An application of BP-Artificial Neural Networks for factory location selection: case study of a Korean factory

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Abstracts:

Factory location selection is very important to the success of operation of the whole supply chain, but few effective solutions exist to deliver a good result, motivated by this, this paper tries to introduce a new factory location selection methodology by employing the artificial neural networks technology. First, we reviewed previous research related to factory location selection problems, and then developed a (neural network-based factory selection model) NNFSM which adopted back-propagation neural network theory, next, we developed computer program using C++ to demonstrate our proposed model. then we did case study by choosing a Korean steelmaking company P to show how our proposed model works,.Finnaly, we concluded by highlighting the key contributions of this paper and pointing out the limitations and future research directions of this paper.

Compared to other traditional factory location selection methods, our proposed model is time-saving; more efficient.and can produce a much better result.

Keywords:

Factory location selection; BP-artificial neural networks; NNFSM.

1. Introduction

Over the last few years, manufacturing field have seen dramatic changes in location and competition. And as is known to all, factory location selection is very important to the success of the whole operation of supply chain in that it determines the high and long-term investment plan, and the role of location in competition is pervasive in the manufacturing sector. In most cases, it is the first priority before any other decisions and the unchangeable hardware investment. Thus, it is difficult to compensate by other methods for the negative influence of a worse location decision. It is especially important where transportation and logistics costs play a large role. An obvious impact of these costs is to limit the market areas in which a plant can effectively compete, to some geographic region around it. This is, of course, the central issue addressed in the classic Hotelling (1929) model [1]. Addition to location competition with respect to markets, it is also important to consider both the location dependent costs that arise due to raw material acquisition and the heterogeneous costs of operation at different sites. More generally, a location decision is one part of overall supply chain design, and location competition could be regarded as a core issue in supply chain competition.

2. Literature review

During the past few years, some previous researches have been done related to the selection of factory location. And most of them either use mathematic methodologies or use human intuition, psychological methods. And location competition has been studied in different forms such as the comprehensive surveys by Friesz et al [2] in 1989, Eiselt and Laporte [3] in 1989, Eiselt et al. [4] in 1993.

Cheng [5] proposed a GIS approach to shopping mall location selection, which uses electronic mapping technology in producing interactive multi-layer maps so that queries are set to find optimal solutions for problems. It combines spatial and non-spatial data to construct visualized information that can be easily analyzed by decision makers and that cannot be achieved in table or list forms. However, it takes a long time to handle with the geographic information.

Yesilnacar [6] proposed a Site selection methodology for hazardous wastes and also made a case study from the GAP area of Turkey, they explained a method to determine how to locate suitable sites for hazardous waste land filling area by using the site screening study. It demonstrated how the criteria such as geology, topography, land use, climate, earthquake and other related factors can be introduced into the overlayer technique to determine the suitable site selection in a region. However, in his research only focus on the hazardous waste handling, which is a special case and is not suitable for all the factory location selection.

Yu and Li [7] proposed a group decision making fuzzy AHP model and its application to a plant location selection problem. however, giving weights of each item in AHP takes a long time, Kahraman[8] used fuzzy group decision-making for facility location selection, Chen-Tung Chen[16] suggested to use fuzzy approach to select the location of the distribution center.

However, just few researches have been done to offer executable solutions on how to select factory wisely and strategically. And what's more, conventional approaches within this domain can only provide a set of systematic steps for problem-solving without involving the relationship among the decision factors globally. Among those researches, most of them use AHP method or options management method, which is not good enough to give a good location selection result, and especially for some complicated factory location selection problem, conventional methods are time-consuming and inefficient, so we want to use neural networks method to handle with this complicated problems and try to produce a better solution.

The reason why we use neural network is because it is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. And it is good at solving problems that are too complex for conventional technologies say AHP, and what's more, it has an ability to learn how to do tasks based on the data given for training or initial experience. It can create its own organization or representation of the information it receives during learning time.

And also because neural network can tolerate certain fault via redundant information coding.

3. Build neural network

3.1 Selection of input variables for neural networks

The first and most important step to build a neural network is selecting input variables, and we should consider the number of entrants in the entry/location game or strategic variables in the post entry/location game. And during the factory location selection process, various factors could be considered such as: distance between factory and distance from raw material suppliers, distance between factory and customers, distance between factory and its competitors. Figure 1 below show the external factors that influence the selection of factory locations. Here, macro-political factors (P)

means whether policy is stable and tax policy is favorable, material cost(M) means the material is cheap or expensive, business factors (B) including competition condition, market statuses,etc.infrastructure means Natural and social environment and transportation condition.

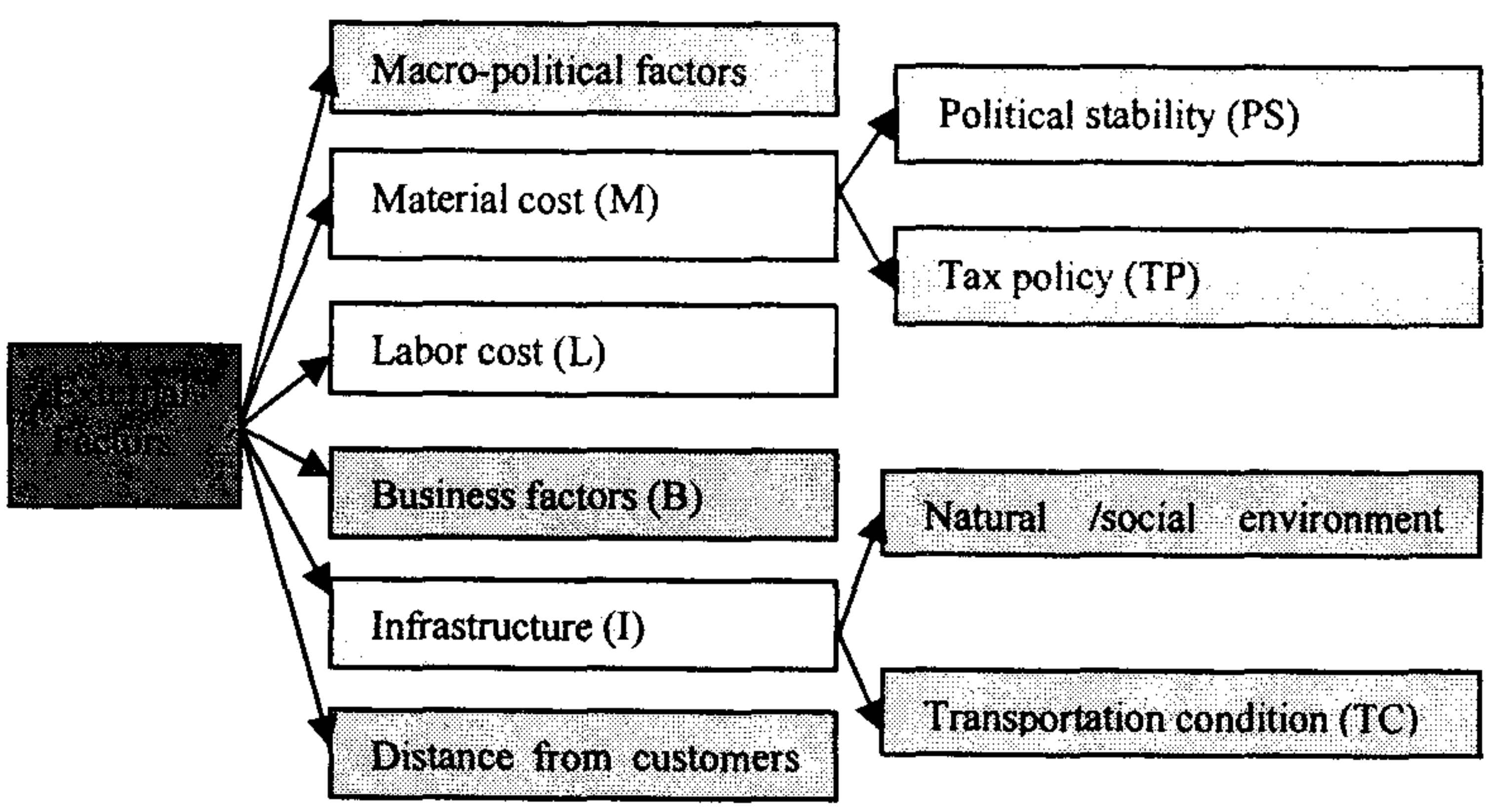

Figure 1- External factors influence factory location selection

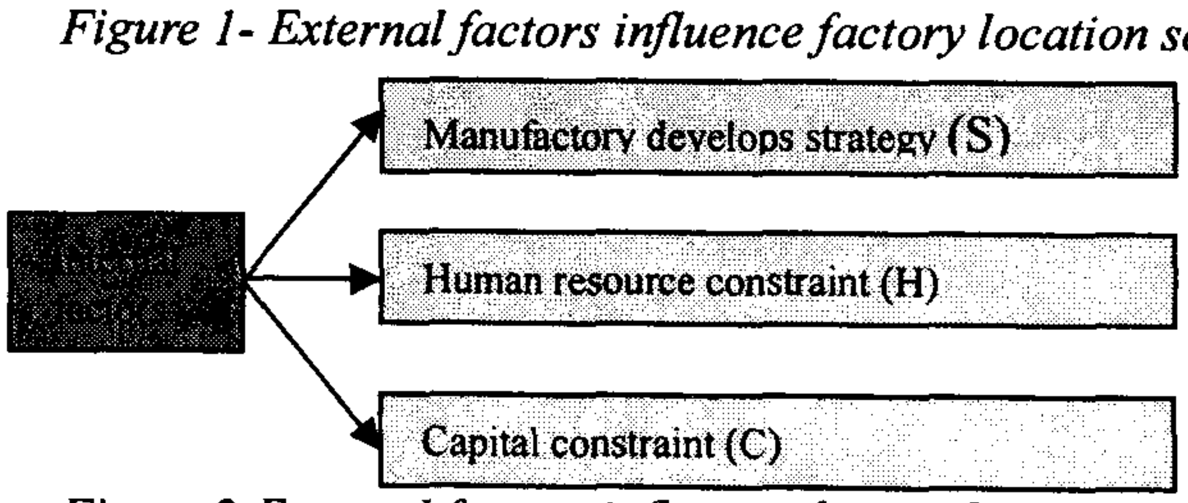

Figure 2-External factors influence factory location selection

Figure 2 above shows the internal factors that influence the selection of factory locations. Manufactory develops strategy (S) means whether the optimized factory location meets the manufactory develops strategy (S), Human resource constraint (H) means whether there are enough human resource in the selected optimized factory location, capital constraint (C) means whether the total operation cost of selected factory meets the company capital constraint(C).

Based on our survey, we finally choose Labor cost (L), Material cost (M) and infrastructure (I) to be the input variables because they are more important than other factors, and what's more, in most of the case, the other factors are the same for the candidate locations (macro-political environment, tax policy are the same), so the other factors are not considered in our research.

3.2 Neural network-based factory selection model (NNFSM)

In order to select the best factory location among many candidate cities, we proposed the following model shown in figure 3 below, and our model consists of three main modules: system input, system process, and system output. The system input module includes Potential alternative factory location, and the system process is using artificial neural networks based algorithms to train the network and calculate the result. Finally, the system will give the optimized profit and best factory location as output.

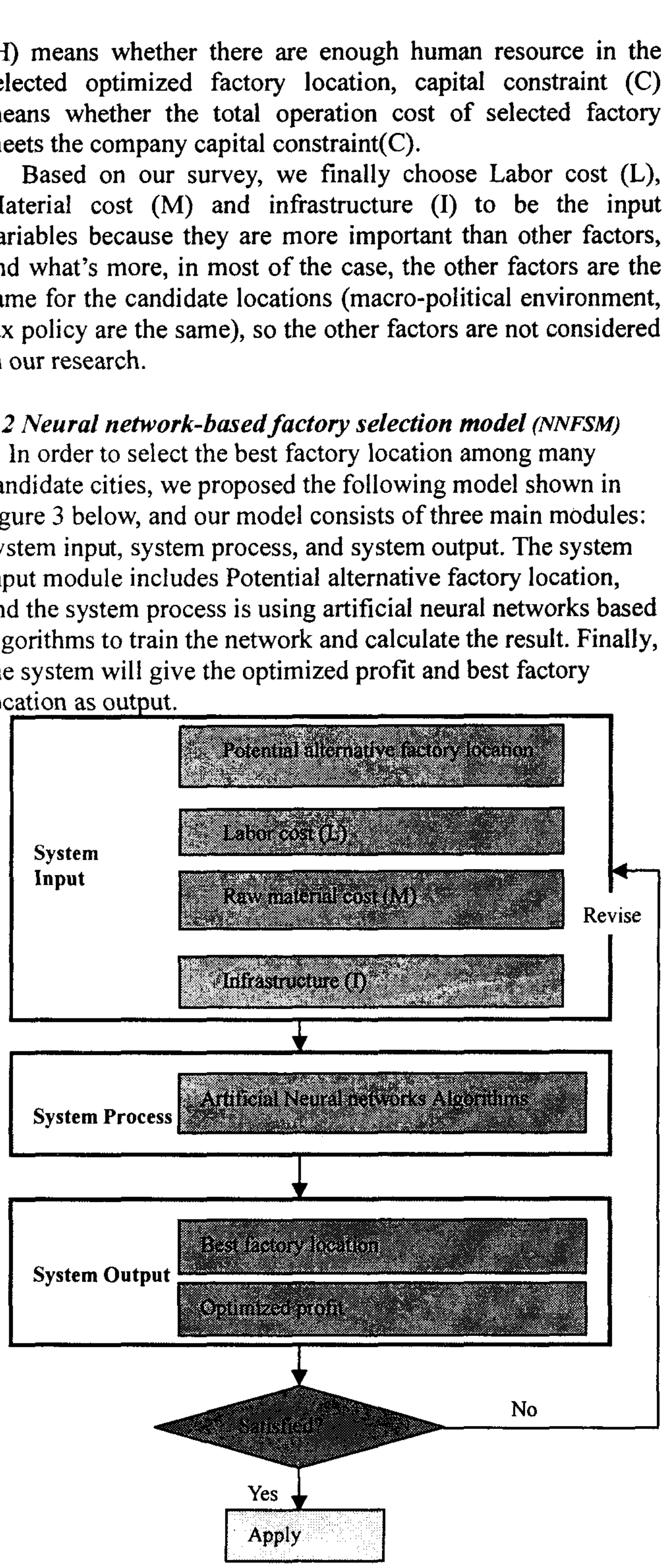

Figure 3- NNFSM model

3.3 Transportation cost-sensitive factory selection

In out proposed NNFSM model, we didn't consider the transportation cost, but if the manager was interested in the reduction of transportation cost and only one factory is needed, we could use the model shown in figure 4 below as a complementary module to our proposed NNFSM model. supposed that there are n cities (Xi , Yi) representing requirement areas, each city i orders some goods to be transported from the factory, we can use the model of single factory location selection to find the optimized factory location($\bar{X}$, $\bar{Y}$).the selected algorithm is shown in figure 5 below:

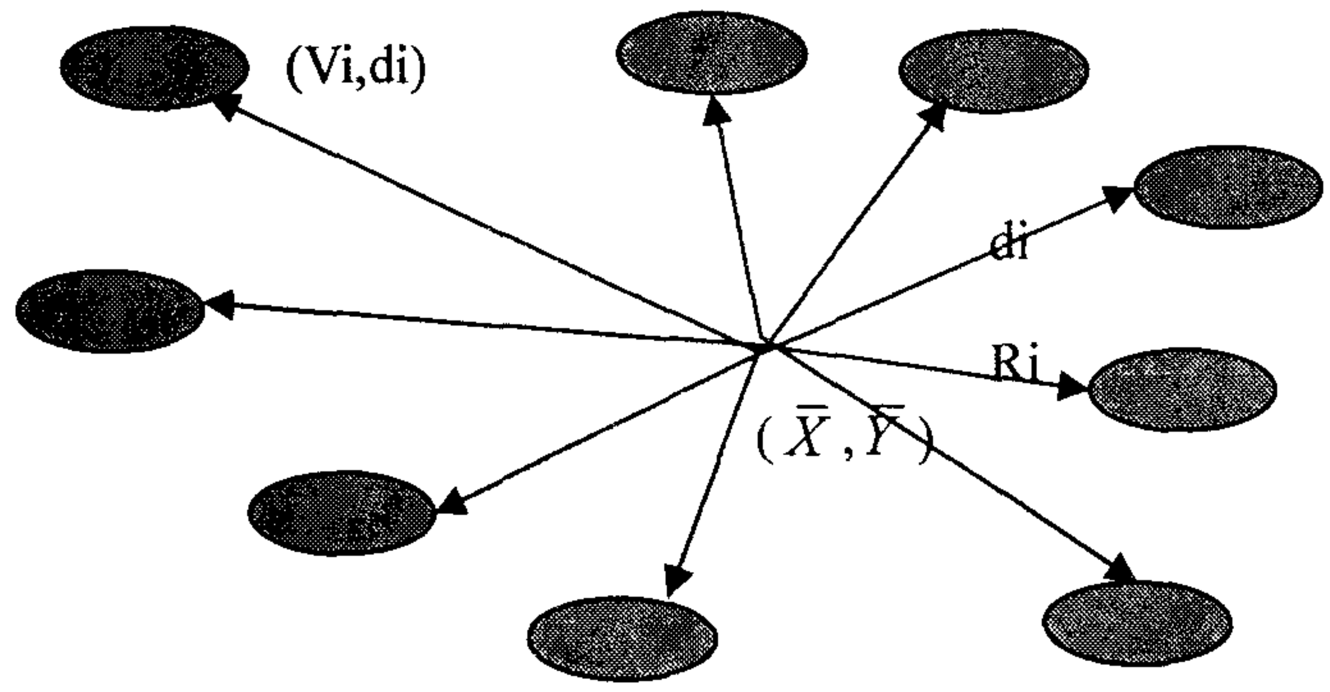

Figure 4-Simple map of single location selection

$$MinTC = \sum_i V_i R_i d_i \qquad \bar{X} = \frac{\sum_i V_i R_i X_i / d_i}{\sum_i V_i R_i / d_i} \qquad \bar{Y} = \frac{\sum_i V_i R_i Y_i / d_i}{\sum_i V_i R_i / d_i}$$

$$d_i = K\sqrt{(X_i - \bar{X})^2 - (Y_i - \bar{Y})^2}$$

Figure5-Selected Algorithm

Here,TC means transportation cost, Vi means transportation volume of city I;Ri means the rate of transportation fee to node I;di means the distance from factory to city I; and the calculation process is shown in figure 6 below:

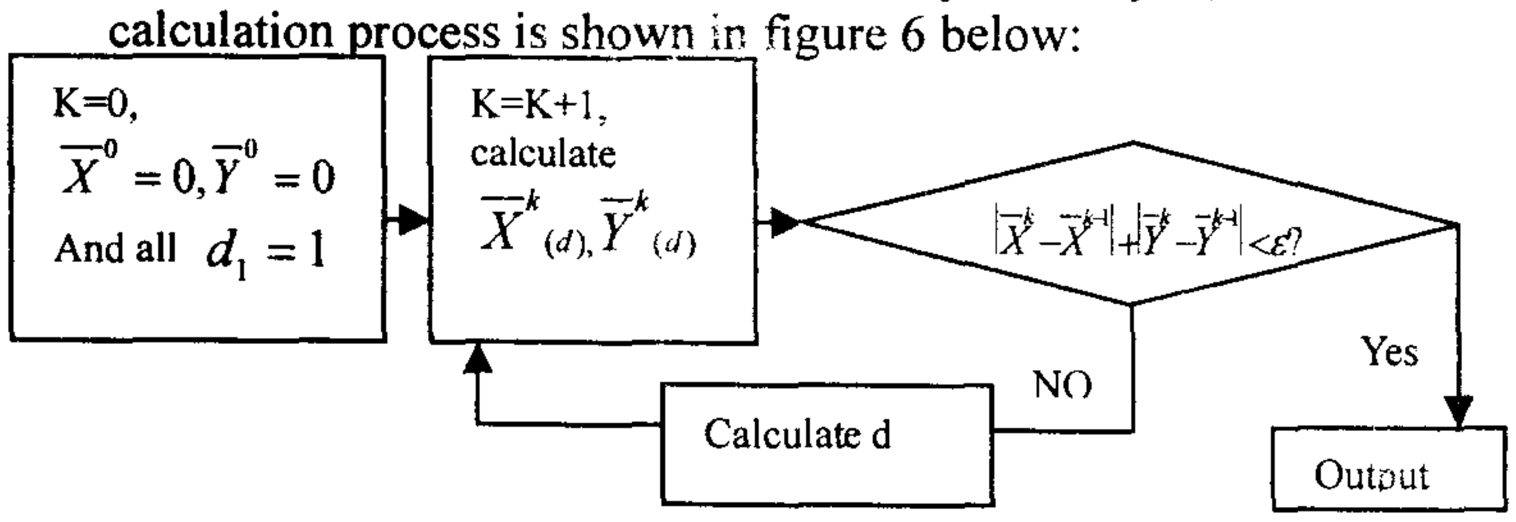

Figure 6-Model of single location selection

4. Neural network factory location selection model (NNFSM)

4.1 Back-Propagation neural network

Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. and the back-Propagation neural network belongs to the category of supervised learning networks because it uses target output to check whether the error is acceptable, and it includes one or more layers of hidden neurons, and the target outputs are employed to evaluate the error between target output and actual output (serves as a teacher).if the teacher determines that the error between itself and each actual output is larger than a tolerance, the learning process continues until the error is within the tolerance.

In order to determine how the selected factors influence the selection of factory location, we try to use the back-propagation neural network theory to map the input factors (Material cost, Labor cost, Infrastructure) to output factor (Profit), and determine the weights on the paths. And we collect certain historical data to train the network to get the optimized mapping function F.so next time, when we want to selection the best factory location, we just need to input the parameters of each city and the neural network will automatically produce the profit according to the mapping function F.and then rank the profit of each city, and city with the largest profit will be the best factory location.

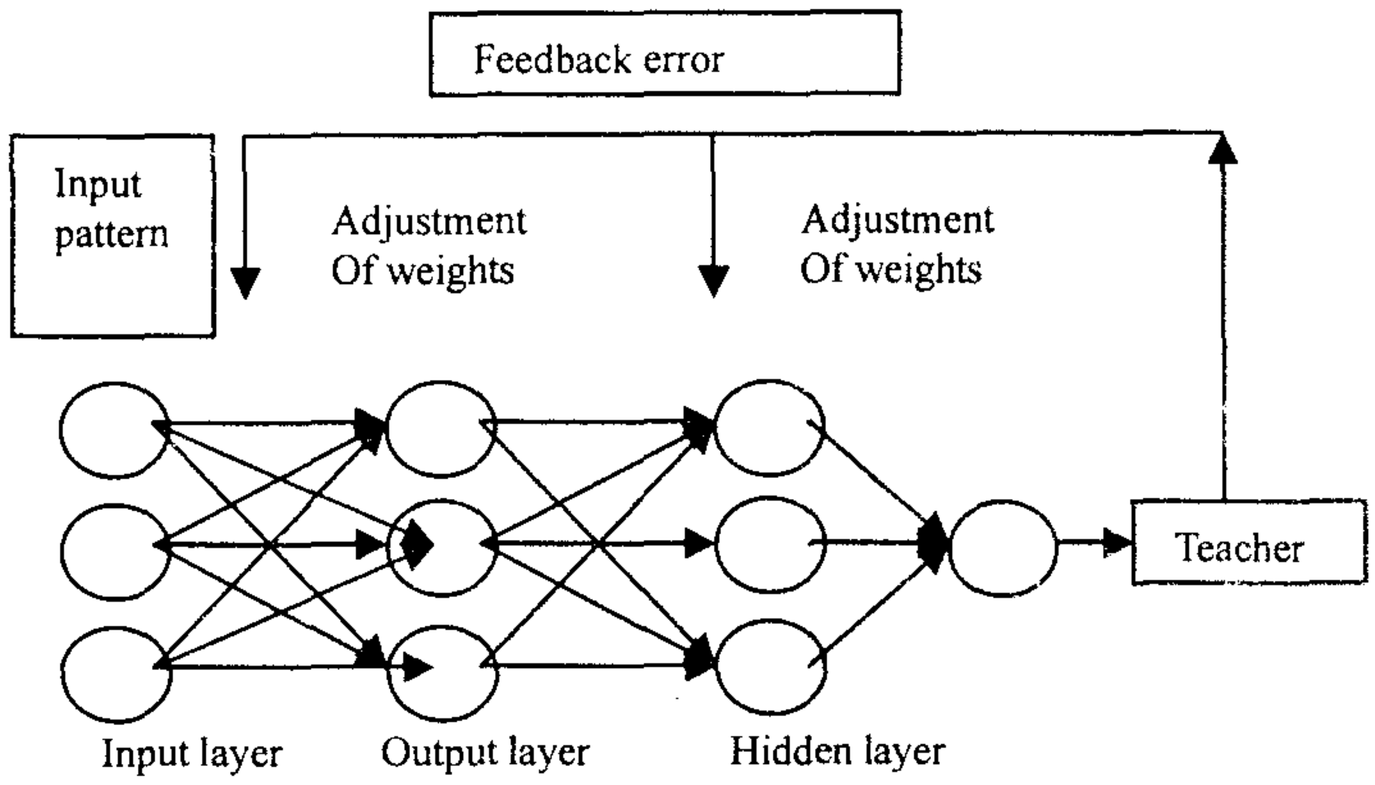

Figure7-proposed back-propagation neural network

We defined a neural network with 4 layers having 3, 3, 3, and 1 neuron respectively as shown in figure 7. Since the first layer is the input layer, a placeholder for the input parameters, it has to be the same size as the number of input parameters, and the last layer being the output layer must be same size as the number of outputs - in our example, these are 3 and 1.

And we developed software by using C++ to realize the back-propagation neural network theory, and we used the algorithm proposed by Rumelhart el al. (1986).in order to train the network, we tried to collect some historical data from P company, in our proposed system, the input variables are: Labor cost (L), Material cost (M) and infrastructure (I),and output variable is Profits(P),so we used eight units of data in table to train the neural network to determine the optimized weights which indicate how the input factors influence the output. Each variables range from 0 to 1, and the closer it is to 1, the better the variable is. (For example, if the Labor cost (L) is 1, it means that the labor cost is the cheapest among all the candidate locations).

4.2 Back-propagation learning algorithm

W e modified the back-propagation proposed by Rumelhart el al. (1986) and add our definition of Mean square error (MSE), the algorithm in our research as shown below:

Step 1. Weight initialization:

Set all weights & node thresholds to small random numbers

Step 2. Calculation of output levels:

(a). The output level of an input neuron is determined by the instance presented to the network.

(b).The output level oj of a hidden neuron is determined as

$$O_j = f(\sum w_{ji}O_i - \theta_j) = \frac{1}{1 + e^{-\alpha(\sum w_{ji}O_i - \theta_j)}}$$

Where wji = weight of input i to neuron j, α is a constant, θj =node threshold and f=sigmoid function.

Step 3. Weight training:

(a). The error gradient is computed as:

For the output neurons: $\delta j = oj\ (1 - oj)(dj - oj)$

Where dj = desired output, and oj = actual output

For the hidden neurons: $\delta j = oj\ (1 - oj) \sum \delta\ kwkj$

Where δk is the error gradient at neuron k to which a connection points from hidden neuron j.

(b). Weight adjustment is computed as: $\Delta wji = \eta\delta j\ oi$

Where η is the trial-independent learning rate ($0< \eta <1$) and δj is the error gradient at neuron j.

(c). Adjust weights are computed as: $wji\ (t+1) = wji\ (t) + \Delta wji$

Where wji (t): weight from i to j at iteration t and Δwji is the weight adjustment.

(d). Perform the next interaction (repeat steps 2 and 3) until the error criterion is met, iteration includes presenting an instance, calculating output levels, and modifying weights.

4.3 How learned is the net?

Besides the back-propagation neural network algorithms described above, we additionally tried to calculate the Mean square error (MSE) as a measure of how well the neural net has learnt.if the MSE is small enough and become acceptable, the neural network training process finished and ready to be used for testing. And the mean square error is defined as below:

$$E(\varpi) = \frac{1}{2}\sum_{K \in outputs}(t_k - o_k)^2$$

4.4 NNFSM learning process

T he figure 8 below shows the process of the NNFSM system.

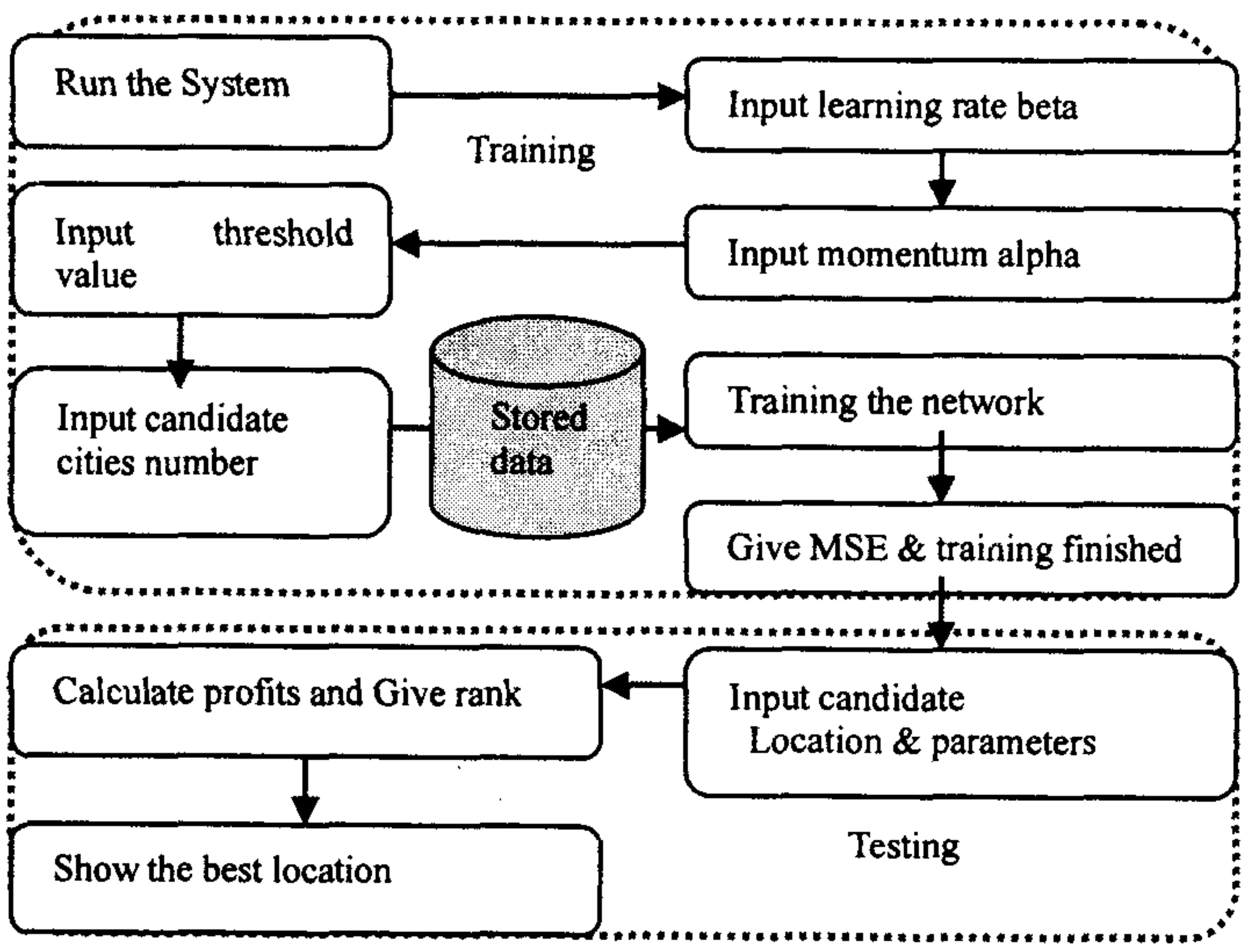

Figure 8-Process of the NNFSM system

Step1. Run the system, user can see the welcome interface

Step2. Users are asked to input the learning rate beta and specify the momentum alpha and threshold value,

Step3. System uses the stored data to train the network, MSE value will be given after the training finished,

Step4. Users is asked to input the candidate cities number and their related parameters as a vector: CITY _Name (Labor cost, Material cost, Infrastructure) or P (L, M, I).

Step5. System will automatically calculate the profit of each city and then give rank of the profits.

Step6. According to the rank of profits, the city with the largest number of profit will be determined as the best factory location.

Here, we should mention that we have arbitrarily given the historical data as the training data, when user wants to use this system in another case; he can easily input the training data by himself to training the neural network again and get a new mapping function F and related weights.

5. Case study

5.1 Objective description

In order to realize the NNFSM system, we tried to apply our proposed system to a Korean steel company P.and our case study consists two main tests, we collected some historical data from P company and use this data to train the "back-propagation neural network", after training, the mapping function between inputs and outputs are determined, then users can input some new candidate factory locations for choosing, our system will calculate and tell users which city is the optimized factory location.

5.2 Data collection

P Company is a famous steelmaking company in Korean, in our case study, we assume that P company want to open another new factory, so the task is to determine the optimized location for the new factory among many candidate cities. And figure 9 below shows the candidate cities for P companies.

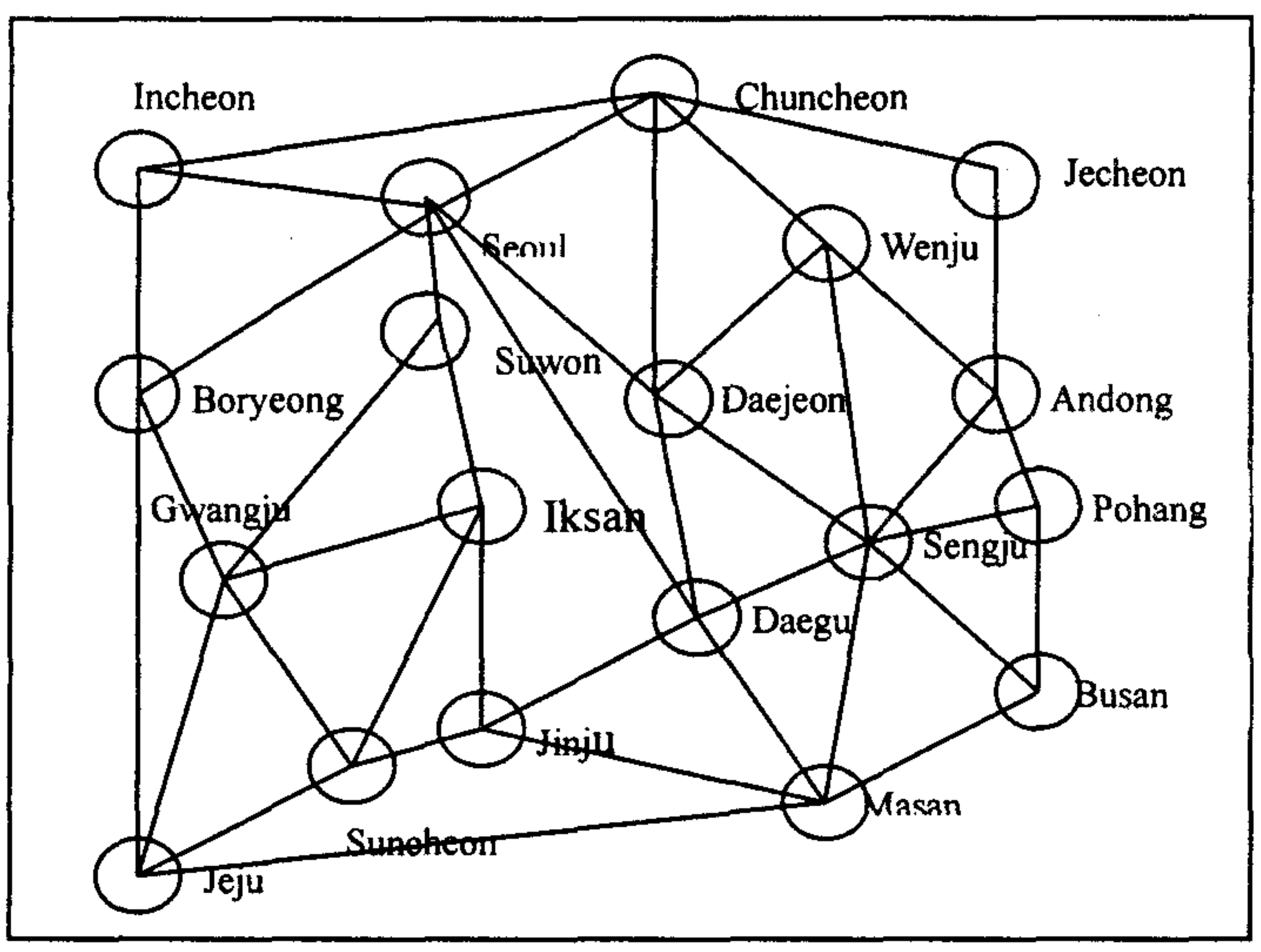

Figure 9-Candidate cities for P companies

5.3 Test: location selection using NNFSM

This test is used to show how to use our proposed NNFSM to select the optimized factory location, because it is very hard to get all the data, so we generated 30 sets of data arbitrarily to train the neural network, the data sets used in this case study are shown in table 1 below:

Labor cost (L)	Material cost (M)	infrastructure (I)	Profits(P)
0.0	0.0	0.0	0.0
0.1	0.8	0.5	0.5
0.2	0.5	0.2	0.3
0.5	0.6	0.7	0.5
0.6	0.7	0.8	0.7
0.5	0.5	0.7	0.6
1.0	0.8	0.4	0.7
1.0	1.0	1.0	1.0
0.1	0.2	0.4	0.2
0.7	0.5	0.4	0.5
0.4	0.1	0.3	0.3
0.3	0.4	0.5	0.4
0.8	0.4	0.3	0.5
0.9	0.5	0.7	0.6
0.1	0.2	0.1	0.1
0.3	0.3	0.3	0.2
0.2	0.8	0.7	0.5
0.5	0.1	0.1	0.2
0.7	0.8	0.5	0.6
0.7	0.5	0.2	0.4
0.4	0.2	0.3	0.2
0.5	0.9	0.6	0.5
0.6	0.1	0.2	0.2
0.8	0.3	0.1	0.3
0.9	0.2	0.6	0.5
0.2	0.1	0.1	0.1
0.1	1.0	0.5	0.4
0.3	0.7	0.5	0.5
0.6	0.2	0.4	0.3
0.8	0.8	0.4	0.6

Table1-Training data sets

Here we must point out that for different area, the network must be trained with their local data, so users have to prepare the historical data before running the system, and this case study just shows the procedures of how to use the NNFSM system to select the optimized factory location.

5.4 Result analysis

After we run the NNFSM, we chose learning rate beta=0.1, the momentum alpha =0.1and threshold value=0.0000001, Table 3 shows that the neuron network training has finished and is ready for using, and then input 3 candidate cities (Pohang,Seoul,Busan) and their parameters for selection, we got the following results shown in table 4. According to the rank of profit of each city: Pohang=0.606488, Seoul=0.553033, Busan=0.582223.soPohang is the best factory location, and in fact company built their factory in Pohang, so the results demonstrate that our proposed model is reliable and useful. And in our experiment, the average time for location selection is 0.12 second, so compared to other methods, our method is time-saving and efficient.

```
Using backprogation nueral network to select the best factory location!:
*************************************************************
Please input the learning rate beta:0.1

*************************************************************
Please specify momentum  alpha :0.1

*************************************************************
Please the threshold value:0.0000001

*************************************************************
```

Table 2-Input parameters for training

```
*******************************************************************

Now training the network....

MSE:  0.28658... Training...

Network Trained. Threshold value achieved in 12457 iterations.
MSE:  5.72842e-008

Now using the trained network to make predctions on test data....
```

Table 3-Neural network training finished

```
Please input the number of cities:3
Please input  city :
Pohang
Please input the candidate city testData[i][j] :0.6
Please input the candidate city testData[i][j] :0.5
Please input the candidate city testData[i][j] :0.8
******************The result is*******************************:
Labor  Material  Infrastructure    Profits
0.6     0.5          0.8           0.606488

Please input  city :
Seoul
Please input the candidate city testData[i][j] :0.4
Please input the candidate city testData[i][j] :0.5
Please input the candidate city testData[i][j] :0.7
******************The result is*******************************:
Labor  Material  Infrastructure    Profits
0.4     0.5          0.7           0.553063

Please input  city :
Busan
Please input the candidate city testData[i][j] :0.6
Please input the candidate city testData[i][j] :0.5
Please input the candidate city testData[i][j] :0.6
******************The result is*******************************:
Labor  Material  Infrastructure    Profits
0.6     0.5          0.6           0.582223

The best factory location is:  Pohang
Press any key to continue
```

Table 4-Location selection results

6. Conclusions and limitations

6.1 Conclusions

In this paper, we developed a neural network-based factory selection model (NNFSM) which adopted back-propagation neural network theory to help managers determine the best factory location, we also developed computer program using C++ to demonstrate our proposed model. And results show that our proposed model an solve very complicated location selection problem in a very short time, it is time-saving and efficient compared to other traditional methods like AHP, so it useful and good enough to help determine the best factory location or classify different factories into certain categories

6.2 Limitations

Our paper has its limitations in that: first, in our NNFSM model, the training data wasn't from the real business world because of the difficulties of data accessing and business secrets; second, we just selected the most important factors for factory location selection, the other factors are neglected, so future research is needed to take all these factors into considerations.

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