第 30 卷 第 3 期　　自 动 化 学 报　　Vol. 30, No. 3
2004 年 5 月　　ACTA AUTOMATICA SINICA　　May, 2004

Genetic Algorithm and Fuzzy Synthetic Evaluation Based Risk Programming for Virtual Enterprise[1)]

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Abstract Virtual enterprise is a potential mode for enterprises in the future. The risk management for virtual enterprises has become a hot research area recently. Risk programming is one of the important stages of risk management. There is always lack of historical data and there are many uncertain factors in a virtual enterprise. Hence, in this paper, a fuzzy synthetic evaluation embedded nonlinear integer programming model of the risk programming is established for the virtual enterprise and a fuzzy synthetic evaluation embedded genetic algorithm is presented for the model. Examples suggest the usefulness of the method. Using this method, the global risk level of the virtual enterprise is minimized by combinatorial optimization of risk solutions with the constraint of risk investment.

Key words Virtual enterprise, risk programming, genetic algorithm, fuzzy synthetic evaluation

1 Introduction

Risk programming as one of the important stage of risk management is a process to determine the risk management strategy and to realize concrete measures and means. In this process, the known risk will be eliminated as soon as possible. For the risk that cannot be eliminated, the characteristics may be changed so that the probability and loss of the risk will be limited. Under certain risk investment, the global risk level of an enterprise or a project is minimized[1~4]. The virtual enterprise is a complex system composed by many functional parts. For risk evaluation of such a complex system, the method of system analysis should be used. In the view of system, operation rules of each risk are investigated to determine the global risk level according to a thorough analysis of the goals and each function of the system as well as the relationships among them. At the same time, a virtual enterprise is a dynamic alliance composed temporarily due to market opportunity[5,6]. The risk management of the virtual enterprise is without historical materials and mainly relies on personnel experiences with subjective judgments being fuzzy. In this paper, the risk programming for a virtual enterprise is considered from the system point of view. Using the theory of fuzzy mathematics, the fuzzy synthetic evaluation embedded nonlinear integer programming model is established and the fuzzy synthetic evaluation embedded genetic algorithm is presented for the model. The simulation analysis suggests the effectiveness of the method.

2 Problem and model description

Risk programming problem of virtual enterprise can be described as the fuzzy description of each risk factor of each risk with and without risk control strategies. By the risk control strategies, the risk factor will be controlled in some way. There are some strategies for each risk. The affection of each strategy on the corresponding risk is different, so

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1) Supported by National Natural Science Foundation(70101006, 60003006), the National High-Tech Research and Development Plan(2001AA121064), the Natural Science Foundation of Liaoning Province(20032018, 20032019, 001015) and the Science Foundation for the Returned overseas Chinese Scholors, State Education Ministry
Received April 13, 2003; in revised form October 8, 2003
收稿日期　2003-04-13；收修改稿日期　2003-10-08

the description of each risk factor and the cost of the different control strategy are different. Risk programming tries to minimize the global risk level by optimally combining these strategies constrained by the certain risk investment. Hence, the risk programming problem can be described as follows.

$$\min(\text{Global risk level}) \tag{1}$$

$$\text{s. t.} \quad \sum_{i=1}^{n}\sum_{j=0}^{J_i} c_{ij}x_{ij} \leqslant S \tag{2}$$

$$\sum_{j=0}^{J_i} x_{ij} = 1, \quad i = 1,2,3,\cdots,n \tag{3}$$

$$x_{ij} = 0, \text{ or, } 1, \quad i = 1,2,\cdots,n, \ j = 0,1,\cdots,J_i \tag{4}$$

where $x_{ij} = \begin{cases} 1, & \text{strategy } j \text{ is selected by risk } i \\ 0, & \text{strategy } j \text{ is not selected by risk } i \end{cases}$

S: the total investment for the risk control

i: the index of the risk

j: the index of the risk control strategy

(strategy 0 for risk i means that no strategy is used for this risk)

c_{ij}: the cost of strategy j for risk i

n: risk number

J_i: available strategy number for risk i

The objective of the model is determined by the fuzzy synthetic evaluation hierarchical model of risk evaluation, which is given in Fig. 1.

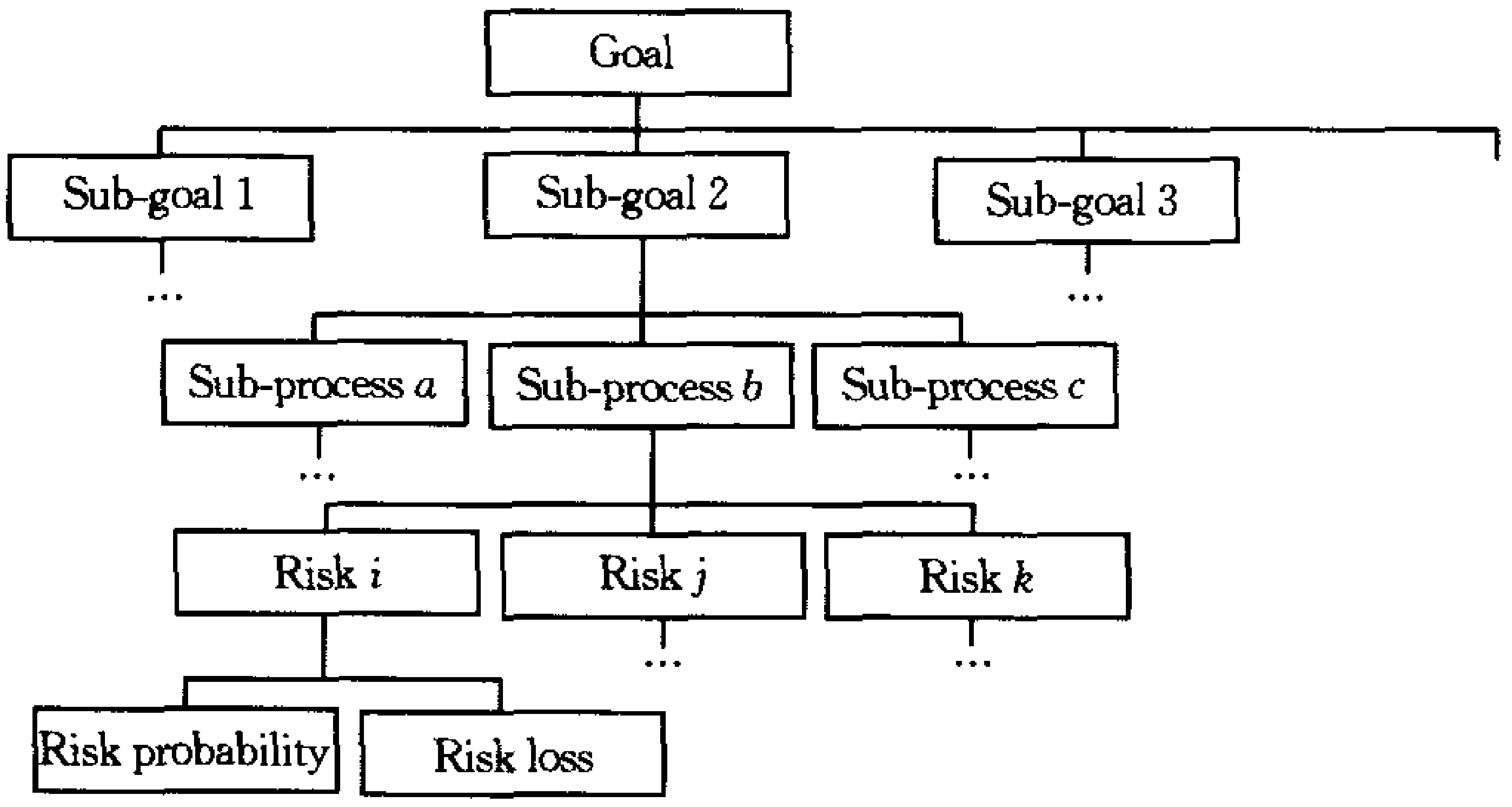


Fig. 1 The hierarchical model for risk evaluation

In Fig. 1, it can be seen that the risk evaluation is dealt from local level to global level. The two risk factors, risk probability and risk loss, are considered. For the virtual enterprise, the fuzzy description of these two factors with different control strategies is known. Also, the relative weights of the lower level factors to the upper level factors are known. Hence, the global risk level for a certain risk programming solution can be obtained by this model.

3 Algorithm

Model (1)~(4) is the hybrid of combination problem and integer programming. The size of the solution space (the number of feasible solutions) of problem (1)~(4) can be determined by the number of risks and control strategies for the risks, which is $\prod_{i=1}^{n} C_{J_i+1}^{1}$ with no constraint. It is easy to see that the problem is NP-hard. Therefore, a heuristic algorithm of this problem is needed for practical use. Due to the advantage of genetic algorithm for this kind of optimization problem[7~9], a fuzzy synthetic evaluation embedded genetic algorithm is designed here.

1) The chromosome representation scheme

For GA in our problem, the natural number string (including 0) is selected as the gene description. Each digit stands for the risk control strategy selected for the corresponding risk. For example:

$$(1,3,4,2,2,2,3,3,3,0,4,\cdots)$$

In the example, bit 1 stands for that control strategy 1 of risk 1 is selected; bit 2 stands for that control strategy 3 of risk 2 is selected, and so on. It is noticed that bit 10(*i. e.*, digit 0) indicates that no strategy of risk 10 is selected. Not all the risks are controlled in a risk programming solution due to the limited risk control investment.

2) The initial population

For each risk, a random number from 0 to J_t is generated. For the individual not satisfying the constraint in the initial population, it is deleted and replaced by a new individual randomly generated till the constraints are satisfied.

3) The fitness

According to the chromosome representation scheme, an individual stands for a risk control solution. For each solution, global risk level under the corresponding solution can be gained by fuzzy synthetic evaluation model[10].

According to the risk fuzzy synthetic evaluation model in Fig. 1, let L be the level number of fuzzy synthetic evaluation model, l be the counter of level. The goal is on the level 0, the sub-goal is on the level 1, and so on. Let K_l be the factor number of level l, k be the counter of factor number, $\boldsymbol{a}_k=(a_{k1},a_{k2},\cdots,a_{kM})$ be the weight vector of factors under factor k on level l, M be the factor number under factor k on level l, m be factor counter under factor k on level l, $V=\{v_1,v_2,\cdots,v_n\}$ be the set of evaluation, $\boldsymbol{b}_k$ be the fuzzy evaluation of factor k on level l, R_k be the fuzzy evaluation matrix composed of fuzzy evaluation of each factor under factor k on level l. The steps of fuzzy synthetic evaluation are as follows.

1) $l=L-2$; k from 1 to K_l, determine R_k according to V, then:

$$\boldsymbol{b}_k=\boldsymbol{a}_\kappa\circ R_k=(b_{k1}\quad b_{k2}\quad\cdots\ b_{kn})\ (k=1,2,\cdots,K_l) \tag{5}$$

The synthetic evaluation of level l is finished, and

2) If $l=0$, stop. Otherwise, let $l=l-1$ and

3) Let k from 1 to K_l, according to

$\boldsymbol{b}_m=(b_{m1}\quad b_{m2}\quad\cdots\quad b_{mn})\ (m=1,2,\cdots,M)$, R_k is given as follows.

$$R_k=\begin{Bmatrix}B_1\\B_2\\\vdots\\B_M\end{Bmatrix}=\begin{Bmatrix}b_{11}&b_{12}&\cdots&b_{1n}\\b_{21}&b_{22}&\cdots&b_{2n}\\\cdots&\cdots&\cdots&\cdots\\b_{M1}&b_{M2}&\cdots&b_{Mn}\end{Bmatrix}$$

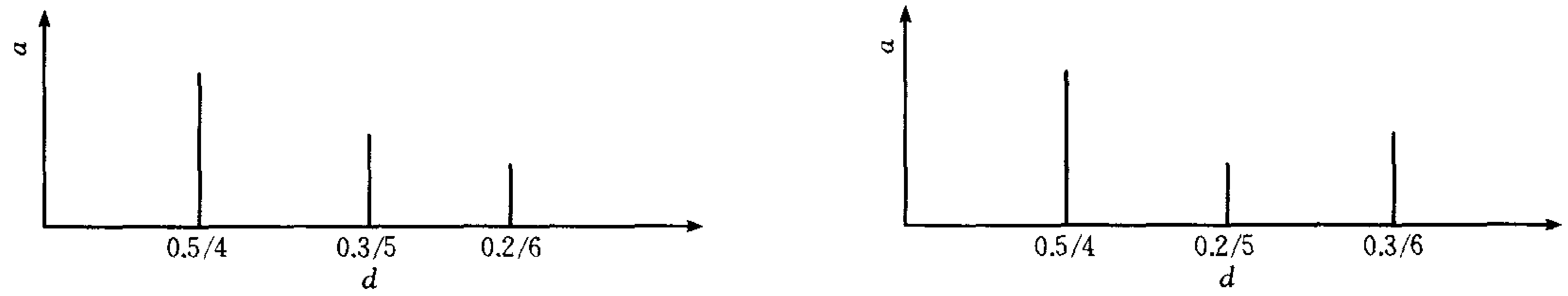
Then, according to (5) the synthetic evaluation of level l is finished, and turn to 2).

In order to give the evaluation of the global risk, the evaluation criteria for the global risk level are given in Table 1.

Table 1 The evaluation criteria for the global risk level

Risk rank	0	1	2	3	4	5	6	7	8
Risk level	None	Smallest	Smaller	Small	Medium	Not too big	Big	Bigger	Biggest

The global risk level can be determined according to the rule of maximum membership degree, as the solution of fuzzy synthetic evaluation is fuzzy. However, many solutions may have the same global risk level by this way, as shown in Fig. 2, where d is the risk rank, and α is the membership degree.



(a) (b)

Fig. 2 The fuzzy synthetic evaluation values of different solutions

According to the rule of maximum membership degree, the global risk level of the two solutions in Figs. 2(a) and 2(b) are the same, that is, 4. However, the risk state of Fig. 2(a) is better than that of Fig. 2(b) when considering all the membership degrees of these solutions, which cannot be shown according to the rule of maximum membership degree. Therefore, considering the membership degree and risk states, the objective is modified as follows.

$$\min\left(\sum_{q=1}^{Q} d_q^p \alpha_q^p\right) \tag{6}$$

where q is the risk rank, Q is the number of risk rank and p is an integer larger than 0.

According to the objective in equation(6) and the proportionate selection strategy of genetic algorithm, the fitness function is defined as the reciprocal of the objective as follows.

$$FIT = 1\Big/\left(\sum_{q=1}^{Q} d_q^p \alpha_q^p\right) \tag{7}$$

4) Selection strategy

Roulette wheel selection strategy is used for this problem.

5) Crossover

The individuals selected by the roulette wheel selection strategy are used as fathers separately, the selected individuals by the roulette wheel selection strategy are selected randomly as mothers. Generate a cut-point randomly; the parts before the point and the parts after the point of the two parents are exchanged. The offsprings generated by crossover can be legal, however, may not satisfy the cost constraint (2). If the constraint (2) is not satisfied, the offspring is given up and the new offspring is generated till the constraint is satisfied.

6) Mutation

The individuals selected by the roulette wheel selection strategy are selected randomly as father. Then, bit i is selected from the father chromosome randomly and alerted between 0 and J_i. The offspring generated by mutation may not satisfy the cost constraint (2). If the constraint (2) is not satisfied, the offspring is given up and the new offspring is generated again by changing alerted bit till the constraint is satisfied.

7) Stopping rule

The maximum number of generations is used as the stopping rule.

4 Simulation analysis

Setting the values for various parameters in the genetic algorithm affects the efficiency of the algorithm. Simulation analysis has shown that the population size Pop_size=250, the maximum number of generations $GN=250$, the crossover probability $P\_c=1$ and the mutation probability $P\_v=0.5$ are the reasonable parameter combination for this problem. And then, the effect of problem scale on the algorithm is studied.

The first problem is with 5 sub-goals, 5 sub-processes and 20 risks. The control strategies (including no control strategy) number for each risk is shown in Table 2. There are 96,745,881,600 solutions for this problem with no constraint.

Table 2 The number of risk solutions for each risk

Risk	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Strategy number	3	3	3	3	3	3	3	3	3	3	4	4	5	5	4	4	4	4	4	4

The second problem is with 5 sub-goals, 5 sub-processes and 30 risks. The control strategies (including no control strategy) number for each risk is shown in Table 3. There are 8,916,100,448,256,000 solutions for this problem with no constraint, which is 92160 times larger than the first problem.

Table 3 The number of risk solutions for each risk

Risk	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Strategy number	4	4	5	5	3	4	3	3	3	4	3	3	5	4	3
Risk	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Strategy number	3	2	2	4	4	4	3	2	3	4	4	4	4	3	3

Using the reasonable parameter combination, the optimal rate is given in Table 4. It has shown that the optimal rate is lower as the scale of problem is bigger. However, the optimal rate is stable as the scale enlarges. Moreover, the increase of CPU time is acceptable. And the increase is mainly due to the effect of problem scale on fuzzy synthetic evaluation. In general, the algorithm is better.

Table 4 The effect of problem scale on optimization rate

Problem scale	Pop_size	*GN*	P_c	P_v	Rate(%)	CPU time(s)
96,745,881,600	250	250	1	0.5	98	3.7
8,916,100,448,256,000	250	250	1	0.5	73	4.2

5 Conclusions

In this paper, the fuzzy synthetic evaluation embedded nonlinear integer programming model of the risk programming for virtual enterprise is established according to the uncertain and fuzzy information of virtual enterprise. Further, considering the characteristics of model and the advantage of genetic algorithm for combination optimization problem, the fuzzy synthetic evaluation embedded genetic algorithm is presented for the model. Finally, the effectiveness of the proposed method for the problem is verified by simulation analysis.

References

1 Kliem R L, Ludin I S. Reducing Project Risk. England:Gower,1997

2 Rogers G O. Survey of approaches for assessing and managing the risk of extremes. *Risk Analysis*, 1999, **19**(1): 83~94

3 Haimes Y Y. Risk Modeling, Assessment and Management. New York: Wiley, 1998

4 Lu Y, Lu J. Project Risk Management. Beijing: Tsinghua University Press,1998(in Chinese)

5 Park K H, Favrel J. Virtual enterprise-information system and networking solution. *Computers and Industrial Engineering*, 1999, **37**(1): 441~444

6 Davis M, O'Sullivan D. Systems design framework for the extended enterprise. *Production Planning and Control*, 1999, **10**(1): 3~18

7 Michalewicz Z. Genetic Algorithms+Data Structure=Evolution Programs. Second ed. New York: Springer-Verlag, 1994

8 Gen M, Cheng R. Genetic Algorithms and Engineering Design. New York: John Wiley & Son Press, 1996

9 Dai J, Zhang J, Mao J. Fuzzy-tree modeling based on genetic algorithm. *Acta Automatica Sinica*, 2000, **26**(5): 707~710(in Chinese)

10 Zimmermann H J. Fuzzy Set Theory and Its Applications. Third ed. Norwell, Mass. : Kluwer Academic, 1996

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基于遗传算法和模糊综合评价的虚拟企业风险规划

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摘 要 虚拟企业是未来企业的潜在发展模式，虚拟企业的风险管理是当前研究的热点问题，风险规划是风险管理的重要阶段之一. 本文针对虚拟企业缺少历史资料、不确定因素多等特点，提出了非线性整数规划和模糊综合评价相结合的风险规划问题描述模型以及遗传算法与模糊综合评价相结合的问题求解算法. 实例仿真验证了该方法的有效性. 该方法能够实现在一定风险费用投入的情况下，通过优化组合风险处理措施，达到虚拟企业整体风险水平最低的目标，是虚拟企业风险规划的科学管理方法.

关键词 虚拟企业，风险规划，遗传算法，模糊综合评价

中图分类号 TP29