Proceedings of the 13th Asia Pacific Management Conference, Melbourne, Australia, 2007, 1159-1165

A Hybrid Genetic Algorithm Approach to Multi-objective ERP Training Scheduling Problems

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Abstract

It mainly addresses a hybrid multiobjective training scheduling genetic algorithm in this research. We can get the schedule that almost matches the real decisive results to help enterprises proceed with training scheduling successfully by the algorithm. It can reduce from a week to twenty minutes in schedule. The enterprise can cost less to proceed with the schedule and have great elasticity to make decision. Finally, it lets employee in the enterprise help ERP (enterprise resource planning) system working successfully by joining the training though the establishment of enterprise decision support system and makes the enterprises' operation cope with changeable businessenvironment with the most effective ways.

Keywords: Enterprise resource planning; Training scheduling; Competence sets; Pareto optimal solutions; Multi-objective Genetic algorithms

1. Introduction

After the liberalization and the internalization of the economy, the enterprise' strategy of the production and marketing must keep a close watch on the market and adjust in time. Therefore, the enterprise leads in the model that after receiving an order for goods then producing to meet the coming competition. Managers in the enterprises must understand the resources in all conditions in the enterprises and combine all of the resources to provide useful information for making decision instantly. Therefore, ERP comes with the tide of fashion. It promotes the competition and expands enterprises' turning points. To let the employee in the enterprise understand the systems' operation and the relationship of enterprises' business achievements, the enterprises need to proceed with training without a fixed schedule to make employee have good operational efficiency and information quality of ERP system. This research proposes hybrid multiobjective training scheduling genetic algorithm helps enterprise finding a program that matches enterprises' goals for consideration of many decisive factors. It can assist the system with efficient operation. It makes the enterprises control all of kinds of relative information, helps decisive supervisors analyze markets' environment. At the same time, it lets them know the characteristic of products' marketing, and sets up the strategy immediately to manage more efficiently.

When enterprises carry out the ERP, ERP training usually proceeds continuously. It considers varied factors like cost and expected beneficial profits for training activities. In tradition, the MIS staff in the enterprise is responsible for communicate to the relative staff in other departments to proceed with arranging schedule. Because it often needs to think about many conditions, it makes the arrangement in the schedule not proceed successfully. When the schedule proceeds, many staff withdraws from training for busy businesses themselves to result in ineffective usage and bad information system quality. So, it influences the profit in enterprises' business eventually. This research mainly addresses the improved algorithm to help enterprises proceed with the arrangement in training, and hopes to achieve the good for both enterprises and employees for promoting the enterprises' competition to increase the enterprises' values.

To ERP training, the enterprise hopes to supply with a decision model that combines with multiple objectives and gives consideration to employees' work. Under thinking over the employees' schedule and enterprises' profits and costs, we must let the employees understand the whole concepts of ERP systems under the appropriate arrangement. We except the employees learn well and solve new problem from training and promote systems' information quality at last. The research problems in this study sum up two points below:

1. Improving original single objective's optimal expansion path algorithm, and establishing multiob-

jective training scheduling algorithm.

2. Applying the improved scheduling algorithm to the arrangement of ERP training schedule for improvement of information quality of system as well as the usage efficiency and help reach the business achievements.

2. Literature Review

2.1. ERP Training

ERP system now turns into the mode of n-tier/web service in accordance with the characteristics of continuous changeable business procedures in the enterprises. Besides, owing to the enterprises' demands for the customized ERP system, it makes the whole system's structure change without a fixed schedule. (Xue et al., 2005; Light, 2005).So, the enterprises face the problem of the systems' re-adjustment. It lets the employees need to understand the procedure logic that the whole ERP operates through the continuous training.

(Coulson et al., 2003) proposes a training model that is based on the whole ERP concepts. They emphasize the operators have to understand the entire "Blue Print" of the system continuously so that it can make the quality of entire ERP usage and efficiency reach to the optimization. They provide with another training strategy and make the users' learning come to all kinds of knowledge levels. After adopting the training model, the users still remind the concepts of ERP. Therefore, the ERP system is implemented into usage efficiently. So, it is necessary to help the enterprises proceed with the training schedule by a decisive model of training.

2.2. Competence Set

Because ERP itself combines with the interior resources in the enterprise, ERP is a system that goes beyond the general information system. Therefore, the operator still needs to understand other relative procedures. So, in the process of using ERP system, operators still have an opportunity of having to learn the relative knowledge. At the same time, the enterprise aims at employees' learning knowledge and also aims at resources to arrange appropriately for the great efficiency.

(Yu, 1990) points out the competence sets are about the thoughts, the knowledge, the information, and the skill. These things can help the decision maker solves the problems. So what it mentions above takes as a competence. When the decision maker faces fuzzy problems or challenging problems and his competence sets (Sk) can't include the real necessary competence sets of decision problems, he has to increase his competence sets so that he is confident of facing problems to decide at this time. (Yu et al., 1992) already makes use of the concept of Minimum Spanning Tree to find the optimal competence set expansion paths. However, it only aims at the cost of competence sets to find the way that can get competence sets the most efficiently. But, it doesn't point out when the concepts have the profits, how can get competence sets efficiently. In 1993, they address the way of margin analysis further to establish the way that gets this kindof competence sets (Yu et al., 1993.Lin, 2006) aims at the expansion of competence sets, he considers multiple factors like costs and profits further. It proposes a main single objective as a way that hybrid genetic algorithm of the optimal competence set expansion. It mainly thinks when the former scholars consider the optimal expansion paths, they all think over single-stage and single objective. In fact, competence and the learning of knowledge are multiple stages and may be include the factors that must consider like time, efficiency. It hopes to find an expansion path of competence sets that have the lowest costs and the highest profits. The analysis and the expansion of competence sets also apply to a general decision problem. (Chen, 2002) applies them to consumers' decision problems. Using the analysis of competence sets can recognize the type of decisive problems. It can let the decision makers be able to get the competence what they need more efficiently to make the decision makers be confident of making decision by the optimal competence sets.

Therefore, the study mainly considers when the enterprises face the training scheduling problems, they must think over multiple objectives at the same time and they find a compromising proposal to decide the optimal learning expansion paths. Hence, we discuss multiobjective optimization algorithm and try to integrate with the relative algorithm for improvement of efficiency.

2.3. Multiobjective Optimization Algorithm

(Fleming and Purshouse, 2002) point out there are more and more researches using evolutionary algorithms to solve the multiobjective optimization problems. Hence, this study wants to make use of the relative evolutionary algorithms to solve the multiobjective training scheduling problems.

(Tan et al., 2006) explains although now there are many multiobjective optimization algorithms, each algorithm is designed to be aimed at different problems. Although some algorithms have good solutions for specific problems, it may be have limitation of algorithm and make solutions inefficiently. According to (Poorzahedy and Roubani, 2006) point out many specific problems need to adopt specific algorithm for the structure itself. Their study is designed for network problems and tries to use many various algorithms to solve them. Because of problems' complication, individual algorithm meets the obstacles. They suggest adopting multiple algorithms to get the optimal solutions. Hence, our study also tries to integrate with multiple algorithms to solve the problems of ERP training scheduling.

3. Research Framework

In the literature review, we discover now the most solutions for multiobjective problems are based on genetic algorithms (GA) and tabu search. Hence, this study will construct an algorithm of training scheduling based on above algorithms.

3.1 The Research Framework

Figure 1 is the research framework. First, selecting and collecting the information. It recognized the definition of problem and the confirmed objectives though the data analysis. Last, apply the algorithm to solve the problems of ERP training scheduling.

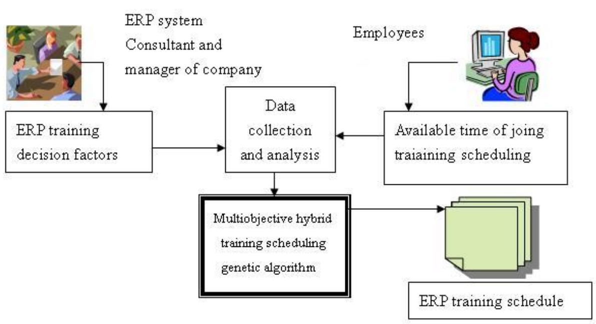


Figure 1. The Research Framework

3.2. The Explanation of Algorithm Symbol

Table 1. Symbol Explanation Table

Symbol	Definition
S	Population size
G	Generation
G_{max}	Maximum number of generation
M	Mutation rate
C	Crossover rate
E	Elitism percent

3.3. The Improved Multiobjecitive Optimal Expansion Path GA

(1) Initialization

According to the pre-defined population size, we produce the chromosome randomly. Each chromosome represents the combination of the nodes that the paths pass. It shows in Fig 2.

X_{1i}	X_{2j}	…	$X_{(n-1)m}$	X_{nk}

Figure 2. Structure of A Chromosome

X_{1i} : The beginning node of path
X_{nk} : The end node of path
Others are the passing nodes of path

(2) Rejection of the illegal chromosome

Because we produce the chromosome randomly, it produces some illegal individual in the population. Hence, before proceeding with the algorithm, we give these chromosomes a penalty function to vanish in future generation (Michalewicz, 1995).

(3) Calculating objective function values

Owing to the Pareto optimal solutions don't give fixed weight to each objective in advance. So, the process of solutions can search the entire spaces to get the Pareto optimal solutions. We assume each objective a random weight to get objective function values and the weighted values' sum is 1 (Murata et al., 1996). The weighted-sum objective is given as follows:

$$f(x) = w_1 f_1(x) + \ldots + w_i f_i(x) + \ldots + w_p f_p(x) = \sum_{k=1}^{p} w_k f_k(x) \quad (1)$$

(4) Finding non-domination solution

Consider a set of population members, each having P (P>1) objective function values. So, we hope to find non-dominated solution with the following procedure (Srinivas and Deb, 1999):

If it doesn't reach to the condition as below, the path will be marked as dominated solution from comparing with any two expansion path X,Y with each object function value in X,Y. Otherwise, it will be marked as non-dominated solution.

i. If the path X is better than all of individual objective function value in the path Y.

ii. If the path X is better than one of individual objective function value in the path Y.

Last, we will save non-dominated solution path X into the temporary Pareto optimal solutions.

(5) Selection

Selection operator is intended to improve the average quality of the population by giving the high-quality chromosomes a better chance to get copied into the next generation. This study makes use of tournament selection to evolve from the excellent parent into offspring.

(6) Crossover

According the pre-defined rate of crossover, we extract from the chromosome in groups to proceed with crossover. We generate a random value Rnd_c .When the random value Rnd_c is smaller than the rate of crossover, we proceed with uniform crossover. It shows in Fig 3.

Random mask	0	1	1	0	0	0
	Parents under mask					
Parent individual 1	1	3	2	3	3	2
Parent individual 2	1	1	4	3	1	2
	Offspring after exchange relative genes					
Offspring individual 1	1	1	4	3	3	2
Offspring individual 2	1	3	2	3	1	2

Figure 3. The Crossover Operation

We generate a set of mask by the combination of 0, 1. Then, we proceed with crossover to generate next-generation chromosome by the part that parental chromosomes generate the mask "1".

(7) Mutation

After proceeding with crossover, next step is mutation. We have a pre-set rate of mutation in advance. When random value Rnd_M is smaller than mutation rate M, mutation starts to proceed. We use the mutation and crossover operator to generate the population size of S-(E*S).

(8) Local search

We adopt local search for consideration as below:

i. To avoid visiting the path in fixed circulation.
ii. To avoid falling into local optimization solutions.

In the literature review, we find the effects that show in tabu search is mainly the size of tabu list and the principle of unbanning. (Xu et al., 2006; solimapur et al., 2004). We hope to avoid the effect of the conditions above by considering the characteristic of multiobjective problems. In other words, we don't limit the size of tabu list and don't consider the principle of unbanning.

			Mutation gene			
Parent individual	1	1	2	3	1	2
Possible offspring 1	1	1	3	3	1	2
Possible offspring 2	1	1	2	3	1	2

Figure 4. The Mutation Operation

The algorithm explains as follows:

(a) Choosing a chromosome generating in Pareto optimal solutions in sequence after mutation.
(b) If this chromosome extracts from present Pareto optimal solutions in tabu list then goes back to (1). Otherwise, go to the next step.
(c) Aiming at this chromosome to generate the scale of group(S) neighboring chromosome. It shows in Fig. 5.
(d) Repeating S steps, until finish visiting neighboring chromosome. We retract chromosome from neighboring chromosome groups in sequence. If this chromosome is not in tabu list and is non-dominated solution, we will update tabu list and save this chromosome into temporary area.
(e) If all of Pareto solutions are to be visited after mutation, then, algorithm ends. Otherwise keep going.

Randomly selection of chromosome	1	2	3	1	2	2
Possible neighbor 1	1	2	3	1	2	2
...						
Possible neighbor pop_size	1	1	2	1	2	1

Figure 5. The Neighbor of the Chromosome

(10) Termination test

When evolution generations G = G_{max}, it represents having executed the last generation. Then, algorithm stops right away and it selects Pareto optimal solutions from all parent to be final solution.

The executive procedure of algorithm shows in Fig 6.

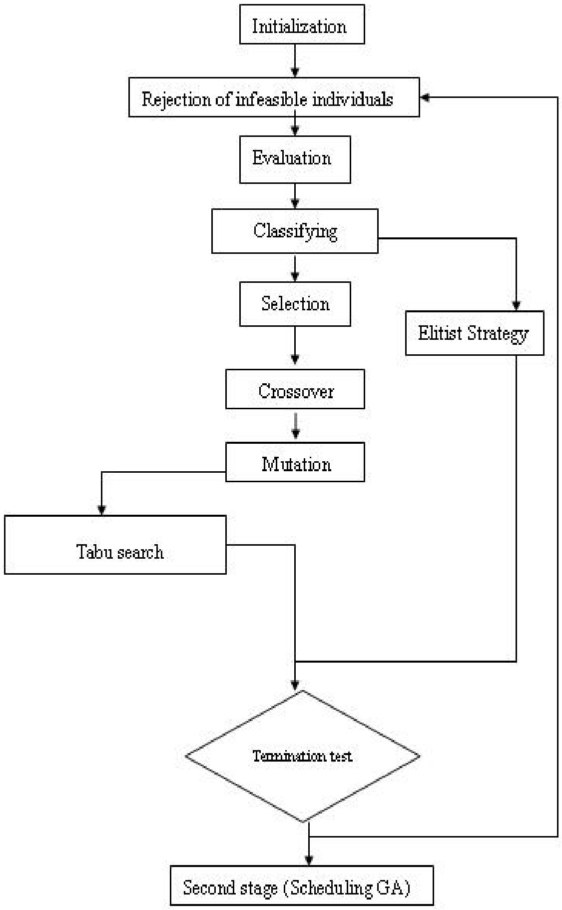


Figure 6. The Block Diagram of Multiobjective Optimal Expansion Path GA

3.4 Training Scheduling Genetic Algorithm

After finishing first stage of algorithm, we start to matches up the schedule in accordance with company's strategy from multiple sets of Pareto optimal solutions that generate and the schedule of employees that wants to receive training. We adopt training scheduling genetic algorithms (GA) to start training scheduling here and generate the final decisive information. The executive procedure of algorithm shows in Fig. 7.

(1) Initialization

First, It turn the Pareto optimal solutions that want to join the scheduling into training schedule time table(0 represents the staff don't join training in that time, 12 represents the staff join training in that time.). It shows in Table 2:

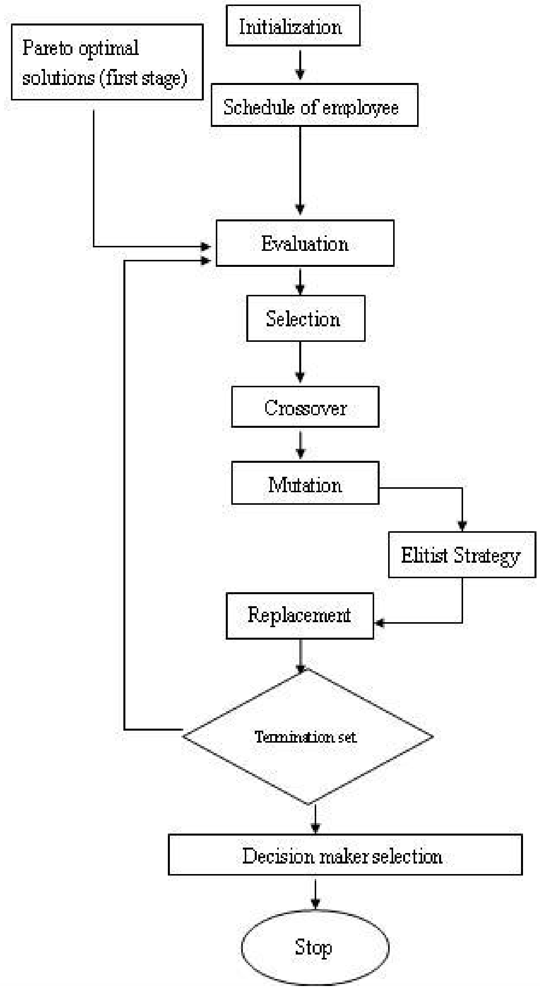


Figure 7. The Block Diagram of Training Scheduling GA

Table 2. The Training Schedule Time Table

	Mon		Tue		Wed		Thu		Fri	
Eemployee ID	am	pm	am	pm	am	pm	am	pm	am	pm
P1	0	12	12	0	12	0	0	0	12	0
P2	12	0	0	12	0	12	12	12	12	12
					…					
Pn	12	0	0	0	0	12	12	0	12	12

Next, we will select the time available based on the time that users provide with participatory arranging training schedule and generate 100 sheets (the population size) of the schedule table that participatory training. (2 represents that staff have time to take part in training in that time, 3 represents that staff have no time to take part in training in that time). It shows in table 3. If the variables in table 2 is I (have 0, 12) the variables in table 3 is J (have 2, 3). Then, K=J-I . We hope to find the participatory schedule table that the least K values.

Table 3. The Available Schedule Time Table of Employees

	Mon		Tue		Wed		Thu		Fri	
Employee ID	am	pm	am	pm	am	pm	am	pm	am	pm
P1	2	3	3	2	3	2	2	2	3	3
P2	3	2	2	3	2	3	3	3	3	3
…										
Pn	3	2	2	2	2	3	3	2	3	2

To avoid the condition the staff joins many-day training and is exhausted and can't absorb in continuously, so, schedule has the limitation of fixed hours and days. If part of staff participates two days above, we will give punishment value to the schedule table. Last, we hope to add up collision values and punishment values, and find the table of the least value.

(2) Selection

We adopt tournament selection. It adds up individual table then chooses the least and put into matching pool.

(3) Crossover

According to the rate of crossover, we select n lines from two schedule tables based on the same positions randomly. (n is decided by random numbers.)

(4) Mutation

We swap any two lines from any two schedule tables randomly based on mutation rate.

(5) Replacement

It reserves for the best solution after crossover, mutation each time. If reach the default population size, then, proceeding to replace. Otherwise, go back step 2 to continue.

(6) Termination test

If reaches the pre-set generation or the constant fitness values for many generation, then algorithm ends and exports the decision information for training schedule.

4. Case Study

Case company is founded in 1990. The company is headquartered in Kaohsiung country. The business of the company is hydroxide flame devices, the solar heaters and solar photoelectric system etc. Because the developments mature gradually, the business grows up to more tenfold than in the corresponding period of time last year. Owing to at present the relative information system not corresponding to the present business and the company's need of future development, case company decide to re-implement ERP information system. The lack of staff in the company of MIS department often causes company's interior information system push slowly. The study mainly assists case company in proceeding ERP system that being implemented into the relative training scheduling and provides case company with a training scheduling decision support system.

4.1. System Process Logic

(1) The team of ERP and managers in company discuss with ERP training relative decision factors to decide the objective function that what the algorithm bring into.

(2) The users themselves input the schedule that can jointraining.

(3) Input decision objectives and the available time schedule of employees.

(4) If having any questions then going back (3). Otherwise, generates decision information to help enterprises arrange training schedule.

4.2. System Explanation

We refer to the experiment parameters' (Lin, 2006) suggests. The results of system execution show as follows:

(1) The employees can arrange the schedule to participate in ERP training suitably by themselves.

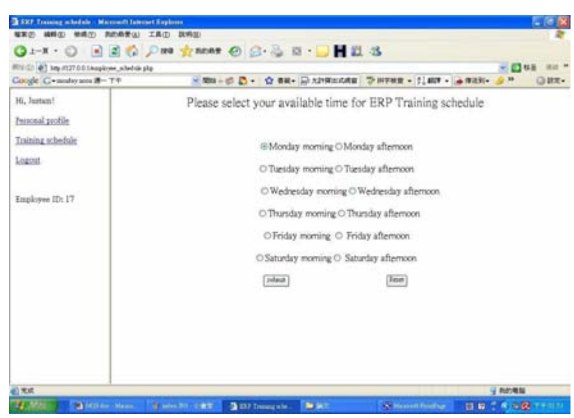
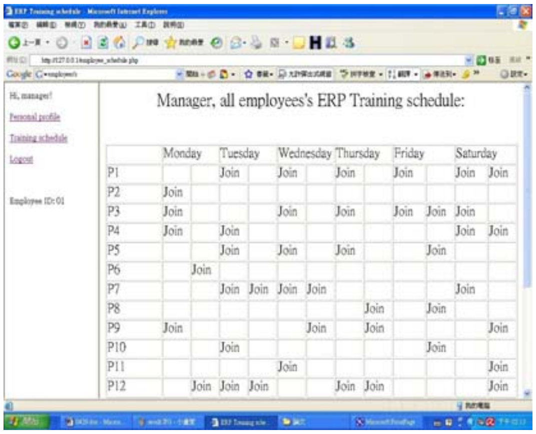


Figure 8. Input Available Time for ERP Training Scheduling

(2) Manager starts to proceeds the ERP training schedule based on schedule information.



	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday	
P1			Join		Join		Join		Join		Join	Join
P2	Join											
P3	Join				Join		Join		Join	Join	Join	
P4	Join		Join								Join	Join
P5			Join		Join		Join			Join		
P6		Join										
P7			Join	Join	Join	Join					Join	
P8								Join		Join		
P9	Join					Join		Join				Join
P10			Join							Join		
P11					Join							Join
P12		Join	Join	Join			Join	Join				Join

Figure 9. The Results of All Employees' Schedule

5. Discussions

We propose hybrid multiobjective training scheduling genetic algorithms (GA) to help enterprises proceed with training schedule of ERP system. The concrete results shows as below:

First, improvement of decision quality and time: We can get the schedule that matches up the real decision results approximately by this algorithm. In the past, the relative ERP research mainly probes into the contents and methods of training. It seldom raises relative research based on schedule arrangements. The main reason is that training scheduling usually with many decision factors. So, it has a specific complication. This study tries to raise an algorithm to help enterprises' training proceed successfully for the schedule time that take reduces froma week to twenty minutes.

Second, the improvement of algorithm: This study improves (Lin, 2006) that addresses the optimal expansion path algorithm base on a single objective. we adopts tabu search to accelerate the solution efficiency of genetic algorithms (GA) and improves the quality of solutions in local search.

6. Conclusions

Because the ERP system is a multiple functional system, it usually has a close relative each function. The users must understand the whole process of workflow. So, there are usually various chances to proceed with training in the interior of the enterprises. ERP system is implemented to help enterprise proceed by consultants. However, their role is an enterprise's external employees. When they encounter problems, they still need the interior employees to solve during implementation of ERP system. Hence, the research yields a rich harvest that can help the enterprises proceed with decision and shorten decision schedule time to make the relative training proceed successfully.

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