An aircraft service scheduling model using genetic algorithms

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Received 11 July 2003
Accepted 6 February 2004

Abstract

Purpose – In this paper, the authors propose the application of an intelligent engine to develop a set of computational schedules for the maintenance of vehicles to cover all scheduled flights. The aim of the paper is to maximize the utilization of ground support vehicles and enhance the logistics of aircraft maintenance activities.

Design/methodology/approach – A mathematical model is formulated and the solution is obtained using genetic algorithms (GA). Simulation is used to verify the method using an Excel GA generator. The model is illustrated with a numerical case study, and the experience of this project is summarized.

Findings – The results indicate that this approach provides an effective and efficient schedule for deploying the maintenance equipment resources of the company, China Aircraft Service Limited.

Originality/value – The proposed model using the GA generator provides an effective and efficient schedule for the aircraft maintenance services industry.

Keywords Production scheduling, Aircraft industry, Maintenance

Paper type Research paper

1. Introduction

Accurate planning, scheduling and control systems are important in enabling airport support services companies to achieve effective and efficient operations in the supply chain. However, two major problems in this supply chain element are the dynamic nature of flight schedules and variations in aircraft service requirements. The traditional approach is to prepare planning and scheduling based on the experience and expert knowledge of a few veterans inside the aircraft maintenance organization. Such an approach is unreliable – the resources are not allocated optimally, and a systematic approach is therefore required.

Indeed, earlier researchers have developed different methods for solving scheduling problems (Prabir and Barin, 1991). Some of the research was affiliated with airline

Journal of Manufacturing Technology Management
Vol. 16 No. 1, 2005
pp. 109-119

1741-038X
DOI 10.1108/17410380510574112

ground service scheduling in passenger and baggage services: Lufthansa built the PERSEUS project (www.groundstar.de) and its support staff demanded planning, shift planning and the allocation of staff in real time for Lufthansa's passenger services. Another example is the CHIP system (www.groundstar.de), which was developed by KLM to replace manual planning and allocation procedures, ensuring transparency and the efficient support of airline planners. Recent studies carried out by different aviation organizations have confirmed the importance of human factors and training in improving aircraft maintenance crew effectiveness. The conclusion of these studies was that "technology may advance but people remain the same". As a result, aviation regulatory authorities such as the European Joint Aviation Authority (JAA) have issued guidelines (*CAP 716* (JAA, 2003), *CAP 715* (JAA, 2002)) on human factors in aviation maintenance. Aircraft manufacturers like Boeing have developed a system called Maintenance Error Decision Aid (MEDA) to assist AMO personnel in dealing with the management of maintenance errors caused by human factors.

Nevertheless, research into scheduling problems in aircraft ground support operations is limited. In this study, the author developed a set of vehicle routings to cover each scheduled flight: the objectives pursued are the maximization of daily vehicle schedules. In this proposed system, flight schedule and aircraft type are used to generate a feasible vehicle schedule that maximizes the utilization of the vehicles or minimizes the idle time of vehicles. In this way, excessive resources can be eliminated and the cost of operations decreased.

2. Methodology

2.1. Genetic algorithm-based optimization schedule

In the modeling of this aircraft maintenance resources scheduling problem, genetic algorithms (GAs) are used to search for the solution. This is based on evolutionary adaptation (Davis, 1991; Goldberg, 1989; Holland, 1975): the GA works with a population of possible solutions and creates successive generations of the population by several simple genetic operators. The objective function is absorbed into a fitness function, which may take account of constraint violations via penalty terms. In each generation, solutions are selected stochastically according to their fitness in order to contribute to the next generation. The fit solutions survive and unfit ones tend to be discarded. A new generation is created by stochastic operators, typically cross-over, which swaps parts of binary-encoded solution strings. Successive generations yield fitter solutions that determine the optimal solution to the problem. GAs are inherently simple, naturally parallelizable, and can generate a set of near-optimal solutions for evaluation. A review of different approaches and results is given in Holland (1975). Most studies have employed a single GA for the entire scheduling period. Liepins *et al.* (1987) investigated the simplest scheduling problem, i.e. a static queue of jobs with specified due dates and run times without precedence constraints, with a single server, using minimal lateness as the criterion. Falkenauer and Bouffouix (1991) applied genetic algorithms to small, medium and large job shop problems. They compared the performance of their genetic algorithms with the two most widely used scheduling heuristics, namely least slack time (LST) and shortest process time (SPT). Their experiments revealed the superiority of the genetic algorithms approach over common scheduling heuristics and a slight superiority of the LOX operator. Gupta *et al.* (1993) addressed an n-job, a single-machine problem with the objective of minimizing flow time variances. They generated a data set of ten problems and found optimal solutions for all of them using GAs with very simple modifications. Nakano and Yamada (1991) used a conventional GA to solve a job shop-scheduling problem. They introduced three unique ideas in representation, evaluation and survival. They used binary representation, as opposed to string representation, which made it possible for them to use conventional GAs. To help chromosomes survive, they introduced a new treatment, call forcing, which replaces an illegal chromosome with a legal one. The results obtained indicate that GAs present a good scheduling alternative: they are reasonably fast, gradual and provide better results than heuristics, depending on the objective function of the problem.

2.2. Model structure

In this research, the author adapted a representation method based on sequential and open shop scheduling problems. Each flight is scheduled to travel at an expected time, and flights are timetabled to land or depart in a sequential manner. From Figure 1, we can see that each vehicle is required to operate on one flight schedule. All vehicles are used to provide services according to their arrival or departure time.

There are 18 vehicles divided into three categories (i.e. toilet, water and tractor). Each job, consisting of a single flight, has to be processed again on each type of machine or vehicle; there are no restrictions with regard to the routing of each type of vehicle. This provides various choices to determine the route for each job. Their routes occur in different jobs – flights with different aircraft types. For example, if the aircraft did not request the water refreshment operation, the routing of the vehicles on those flights would omit the water truck. This means that there is no routing of operations to be done on each flight. And there is no direct relationship between all operations, since all the processes (i.e. unloading dirty materials, supplying fresh water and pushing the plane back to the runway) have their own determined ready times. This situation is similar to the definition of an open shop in job shop machine scheduling. Figure 2 illustrates examples of different flights with different operation routings.

In order to develop the scheduling model, several assumptions are made. Some of these assumptions are:

- pre-emption is not allowed (i.e. operations that begin processing are completed without interruption);
- there is no break-down;

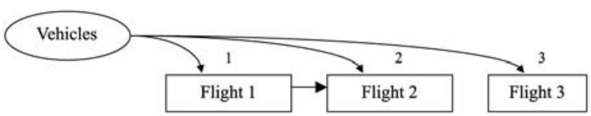


Figure 1.
Process flow of each vehicle

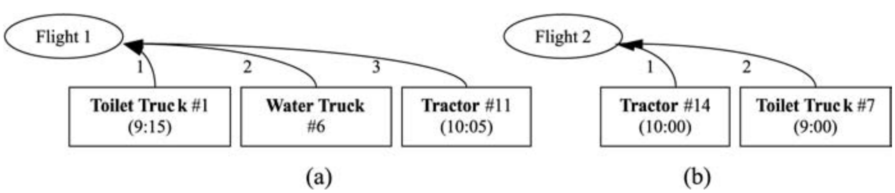


Figure 2.
(a) Normal operation route: (b) operation route without water truck

- the vehicles are unable to perform a required task for lack of an operator, tool, or material;
- due dates, if they exist, are fixed;
- processing times are determinable and known in advance;
- each vehicle can be processed only one operation at a time;
- each service, once started, must be performed to completion (no cancellations);
- there is no service re-processing;
- there are no restrictions with regard to the routing of each type of vehicle; and
- there are no peak and non-peak time service time considerations.

3. The optimization of aircraft service schedules

3.1. Objective function and constraints

In this optimization problem, we define the performance assessment (i.e. objective function) for this scheduling problem as the total flow time minimization between each service of all maintenance vehicles. The flow time of the model is calculated from the starting time of the first operation to the completion time of the last operation; each vehicle has idle time between each operation. The total flow time of the model was calculated as the sum of the ready time of arrival task minus the completion time of the previous task among all the vehicles. The constraint in the model is defined as the completion time of the previous operation, which is less than or equal to the ready time of the next operation of a vehicle. In general, we assume that a five-minute deviation is an acceptable performance measurement. If the completion time of the previous operation is five minutes over the ready time of the next operation, it will also be acceptable. The general model is therefore as follows:

$$\text{Total flow time} = \sum_{j=1}^{n} t_i$$

where:

$$t_i = r_j - C_{j-1}; C_j = \mathrm{ETA}_j + \text{process time}$$

and

$$\text{Constraint} = C_{j-1} \leq r_j + 5$$

where:

$$t_i = r_j - C_{j-1}; C_j = r_j + \text{process time}; r_j = \mathrm{ETD}_j - \text{arrival time}.$$

Notation:

j = services number j (i.e. $j = 1, 2, 3 \ldots n$).

t = flow time between each job.

C_j = completion time of each job.

r_j = ready time of each job.

ETA = estimated time of arrival.

ETD = estimated time of departure

The first equation is used to calculate the total flow time among toilet vehicles, where the process time would be set at 15 minutes and the arrival time would be 5 minutes. The constraint equation is used to calculate the water and tractor models. Their process times are 20 and 15 minutes respectively. The arrival time, however, is slightly different: water trucks require a ready time of 30 minutes prior to the ETD of the plane, while tractor trucks should be ready 15 minutes in advance. There are some further constraints because the variation of aircraft type also affects the service. For example, if the flight is a large plane it should be served by a large tractor. Water service is another constraint in the model – not all flights require water services. If the engineer finds that the landed plane still has adequate water for another journey, he/she does not ask for this service. Therefore, this affects the number of operations that need to be processed by water trucks.

3.2. Simulation data

Much simulation data and information are used for the analysis. The data can be divided into input data, process data and output information.

Input data:

- Flight number (e.g. 1, 2, 3, 4 ... 78, 79 ... etc.).
- Flight name (e.g. CZ3037, MU591, CA117 ... etc.).
- Aircraft type (e.g. A320, B747, DC10 ... etc.).
- ETA (i.e. arrival time of each flight).
- ETD (i.e. departure time of each flight).
- Water truck requirement decision (i.e. yes or no).
- Vehicle number (e.g. 1, 2, 3, 4, 5 ... 16, 17, 18).

The flight numbers and names act as the reference code that determines which flight should be processed by which vehicle. The aircraft type and water truck requirement decisions are used to define the service provided by different types of vehicles on the flights. ETA and ETD are used in the calculations of ready time and completion time.

Process data:

- Standard operation time (i.e. toilet – 15 mins; water – 20 mins; tractor – 15 mins).
- Ready time (i.e. toilet – ETA 5 mins; water – ETD 30 mins; tractor – ETD 15 mins).
- Completion time (i.e. ready time + standard operation time).
- Total number of toilet trucks required.
- Total number of water trucks required.
- Total number of large tractors required.
- Total number of small tractors required.

These process data are used to set up the objective function and constraints. The standard operation time, ready time and completion time facilitate the calculation of the total flow time. In fact, the total number of toilet and water trucks, large and small tractors included in the GA structure will be further explained in Section 3.3.

Output information:

- Total flow time (e.g. 153 hours, 175 hours … etc.).
- Total number of flights possible.
- Total number of flights not possible.
- Flight numbers needing to be processed for each vehicle.
- Gantt chart of each type of vehicle.

The simulation output produces the total flow time and the number of flights. The Gantt chart gives a clear prescription to each vehicle that it has to provide services to the scheduled flights within a certain time, which can also be further adjusted based on the GA-generated schedule. GAs are used to generate a schedule for each vehicle with a minimum total flow time.

3.3. Genes representations

In the GA representations, all the genes are considered as vehicle numbers. Vehicle numbers 1 to 5 represent five toilet trucks; numbers 6 to 8 refer to the three water trucks; numbers 9 to 12 are the four large tractors, and numbers 13 to 18 the six small tractors. The gene's format is represented as an integer that belongs to the permutation encoding method instead of the ordinary one, i.e. the binary method. Indeed, permutation means a string of numbers that represents numbers in a sequence. For example, in Figure 3(a), the first operation would be taken by vehicle number 10; the second operation would be taken by vehicle number 8, and so on. However, in Figure 3(b), there is no such order of work that can be observed in the chromosome. The figures also illustrate the differences between permutation encoding and binary encoding.

Numerous gene representations have been defined by the savants. In fact, operation-based chromosome representation has been used. This representation encodes a schedule as a sequence of operations, where each gene stands for one operation. All the operations for a vehicle are named with the same symbol (= vehicle #) and they are interpreted as operations required for the vehicle in accordance with their order of occurrence along the length of the chromosome (from left to right).

In this example, the vehicle is similar to the job (i.e. the traditional definition in machine operation-based representation), and the flight is equal to the machine.

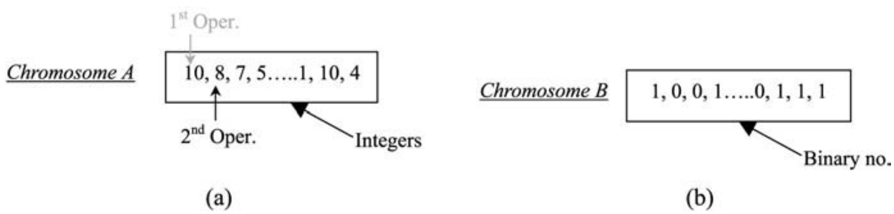


Figure 3.
Encoding method: (a) permutation; (b) binary

Figures 4 and 5 depict the differences between the machine operation-based chromosome representation and our proposed one.

The chromosome's length depends on the total number of vehicles required daily. For example, the solution representation length of 75-flight 18-vehicles with 34 requested water refreshment operations would be expressed as: 75 toilet trucks plus 75 tractors (including large and small tractors) plus 34 water trucks required as predetermined. Hence, after the calculation, the total gene length should comprise 184. The gene would consist of 75 occurrence times of any number from 1 to 5 (i.e. toilet vehicle number); 34 appearance times of any number from 6 to 8 (i.e. water vehicle number) and totally 75 occurrence periods of any number from 9 to 18 (i.e. large and small tractor numbers).

4. Simulation results and analysis

In this research, Excel spreadsheets are used to construct the GA generator. Figures 6-8 show the database file in Excel spreadsheets, and Figure 9 shows the schedule generation in Excel. Figure 10 shows the input for the GA generator.

We can see that two types of genes are used. Three generations have been done for each type of gene input. In fact, four trials have been carried out among each generation, since variations would result from each generation and the average from each trial would produce a reasonable result. The figures in Figure 11 and Table I show the graphical results after taking the average.

From Figure 11 and Table I, the result shows that when taking more numbers of generations, the solution is better. In the case of using random genes as the initial population, the total flow time dropped from 158 hours (i.e. the initial total flow time) to 137 hours after the first generation. After the second generation, the value was reduced to 131 hours and finally to 129 hours in the third generation. There was no significant drop of the flow time when using a random gene as the initial gene. However, the

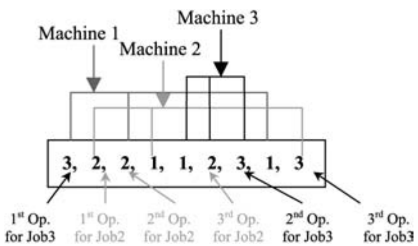


Figure 4. Traditional operation-based chromosome representation

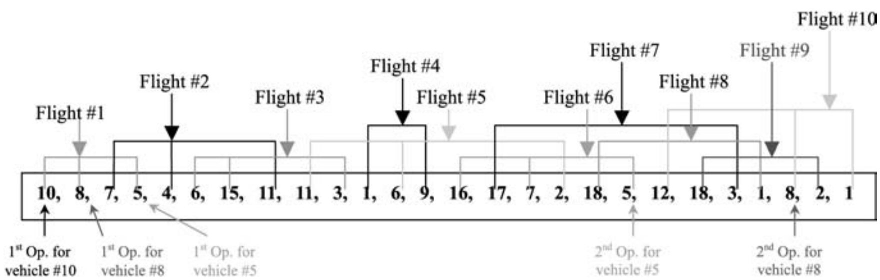
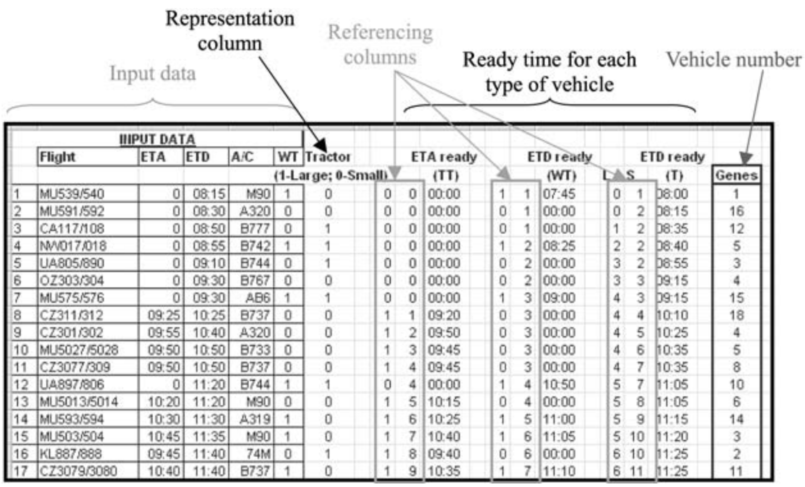
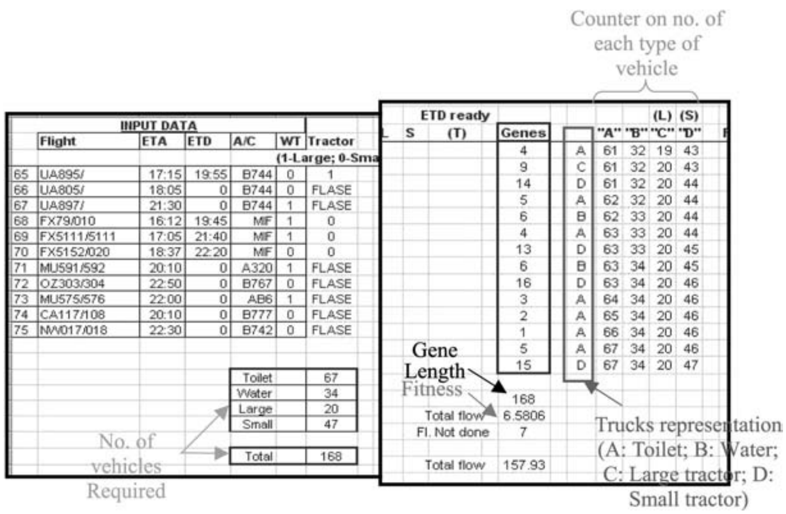


Figure 5. Modified operation-based chromosome representation



	INPUT DATA																
	Flight	ETA	ETD	A/C	WT	Tractor (1-Large; 0-Small)			ETA ready (TT)			ETD ready (WT)	L	S	ETD ready (T)	Genes
1	MU539/540	0	08:15	M90	1	0	0	0	00:00	1	1	07:45	0	1	08:00	1
2	MU591/592	0	08:30	A320	0	0	0	0	00:00	0	1	00:00	0	2	08:15	16
3	CA117/108	0	08:50	B777	0	1	0	0	00:00	0	1	00:00	1	2	08:35	12
4	NW017/018	0	08:55	B742	1	1	0	0	00:00	1	2	08:25	2	2	08:40	5
5	UA805/890	0	09:10	B744	0	1	0	0	00:00	0	2	00:00	3	2	08:55	3
6	OZ303/304	0	09:30	B767	0	0	0	0	00:00	0	2	00:00	3	3	09:15	4
7	MU575/576	0	09:30	AB6	1	1	0	0	00:00	1	3	09:00	4	3	09:15	15
8	CZ311/312	09:25	10:25	B737	0	0	1	1	09:20	0	3	00:00	4	4	10:10	18
9	CZ301/302	09:55	10:40	A320	0	0	1	2	09:50	0	3	00:00	4	5	10:25	4
10	MU5027/5028	09:50	10:50	B733	0	0	1	3	09:45	0	3	00:00	4	6	10:35	5
11	CZ3077/309	09:50	10:50	B737	0	0	1	4	09:45	0	3	00:00	4	7	10:35	8
12	UA897/806	0	11:20	B744	1	1	0	4	00:00	1	4	10:50	5	7	11:05	10
13	MU5013/5014	10:20	11:20	M90	0	0	1	5	10:15	0	4	00:00	5	8	11:05	6
14	MU593/594	10:30	11:30	A319	1	0	1	6	10:25	1	5	11:00	5	9	11:15	14
15	MU503/504	10:45	11:35	M90	1	0	1	7	10:40	1	6	11:05	5	10	11:20	3
16	KL887/888	09:45	11:40	74M	0	1	1	8	09:40	0	6	00:00	6	10	11:25	2
17	CZ3079/3080	10:40	11:40	B737	1	0	1	9	10:35	1	7	11:10	6	11	11:25	11

Figure 6.
Excel spreadsheet representation (input)



	INPUT DATA					
	Flight	ETA	ETD	A/C	WT	Tractor (1-Large; 0-Sma
65	UA895/	17:15	19:55	B744	0	1
66	UA805/	18:05	0	B744	0	FLASE
67	UA897/	21:30	0	B744	1	FLASE
68	FX79/010	16:12	19:45	MF	1	0
69	FX5111/5111	17:05	21:40	MF	1	0
70	FX5152/020	18:37	22:20	MF	0	0
71	MU591/592	20:10	0	A320	1	FLASE
72	OZ303/304	22:50	0	B767	0	FLASE
73	MU575/576	22:00	0	AB6	1	FLASE
74	CA117/108	20:10	0	B777	0	FLASE
75	NW017/018	22:30	0	B742	0	FLASE

Toilet	67
Water	34
Large	20
Small	47
Total	168

Genes		"A"	"B"	"C" (L)	"D" (S)
4	A	61	32	19	43
9	C	61	32	20	43
14	D	61	32	20	44
5	A	62	32	20	44
6	B	62	33	20	44
4	A	63	33	20	44
13	D	63	33	20	45
6	B	63	34	20	45
16	D	63	34	20	46
3	A	64	34	20	46
2	A	65	34	20	46
1	A	66	34	20	46
5	A	67	34	20	46
15	D	67	34	20	47

	168
Total flow	6.5806
Fl. Not done	7
Total flow	157.93

Figure 7.
Excel spreadsheet representation (constraints)

results taken from the genes generated earlier as input into the simulation showed that there was a large drop in the flow time between each generation, except the last one. The value was reduced from 174 hours to 165 hours, and went down to 140 after the second generation. There was only a nine-hour reduction (i.e. 131 hours) in flow time after the third generation. According to the graph (i.e. Figure 11), the two types of gene input would yield similar results (i.e. a flow time of nearly 130 hours), which should be the optimum solution.

5. Discussion and conclusion

We have seen that the proposed model using the GA generator provides an effective and efficient schedule for the aircraft maintenance services industry. The results were

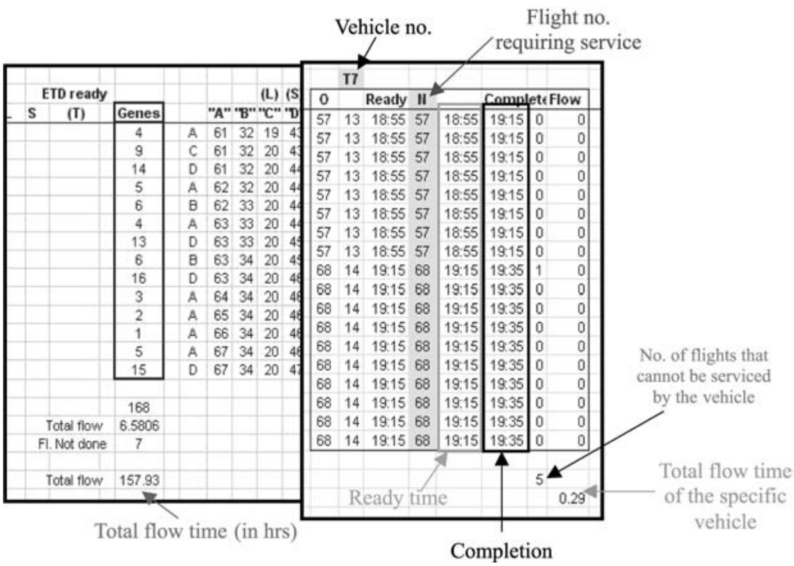


Figure 8.
Excel spreadsheet representation (output)

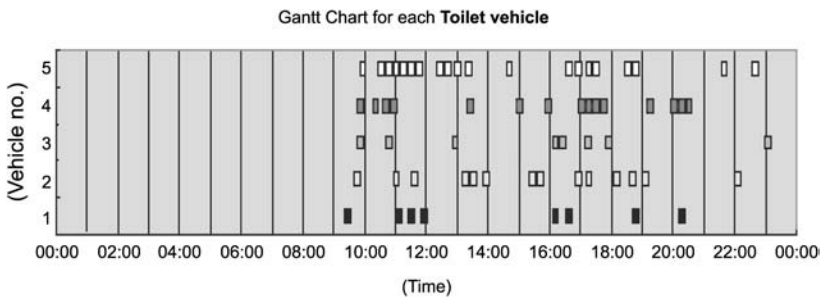


Figure 9.
Excel spreadsheet Gantt chart (output)

depicted using Gantt charts of the flights serviced by each vehicle and the related time slot as well as the operations carried out by each vehicle. The total flow time was minimized. The results were also verified by the number of flights that could not be served – this was due to the peak and non-peak time, since many planes came to the airport for a short period of time which was not enough to enable the vehicles to serve them – the number of cases dropped considerably. The system is therefore valuable for planners or engineers in the manpower and equipment departments of maintenance operators in the airport. They can generate schedules daily or in real time to meet the variation of flight schedules, developing contingency plans to handle any unexpected situations. Moreover, capacity planning can be carried out, and any shortage of resources is identified and idle vehicles monitored. The company is thus able to focus its efforts on providing better customer services and managing its business. Finally, further enhancements are being carried out to identify the robustness of the GA operators for changing environments such as the cancellation of flights and re-scheduling of activities because of supply chain fluctuations.

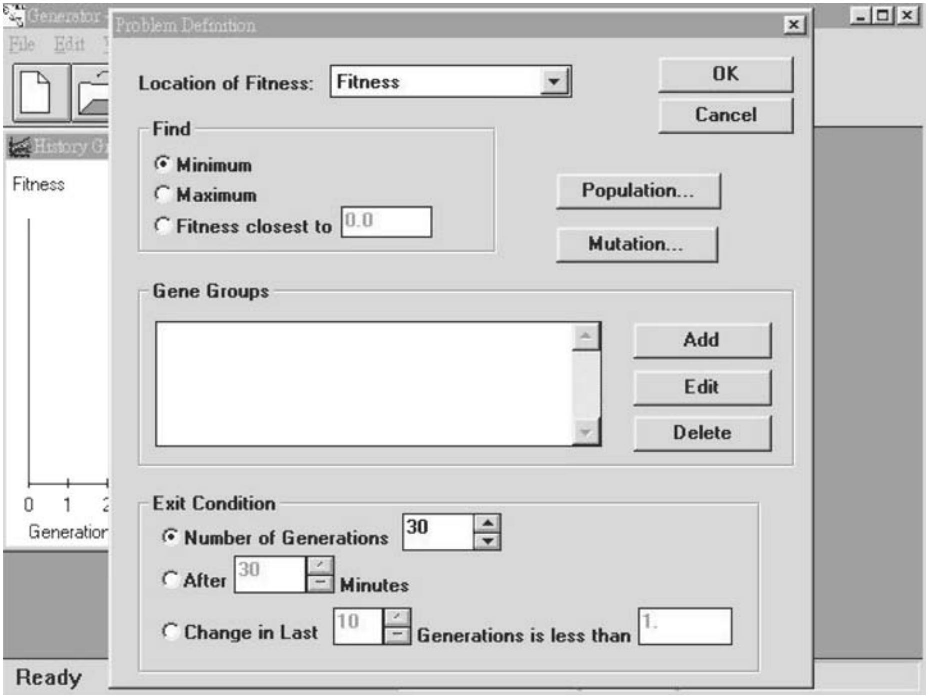


Figure 10.
GA generator components

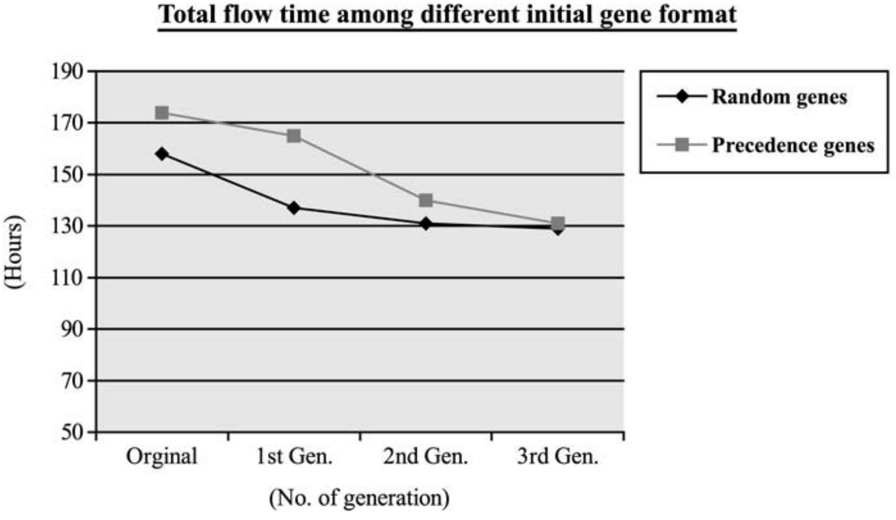


Figure 11.
Results trend among different number of generations

Table I. Number of generations taken

	Trial 1	Trial 2	Trial 3	Trial 4	Average
1st generation (total flow time in hrs)					
Random gene input	125	154	148	118	137
Precedence gene input	167	152	169	171	165
2nd generation (total flow time in hrs)					
Random gene input	123	146	135	118	131
Precedence gene input	142	135	147	136	140
3rd generation (total flow time in hrs)					
Random gene input	123	139	135	116	129
Precedence gene input	133	120	142	123	130

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