Zhi-peng CAO  Fan XIE  
(Faculty of Economic and Management Sciences, Shaanxi University of Science and Technology, Xi-An 710021, P.R. China)

Investment Decision-making Scheme Evaluation Method based on Multi-objective Neural Network / Método de avaliação do processo de decisão de investimento com base na rede de neurônios multi objetivos

abstract

As the investment directions and importance of high-tech enterprises increased largely, it is especially important to choose the most appropriate and effective investment for high-tech enterprises according to national conditions and economic conditions. In view of this, this paper proposes and constructs an investment decision-making scheme evaluation method of high-tech enterprises based on multi-objective neural network. First of all, two evaluation indexed were defined. Then, local search was applied to merge parent group and descendant group. Only those individuals from the first Pareto front could be optimized. The feasibility of the method was verified by investment decision-making scheme evaluation example of commercial bank. The results show that investment decision-making scheme B can best balance initial investment and capacity elasticity. The method proposed in this paper can be generalized to evaluation of other similar investment decision-making schemes.

PALAVRAS-CHAVE:
- rede neural multi-objetivo;
- empresa de alta tecnologia;
- esquema de decisão de investimento;
- banco comercial

resumo

À medida que as orientações de investimento e a importância das empresas de alta tecnologia aumentaram em grande parte, é especialmente importante escolher o investimento mais adequado e efetivo para empresas de alta tecnologia de acordo com as condições nacionais e as condições econômicas. Em vista disso, este artigo propõe e constrói um método de avaliação de planos de decisão de investimento de empresas de alta tecnologia com base em rede neural multi-objetivo. Em primeiro lugar, foram definidas duas avaliações indexadas. Então, a pesquisa local foi aplicada para fundir grupo pai e grupo descendente. Somente aqueles indivíduos da primeira frente de Pareto poderiam ser otimizados. A viabilidade do método foi verificada pelo exemplo de avaliação do esquema de decisão de investimento do banco comercial. Os resultados mostram que o esquema de decisão de investimento B pode equilibrar melhor o investimento inicial e a elasticidade da capacidade. O método proposto neste documento pode ser generalizado para a avaliação de outros esquemas similares de decisão de investimentos.
section i

introduction

High-tech enterprises have unique complexity, so great efforts are required to carefully study the investment of high-tech enterprises. High cost is the first problem that high-tech enterprises need to consider in the investment process. The investment scope of high-tech enterprises is very wide, and many complex factors should be taken into account. There is a complex dynamic system with great influence in the high-tech enterprise. Multiple factors such as social factor, urbanization, environmental condition, energy supply and political balance coexist in the investment of high-tech enterprises and influence any investment decision of high-tech enterprises. Besides, the investment scheme also influences these factors. These complex factors interact and jointly influence high-tech enterprises in the formulation of investment schemes. With the increasingly rise of investment directions and importance of high-tech enterprises, such interaction becomes more and more prominent. During investment evaluation of high-tech enterprises, the interactive effect of these complex factors should be considered, apart from the relevant abilities of high-tech enterprises. Therefore, it is very important to choose the most appropriate and effective investment for high-tech enterprises according to national conditions and economic conditions.

Caliskan proposed a new investment evaluation scheme on the basis of information exchange between the decision maker and the model. Since the scheme has experts’ subjective assessment and takes into account of all possible information, it plays an important role for decision making. In the opinions of Dixit and Pindyck, the method to maximize the project value should be sought in the investment process, and probability method or utility function could not be applied mechanically. They also studied the pricing model of real option. The experience of developed countries show that for high-tech enterprises, they need to effectively reduce the risks caused by technical factors and market factors through making rational and objective decisions when the market fails to form preliminarily and the investment cost is too high. In modern fierce market competition, numerous uncertain factors are often confronted in technology research and development.

According to the information known by the author, domestic and overseas scholars generally apply common investment evaluation systems (such as cost/benefit analysis system) to research investment scheme evaluation problem of social system. However, for the investment decision-making scheme evaluation which involves a wide area and is not easy to control, it is difficult for the common evaluation systems to achieve satisfactory results. In view of this, this paper proposes and constructs an investment decision-making scheme evaluation method of high-tech enterprises based on multi-objective neural network.

section ii

literature review

At present, there is still no widely-accepted investment decision-making evaluation method of high-tech enterprises. Thus, enterprises need to research and develop new decision support methods. Elastic multi-dimension makes high-tech enterprises difficult to evaluate investment decision-making schemes. For high-tech enterprises, their investment can be easily quantified, but it is hard to define the economic benefit. On the basis of summarizing and reviewing enterprise production elasticity evaluation methods, this paper puts forward an investment decision-making evaluation method of high-tech enterprises based on multi-objective neural network.

Schuh et al. developed an evaluation system for key factors in product elasticity, hybrid elasticity and capacity elasticity. This system can effectively assess elasticity of different organizations in an enterprise (workstation, production line, production system or production network), but a specific elastic value estimation method is still not proposed. Abele et al. discussed elastic evaluation with the method of analyzing expanded net present value through real option, and considered the time series structure of decision-related cash flow. Zah et al. also used real option analysis method in relevant researches. The precondition of real option analysis method is as follows: there is a financial option in market transaction, and the cash flow remains unchanged. Thus, the application scope of such elastic evaluation method is very limited.

For different quantity demanded, Alexopoulos et al. calculated the estimated values of production system life cycle
cost through linear programming according to discount cash flow in different market situations within certain time period, then analyzed the estimated values and finally proposed DESYMA method to evaluate the elasticity of production system. Elastic evaluation method proposed by Reinhart includes three steps (definition of evaluation scheme, futures modeling based on uncertain environmental factors and confirmation of economical evaluation scheme). In this method, economic evaluation is conducted with discount cash flow. However, such method is only suitable for capacity elasticity evaluation.

Rogalski et al. came up with an elastic comparison method among different production systems. The method mainly aims at hybrid elasticity and capacity elasticity of systems, figures out elastic area of each system through linear programming and then carries out comparison. Ruhl started from elastic risk standard and studied economic evaluation of production in the system design stage. This research is not oriented to the whole system life cycle, so it is only suitable for capacity elasticity and hybrid elasticity evaluation. So far, there has been no method which can completely achieve scientific evaluation of investment decision-making schemes of high-tech enterprises.

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proposed Method

In this research, one of the objectives (or non-cooperative measure index) is non-continuous measure. The non-continuity is especially obvious in the data sets with few modes. Since such measure makes neural network optimization process difficult to converge, this paper adopts cross entropy method to gain a continuous function and regards it as the first objective.

\[
E(g, \theta) = -\frac{1}{N} \sum_{n=1}^{N} [y_n \log g(x_n, \theta) + (1 - y_n) \log(1 - g(x_n, \theta))]
\]

Here, the advantage of using error function is that it is a continuous function and can promote optimization of more stable and thorough convergence. As the first objective, the function \(E(g)\) is transformed by decreasing progressively, and the transformed function as the fitness standard for optimization, as follows:

\[
A_1(g, \theta) = \frac{1}{1 + E(g, \theta)}, 0 < A_1(g, \theta) \leq 1
\]

Here, \(g\) is a multi-valued function.

\[g(x, \theta) = (g_1(x, \theta_1), g_2(x, \theta_2))\]

The second objective which needs optimization is the minimum sensitivity of classifier. The second fitness function is as follows:

\[A_2(g) = MS(g)\]

In this algorithm, initial population is any group which consists of \(N\) neural network individuals. In the population, the connection weight among individuals is an interval which is established at random (the weight between input layer and hidden layer is \([-2, 2]\); the weight between output layer and hidden layer is \([-10, 10]\); the range values of these intervals are confirmed through experiments). After the initial population is produced, the above two objective functions are used to evaluate it. After the evaluation, Pareto optimality principle can be used to classify individuals in the population, and each individual is given the fitness same with respective non-dominance level. Those non-dominance individuals are selected as parent individuals for genetic manipulation. Then, binary system elimination is conducted for them (the better individuals are chosen after pairwise comparison).

To generate new descendant individuals, mutation operation is required for the chosen parent individuals. Here, there are 5 kinds of mutation operators for choice, where 4 kinds of mutation operators belong to structural mutation and one kind of mutation operators belong to parameter mutation. The probability of choosing any kind of mutation operators and carrying out individual mutation is 1/5. For parameter mutation, Gaussian noise is added in parent connection weight. For structural mutation, population diversity is applied to increase the diversity of search space. To be more specific, mutation operators are actually ‘add/delete neuron’ and ‘add/delete connection’. The newly-generated descendant individuals are added in the next generation of population to repeat the above process until the descendant population quantity reaches \(N\). Then, evaluation of two indexes is conducted for the descendant population and it is merged with the parent population. The newly-generated population is classified according to Pareto principle. The optimal \(N\) individuals
Section iv

Experimental Results

In this chapter, the example of investment decision-making evaluation of commercial bank is applied to verify the feasibility of the method. In the production process of electronic components, there are three investment decision-making schemes for the assembly system. The quantity of products produced by assembly system used in this chapter increases annually.

In investment decision-making scheme A, the whole assembly process includes the following orderly operations: automatic product preassembly, two-level manual assembly, testbed test, soldering station soldering, secondary testbed test, three-level assembly, automatic labeling and packaging. The difference between investment decision-making schemes A and B is that the three-level assembly is changed to automatic assembly. Based on Scheme B, the packaging in Scheme C is upgraded to automatic packaging. Table 1 summarizes the main information of three investment decision-making schemes. It can be seen from Table 1 that, Scheme A presents the minimum initial investment in the assembly system and the output is also the lowest. For Scheme A, three-level assembly is the first operation of capacity limitation, and the second one is packaging. If the capacity of Scheme A can rise to that of Scheme C, the improvement cost of three-level automatic assembly station is 100,000 Yuan, and the improvement cost of automatic packaging station is 120,000 Yuan. The operation cost of each kind of system configuration can be worked out according to non-fixed cost of each production unit and fixed cost decided by the number of employees (40,000 Yuan/year for one employee). For each investment decision-making scheme, the adjustable price of each production unit is 3 Yuan.

### Table 1. Detailed information about three investment decision-making schemes

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Investment</th>
<th>Number of employees</th>
<th>Annual capacity</th>
<th>Per-Unit non-fixed cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>800,000</td>
<td>4</td>
<td>305,000</td>
<td>1.72 Yuan</td>
</tr>
<tr>
<td>B</td>
<td>900,000</td>
<td>3</td>
<td>320,000</td>
<td>1.75 Yuan</td>
</tr>
<tr>
<td>C</td>
<td>1,020,000</td>
<td>2</td>
<td>330,000</td>
<td>1.82 Yuan</td>
</tr>
</tbody>
</table>

Table 2. Product demand situations

<table>
<thead>
<tr>
<th>Year</th>
<th>Situation I (+2% annually)</th>
<th>Situation II (+5% annually)</th>
<th>Situation III (+10% annually)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>280,000</td>
<td>288,000</td>
<td>302,000</td>
</tr>
<tr>
<td>2</td>
<td>286,000</td>
<td>294,000</td>
<td>308,000</td>
</tr>
<tr>
<td>3</td>
<td>291,000</td>
<td>300,000</td>
<td>314,000</td>
</tr>
<tr>
<td>4</td>
<td>297,000</td>
<td>306,000</td>
<td>320,000</td>
</tr>
<tr>
<td>5</td>
<td>303,000</td>
<td>312,000</td>
<td>327,000</td>
</tr>
<tr>
<td>Possibility</td>
<td>50%</td>
<td>35%</td>
<td>15%</td>
</tr>
</tbody>
</table>

Since capacity elasticity is the elasticity requirement required by the assembly system, descriptive contrast is carried out for three kinds of different product demand situations (as shown in Table 2). Their main difference lies in annual demand growth percentage and occurrence possibility. The growth percentage of Situation I is the smallest, but the growth possibility is the largest. Thus, Situation I is a basic situation in the future. Situation II and Situation III are future possible situations.
According to the above information, we assume annual interest rate of demand is 9%, and the return on assets (ROA) of different investment schemes can be gained. The results indicate all schemes can meet the demand of future basic situations, so it is unnecessary to improve the investment decision-making schemes. Table 3 shows the evaluation results of different decision-making schemes. Scheme B has the highest ROA (5.04%), so it is an economical configuration for achieving future basic situations. ROA of Scheme C is very low, because its initial investment and variation cost of each production unit are high.

In this case, the comparison product demand of the system and capacity can display whether it is necessary to improve such assembly system. In Situation II, Scheme A needs to be improved in the fourth year, because the quantity of products demanded has exceeded the production capacity of the system. The improvement cost is 100,000 Yuan. In Situation III, Scheme A needs to be improved twice (the second year and the fourth year). Scheme B needs to be improved in the fourth year. The expected ROF indexes (Resources, Output, Flexibility) of different system configurations are shown in Table 3. Since Scheme A needs improvement in all situations, its expected ROF is 1.7%. Scheme C has the highest capacity elasticity, so its expected ROF is also the highest, i.e. 2.9%.

<table>
<thead>
<tr>
<th>Investment decision-making scheme A</th>
<th>ROA index</th>
<th>ROF index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scheme A</td>
<td>2.9%</td>
<td>1.7%</td>
</tr>
<tr>
<td>Scheme B</td>
<td>5.0%</td>
<td>2.4%</td>
</tr>
<tr>
<td>Scheme C</td>
<td>0.2%</td>
<td>2.9%</td>
</tr>
</tbody>
</table>

Table 3. Detailed information about three investment decision-making schemes

The calculation results show Scheme B is an economical system configuration in all situations. Its ROA is 5%, and the sum of ROA and expected ROF is as high as 7.4%. Therefore, Scheme B is the optimal configuration which balances initial investment and capacity elasticity.

Section V

Conclusions

The investment scope of high-tech enterprises is very wide, and many complex factors need considering. Multiple factors such as social factor, urbanization, environmental condition, energy supply and political balance coexist in the investment of high-tech enterprises and influence any investment decision of high-tech enterprises. In accordance with the information known by the author, for the investment decision-making scheme evaluation which involves a wide area and is not easy to control, it is difficult for the common evaluation systems to achieve satisfactory results. In view of this, this paper proposes and constructs an investment decision-making scheme evaluation method of high-tech enterprises based on multi-objective neural network.

In the method proposed in this paper, the author first defines two evaluation indexes: non-continuous measure index and minimum sensitivity index. The initial population is any group which consists of multiple neural network individuals. After the initial population is generated, the two objective functions mentioned above are used to evaluate it. After the evaluation, the individuals in the population can be classified according to Pareto optimality principle. Each individual is given the fitness same with respective non-dominance level. Those non-dominance individuals are selected as parent individuals for genetic manipulation. Then, binary system elimination is conducted for them. In this algorithm, local search is applied to merge parent group and descendant group. Only those individuals from the first Pareto front could be optimized. After the optimization, the fitness of each individual is updated in terms of approximate error.

The example of investment decision-making evaluation of commercial bank is applied to verify the feasibility of the method. The results show Scheme B is the optimal configuration which balances initial investment and capacity elasticity. This method can be generalized to evaluation of other similar investment decision-making schemes.
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acknowledgments

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reference

Biography

Zhi-peng CAO (1971-), Male (Han Nationality), Xi-an City, Shaanxi Province, associate professor, Shaanxi University of Science and Technology, his research interest is applied economics.

Fan XIE (1977-), Female (Han Nationality), Tian-shui City, Gan-su Province, Ph. D student, Shaanxi University of Science and Technology, her research interest is Light industry technology economy and management.

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