AI-based project risk management process for a kind of manufacturing alliance

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Abstract: In this paper, an artificial intelligence-based project risk management process is proposed to implement quantitative risk management for a kind of manufacturing alliance in the agile manufacturing environment. After the literature review, a multiphase project risk management process is formed consisting of risk analysis, risk evaluation and risk control. Probability Risk Analysis is used as the main quantitative risk analysis technique. Some forms of mathematical programming models are formulated in risk evaluation and risk control phases. Because of the complexity, non-linearity, multiobjective stochastic constraints or interval or fuzzy coefficients of these models, they cannot be solved easily by conventional methods. Genetic algorithms are designed. A real life example is also given and the computational results illustrate the efficiency of the algorithms.

Keywords: risk management; virtual organisation; genetic algorithm; agile manufacturing.

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1 Introduction

Since the concept of agile manufacturing was proposed in 1991, it has been attracting great attention from the academic and industrial society (Nagel and Dove, 1991). With total integration of virtual organisations, the advanced flexible manufacturing techniques and the high quality staff, agile manufacturing can enable enterprises to cope with the rapidly changing and unpredictable market needs and eventually to gain long-term profits. As a totally new mode of manufacturing organisation to improve enterprises' competitiveness, agile manufacturing will be the future direction for the manufacturing industry in the 21st century (Kidd, 1994).

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As an important realisation of agile manufacturing, virtual organisation is an alliance or a party composed by several enterprises and aims to respond to market opportunities that ever happened or are forthcoming (Goldman et al., 1995). Usually, in virtual organisation, there is a sponsor, each enterprise has its own core competence, all enterprises share common risk and profits (Heather, 1994). How to quantify, analyse and control risk, how to set up and solve quantitative mathematical models in virtual organisation is an important research area (Cao, 2002).

In this paper, an artificial intelligence-based project risk management process is proposed to implement quantitative risk management for a kind of manufacturing alliance. The sponsor of the alliance is a global enterprise who establishes the virtual organisation in order to complete a manufacturing project according to a customer contract. The manufacturing project is divided into several tasks based on Work Breakdown Structure (WBS) and the precedence relationships between the tasks form an activity network (Elmaghraby, 1997). The sponsor subcontracts out some portions of the project by tendering and finds the best partners to complete the tasks because the realisation of all the tasks requires capabilities outside its expertise.

Firstly, we make a literature review of virtual organisation, risk management, mathematic programming and genetic algorithm. Then, we give a formal definition of risk and construct the framework of the project risk management process based on this review. The main risk analysis techniques used here is Probability Risk Analysis (Miller and Rubin, 1979). After designing the project implementation strategy, one theorem is proposed on the relationship between activity risk and project risk by using Event Operation Theory and Probability Theory (Parzen, 1960). Two project risk control methods are proposed and carried out when the project risk is high. One is risk control funds distribution. The other is backup partner selection.

In order to implement quantitative risk management, the related problems are formulated into mathematic programming models. Because of the complexity, non-linearity, multiobjective stochastic constraints or interval or fuzzy coefficients of the above models, they cannot be solved easily by conventional methods. Several genetic algorithm approaches are proposed. The approaches are demonstrated by some numerical examples. The results show that the suggested approaches have high efficiency and the models have potential for practical applications.

This paper is organised as follows. We give a literature review in the next section. The basic theory of this paper is outlined in Section 3. In Section 4, a multiobjective mathematical programming model in risk evaluation phase is illustrated and solved by using genetic algorithm. The research work introduced in this paper is part of a project. The researching achievements of the project are applied to one-of-a-kind manufacturer in eastern China. A real life example is given to illustrate the efficiency of the algorithm in Section 5. The final section concludes the work of this paper and discusses the future research directions.

2 Literature review

2.1 Virtual organisation

Organisations today must constantly adapt to the ever-changing, fiercely competitive business environment not only to be successful but also to survive. There are a host of external and internal forces that make constant change almost a necessity. Rapid changes in customers' tastes and needs, incredible advancements in technologies, phenomenal growth in the internationalisation of business, volatile capital markets, varying employee attitudes and changing customer demographics are all part of the fluid scenario (Nagel and Dove, 1991).

Because it is difficult to keep pace with these forces and because resources are limited, many organisations forge alliances and/or partnerships with other organisations to share skills, technologies, costs and access to one another's markets and data. More now than ever, organisations must share skills and technologies. Network organisations, modular organisations and virtual organisations have evolved as a result of the new need for interdependence. Virtual organisations have become particularly popular in recent years (Martinez et al., 2001).

A virtual organisation is a temporary network or loose coalition of manufacturing and administrative services that comes together for a specific business purpose and then disassembles when the purpose has been met. Firms team up in a virtual organisation to exploit an opportunity in the market before it evaporates. Shared costs, shared profits and shared risks are components of the virtual organisation (Mikhailov, 2002). Because virtual organisations offer advantages such as profitability and efficient use of time, they have been growing in number.

Focus on customer needs, choice of right partners with the right core competency and win-win outcome of all participating organisations are the key success factors of virtual organisation (Wu and Su, 2005). The success of a virtual organisation also depends on the rapidly developed communication technology, information technology and advanced manufacturing technologies (Aagedal et al., 1999). The research works on virtual organisation mainly focus on three fields, the drivers (Christie and Levary, 1998), the implementing technologies (Lau et al., 2000) and management (Gou et al., 2003) of virtual organisations. How to quantify, analyse and control risk, how to set up and solve quantitative mathematical models in virtual organisation is an important research area (Cao, 2002).

2.2 Project risk management

Projects differ from routine operations. A project is generally considered to be a one-time endeavour with a specific goal, constrained by time and resources (Dawson, 2000). As globalisation increases, project-style work becomes an increasingly important aspect of business life. Project management is a topic that has recently generated great interest in organisations worldwide (Do and Yin, 1999). Projects are often executed by interdisciplinary teams and supported by outside entities such as subcontractors, partners and suppliers. Modern tools, techniques and methodologies for project management were applied in the defence, aerospace, science and construction sectors (Turner, 2000), such as net income, return of investment, payback period, internal rate of return and net present values. Managers are highly aware of and regularly use some advanced techniques that account for uncertainty, namely forecasting, risk analysis and risk-adjusted NPV. Risk management, currently, has an important bearing on the outcomes of major projects (Chapman, 1997).

The words of risk have been and continue to be a problem. Kaplan (1997) suggested that each author defines risk in his own way, only that each should explain clearly what way that is. Usually, in order to define risk, one needs to know three points, What can happen? (What can go wrong?), How likely is it? (What is its frequency probability?) and What are the consequences? (What is the damage?).

Risk management has been widely applied in many fields (Kaplan and Garrick, 1981). Several authors have formulated different risk management approaches. Cooper and Chapman (1997) and Chapman and Ward (1997) identified risk management approach as a multiphase 'risk analysis' which covers identification, evaluation, control and management of risk. Hertz and Thomas (1983) proposed it as a logical sequence of steps consisting of risk identification, risk measurement, risk evaluation and reevaluation. Similarly, Hayes et al. (1987) formulated a risk management approach consisting of risk identification, risk analysis and risk response. In this paper, the project risk management process consists of three main phases – risk analysis, risk evaluation and risk control. The risk analysis phase involves evaluating the extent and the consequence of the risk events. The risk evaluation phase involves identifying several decision alternatives (or scenario) and selecting the best one by evaluation and comparison. In the risk control phase, the alliance can examine the progress as well as any deviations that would occur and corrective actions required for achieving the desired objectives of the project.

Risk analysis has been developed into a subject in the last two decades. The main decision in risk analysis field is the choice of techniques (Baker et al., 1998). The techniques of risk analysis are broadly categorised into two groups, namely qualitative and quantitative methods (Miller and Rubin, 1979). Qualitative techniques are used to distinguish the possibility of a risk occurring in a linguistic manner and usually employed at the beginning to identify and rank risk. Those risks with a high or intermediate rank may be further analysed through quantitative techniques. Quantitative techniques are normally mathematically and/or computationally based and provide numerical probabilities or frequencies of the consequences and likelihood of identified risk. The value used in these techniques can be obtained from historical databases or are estimates and they still contain some extent of uncertainty, due to the possible use of subjectively attained values. Usually, the project manager can take four countermeasures to control risk, namely, risk obviation, risk retention, risk transfer and risk reduction (Miller and Rubin, 1979).

In this paper, Probability Risk Analysis is used as the main quantitative risk analysis technology. In this method, the probabilities of basic events are the variables of the probability in the whole event. In order to apply this method, researchers need to follow the steps, giving the definitions of the two kinds of events, assessing the probabilities of the basic events, finding the relationships between the probabilities of the basic events and the whole event, and analysing the probability of the whole event. In the risk evaluation and risk control phases, some forms of mathematical programming models are formulated to make final decisions among various scenario and genetic algorithm approaches are proposed to solve these models. Risk reduction is carried out in the risk control phase.

2.3 Mathematical programming and genetic algorithm

For conventional mathematical programming, it is assumed that the coefficients are deterministic and there is a single objective. These assumptions cannot always be satisfied in many real world situations. In some cases, the complexity of the problem increases as the number of objectives increases because the objectives considered are often contradictory to one another (Cohon, 1978). In other cases, decisions are made in uncertain environments. Unconventional forms of mathematical programming are also proposed for real life problems, including Stochastic Programming (Sengupta, 1972), Fuzzy Programming (Tanaka, 1984), and Interval Programming (Hansen, 1992). In the last several decades, they are developed rapidly and applied to many fields. Many techniques are proposed to solve these models and artificial intelligence techniques are widely applied because of its computational efficiency (Bender, 1996).

The choice among the possible artificial intelligence techniques highly depends on experiential knowledge in the area of application and on the specific problem. Genetic algorithms are capable of handling relatively complex combinatorial problems and to manage large numbers of process variables without any training on historical data (Goldberg, 1989). Each iteration can be seen as an evolutionary step in which the least efficient solutions are discarded. The next iteration is an attempt to improve the remaining solutions through mutation and cross-over techniques. The problems investigated here seems to be better addressed using genetic algorithms, given the lack of historical data relevant to the specific areas and their combinatorial forms.

The rudiment of genetic algorithm appeared in this paper of Fraser (1957) when he attempted to imitate the evolution process by recombination and mutation. Holland (1975) introduced genetic algorithm in *Adaptation in Natural and Artificial Systems*. Up till now, the researching works about genetic algorithm covers three fields, basic research, optimisation and machine learning. All these were concluded in *Genetic Algorithms in Search*, *Optimisation and Machine Learning* by Goldberg (1989).

In the last two decades, many researchers developed new data structure for genetic algorithms. The expansion and improvement made genetic algorithms become a promising tool to solve various problems. All the above works were discussed in detail in Genetic Algorithms + Data Structure = Evolution Programs by Michalewicz (1994). The successful application areas include production planning, reliability design, vehicle routing, facility location and so on (Gen and Cheng, 1997). Some multiobjective programming, stochastic programming, fuzzy programming and interval programming models in the above application areas are also solved successfully by genetic algorithms (Fonseca and Fleming, 1995; Gen and Cheng, 1994; Iwamura and Liu, 1996; Jablonowski, 1994).

3 The project risk management process

3.1 The theoretical basis

In this paper, the project activity network is represented in the activity-on-node format (i.e. a directed a-cyclic graph in which the nodes represent the activities and the arcs denote the precedence constraint). No activity can be started before the completion of all its predecessors. Once started, an activity is not interrupted and runs to completion. Each activity has to be processed in order to complete the project.

The following notions are used in this paper.

i activity index

m_i the number of candidate entities (shorten for 'candidates') bidding to be activity i's partner

j	candidate index
d_{ij}	the bidding processing time of candidate j for activity i
c_{ij}	the bidding cost of candidate j for activity i
r_{ij}	the failure probability of candidate j for activity i
A_i	the event that activity i is completed successfully
S	the event that the whole project is completed successfully
d	the duration of the project
D	the deadline of the project
n	the number of real activities in the project
(k, i)	connected activity pair, for which activity k is the direct predecessor of activity i
H	the set of all the connected activity pairs of the project
F_i	the set of all the predecessors of activity i

The strategy of the manufacturing project is made by the alliance in order to share risks among the partners. Firstly, activity i is begun only when all the activities in F_i are completed successfully. Secondly, if activity i fails, the partner charged for this activity need to pay compensation to the alliance, $i = 1,\ldots, n$.

In this paper, $\bar{A}_i$ is the basic event and $\bar{S}$ is the whole event to be investigated in our project risk management process. When the set of events $\{A_1, A_2,\ldots, A_n\}$ is mutually independent (Parzen, 1960), we have Equation (1) proved by Cao and Wang (2003).

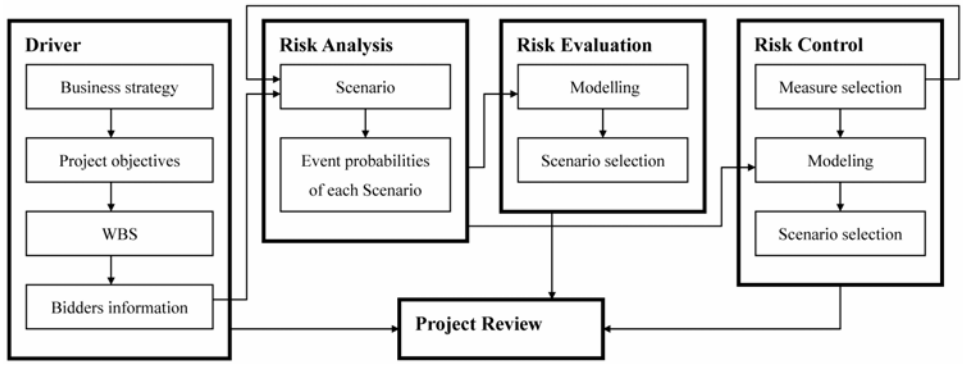
$$P\{S\} = \prod_{i=1}^{n}\left(1 - P\left\{\bar{A}_i\right\}\right) \tag{1}$$

3.2 The framework of the decision process

The project risk management process is illustrated in Figure 1. It begins with identifying the strategic importance of the project and the corresponding project objectives. The objectives must be driven by the overall business strategy. The overall business strategy here is to compete and survive in an agile manufacturing environment. The project objective is to complete the manufacturing project successfully on time and within budget. When the WBS of the project is established, the sponsor will call tender. For each activity, there are several candidate entities (shorten for ‘candidates’) with different bidding processing time and bidding costs. All these information forms the driver for the phases of risk analysis, risk evaluation and risk control.

Equation (1) states the relationship between the probabilities of the basic events and the whole event. Depending on the nature of the candidates, $P\{\bar{A}_i\}$ varies widely, $i = 1,\ldots, n$. Then, $P\{\bar{S}\}$ varies with the scenario and can be calculated in risk analysis phase based on Equation (1). Here, a scenario is a set of candidates selected to be partners for the activities. For candidate j of activity i, its failure probability r_{ij} can usually be obtained from the combination of experts' experience and engineering judgements or by using mathematical methods such as the Delphi method (Sioshansi, 1983), $j = 1,\ldots, m_i$, $i = 1,\ldots, n$.

Figure 1 The project risk management process



In risk evalaution phases, several mathematical programming models are formulated. For these models, the main objective is to minimise $P\{\bar{S}\}$ by finding the best scenario. Other objectives may be minimising project total cost and so on. Depending on the number of the objectives, the forms of the constraints and the precision of the coefficients, the models can be constructed into various formulations, including multiobjective programming, interval programming, fuzzy programming or stochastics programming. The results of risk evaluation phase are used in the project review process to examine the progress as well as any deviations that would occur and corrective actions required for achieving the desired objectives of the project.

In this paper, risk control strategy is risk reduction. The alliance takes two countermeasures, risk funds distribution and backup partner selection. A useful guideline to reduce risks is to change the balance between resources and risk targets by allowing more cost and/or time (Su and Poulin, 1996). From Equation (1), we can infer that the failure risk of every activity contributes to the project failure risk and lower the activity failure risk is, the lower the project failure risk is. Usually, activity risk is a non-incremental function of its cost. The alliance can invest more manufacturing cost (we call it project risk control funds) and distribute it into activities to reduce their failure risk so as to ultimately reduce the project failure risk, or the sponsor can invest more cost and time in order to choose another partner for each activity to reduce the activity failure risk so as to ultimately reduce the project failure risk. Then, there are two types of partners, the primary partners and the backup partners. Mathematical programming models are also constructed based on these two countermeasures with the main objective to minimise $P\{\bar{S}\}$.

Because of the complexity, non-linearity, multiobjective stochastic constraints or interval or fuzzy coefficients of the above models, they cannot be solved easily by conventional methods. Genetic algorithms are proposed. A multiobjective mathematical programming model in risk evalaution phase and its corresponding genetic algorithm approach are illustrated in the next section.

4 Multiobjective mathematical programming in risk evaluation phase and its genetic algorithm approach

4.1 The multiobjective mathematical programming model

Defining decision variables,

$$w_{ij}(t)=\begin{cases}1 & \text{candidate } j \text{ is selected for activity } i \text{ and begins at } t\\ 0 & \text{otherwise}\end{cases},\ j=1,\ldots,m_i,\quad i=1,\ldots,n \quad (2)$$

The multiobjective mathematical programming model in risk evaluation phase can be formulated into Equations (3)–(8). The first objective $z_1(w)$ is to minimise project failure risk in Equation (3). The second objective $z_2(w)$ is to minimise project total cost in Equation (4). The third objective $z_3(w)$ is to complete the project no later than the project deadline in Equation (5), where $[d–D]^+ = \max\{0, (d–D)\}$.

$$\min_w z_1(w)=1-\prod_{i=1}^{n}\sum_{j=1}^{m_i}\sum_{t=1}^{d}w_{ij}(t)\left(1-r_{ij}\right) \quad (3)$$

$$\min_w z_2(w)=\sum_{i=1}^{n}\sum_{j=1}^{m_i}\sum_{t=1}^{d}w_{ij}(t)\ c_{ij} \quad (4)$$

$$\min_w z_3(w)=[d-D]^+ \quad (5)$$

$$\text{s.t.}\quad \max_i\left\{\sum_{j=1}^{m_i}\sum_{t=1}^{d}\left(t+d_{ij}\right)w_{ij}(t)\right\}=d \quad (6)$$

$$\sum_{j=1}^{m_i}\sum_{t=1}^{d}\left(t+d_{ij}\right)w_{ij}(t)\le\sum_{j=1}^{m_k}\sum_{t=1}^{d}tw_{kj}(t),\forall(i,k)\in H \quad (7)$$

$$\sum_{j=1}^{m_i}\sum_{t=1}^{d}w_{ij}(t)=1,\quad i=1,\ldots,n \quad (8)$$

Constraints (6) and (7) represent the precedence relationships between activities. Constraint (8) ensures that only one candidate is selected as partner for each activity. Model (3–8) is a 0–1 integer non-linear programming with three objectives. It cannot be solved easily by conventional methods.

4.2 The genetic algorithm approach

Multiobjective decision making is practically important in the real world. In these problems, we can seldom expect the existence of the dominating solution, which optimise the several objectives simultaneously. Therefore, Pareto optimal solutions are crucial (Cohon, 1978). In multiobjective decision making, we have two important issues. The first issue is generating feasible Pareto optimal solutions. The second is making a decision using decision maker's preference among Pareto optimal solutions.

In the traditional multiobjective decision making methods, the first problem was reduced to the mathematical programming problem by aggregating the vector objective function into a scalar in a predetermined manner or by some interactive manner (Chan and Haimes, 1983). This method intrinsically produces a single solution and thus the searching point is usually only one. The primordial drawback of the traditional method is that they all lack the parallel production of searching points. Considering the human's decision process, we cannot be satisfied without comparing many alternatives simultaneously. Even if the shown alternative is the 'best one', we may have a difficulty in decision making and doubt whether there are no better ones.

In this paper, we are interested not only in the generating of Pareto optimal solutions, but also the decision maker's trade-off procedures with preference information. There are usually four approaches for decision makers' preferences entering into the formal decision making process (Hwang and Masud, 1979), namely no articulation of preference information, a priori articulation of preference information, progressive articulation of preference information and a post articulation of preference information. For the problem (3–8), decision maker has no prior knowledge. After a initial study, we find that the number of Pareto optimal solutions increase with the size of the research problem. There are difficulties in the using of the fourth approach. This paper focuses on the third class of method. A set of efficient solutions are generated in each generation and the decision maker's preferences come in to choose the most appropriate out of this generation solution pool.

In designing a genetic algorithm, it is necessary to specify a suitable representation for genes, a fitness function, a selection strategy, some genetic operators and a stopping rule. Natural strings, adaptive weight fitness function, roulette wheel selection, uniform crossover, perturbation mutation and maximum of generation are used here for the above issues (Gen and Cheng, 1997).

Let $x = [x_1, x_2, \ldots, x_n]$, where x_i is a non-negative integer between 1 and m_i, $i = 1, 2, \ldots, n$. If $x_i = 1$, x_i stands activity i is subcontracted to bidder x_i, $i = 1, 2, \ldots, n$. Thus, $x = [x_1, x_2, \ldots, x_n]$ is referred to as a selection (of bidders) and represents a chromosome or an individual in the genetic algorithm. Then, model (3–8) can be rewritten by the following model.

$$\min_x z_1(x) = 1 - \prod_{i=1}^{n} \left(1 - r_{ix_i}\right) \tag{9}$$

$$\min_x z_2(x) = \sum_{i=1}^{n} c_{ix_i} \tag{10}$$

$$\min_x z_3(x) = [d - D]^+ \tag{11}$$

$$s.t. \quad \max_i \left\{ \left(t_i(x) + d_{ix_i} \right) \right\} = d \tag{12}$$

$$\left(t_i(x) + d_{ix_i} \right) \le t_k(x), \quad \forall (i,k) \in H \tag{13}$$

$$x_i = 1, \ldots, m_i, \quad i = 1, \ldots, n \tag{14}$$

For any given x, we can determine the beginning time and completion time of all the activities by project scheduling. In project scheduling, each activity begins as early as possible. Project scheduling procedure can be carried out in two steps. First, to calculate beginning time $t_i(x)$ of each activity by Equation (15), $i = 1,\ldots,n$. Then, calculate project completion time by Equation (12).

$$t_i(x) = \begin{cases} 1 & \text{there is no}(k,i) \in H \\ \max\left\{t_k(x) + d_{kx_k} \mid (k,i) \in H\right\} & \text{otherwise} \end{cases}, i = 1,\ldots,n \quad (15)$$

In the case of multiple objectives, the selection operator steers the search in the direction of the non-dominated front and is controlled by the individual's fitness that reflects its Pareto-optimality. Therefore fitness assignment is the main issue in multiobjective problems. In order to evaluate the fitness of each individual, we design an adaptive evaluation function as Equation (16) based upon the method of objective weighting. The fitness values of all individuals are calculated to this adaptive evaluation function. In each generation, the set of Pareto solution candidates is updated and the adaptive evaluation function is reformed again and again with the search process. In objective space, the adaptive evaluation function acts as a hyperplane. Under the pressure of selection, the hyperplane enforces all Pareto solution candidates to move towards all ideal points as close as possible.

$$F(x) = \sum_{l=1}^{3} a_l \left(z_l(x) - z_l^{\min}\right) \quad (16)$$

where,

$$a_l = \frac{1}{z_l^{\max} - Z_l^{\min}}, \quad z_l^{\max} = \max_{x \in E}\left\{z_l(x)\right\}, \quad z_l^{\min} = \min_{x \in E}\left\{z_l(x)\right\}, \quad l = 1,2,3$$

and E is the set of Pareto candidates.

The framework of the genetic algorithm is as follows.

Step 1 Parameters setting.

Step 2 Initialisation.

Step 3 Calculating the objective functions values.

Step 4 Updating Pareto optimal solution pool.

Step 5 Interaction with the decision maker.

Step 6 Calculating fitness function value.

Step 7 Genetic operation.

Step 8 Termination.

5 Computation results

The algorithm was coded in Visual C++ language and run on a PC/586. To test the performance of the genetic algorithm, some problems with different sizes were randomly generated. Satisfactory computation results were achieved. Table 1 summarised the experimental results. For activity i, it has m_i candidates and only one candidate can be selected as partner. Then, for any given problem, 'Size of problem' in Table 1 is equal to $\prod_{i=1}^{n} m_i$. The problem of each given size is tested N times and N solutions are worked out. Among the solutions of these N tests, there is a best solution. Let L be the times that reached the best solution. The Optimal Rate is equal to L divided by N. Average

CUP Time is equal to the total computation time of the *N* tests divided by *N*. The Optimal Rate and Average CUP Time are listed in Table 1.

Table 1 The performance of the genetic algorithm

Size of problem	*Optimal rate*	*Average CUP time (Minutes)*
3125	0.93	1.32
9765625	0.92	3.11
30517578125	0.88	7.35

The problem (3–8) is applied to a real life project, the aim of which is to construct a small-sized, clean and efficient core-fired power station in ZW. ZW is located in northeastern China. Demand for electricity in northeastern is growing faster because of China's policy of 'Reforming the Northeastern Old Industries Base'. The output capacity of the new station will provide enough power to meet 10% of the city's electricity needs. There are abundant coal deposits near ZW and this ready supply of local low cost, good quality coal will make the new station one of the lowest cost producers in the northeastern area. PG is responsible for the whole project. PG is a government owned corporation and it is experienced in the planning, construction, installation and commissioning of the power station. PG subdivides the project into 15 jobs as shown in Table 2 and the precedence relationship is shown in Figure 2. Its deadline is 36 months. The payment rule for all jobs is 30% at the beginning of the jobs and the rest when the job is completed. The failure punishment rate for the partners is 1.0. The candidates who responded to tenders of all jobs are listed in Tables 3 and 4. The parameters of the genetic algorithm are equated to: crossover probability = 0.8, mutation probability = 0.1, population size = 100, maximum number of generations = 100. The result selection is {A1, B1, C5, D2, E1, F3, G2, H2, I3, J3, K3, L1, M3, N2, O2} and the total investment, duration and failure probability of the project is 359 million, 39 months and 0.258, respectively.

Table 2 The activities list

No.	*Activity name*
1	Total design of system
2	Design of railway for coal
3	Construction of railway
4	Design of boiler system
5	Manufacturing of boiler system
6	Design of buildings
7	Construction of buildings
8	Design of generators
9	Design of electric transmission
10	Manufacturing of generators
11	Assembling of boilers
12	Manufacturing of transmission equipment
13	Design and assembling of computer control systems
14	Assembling of generators
15	Assembling of transmission systems

Figure 2 Project activity network

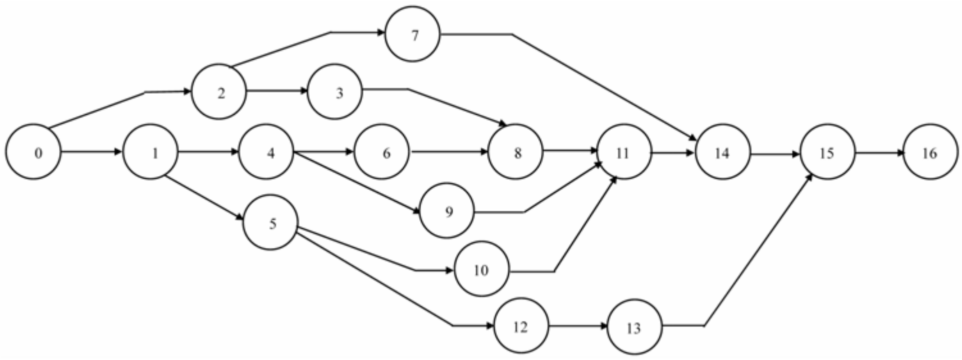


Table 3 The list of candidates for all the activities

Activity No.	*Candidate code*	*Cost (Millions of RMB)*	*Processing time (Months)*	*Failure probability*
1	A1	18.0	7.0	0.015
	A2	14.0	5.0	0.015
	A3	23.0	5.0	0.010
	A4	15.0	6.0	0.015
2	B1	19.0	9.0	0.015
	B2	25.0	8.0	0.010
	B3	20.0	10.0	0.020
3	C1	75.0	8.0	0.015
	C2	60.0	10.0	0.010
	C3	55.0	7.0	0.025
	C3	59.0	9.0	0.020
	C5	65.0	11.0	0.030
4	D1	22.0	8.0	0.015
	D2	20.0	7.0	0.010
	D3	23.0	9.0	0.015
	D4	25.0	10.0	0.010
	D5	16.0	14.0	0.015
5	E1	11.0	10.0	0.010
	E2	10.0	9.0	0.010
	E3	12.0	12.0	0.015
	E4	15.0	11.0	0.025
	E5	13.0	13.0	0.015
6	F1	6.0	6.0	0.020
	F2	9.0	5.0	0.025
	F3	8.0	5.0	0.015
7	G1	28.0	8.0	0.015
	G2	27.0	9.0	0.020
	G3	35.0	7.0	0.035
	G4	20.0	7.0	0.025
	G5	25.0	10.0	0.030

Table 3 The list of candidates for all the activities (continued)

Activity No.	*Candidate code*	*Cost (Millions of RMB)*	*Processing time (Months)*	*Failure probability*
8	H1	10.0	2.0	0.025
	H2	14.0	3.0	0.025
	H3	17.0	3.0	0.030
9	I1	10.0	5.0	0.025
	I2	7.0	4.0	0.020
	I3	13.0	6.0	0.025
	I4	9.0	5.0	0.015
	I5	11.0	7.0	0.030

Table 4 The list of candidates for all the activities (I)

Activity No.	*Candidate code*	*Cost (Millions of RMB)*	*Processing time (Months)*	*Failure probability*
10	J1	50.0	11.0	0.015
	J2	40.0	9.0	0.025
	J3	65.0	10.0	0.020
	J4	55.0	10.0	0.025
	J5	48.0	12.0	0.010
11	K1	8.0	2.0	0.030
	K2	12.0	3.0	0.035
	K3	10.0	3.0	0.020
	K4	11.0	2.0	0.040
12	L1	35.0	4.0	0.020
	L2	30.0	5.0	0.020
	L3	48.0	7.0	0.030
	L4	40.0	8.0	0.025
	L5	40.0	6.0	0.020
	L6	45.0	5.0	0.030
	L7	44.0	8.0	0.020
	L8	34.0	6.0	0.035
13	M1	13.0	2.0	0.015
	M2	20.0	3.0	0.020
	M3	17.0	2.0	0.020
14	N1	9.0	4.0	0.030
	N2	11.0	4.0	0.040
	N3	7.0	5.0	0.025
15	O1	22.0	10.0	0.020
	O2	25.5	12.0	0.010
	O3	20.0	9.0	0.025
	O4	23.0	13.0	0.030

Although PG adopted this resulting selection for the project, the model (3–8) has some limitations. In some cases, the failure probabilities of the candidates for each project activity cannot be expressed precisely. The project managers are willing to express their judgement in the form of interval or fuzziness. Then, we developed new models for these cases and discussed them in other studies.

6 Conclusions

The researching works of this paper lead to the following remarks:

- Figure 1 provides a framework for quantitative project risk management process for a manufacturing alliance in agile manufacturing environment.
- The mathematical models provide formal descriptions for the risk evaluation and risk control phases.
- The recommended genetic algorithms can quickly achieve the optimal solutions of the mentioned models with high probability. The computational results show their potential to practical situations.

Our research is still far from being completed. Concerning the future research work, there are two directions to deepen the works in this paper to form an efficient quantitative tool for more complex risk evaluation in the virtual global business environment. The research of this paper is under the supposition that the set of events $\{A_1, A_2,\ldots, A_n\}$ is mutually independent, which is unnecessarily satisfied. It is worthwhile to investigate when the set of events $\{A_1, A_2,\ldots, A_n\}$ is mutually dependent. Other artificial intelligence techniques are widely applied to unconventional programming models including Genetic Programming, Tabu Search, Simulated Annealing and so forth. Research on the application of these techniques in the above framework of project risk management is underway.

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