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應用田口基因演算法於選擇、排程、和平衡專案組合

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摘　要

對組織而言，專案組合選擇是一重要管理活動，也是個複雜決策過程。而兼顧專案組合平衡也是重要議題。因此，本研究所欲探討專案選擇和排程問題為選擇能滿足一組總淨現值最大的專案組合，而且必須兼顧在組織各策略領域的平衡以及在規劃期間內各專案何時開始以不違背年度預算限制額度。本論文所探討問題為兼顧在專案選擇、排程、平衡等三個重要議題，此問題在專案選擇實務中常見但少見於過去文獻。本論文我們建構此問題的 0-1 整數規劃模式，並提出基因演算法（GA）求解。再者，結合田口方法以決定最佳參數水準以提昇所提 GA 的效率。再透過一時小案例就 GA 解與 AMPL 所求得最佳解作比較以證實 GA 的有效性，最後模擬許多大型評估所提 GA 之績效。依運算結果得知，所提 GA 演算法能有效率解決所提之問題。

關鍵詞：專案組合選擇和排程、田口方法、基因演算法、０－１整數規劃

Hybrid Taguchi-genetic Algorithm for Selecting and Scheduling a Balanced Project Portfolio

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ABSTRACT

Project portfolio selection is a crucial management activity for many organizations and it is a complex decision-making process. Maintaining a balancing portfolio is also an important issue. Hence, we consider a project selection and scheduling problem where a set of R&D projects that has to be selected to maximize the overall net present value, a balance in the level of effort focused on each of the key strategies in the selected projects have to be maintained, the selected projects have to be scheduled without violating annually available budget. The problem handles some of the issues that frequently arise in real world applications but three issues（i.e., selection, scheduling, and balance） are not simultaneously addressed by previously suggested models. In this paper a zero-one integer programming model for the considered problem is proposed, then, a genetic algorithm (GA) is proposed to solve the problem. Furthermore, to increase the efficiency of the proposed method, GA parameter design in accordance with Taguchi Method is conducted. Some small problems instances are randomly generated to validate the effectiveness of the GA by comparing with the solutions solved by AMPL in small scale of problem instances. Moreover, six large problem instances are generated and solved by the GA with the most appropriate parameter levels to evaluate the efficiency of the proposed GA. From the computational results, we conclude that the proposed problem can be efficiently solved by the proposed GA.

***Key Words*:** project portfolio selection and scheduling, Taguchi method, genetic algorithm, 0-1 integer programming

Ⅰ. INTRODUCTION

Project portfolio selection is a crucial management activity for many organizations and it is a complex decision-making process. Archer and Ghasemzadeh (1999) defined project portfolio selection as the periodic activity involved in selecting the set of projects, from available project proposals and projects currently underway, that meets the organization's stated objectives in a desired manner without exceeding available resources or violating other constraints. Generally the traditional approach of project selection includes two issues: one is to select a set of projects that meet some predetermined goals and resource constraints, and the other is to schedule this set of projects within planning horizon (i.e. determine in which year a project starts) without violating annual budget limit. The first issue on how to determine the most attractive project portfolio has been widely studied, the interested readers can refer to the survey conducted by Heidenberger and Stummer (2003). Recent works on this issue are presented by Stummer et al. (2009), they developed multicriteria decision support system (MCDSS) that first determines the set of Pareto-efficient solutions and then allows the decision maker to interactively filter and/or explore this set in various ways. Wang and Hwang (2007) proposed R&D project selection models based on linear, non-linear, dynamic, goal, and stochastic mathematical programming. Liesio et al. (2007) developed the Robust Portfolio Modeling methodology which extends Preference Programming methods into portfolio problems where a subset of project proposals is funded in view of multiple evaluation criteria.

Another issue of project selection problem is to schedule this set of projects within planning horizon (i.e. determine in which year a project starts) without violating annual budget limit. Few studies (Schniederjans and Santhanam,1993; Coffin and Taylor, 1996a, 1996b; Kyparisis et al., 1996; Evans and Faibairn,1999; Ghasemzadah et al., 1999) on this issue are published. Recently, Sun and Ma (2005) proposed a heuristic packing-multiple-boxes (PMB) model with recycled 0-1 integer programming to select and schedule R&D projects. They successively decide the projects which start in the first year on planning horizon under annual budget limit, and then select the projects started in the second, to final period of the planning horizon. In the each-round selection model, the resource constraints change, as the annual costs of the already-selected projects must be deducted from the annual budget. Ghorbani and Rabbani (2009) proposed a multi-objective meta-heuristic procedure for a project selection problem which considers two objective functions, i.e. the maximization of the total expected benefit of selected projects and minimization of the summation of the absolute variation of allocated resource between each successive time periods.

As known, balancing the portfolio of projects is also a crucial issue, it is as important as project selection (Gray and Larson, 2006, p. 43). By the literature review, however, it was found out that the number of previous studies which take project portfolio balancing into account is relatively rare. Therefore, a project portfolio selection problem, which is more realistic and practical in the real world, simultaneously involving these three issues, i.e., selection, scheduling, and balancing, is considered in this paper. A zero-one linear programming model is also formulated and a genetic algorithm for the problem is proposed.

The problem considered is an NP hard one and, thus, heuristic approaches come into play as they provide an attractive trade-off between solution quality and the computational effort required for searching a sufficient approximation of the solution space. In this study, hence, a GA incorporating a new efficient experimental design method for parameter optimization using Taguchi method for the problem is proposed. GA employs a structured but randomized way to use genetic information in finding new directions of search. GA is applied in a wide variety of application areas, specifically in combinatorial problems, such as scheduling. The advantages of GA's over other search methods are summarized as follows (Ozdamar, 1999).

A. Search is carried out from a population of points, not a single point.
B. Payoff information is used instead of derivatives.
C. Probabilistic transition rules are used instead of deterministic ones.

To validate the effectiveness of the proposed GA, the solutions obtained by the GA are compared to those by AMPL for some small cases. AMPL is a modeling language for mathematical programming. Robust designs such as Taguchi method borrow many ideas from the statistical design of experiments for evaluating and implementing improvements in products, processes, or equipment. Its fundamental principle, generally speaking, is to improve the quality of characteristic of interest by minimizing the effect of the causes of variation, but not eliminating those causes themselves.

The rest of this paper is described as follows. In section 2 the problem definition is provided and a zero-one linear programming for project selection, scheduling and balancing problem is formulated. Section 3 presents a genetic algorithm. Section 4 describes the design of experiment and evaluates the performance of the proposed GA. Section 5 summarizes the conclusions.

Ⅱ. PROBLEM DEFINITION

1. Problem Statement

Generally, there are usually more potential projects to be carried out than can be undertaken within the physical and financial constraints of a firm, so choices must be made so as to meet the predefined objectives for many organization. In this paper, three following issues are considered. First issue is to select a set of projects that meet some predetermined goals and resource constraints. Second one is to schedule these selected projects within planning horizon without violating annual budget limit. The final is to balance the project portfolio so as to meet the strategic intents. For a large firm like Siemens Corporation, there are many R&D departments such as materials research, medical imaging, robots and agents, clean energy and etc. Each department has its strategic intents. For R&D manager of Siemens Corporation, he must consider either the balance between basic and applied research for the whole corporation or the balance among different strategic intent categories of the R&D budget. In this paper, our objective is to select a set of projects, organized around a set of key corporate strategies, which maximize their NPV and satisfy the strategic intent targets with balance, constrained by total and annual budget availability, and precedence relationships. The balance is measured in terms of the percent of spending directed at each strategy.

The notation used to describe the model is displayed in Table 1.

Table 1. Notation

Symbol	Definition
SC	strategic intent categories
T	planning horizon periods
n_i	total number of projects in strategy intent category i
x_{ijt}	a binary variable, if project j in strategic intent category *i* is selected and starts at period t, then x_{ijt}=1; otherwise, 0.
p_{ij}	expected net present value of project j in strategic intent category i
w_{ij}	required cost of project j in strategic intent category i
TC	total budget available spending in portfolio
SI_LB_i	minimum fraction of the budget that can be spent on projects in strategic intent category i
SI_UB_i	maximum fraction of the budget that can be spent on projects in strategic intent category i
$C_{ij,k-t+1}$	required cost of project j in strategic intent category i at period k
AF_k	available budget at period k
Dij	duration of project j in strategic intent category i
P_l	set of predecessor projects of project l in N_i , $i=1,\cdots,s$
HR	Set of high risk projects
IP	set of ongoing projects must be included from the portfolio
EP	set of ongoing projects must be excluded from the portfolio

2. Proposed Model

We consider the situation where there are S strategic intent targets in a firm and T planning horizon periods. Suppose that there are ni candidate projects in strategy category *i*. Our objective is to select a set of projects, organized around a set of key corporate strategies, which maximize their NPV assumed and satisfy the strategic intent categories with balance, constrained by total and annual budget availability, and precedence relationships. The balance is measured in terms of the percent of spending directed at each strategy. In this paper, we set the maximum and minimum fraction of the total budget that can be spent on projects contributing to achievement of strategy i.

The decision variables are defined by:

$$\text{Maximize } Z=\sum_{i=1}^{S}\sum_{j=1}^{n_i}\sum_{t=1}^{T} p_{ij}\,x_{ijt} \quad (1)$$

Subject to

$$\sum_{i=1}^{SC}\sum_{j=1}^{n_i}\sum_{t=1}^{T} w_{ij}\,x_{ijt} \le TC \quad (2)$$

$$SI\_LB_i \le \sum_{j=1}^{n_i}\sum_{t=1}^{T} w_{ij}\,x_{ijt} \le SI\_UB_i \quad (3)$$

$$\sum_{i=1}^{SC}\sum_{j=1}^{n_i}\sum_{t=1}^{T} C_{ij,k-t+1}\,x_{ijt} \le AF_K \text{ , for } k=1,\ldots,T \quad (4)$$

$$\sum_{j\in N_i}\sum_{t=1}^{T} t\,x_{ijt} + D_{ij} \le T+1 \quad (5)$$

$$\sum_{t=1}^{T} x_{ijt} \le \sum_{t=1}^{T} x_{ikt}\ , \quad j\in P_k \quad (6)$$

$$\sum_{t=1}^{T} t\,x_{ikt} + (T+1)*\left(1-\sum_{t=1}^{T} x_{ikt}\right) - \sum_{t=1}^{T} x_{ijt} \ge D_{ij}\sum_{t=1}^{T} x \quad (7)$$

$$, j\in P_k$$

$$\sum_{i\in HR}\sum_{j\in n_i}\left(w_{ij}\sum_{t=1} x_{ijt}\right) \le PHR*\left(\sum_{i=1}^{SC}\sum_{j\in n_i} w_{ij}\,x_{ijt}\right) \quad (8)$$

$$\sum_{t=1}^{T} x_{ijt} \le 1 \quad (9)$$

$$\sum_{t=1}^{T} x_{ijt} = 0 \qquad \text{for } j\in EP \quad (10)$$

$$x_{ijt} = 1 \qquad \text{for } i\in IP \quad (11)$$

Constraint (2) addresses the total budget spending in R&D. Constraint (3) limits lower and upper budget spending in each strategy intent category *i*. Constraint (4) shows annually available budget spending in all R&D. That all selected projects must be completed within the planning horizon *T* is shown in constraint (5). Technical interdependence among projects is presented in constraints (6) and (7) describe these constraints. For instance, if project A is dependent on project B, then project B must be included in the portfolio if project A is selected. Nevertheless, if project A is not selected in the portfolio, project B may be included. Moreover a risk-related constraint is considered in constraint (8), the ratio of the high risk projects selected in the portfolio is no more than PHR (i.e. the maximum allowed percentage of investment in high risk projects). Constraint (9) guarantees that each project will only start once during the planning horizon. Constraint (10) shows that project *i* in set *EP* must be excluded from the portfolio. Constraint (11) shows project i in set *IP* must be included in the portfolio.

Ⅲ. GENETIC ALGORITHM

Before a genetic algorithm (GA) can be run, a suitable representation for the considered problem must be devised. We also require a fitness function, which assigns the project profit to each representation. During the run, parents must be selected for reproduction, and use genetic operators to generate offspring.

1. Direct Representation

In a direct problem representation, the problem itself is used as a chromosome. No decoding procedure is necessary. All information relevant to the problem at hand is included in the problem representation. A complete direct representation of a chromosome (i.e., project portfolio) comprises each candidate project of all strategic categories with associated X_{ij} representing whether a project is selected/non-selected and Y_{ij} denoting the starting period of the selected/non-selected project, as shown in Figure 1.

1				2			…	*SC*		
X_{11}	X_{12}	…	X_{1N1}	X_{21}	…	X_{2N2}	…	X_{SC1}	…	X_{SCNSC}
Y_{11}	Y_{12}		Y_{1N1}	Y_{21}		Y_{2N2}		Y_{SC1}		Y_{SCNSC}

Figure 1. Direct representation of a chromosome

Each cell (i.e. gene) contains three elements: the upper one, N_i, represents category i; the middle one, X_{ij}, denotes whether a candidate project *j* in category *i* is selected; the lower one, Y_{ij}, means the starting period of the selected project j in category *i*. Suppose there are *SC* strategic categories, N_1 to N_{SC}, and each category *i* has n_i candidate projects. If a candidate project j in category *i* is selected into project portfolio, then the value of X_{ij} is set as 1; otherwise, 0. If X_{ij} = 1, then the value of Y_{ij} is assigned randomly as a value from 1 to T - D_{ij} + 1; otherwise, Y_{ij} = 0. The fitness function is defined as the overall profit of a project portfolio and given as follows.

$$fitness \quad function \quad = \sum_{i=1}^{s}\sum_{j=1}^{n_i} p_{ij}\,X_{ij} \quad (12)$$

where p_{ij} represents the net present value of project j in strategic intent category i; X_{ij} is either 1 or 0.

2. Initialization and Sorting

The initial generation of complete and consistent project portfolios can be generated as follows. For each project portfolio of initial generation, we first randomly decide X_{ij} as 0 or 1. If X_{ij} equals 1, then the value of Y_{ij} is set randomly as from 1 to T - D_{ij} + 1. If the generated project portfolio is feasible when it meets the all above constraints, generate a new portfolio until the first generation is produced. Once one generation which consists of a certain number of feasible portfolios is constructed, the chromosomes are sorted in descending order by their NPVs.

3. Genetic Operators

The introduction of a non-standard chromosome representation necessitates the definition of new crossover and mutation operators which are usually more complicated than traditional ones.

A. Elitism: Rather than the mechanism of reproduction of GA, the mechanism of elitism instead is applied. In the function of elitism, a certain ratio of elitist chromosomes is kept into the next generation to avoid losing larger fitness-value chromosomes. By applying the mechanism of elitism, the maximum fitness value of chromosome in each generation will ensure reserving into the next generation.

B. Crossover: The crossover operator generates an offspring portfolio by combining features of two selected parent portfolios. The crossover point occurs at the gene point (i.e. gene point divides department) of a chromosome. That is, if a firm has SC strategic categories, there will be SC - 1 possible crossover points. To support the inheritance of good features of a portfolio, the crossover generator is designed to hold the good retention of parent portfolio. The scheme of the crossover generator is devised as follows. Selected two portfolios as parent chromosomes, one is to choose randomly from the first fifty percent of chromosomes, the other is from other part. Randomly choose one of SC - 1 crossover points, then crossover two parent portfolio.

C. Mutation: The mutation operator must be able to alter some information represented in the chromosome. It must also provide the possibility to reintroduce lost genetic material. The goal of mutation is avoiding falling into local optimal solution in the solving process. Thus we adopt the following method to mutate the chromosome. Randomly choose a chromosome. First we select one X_{ij} whose value equals to 1 in a chromosome randomly and change its value to 0; it means we exclude it out of our portfolio. Next we select one X_{ij} whose value is 0 in the same chromosome randomly and change it from 0 to 1; it means we put it in our portfolio.

Ⅳ. COMPUTATIONAL RESULTS

1. Generating Problem Instances

In this paper a genetic algorithm is proposed for the considered problem. To investigate the performance of the proposed genetic algorithm, the solutions solved by the proposed GA are compared with those solved by AMPL. Since AMPL is intractable to large scale of problem instance, six generated problem instances are considered. Each instance includes three strategic categories in which each has from 6 with increment 2, to 12 candidate projects, shown in Table 2. The required information in each problem instance includes required annual cost of each project, the risk value of each project, total budget limit of each strategic intent category, and annual budget limit of an organization.

Table 2. Cases of generated problem instances

Problem instance	Number of strategic categories	Number of candidate projects	Total candidate projects
1	3	6	18
2	3	8	24
3	3	10	30
4	3	12	36
5	3	14	42
6	3	16	48

Steps to generate a problem instance are described as follows. First, the annually required amount cost for each project was randomly generated between 0.3 and 1.0 times of the upper bound, here set 200 (thousand US dollars). Second, the project duration spans are generated also between 0.3 and 1.0 times of a certain planning horizon, here set eight periods. Third, investment on high risk project may not exceed an upper ratio of total investment in a department. The ratio is set at 0.5 and the risk value above 0.7 is called high risk project. Fourth, total department’s budget limit is randomly generated between 0.7 and 0.9 times of total sum of the candidate project costs for each department; and total annual budget limit is randomly generated between 0.1 and 0.2 times of total sum of the all candidate project costs. Fifth, we assume that the revenue of each project is function of required total cost. The much more cost required by a project, the more benefit obtained by the project; hence, the annual required costs are used to estimate the net present value (NPV) of each project.

Once a problem instance is generated, it is solved by the GA algorithm. Taguchi method is used to determine the appropriate value of the parameters of the proposed GA. After the values of the parameters are determined, the relative better solutions may be theoretically obtained. These results then can be compared with those obtained by AMPL. Time consumption and objective value difference will be compared. The proposed GA has been coded in Microsoft Visual Basic 6.0 and executed on a Pentium 4.2GHz, and Windows XP using 512 MB of RAM. All experiments are conducted on Pentium® M processor 1.5GHz and 256MB RAM. At first we code the proposed GA in VB with Microsoft Visual Basic 6.0, and then using AMPL to solve the generated problem instances.

Table 4. Average values of three levels for each parameter for Case 6

Level	Elitism rate	Crossover rate	Mutation rate	Population size	Generation size
Level 1	79.88076164	79.83005777	79.84899446	79.79749717	79.82297967
Level 2	79.81992428	79.85297404	79.83328824	79.84716448	79.8271885
Level 3	79.81805289	79.83570701	79.83645611	79.87407716	79.86857064

2. Parameters' Design

Once a genetic algorithm is developed, its performance strongly depends on the parameters of GA. In this study, we select five most commonly studied GA parameters, i.e. elitism rate, crossover rate, mutation rate, population size, and the number of generations. Different parameter level causes different result even in the same problem instance. After an extensive preliminary analysis of the algorithm, three levels for each parameter values are chosen. Selected design factors and their levels are listed in Table 3. Therefore, to decide the most suitable level of the parameters to get stable solutions is an important issue. Taguchi method then could be applied to decide these parameters.

In this study, we want to estimate the main effects of design factors (the interaction among factors is neglected). An efficient way of studying the effects of several design factors simultaneously is to plan a matrix experiment using an orthogonal array. For the inner array, we choose orthogonal array L_{27} (3^{13}) which has 13 three-level columns and 27 rows. Each row of the inner array L_{27} represents a design of the process. Performance (NPV) of each design is evaluated by computer experiment under each noise condition specified by the outer array.

Table 3. Design factors and levels

Parameters	Level 1	Level 2	Level 3
Elitism rate (A)	0.2	0.4	0.6
Crossover rate (B)	0.2	0.4	0.6
Mutation rate (C)	0.2	0.4	0.6
Population size (D)	50	100	150
Generation size (E)	50	100	150

After confirming the orthogonal arrays, the next step is to determine the signal-to-noise ratio by the experiment data. By defining our case as a type of maximum problem, the objective function to be maximized can thus be represented by the following equations:

$$\eta = S/N = -10\log_{10}(MSD) = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{y_i^2}\right)\right] \qquad (13)$$

where η is the S/N ratio for each experiment; n is the representative number of measurements and y_i is each observation of experiment.

Here Case 6 is taken as an illustration of Taguchi method. Firstly, 27 S/N ratios of Case 6 are calculated, and then the average of three levels for each parameter can be obtained, shown in Table 4. According to Table 4, the plots of the main effects are provided in Figure 2.

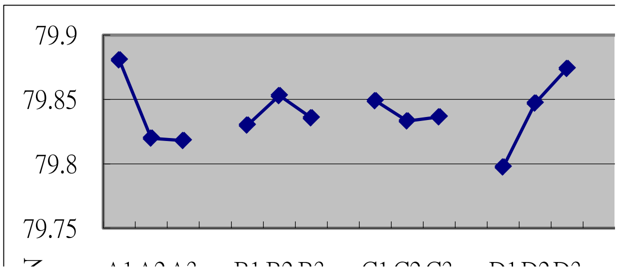

Figure 2. Plots of the main effects of for Case 6

Table 5 The optimal project portfolio of Case 6

2nd row of chromosome	0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1,
3rd row of chromosome	0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 4, 1, 1, 1, 1, 0, 1, 1, 1, 4, 0, 1, 4, 1, 0, 0, 4, 1, 0, 0, 0, 1, 5, 1, 1, 1, 0, 1, 4, 1, 0, 4,

From Table 4, A1, B2, C1, D3 and E3 are the best parameter combination to this case. The next step is input the above parameter combination to the GA system again. The output result to Case 6 under this parameter combination is 10044, and the result of the chromosome representation of this case can be shown in Table 5. In Table 5, the second row of the chromosome representation means whether the candidate

Table 6 ANOVA of Case 6

Parameter	Degree of freedom	Sum of square	Variance	F-ratio	Pure sum	Contribution
A	2	0.022911221	0.01145561	12.03493821	0.021007495	25.38%
B	2	0.002565659				
C	2	0.001241793				
D	2	0.027166882	0.013583441	14.27037655	0.025263157	30.52%
E	2	0.011426195	0.005713098	6.002017672	0.009522469	11.50%
Error	16	0.017471843	0.00109199			
Pooling error	4	0.003807451	0.000951863		0.026990471	32.60%
Total	26	0.082783592			0.082783592	100.00%

project is selected or not. If the candidate project is selected, it will show as 1. The third row of the chromosome representation means which period the selected project will start. In Case 6, we can obtain the fitness value of 10044 by the GA method.

Moreover, to confirm the effect of using the best parameter combination which solved by Taguchi method, a confirmatory of the experiment has to be undertaken. The following steps are the procedure of the confirmatory experiment.

Step1. Calculate the S/N optimum.

$$\eta_{opt} = \bar{\eta} + \left(\eta_{A1} - \bar{\eta}\right) + \left(\eta_{D3} - \bar{\eta}\right) + \left(\eta_{E3} - \bar{\eta}\right)$$

In the above equation,

$$\bar{\eta} = \frac{\eta_1 + \eta_2 + \cdots + \eta_{27}}{27} = \frac{2155.668649}{27} = 79.8396$$

$$\therefore \eta_{opt} = 79.8808 + 79.8741 + 79.8686 - 79.8396 - 79.8396 = 79.94425$$

Step2. Calculate the average S/N values.

In step2, we experiment several times by using the best parameter combination to get the S/N value of the results. Here three times are performed, the average S/N value, 79.998 is obtained.

Step3. Calculate the difference between S/N optimum and the average S/N value obtained in Step2.

$$\frac{\left|S/N - S/Nopt\right|}{S/Nopt} * 100\% = \frac{79.998 - 79.94425}{79.94425} * 100\% = 0.067\% .$$

Due to 0.067% (less than 20%), this experiment can be confirmed. In addition, ANOVA is used to calculate the contribution of each parameter of our proposed GA. The ANOVA table is shown in Table 6.

The results for Cases 1 to 5 can be obtained by the same approach. Finally, optimum levels of design factors of each problem instance are shown in Table 7. Note that there is no difference among levels of design factors for case 1.

Table 7 Optimum levels of each problem

Problem instance	Optimal level
1	-
2	A1B2C1D3E2
3	A1B3C2D2E2
4	A1B3C3D3E3
5	A1B1C1D3E3
6	A1B2C1D3E3

3. Performance Evaluation of Proposed GA

To evaluate the performance of the proposed GA, the solutions obtained by the GA are compared with those by AMPL modeling language. Therefore, the value of Difference = [(AMPL value – GA value)/AMPL value] is computed. GA value represents the maximal value is obtained by the GA, and AMPL value represents the maximal value obtained by AMPL software. Given by the six generated problem instances, Table 8 shows that the proposed GA can find the optimal solutions as found by AMPL in small problem instances or the near-optimum solutions even for some slightly larger problem instances. Moreover, the GA solves our considered problem more efficiently than AMPL does. That is to say, the time required to find the solution found by GA is far less than by AMPL.

Table 8 Solutions found by AMPL and the proposed GA

Problem instance	1	2	3	4	5	6
GA value	3747(0.586)*	6434(11.594)	7614(19.133)	7846(27.277)	10341(30.906)	10044(33.625)
AMPL value	3747(0.45)	6434(1.2)	7716(1.5)	7962(3.6)	10461(198)	10306(3507)
Difference	0.00%	0.00%	1.32%	1.46%	3.15%	2.54%

V. CONCLUSION

The problem considered in this paper is to deal with the issue, balancing the strategic intent targets, added to a traditional project selection problem which comprises two issues. The first is to select a set of projects that meet some predetermined goals and resource constraints. The second is to schedule this set of selected projects within planning horizon (i.e. determine in which year a project starts) without violating annual budget limit. The problem is a NP-hard problem which is not easily by exact algorithms, even by some specific heuristic algorithm. To solve the problem efficient, a genetic algorithm is developed. In this paper a zero-one integer linear programming model for the considered problem is proposed and a genetic algorithm (GA) is proposed to solve the problem. Furthermore, to increase the efficiency of the proposed method, GA parameter design in accordance with Taguchi Method is conducted. Some problem instances are randomly generated to evaluate the performance of the proposed method by comparing with the solutions solved by AMPL in small scale of problem instances. From the computational results, it can lead to a conclusion that the proposed GA provides an efficient solution to the problem.

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