TOOL OUTSOURCING RISK RESEARCH BASED ON BP NEURAL NETWORK

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ABSTRACT. Tool outsourcing faces many risks. If the outsourcing enterprise cannot carry out the analysis, appraisal and control of tool outsourcing sufficiently, then the outsourcing enterprise obtains no benefits and suffers losses. This paper analyzes the risk factors of tool outsourcing and then establishes an index system that provides forewarning of problems in tool outsourcing. Finally, we provide a theoretical basis for the risk management of tool outsourcing.

Keywords: BP Neural Network; Fishbone Diagram; Tool Outsourcing; Risk Estimation

1. Introduction. The essence of tool outsourcing management is the principal-agent relationship between outsourcing enterprises and tool service suppliers (Aron et al., 2005). Information asymmetry, information distortion and the uncertainty of market environment between client and agent will cause many kinds of risk during the period of implementing tool outsourcing.

After implementing tool outsourcing, the service quality and quality supervision system are not perfect. How to effectively encourage tool service suppliers and gain win-win result between outsourcing enterprises and service suppliers is an important problem. Consequently, because there are still many risk factors during the period of tool outsourcing, the outsourcing enterprise should take considerate analysis and avoidance.

Lonsdale (1999), Whitmore (2006), Pettibone (2009) respectively studied outsourcing risk problems in aspects of outsourcing risk source, outsourcing risk estimation and outsourcing risk avoidance policy. Zhang (2005), Da (2005), Kainz (2001) studied tool management from the following aspects as management model and management process. Nowadays, domestic and international research about outsourcing risk is mainly limited to risk identification and control strategy in the period of outsourcing. A completely reasonable method of outsourcing risk evaluation which can gain a global admission and acceptance does not exist.

2. BP Neural Network Model.

2.1. The Introduction of BP Neural Network. BP neural network is a multi-level feed-forward neural network based on BP algorithm. As a paralleled and dispersed treatment model, BP neural network has the characteristics of nonlinear mapping, self-adapting
learning and fault-tolerance property and could simulate in the complicated and capricious investment and operation environment. This paper makes full use of BP neural network to estimate tool outsourcing risk, which can provide alarm for outsourcing enterprises when abnormal situation appears and attract more attention from outsourcing enterprises to solve this problem and then guarantee company’s tool outsourcing safety. Tool outsourcing risk evaluation making use of BP neural network is not only more objective and accurate, but also states the close relationship between the factors of tool outsourcing risk index system and evaluation outcomes. So the tool outsourcing risk evaluation model based on BP neural network has a great priority.

2.2. BP Neural Network Structure and Algorithm. The learning process of BP neural network consists of four parts (Wang et al., 2000):

(1) Input model clockwise propagation (Input model is from input layer to output layer via middle layer);

(2) Output error anticlockwise propagation (The output error is from output layer to input layer via middle layer);

(3) Circular memory training (The calculation process is operating in the rotation and circulation between model clockwise propagation and error anticlockwise propagation);

(4) Judge of learning results (It is to judge the global error whether prone to minimum value or not).

The Procedure of whole learning process of BP neural network:

(1) Initialization, assign connection weights $W_{ij}$, $V_{jt}$ and threshold $\theta_j$, $\tau_t$, $i=1,2,...,n$, $j=1,2,...,p$, $t=1,2,...,q$, $k=1,2,...,m$, a random value between -1 to +1.

(2) Randomly select a couple models $A_k = [a_1^k, a_2^k, ..., a_n^k]$, $Y_K = [y_1^k, y_2^k, ..., y_q^k]$ and then provide it to BP neural network, and then calculate middle layer’s different neurons input $s_j$ (activated value) using input model $A_k = [a_1^k, a_2^k, ..., a_n^k]$ with connection weights $W_{ij}$ and threshold $\theta_j$, and then calculate the response value $t_c$ of different unites by activation function with $l_t$,

$$f(x) = \frac{1}{1+e^{-x}} \quad (1)$$

(3) Calculate different unites output of middle layer $b_j$ :

$$b_j = f(s_j) \quad (2)$$

$$s_j = \sum_{i=1}^{n} W_{ij} a_i - \theta_j \quad (3)$$

(4) Calculate different unites input $l_t$ (activated value) of output layer with output $b_j$ of middle layer, connection weights $V_{jt}$ and threshold $\tau_t$ and then calculate the response value $c_t$ of different unites by activation function with $l_t$ ,

$$c_t = f(l_t) \quad (4)$$

$$l_t = \sum_{j=1}^{p} V_{jt} b_j - \gamma_t, t=1,2,...,q \quad (5)$$
(5) Calculate calibration error \( d^k_t \) of different units with expected output model \( Y_k = [y_1^k, y_2^k, \ldots, y_q^k] \) and BP neural network’s practical output \( C_t \) :

\[
d^k_t = (y^k_t - c_t) c_t (1 - c_t), \quad t = 1, 2, \ldots, q (6)
\]

(6) Calculate correction error \( e^k_j \) of middle layer with \( V_j, d^k_t, b_j \):

\[
e^k_j = \left[ \sum_{i=1}^{q} d^k_i V_j b_j (1 - b_j) \right], \quad j = 1, 2, \ldots, p (7)
\]

(7) Calculate new connection weights between middle layer and output layer with \( d^k_t, b_j, V_j \), and \( R_t \) :

\[
V_{jt}(N + 1) = V_{jt}(N) + \alpha d^k_t b_j (8)
\]

\[
\gamma_t(N + 1) = \gamma_t(N) + \alpha d^k_t (9)
\]

\( N \): learning times

(8) Calculate new connection weights between input layer and middle layer with \( e^k_j, a^k_i, W_{ij} \) and \( \theta_j \) :

\[
W_{ij}(N + 1) = W_{ij}(N) + \beta e^k_j a^k_i (10)
\]

\[
\theta_j(N + 1) = \theta_j(N) + \beta e^k_j (11)
\]

(9) Randomly select next couple of learning model and then provide it to BP neural network, return to step 3, until all \( m \) couples models could be trained.

(10) Randomly re-select a couple models from \( m \) learning models and then return to step 3, until the network global error function \( E \) is less than the preliminarily-setting limit value(network can converge) or learning circuit number is greater than preliminarily-setting value(network can’t converge).

(11) The end: In the above learning procedures, step 3—6 is the clockwise propagation process of input learning model; step 7—8 is the anticlockwise propagation process of network error; the training and convergence process is fulfilled respectively by step 9and step 10.

### 3. Tool Outsourcing Risk Identification and Design.

#### 3.1. Tool Outsourcing Risk Source.

Tool outsourcing risk mainly arises from outsourcing decision and outsourcing execution two periods, as following table 1.

<table>
<thead>
<tr>
<th>Tool outsourcing risk source</th>
<th>Outsourcing Decision Stage</th>
<th>Outsourcing Execution Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strategy risk</td>
<td>Transaction risk</td>
<td>Management risk</td>
</tr>
</tbody>
</table>

**TABLE 1.** Tool outsourcing risk source

3.2. The Factors of Tool Outsourcing Risk. Tool outsourcing risk contains strategy risk, transaction risk, management risk, relationship risk and out-of-control risk. The fishbone diagram as figure 1 (Cai et al., 2009):

![Fishbone Diagram](image)

**FIGURE 1. Tool outsourcing risk source fishbone diagram**

(1) Lacking of effective incentive mechanism
(2) Competition mechanism is not sufficient
(3) Business process in disorder
(4) Lacking of effective tool management performance estimation system
(5) Culture difference and unsatisfactory communication
(6) Lacking of executable service level agreement
(7) Lacking of recurrent job examination
(8) Vendor supervision is deficient
(9) Determination of outsourcing limit is indistinct
(10) Lacking of market maturity analysis
(11) Key business identification is not sufficient
(12) Contract clause is not perfect
(13) Lacking of professional outsourcing team

According to the principle of authenticity, comprehensiveness, scientific property and fairness for indicator system, taking into account of sensitivity and dynamic of the indicators, and simultaneously, every index could be complementary and could not be reduplicative to comprehensively reflect tool outsourcing risk situation. Consequently, every forewarning module has several representative indicators and all indicators construct tool outsourcing risk forewarning indicators system. The figure 2 is the tool outsourcing risk forewarning indicators system.
3.3. Tool Outsourcing Risk Evaluation Indicator System. According to the tool outsourcing risk source fishbone diagram, tool outsourcing risk, for instance, the strategy risk, transaction risk, management risk, relationship risk and out-of-control risk, can be embodied by 13 different indicators. Every indicator has different score form 1 to 7, 7 means the most important, 1 means the least important, as following table 2.

![Diagram of tool outsourcing risk evaluation indicator system]

**FIGURE 2. Tool outsourcing risk indicators forewarning system**

\[ X1 \] Tool Performance Estimation System  
\[ X2 \] Business Process  
\[ X3 \] Culture Communication Degree  
\[ X4 \] Contract Clause Perfect Degree  
\[ X5 \] Outsourcing Team Specialization Degree  
\[ X6 \] Outsourcing Scope Determination Accuracy  
\[ X7 \] Outsourcing Market Maturity  
\[ X8 \] Key Business Identification  
\[ X9 \] Effective Incentive Mechanism  
\[ X10 \] Competition mechanism  
\[ X11 \] Service Level Agreement  
\[ X12 \] Job Assessment  
\[ X13 \] Vendor Supervision
TABLE 2-1. Tool outsourcing risk quantitative index

<table>
<thead>
<tr>
<th>Related Factors</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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TABLE 2-2. Tool outsourcing risk quantitative index

<table>
<thead>
<tr>
<th>Related Factors</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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</table>

4. Evaluation of Tool Risk by BP Neural Network Model.

4.1. Constructing the Tool Outsourcing Risk Forewarning Model. This paper is to operate the neural network design procedure by MATLAB. When designing BP neural network, the following problems should be taken into consideration: determining the network’s topological structure, neuron’s transmission function, network’s initialization (the initialization of connection weights and threshold); training samples’ normalization processing; training parameters setting; sample data input mode and so on Zhou and Kang (2005). The network’s topological structure contains the number of hidden layer, network input, hidden layer, output layer.

(1) The number of hidden layer: BP neural network is to calculate from input layer to output layer. Although the speed is faster when the number of hidden layer becomes more, it costs more time in practical application. The speed can be improved by adding nodes number of hidden layer. Consequently, when applying BP neural network to forecast tool outsourcing risk, it is best to choose 3-hierarchy BP neural network with only one hidden layer.

(2) Decision of the input layer’s unit number: According to tool outsourcing risk indicator forewarning system, it is to input 13 indicators. The factors of this model are all qualitative factors. When inputting nodes input, it is better to limit the indicator between 0 and 7 in order to apply in network model.

(3) Decision of the hidden layer’s unit number: The number of hidden layer nodes has an impact on neural network performance. When the quantity of hidden layer nodes is less,
learning capacity is so limited that it is too difficult to store all laws which training samples contain. The quality of hidden layer nodes is so more that it costs more network training times and non-regular contents of the samples, for instance, noise and disruption, could be stored, which has a bad generalization. According to the empirical formula \( i = \sqrt{n + m + a} \), \( i \) is the number of neurons in hidden layer, \( n \) means the number of neurons in input layer, \( m \) means the number of neurons of output layer, \( a \) is a constant which is from 0 to 1. Therefore, based on different models with different numbers of neurons in hidden layer, the author is about to respectively simulate, compare and then determine the most suitable number of neurons in hidden layer. It is supposed to be 12.

(4) Select unite number of output layer: Selection of output nodes corresponds to estimation results. In the model the ultimate result is an estimation value, which is tool outsourcing risk’s comprehensive estimation value representing different risk degrees.

Hence the author chooses one output nodes.

The author constructs the enterprise tool outsourcing risk forewarning system by adopting 3-layer BP neural network. The node number of input layer, hidden layer and output layer is respectively 13, 12, 1.

(5) Select neurons’ transmission function: The hidden layer of this model adopts tangent S form neurons and the output layer of this model adopts linear neurons, which can be approximate to any continuous functions. If the hidden layer contains enough neurons, it can be approximate to any discontinuous functions which have limited breakpoints.

(6) Data’s normalization processing: Quantitative indicator data can not be directly taken into estimation in the researches of tool outsourcing risk. Because tool outsourcing risk forewarning system is a complicated system, the indicators taken into risk estimation are not only so many, but also have different properties, dimensions and magnitudes. In order to compare different quantities which have different dimensions, all data need to be transformed appropriately, which is the dimensionless processing.

<table>
<thead>
<tr>
<th>Index</th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
<th>Sample 4</th>
<th>Sample 5</th>
<th>Sample 6</th>
<th>Sample 7</th>
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</table>
4.2. Model Training and Verification. This paper chooses MATLAB 6.5 to train and verify tool outsourcing BP neural network for warning model. The author collects 15 questionnaires from 15 different tool outsourcing enterprises which participate in the 4th manufacturing enterprise outsourcing forum in the 12th 2008. The members of Outsourcing Committee of Shanghai Science Management gave these estimable values. The comprehensive value of risk rating is given by several leading experts through analyzing indicator values, as well as empiricism and relative theories.

The author adopts one-hidden-layer BP network and uses tool outsourcing risk estimation indicator as input variable. The input variable is respectively $X_1, X_2, \ldots, X_{13}$, and the input nodes number is 13. The value range of output nodes is from 0 to 7 and the number of output nodes is 1. The author divides the enterprise tool outsourcing risk grade. According to the closeness degree between the output results and standard value of enterprise tool outsourcing risk, the author judges the enterprise’s risk grade. The Table 3.2 states the enterprise tool outsourcing risk grade coefficient.

**Table 3.2. Samples normalization processing**

<table>
<thead>
<tr>
<th>Sample8</th>
<th>Sample9</th>
<th>Sample10</th>
<th>Sample11</th>
<th>Sample12</th>
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</table>

**Table 4. Enterprise tool outsourcing risk grade coefficient**

<table>
<thead>
<tr>
<th>Enterprise Tool Outsourcing Risk Grade</th>
<th>Enterprise Tool Outsourcing Risk Grade Coefficient</th>
</tr>
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<tbody>
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<td>Low risk</td>
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<tr>
<td>Low to moderate risk</td>
<td>4.5-5.5</td>
</tr>
<tr>
<td>Moderate risk</td>
<td>3.5-4.5</td>
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<tr>
<td>Moderate to high risk</td>
<td>2.5-3.5</td>
</tr>
<tr>
<td>High risk</td>
<td>0-2.5</td>
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</table>
When the author adopts levenberg-Marquardt training algorithm, the training error and training time of network gain a minimum value at the same time. Hence trainlm training function is used by this model.

By indicators’ normalization processing, all basic data is ready for training and test, which can be seen in table 3. The author uses the first 12 couples’ data of normalized data table as learning training dataset to input the network and then makes the last 3 couples data of normalized data table as network’s test dataset. The number of hidden layer nodes is 13 and the threshold function is tansig function. Purelin linear function is adopted into output layer. In the experiment, the learning rate n is 0.01 and the acceptable error is 0.001. Training time is 5000, using trainlm function. After completing the neural network training, the last 3 couples sample data are used to verify this model. When the network training is at step 3, the network error is 8.65568e-007, network performance reaches the standard.

When training the risk forecast model by Matlab, it can directly call traingda function to train after determining input value and expected output. After building an M file, the author input the following data in interface according to tool outsourcing risk evaluation indicator data.

```matlab
p1=[0.661 0.500 0.703 0.610 0.688 0.705 0.875 0.702 0.734 0.584 0.570 0.707 0.601];
p2=[0.798 0.750 0.731 0.800 0.750 0.745 0.745 0.820 0.759 0.637 0.668 0.644];
p3=[0.867 0.815 0.794 0.797 0.858 0.728 0.693 0.785 0.693 0.664 0.590 0.711 0.771];
p4=[0.266 0.315 0.334 0.314 0.325 0.410 0.250 0.246 0.323 0.345 0.250 0.296 0.356];
p5=[0.734 0.810 0.750 0.608 0.654 0.748 0.568 0.661 0.590 0.613 0.484 0.539 0.495];
p6=[0.798 0.875 0.713 0.774 0.904 0.813 0.693 0.661 0.771 0.624 0.637 0.789 0.795];
p7=[0.468 0.750 0.750 0.863 0.848 0.818 0.785 0.683 0.824 0.762 0.875 0.759];
p8=[0.798 0.745 0.794 0.816 0.802 0.843 0.750 0.745 0.727 0.740 0.590 0.704 0.813];
p9=[0.404 0.560 0.753 0.584 0.752 0.318 0.693 0.323 0.548 0.740 0.629 0.646];
p10=[0.798 0.750 0.753 0.791 0.831 0.815 0.750 0.704 0.728 0.763 0.633 0.750 0.728];
p11=[0.318 0.250 0.246 0.323 0.266 0.250 0.323 0.246 0.296 0.266 0.314 0.246 0.296];
p12=[0.296 0.318 0.399 0.421 0.314 0.653 0.499 0.568 0.563 0.484 0.495 0.323 0.325];
p=[p1 p2 p3 p4 p5 p6 p7 p8 p9 p10 p11 p12];
[tn,mint,maxt]=premnmx(t);
net=newff(minmax(p),[13,1],{'tansig','purelin'},'trainlm');
net.trainParam.epochs=5000;
net.trainParam.goal=0.001;
net=train(net,p,t);
a=sim(net,p);
[m,b,r]=postreg(a,t);
%forecasting risk
p_test=[0.798 0.560 0.875 0.875 0.777 0.845 0.750 0.704 0.814 0.840 0.715 0.875 0.625
0.560 0.435 0.375 0.603 0.463 0.653 0.318 0.499 0.421 0.657 0.484 0.539 0.495
0.246 0.266 0.323 0.296 0.325 0.250 0.246 0.250 0.318 0.266 0.314 0.323 0.296];
y=sim(net,p_test)
```
And then the data is operating in command window and appears in Matlab display interface: TRAINGD, Performance goal met. When the above cue about the target has been achieved appears and the dynamic diagram of training can be seen in the figure 3.

![Training diagram](image)

**Figure 3.** Tool outsourcing evaluation performance diagram based on BP neural network

TRAINLM, Epoch 3/5000, MSE 8.65568e-007/0.001, Gradient 0.0183008/1e-010

TRAINLM, Performance goal met. This states that this network training is successful.

### 4.3. Testing the BP Model.

The 3 couples test values is to verify network’s adaptability. After simulating, the output results are as following: The output Y value is 6.0535, 3.939, 2.1805. The table 5 is the error of network simulation results.

The output results of network model respectively have displayed risk grade, for instance, low risk, moderate risk, high risk. The error rate is less than 5%, which means this model can accurately forecast tool outsourcing risk in accordance with the indicator system. The accurate model needs more training samples in order to be convenient for network learning, which makes the network have a better fault-tolerance property. In the practice, Maximum error of less than 10% can meet the demand of accuracy.

<table>
<thead>
<tr>
<th>Sample for Verification 1</th>
<th>Sample for Verification 2</th>
<th>Sample for Verification 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Simulation Result</strong></td>
<td>6.0536</td>
<td>3.939</td>
</tr>
<tr>
<td><strong>Practical Evaluation</strong></td>
<td>6.195</td>
<td>4.010</td>
</tr>
<tr>
<td><strong>Error</strong></td>
<td>2.283%</td>
<td>1.771%</td>
</tr>
</tbody>
</table>
5. Conclusions. The author constructs tool outsourcing risk evaluation indicator system and tool outsourcing risk evaluation model by BP neural network model. The author adopts 15 auto enterprises data as training sample, which can evaluate the enterprise’s tool outsourcing management risk.

Because the number of enterprise which makes tool outsource is so small and these tool outsourcing enterprises are also in the beginning stage, the training and forecast functions maybe have a better application if the number of sample is much bigger.

REFERENCES