MULTI-OBJECTIVES OPTIMIZATION ON THE DEPARTURE OF AIRPLANES FROM BUSY AIRPORT

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Abstract: The delay of airplanes has been the core negative factor to influence the service quality and development of the airline business. The optimized scheduling the arrival and departure of the airplanes is one of good methods to decrease the delay except the uncontrollable weather. The sequence of take-off can be seen as one machine scheduling problem with two objectives: minimizing the number of tardy jobs and minimizing the maximal tardiness of all the jobs. The mathematical model is formulated and multi-objective GA (Genetic Algorithm) is utilized to solve the Pareto optimization. Computational results show that the proposed algorithm performs well when compared with traditional heuristic methods and also provide some choices to the dispatcher which can decide according to the real condition. The process will promote the flexibility and effectiveness of scheduling the departure of airplanes.

1 INTRODUCTION

The delay of airplane at the busy airport has been regarded as the most negative factor which influences the quality of airlines' service. There are a lot of reasons: air traffic control, weather, flow control, and air path restriction, etc (Song, 2010).

If there are two runways at the airport, the type of parallel pattern is usually used: one runway for landing, another runway for departure and both are independent relatively. The departure of airplanes will be discussed in the paper.

When the airplane is about to leave, it will follow the instruction from the ATC-silde on the taxiway-ready to takeoff-the entering point to the airspace sector-the location point of departure. From the viewpoint of traditonal scheduling theory, the ready time to enter the runway can been the release time of job, the departure time on the plane ticket can be viewed as due time, if the airplane's take-off time is later than that, the delay happens which should be avoided in the real world. The period between the waiting time on the runway and the time passing by the location point point of departure (where means the plan has been out of controlling by the airport) is the processing time, the precise value can been calculated by the flying speed and distance, etc.

Sequencing has been an important issue in the busy aiport, Atkin discusses how one runway controller attempts to find the best order for aircraft to take off with uncertain taxi times (Atkin, 2008). Bai researches on the coordination model with dynamic and open for arrival/departure airport dispatching system using software coordination technology (Bai, 2007). Song introduces immune algorithm to solve the fleet assignment problem (Song, 2007). The same point is that these paper always view the objective as solely. But if the quality of airline's service is considered, the objective of departure's sequnce should be not single, and be a trade-off decision. When the controller plans the schedule of airplane's take-off, that the airplane should leave before their due time must be considered, so one objectiv is minimizing the total weighted number of delayed planes ($1|r_j|\Sigma w_j U_j$). If it's done well, the more flights will depart on time, the passengers will be satisfied and the airline will get higher service evaluation. Meanwhile, the controller also thinks about the average delay time if it cann't be avoided, that idea means the minimum of maximal delay time ($1|r_j|L_{max}$) and there should not be some flights with very long lateness. So the departure of airplanes from busy airport will be discussed as one machine scheduling problem with multi-objectives optimization.

1. Minimizing the total weighted number of delayed airplanes:
2. Minimizing the maximal delay time

Minimizing the total number of delayed jobs and minimizing the maximal delay time with release

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time are both showed to be strongly NP-hard (Lenstra, 1977).Here the trade-off is considered among the so-called non-dominating (efficient) solutions, or pareto-optima. There will not be such solutions which has both objectives better than others in the result.

Many researchers have fouced on the multi-objective scheduling problem in different industry. The result shows that most problems ususally are complex and cann't be solved by conventional optimization techniques (Chen, 1994 and Koksalan, 1998). So there are some proposed heursitc methods to solve these NP problem, such as a multi-objective simulated annealing (MOSA) method (Loukil, 2004), tabu search algorithm (Michael, 2002).

The paper is organized as follows: one machine problem with the multi-objective optimization derived from airplane take-off sequence problem is described in Section 1. In Section 2, GA (Genetic Algorithm) will be introduced. The test instances and results are described in Section 3 and conclusions are given in Section 4.

2 MATHEMATIC MODEL

2.1 Genetic Algorithm

Genetic algorithm (GA) is a powerful and broadly method for many problems which are very hard to solve by mathematical OR techniques and has been successfully applied to solve many scheduling optimization problems. GA simulates the evolution in nature by operators (such as crossover and mutation) and evaluates the middle solution during the searching process, and then the global solution will be found in a high probability.

In GA, each solution is encoded to be a chromosome. By selecting the individuals with best fitness, the better solutions will survive. The method is flexible enough to provide sub-optimal solution of large-scale optimization problems, but will cost a lot of time (Wang, 2003). This paper uses NSGA-II (Deb, 2002) to the solve problem and find the frontier curve $E(P)$ composed of non-dominating solutions.

2.2 Solution and Chromosome

The chromosome scheme must express the solution which is made of n genes, where n is the number of airplanes. The feasibility of the crossover operator depends greatly on the scheme.

The solution here can be encoded as π (an permutation of n) which the each digit means the position where each airplane is scheduled on. The formation is easy to handle because each chromosome represents one feasible solution which will have no conflict. So a solution is formatted as $j_1, j_2, \ldots, j_i, \ldots, j_n$, where gene j_i denotes that the airplane j is operated on the position j_i.

After definition of chromosome, initial populations can be achieved by generating some individuals whose chromosome is a randomized permutation of n.

Figure 1 illustrates an example of chromosome when to schedule 5 airplanes (n = 5) which sequence is {5, 3, 1, 2,4}.

5	3	1	2	4

Figure 1: A chromosome encoded in permutation structure.

2.3 Fitness Function

The fitness function is used to provide a measure of how individuals have performed in the problem domain. In this problem, the most fit individuals will have the minimal value of the associated objective functions. The aim is to find appropriate f and g to construct the curve $E(P)$ so that the different objectives have to search on the non-dominating area as possible as near, the crowding distance will be used to describe the distance between the solution on the frontier curve and other close solution (Deb, 2002). More crowding distance means the well-distribution of all solutions and is the searching direction. For the non-dominating solution, the fitness $F(\pi_k)$ is calculated as followed.

Step 1: calculate objective f and g of non-dominating solutions respectively, and rank the current N non-dominating solutions, set $f_1, f_2, \ldots, f_N$ and $g_1, g_2, \ldots, g_N$, for each solution in the frontier of feasible area .

Step 2: set $y_{[k,f]}$ and $y_{[k,g]}$ represent the final rank according to the objective f and g respectively, set $cd_1(y_{[1,f]})=\infty$, $cd_1(y_{[1,g]})=\infty$, $cd_1(y_{[R,f]})=\infty$ and $cd_1(y_{[R,g]})=\infty$, for other k=2,…,N-1, there is

$$cd_f(y_{[k,f]}) = \frac{f(y_{[k+1,f]}) - f(y_{[k-1,f]})}{f^{\max} - f^{\min}} \qquad (10)$$

$$cd_g(y_{[k,g]}) = \frac{f(y_{[k+1,g]}) - f(y_{[k-1,g]})}{g^{\max} - g^{\min}} \qquad (11)$$

Where $f^{\max}$, $g^{\max}$ and $f^{\min}$, $g^{\min}$ are the minimums and maximums of f and g respectively.

Step 3: the crowding distance is defined as

$$F(\pi_k) = cd_f + cd_g \qquad (12)$$

2.4 Selection

The selection criterion is used to select the two parents in non-dominating solutions to apply the crossover operator which will produce successive generations, and a good method will lead to a fast convergence. The method in which the best fitness have more chance to be selected as parents for creating offspring of subsequent generation and called Rolette Wheel Sampling (RWS) is one of the most common strategies. The parameter selection probability P_s ($0 < P_s < 1$) defines the proportion of the previous generation best chromosomes that are copied to the next. By this scheme, the excellent genes in the chromosome can be inherited to next generation in a higher probability.

2.5 Crossover and Mutation

Two basic types of operators: crossover and mutation are used to create new solutions based on existing solutions in the population. Crossover operates will produce two new individuals by exchanging parent chromosomes, while mutation change two position to produce a single new solution. The application of these two basic types of operators and their derivatives depends on the chromosome representation.

The crossover operator is one-point crossover in the paper and controlled by a pre-specified parameter P_c ($0 < P_c < 1$) called the crossover probability. After two chromosomes are chosen from the old population and the crossover point is decided by crossover probability, Genes after the position of crossover site in chromosome will be exchanged between two chromosomes. Figure 2 shows the sequence of genes {1, 2, 4} in the first chromosome is {4, 2, 1}, so in the new chromosome {1, 2, 4} is placed by {4, 2, 1}. {5, 1, 3} is also changed to {5, 3, 1} at the same principle.

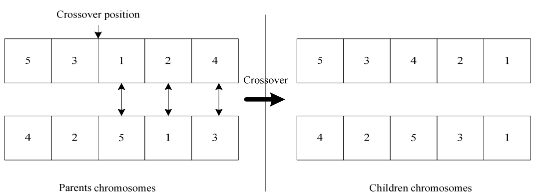

Figure 2: Crossover operation.

Mutation operator is applied to modify a chromosome in order to prevent premature convergence from a local optimization. The genes in the chromosome will be changed as: $j_{i1} \rightarrow j_{i2}$, $j_{i2} \rightarrow j_{i1}$, the quantity and position of mutation is decided by mutation probability P_m ($0 < P_m < 1$).

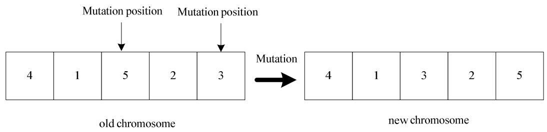

Figure 3: Mutation operation.

By the definition of these operators, the feasibility of each solution is kept.

2.6 Termination Criteria

A pre-determined number of generations are satisfied or the fitness of a population may remain static after a number of generations.

3 CASE STUDY

Experiments and parameters used in GA are proposed to validate the algorithm which is coded with Matlab 6.5 and all experiments are run using an Intel$^{(R)}$ Pentium$^{(R)}$-M 1.70 GHz PC with 512 MB RAM. The computational instances are randomly generated as follows: for each airplane j (j = 1,2,…n, n=40, 80, 100), an integer processing time p_j from the uniform distribution U[1,100]; an integer release time r_j from the uniform distribution U[1, P], where P is the total processing time ($P=\sum p_j$). For a given relative range of due time R (R=0.4, 0.6, 0.8) and a given average delayed factor T (T=0.2, 0.6, 0.8), the integer due time d_j for each job j is generated from the uniform distribution $U[(1-T-R/2)P, (1-T+R/2)P]$. The value R determines the length of the interval from which the due date is taken. T determines the relative position of the centre of this interval between 0 and the sum of the processing time P. there are 5 instances for each example.

The parameters are set at the following values for GA: Population size, 80; number of generation, 100; crossover probability, P_c=0.6; selection probability, P_s=0.1; mutation probability, P_m=0.1.

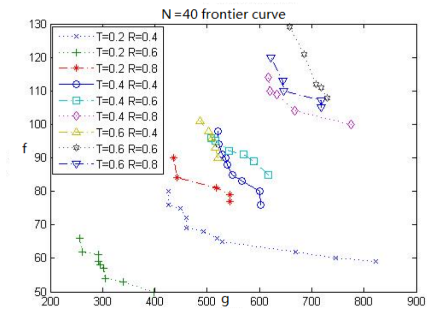

Figure 4: Efficient frontier when N=40.

Fig. 4, 6, 7 represents the corresponding image of the frontier of non-dominating solutions for one instance with 40, 80 and 100 airplanes. Fig. 5 shows the relationship between all solutions and frontier curve of non-dominating solutions, which is the detailed information in Fig. 4 when *T*=*R*=0.4. the non-linked points means dominating solutions and will be discarded.

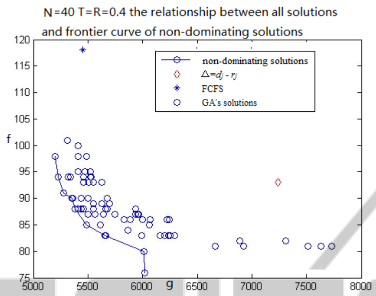

Figure 5: the Detail of efficient frontier when m=40.

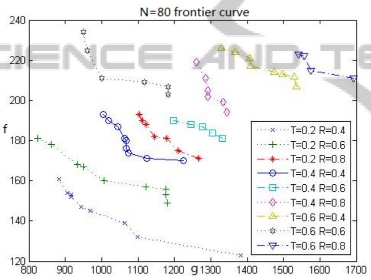

Figure 6: Efficient frontier when N=80.

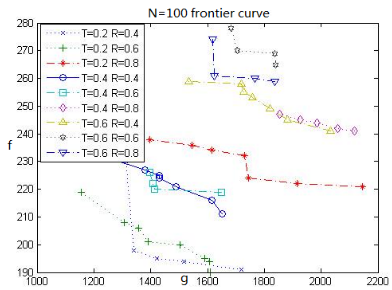

Figure 7: Efficient frontier when N=100.

4 CONCLUSIONS

The paper discusses a special one machine scheduling problem with multi-objectives: minimizing the total weighted number of delayed airplanes; minimizing the maximal delay time of airplanes, which derived from the departure of airplanes from busy airport.

To carry out the playoff between multi-objectives, pareto-optima is considered to provide various choices to the controller. To solve the difficult problem and find the frontier curve containing the non-dominating solutions as more as possible, genetic algorithm is proposed which has been applied to various applications, and proved to be powerful by very good results. The computational result shows the GA can provide more practical solutions than traditional heuristic methods (FCFS and urgency assessment method) and decrease the delay problem because of irrational and wrong sequence or with considering single objective.

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