{43}	0.1
w_{23}	0.15	w_{45}	0.05
w_{24}	0.25	w_{46}	0.55
w_{25}	0.15	w_{51}	0.4
w_{26}	0.45	w_{53}	0.6
w_{33}	0.35		

3. 2 Calculation of engineering similarity

Assume that the fuzzy set of construction project features is U, U = {floors number, floors height, structure type, foundation type, foundation treatment and door/window type}. Fuzzy set U can be expressed according to formula (5).

$$U_i = \frac{u_{i1}}{u_1} + \frac{u_{i2}}{u_2} + \cdots + \frac{u_{ij}}{u_j} \tag{5}$$

Where, U_i represents the fuzzy subset of the i-th engineering feature set U, u_i represents the element name of the engineering characteristic, and u_{ij} represents the membership function value corresponding to the engineering characteristic element. The degree of similarity calculation in literature [11] can be used to get the engineering similarity between different projects.

4 Proposed ant colony optimization algorithm

Suppose the number of ants in a nest is R, and the set of elements that need to be optimized is D, D_{φ_i} represents its i-th element. In this paper, the number of each parameter to be optimized in fuzzy Petri nets is n. Suppose there are K kinds of values for these elements φ_i, then $\zeta_j(D_{\varphi_i})(0)$ is the pheromone of the j-th element under the initial conditions [10].

The parameters of the t-th ant are calculated according to formula (6) in order to distinguish the probabilities of the various possible values.

$$k(\zeta_j^t(D_{\varphi_i})) = \frac{\zeta_j(D_{\varphi_i})}{\sum_{i=1}^{n} \zeta_j(D_{\varphi_i})} \tag{6}$$

Then select the element from the set of large probabilities D_{φ_i} and adjust it according to formula (7).

$$\zeta_j(D_{\varphi_i})(t + \Delta) = \zeta_j(D_{\varphi_i})(t) + \Delta\zeta_j(D_{\varphi_i}) \tag{7}$$

Where, $\Delta\zeta_j(D_{\varphi_i})$ is the information increment on the element φ_i, which represents the sum of all the pheromones left by the ants of this element, and it could be calculated as follows:

$$\Delta\zeta_j(D_{\varphi_i}) = \sum_{k}^{R} \Delta\zeta_j^k(D_{\varphi_i}) \tag{8}$$

Repeat the above process until the maximum number of iterations allowed, or all ants get the only element, that is, the optimized fuzzy neural Petri net parameters.

5 Learning and training steps

The steps of fuzzy Petri net learning and training are as follows:

Step 1: Select the sample to determine the parameters;

Step 2: For all training sample sets, all transitions are triggered in turn according to formula (4);

Step 3: Calculate the error cost function according to the following formula (9);

$$E = 2^{-1} \sum_{l=1}^{r} \sum_{i=1}^{n} (M_l(p_i) - M_l^E(p_i))^2 \qquad (9)$$

Where, n is the number of output locations, r is the number of sample sets, $M_l(P_i)$ is the actual entropy of the output repository p_i, and $M_l^E(p_i)$ is the actual token value of the output place p_i. If the result of E is less than the token value, stop; otherwise, proceed to the next step.

Step 4: Use the proposed ant colony optimization algorithm to adjust the parameters in the model;

Step 5: Return to Step 2 until the error is satisfied.

The use of ant colony optimization and fuzzy Petri nets to establish engineering cost forecasting model, the modeling process is shown in Fig. 2.

6 Construction project cost forecast case analysis

6.1 Sample selection

The cost prediction of construction project is realized by MATLAB. The ant colony optimization algorithm is used to adjust the parameters of the fuzzy neural Petri net model. This paper selected 10 sets of construction engineering sample data, as a network learning sample set. In addition, three sets of construction engineering sample data were selected as test samples to test the effect of cost forecasting. In the cost prediction experiment of this paper, the engineering feature attribute value [11] of the sample set is shown in Table 2.

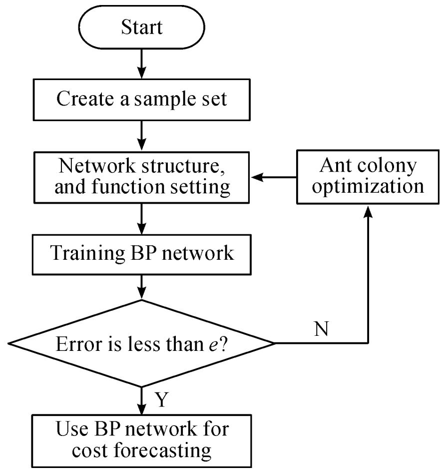

Fig. 2 Modeling process

6.2 Parameter optimization results

BP neural network algorithm [12], BP-Adaboost neural network algorithm [13] and the algorithm proposed in this paper are used to train and test the cost prediction, respectively. The training curve obtained is shown in Fig. 3. The proposed ant colony optimization algorithm is used to optimize the parameters in the fuzzy neural Petri net model. Set the expected error to 0.000 1. The error value will be less than the expected value at the first time after 150 iterations.

Table 2 Engineering characteristics attribute value of the sample set

Project No.	Structure Type	Door Type	Window Type	Foundation Type	Foundation Processing	floors number	floors height
1	1	1	0.1	0.1	0.5	5	3
2	0.8	0.6	0.1	0.3	1	4	2.8
3	0.8	0.6	0.1	0.1	1	4	3.2
4	1	1	0.1	0.3	1	6	2.8
5	0.8	0.6	0.1	0.2	1	5	2.8
6	1	1	0.1	0.3	0.5	4	3.2
7	1	1	0.1	0.1	1	5	2.8
8	0.8	1	0.1	0.1	1	5	2.8
9	1	0.6	0.1	0.1	1	5	3
10	1	1	0.1	0.4	1	5	3.2

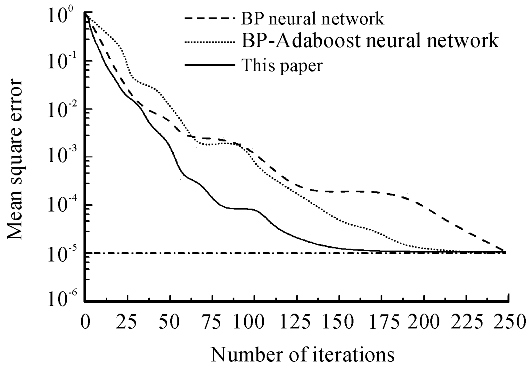

Fig. 3 Predict the iterative error curve

In this case, the thresholds $\lambda_1 - \lambda_5$ are 0.415, 0.451, 0.379, 0.449 and 0.471, respectively, and the reliability $\mu_1 - \mu_5$ are 0.655, 0.731, 0.634, 0.671 and 0.722, respectively. The optimized weights are shown in Table 3.

Table 3 The weights after optimization

arc	weight	arc	weight
w_{11}	0.391	w_{36}	0.602
w_{12}	0.681	w_{42}	0.381
w_{15}	0.124	w_{43}	0.147
w_{23}	0.137	w_{45}	0.042
w_{24}	0.352	w_{46}	0.632
w_{25}	0.118	w_{51}	0.381
w_{26}	0.516	w_{53}	0.678
w_{33}	0.403		

6.3 Fault diagnosis result

The initial parameters of the fuzzy neural Petri net model are used to predict the cost of the 10 test samples mentioned in the previous section. At the same time, using the parameters of ant colony optimization, the cost of the same test sample could be predicted. The results of the two cost forecasts are shown in Table 4. The results show that compared with the model without parameter optimization, the accuracy of the model using ant colony optimization parameters is higher, with an average relative error of 2.12%.

In addition, BP neural network algorithm [12], BP-Adaboost neural network algorithm [13] and algorithm presented in this paper are used to train and test the cost forecast under the same conditions and data sets, respectively. The results are shown in Table 5. It can be seen that the accuracy of the proposed method is higher than those of other methods.

Table 4 Cost prediction results with different parameters

Project No.	Initial parameters		Ant colony optimization parameters	
	Absolute error	Relative error/%	Absolute error	Relative error/%
1	44	2.94	40	2.11
2	43	2.83	38	2.08
3	35	2.86	29	2.16
4	51	2.90	47	2.09
5	27	2.92	24	2.13
6	37	2.87	34	2.07
7	41	2.87	38	2.12
8	29	2.98	25	2.21
9	35	2.91	31	2.14
10	43	2.88	38	2.08

Table 5 Cost prediction results of different methods

Project No.	BP		BP-Adaboost		Ant colony optimization parameters	
	Absolute error	Relative error/%	Absolute error	Relative error/%	Absolute error	Relative error/%
1	52	4.54	47	3.64	40	2.11
2	53	4.53	45	3.63	38	2.08
3	42	4.57	39	3.58	29	2.16
4	58	4.63	55	3.62	47	2.09
5	36	4.65	31	3.65	24	2.13
6	44	4.58	40	3.57	34	2.07
7	49	4.52	45	3.57	38	2.12
8	38	4.68	32	3.65	25	2.21
9	42	4.63	37	3.62	31	2.14
10	51	4.57	46	3.53	38	2.08

7 Conclusion

In this paper, we use ant colony optimization to adjust various parameters of fuzzy neural Petri net model to realize the prediction of construction cost, so as to further improve the accuracy of cost prediction. The result of construction project example shows that compared with other BP neural network cost forecasting methods, the proposed ant colony optimization fuzzy Petri net cost forecasting method has higher accuracy. The conclusion could be drawn that the proposed method of cost forecasting in this paper is feasible for the actual construction project cost management and this paper has some reference value for the real industrial application.

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基于蚁群优化和模糊 Petri 网的建筑工程成本预测研究

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摘要:为了有效提高建筑工程成本动态控制的精确度,提出将蚁群优化算法和模糊 Petri 网理论应用于建筑工程成本预测。首先,通过模糊产生式规则选择样本工程并确定工程之间的相似度,以便建立工程成本预测模型,其权值和阈值等参数由 BP 神经网络训练得出。然后,利用蚁群优化对模型各参数进行优化,从而进一步提高工程成本预测的精确度。实际建筑工程实例分析结果表明:相比传统的 BP 神经网络预测方法,提出的方法具有更高的准确度,能够有效应用于企业建筑工程成本的科学管理。

关键词:建筑工程;工程成本预测;模糊 Petri 网;蚁群优化

基金项目:广东省教育厅,2017 年广东省重点学科 - -管理科学与工程,粤教研函〔2017〕1 号

本文引用格式:黄良辉,王淑苹,王从祥. 基于蚁群优化和模糊 Petri 网的建筑工程成本预测研究[J]. 机床与液压,2018,46(24):68 -73.