A Genetic Algorithm for the Optimization of Admission Scheduling Strategy in Hospitals

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Abstract—**Decisions for admission scheduling in hospitals are a class of optimization problems constrained by many factors. Instead of scheduling the admission of patients directly, this paper proposes a genetic algorithm (GA) designed for the optimization of a long-term admission strategy for the ophthalmology department in hospitals. For the optimization of admission strategy, we devise a coding scheme of strategies and define the objective functions for two objectives: efficiency and fairness. The proposed algorithm utilizes historical data of the hospital for evaluation of chromosomes. Experiments are conducted on several cases, and the strategy optimized by the proposed GA is compared with the first come first serve (FCFS) strategy and the greedy strategy. Experimental results show that strategies optimized by the proposed algorithm outperform FCFS and the greedy strategy.**

I. Introduction

As the demand for medical service increases, the admission scheduling of patients significantly affects the utilization rate of medical resources and the quality of service. However, admission scheduling in hospitals are constrained by factors like the number of beds, category of patients and timetable of surgeries, etc. As these factors make the scheduling of admission complicated, the traditional first come first serve (FCFS) strategy can not guarantee efficiency. Besides, the two major objectives of medical services, i.e. enhancing the utilization rate of medical resources and maintaining fairness, usually contradict each other. Thus an efficient and unbiased strategy is demanded for admission scheduling of patients.

For some typical admission scheduling problems in hospitals, theoretical research works are already done [1]-[3]. Literature [1] built a Markov model for an admission scheduling problem, while literatures [2] and [3] developed statistic and deterministic models respectively for the analysis of utilization rates of bed resource. All of the above works provide guidelines for the admission scheduling problem for patients. However, as the admission scheduling problem is complicated and of various forms, the already-done theoretical research works are not adequate for application [4].

Intelligence systems and intelligence computation are applied to this class of problems for their robustness and no need of precise mathematical models [4][5][6]. Harper *et al.* [4] made the managing and planning of bed capacity in hospitals based on a simulation model. Hutzschenreuter *et al.* [5] built a model of patient flow, and employed an agent system to admit an optimal mix of patients from different departments. Demeester *et al*. [6] designed a hybrid tabu search algorithm that assigns patients to beds in the appropriate departments. All of the above algorithms are run every day to do the scheduling work. However, optimization of the scheduling every day can not always guarantee optimized long-term effect of the algorithm.

The genetic algorithm (GA) [7][8][9] is a technique of evolutionary computation based on population and has been applied to various fields like neural network training [10], image processing [11], and power electronics [12]. It is characterized by its robustness and ability of global convergence. Thus GA is suitable for solving the admission scheduling problem. This paper proposes a new GA for the optimization of admission strategy, different from all the above-mentioned approaches. The algorithm utilizes historical data in a period, and optimizes a long-term admission strategy instead of doing the scheduling work directly. Thus the algorithm has a global perspective, and only need to be run once to obtain an optimized strategy.

The proposed GA is designed for a class of medical systems where the bed resources are the main bottleneck of medical services. In the system, most of the patients that need surgery are not emergency cases, and can wait for a few days before admission. As the timetable of surgeries is constrained by several factors, a proper strategy for admitting patients is required for efficiency and fairness of the system. For the optimization of admission strategy, we devise a coding scheme of chromosomes for the proposed GA. Also, we design the evaluation functions for two objectives: efficiency and fairness. For evaluation of chromosomes, the algorithm utilizes historical data of the hospital and calculates the value of objective functions through simulation. Finally, the strategy optimized by the proposed GA is compared with the

This work was supported in part by the NSFC Joint Fund with Guangdong under Key Project U0835002 and the National High Technology Research and Development Program ("863" Program) of China, No.2009AA01Z208.

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978-1-4244-8126-2/10/$26.00 ©2010 IEEE

FCFS strategy and a greedy strategy. Experimental results show that strategies optimized by the proposed algorithm outperform FCFS and the greedy strategy on the two objectives.

The rest of this paper is organized as follows. Section II presents the background and analysis of the considered problem. Section III describes the proposed GA. The experimental results and performance comparison for the FCFS strategy, the greedy strategy, and strategies used in the proposed GA are presented in Section IV. Section V concludes this paper.

II. Background and Analysis of the Problem

A. Background

In this paper, we consider one specialized department of the hospital, i.e. department of eye diseases, to be a relatively independent medical system. In a hospital, the ophthalmology department admits four kinds of patients: patients with cataract, with retinal diseases, with glaucoma, and with ocular trauma, respectively. All the four categories of patients need surgery, and they arrive every day waiting for admission. However, as vacant beds are limited, most of the patients can not be admitted immediately. In each day, the hospital admits some patients in the waiting line according to the number of vacant beds and a certain strategy such as the FCFS.

As doctors and resources are limited, there are some constraints for the surgeries listed as follows.

1) Patients with ocular trauma require surgery in the day after their arrival. If this requirement can not be satisfied, the patient will be transferred to another hospital immediately.

2) Cataract surgeries and other surgeries (except ocular trauma surgeries) should not be assigned in the same day.

3) Some patients with cataract needs surgery for only one eye, but some patients need surgery for both eyes. The latter should have surgery for one eye first, and have surgery for the other eye two days later.

B. Analysis

Once a patient is admitted for surgery, the patient will go through four stages before he leaves the hospital. These four stages are presented in Fig. 1. Stage 1 is the preparation stage, in which the hospital makes preparation for the surgery. During stage 2 the patient waits for the surgery in case the surgery can not be scheduled immediately after stage 1. This means that stage 2 is a waste of resources and can be reduced if the patients are admitted according to a proper strategy. Stage 3 is for the surgery and stage 4 is for the resumption after surgery.

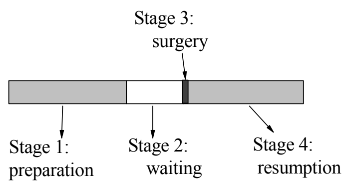


Fig. 1. Four stages after a patient is admitted.

As mentioned above, the length of stage 1, stage 3, and stage 4 are all decided by the condition of a patient, and thus can not be optimized. On the other hand, stage 2 is a waste of resources and its length can be reduced. Besides wasting the time and money of a patient, stage 2 also makes the bed resource not fully utilized. In this system of medical service, the bed resource is one of the bottlenecks that affect the efficiency rate of medical services. Thus minimizing the average time of stage 2 means promotion to the serving rate.

If the department sticks to the FCFS strategy, the system is fair but probably inefficient, as the FCFS strategy may result in a long average length of stage 2. On the other hand, if the department only admits patients with the minimum expected time of stage 2 (and this is a greedy strategy), imbalance of admission may occur among different categories of patients, which may finally affect the efficiency of system. Thus a strategy other than FCFS and greedy is necessary for an efficient and fair medical system.

In this work, the objective of optimization is to find an optimal strategy so that the waste of resources is minimized, and that all kinds of patients are treated fairly. Here we apply GA to the problem for finding an efficient and fair admission scheduling strategy instead of scheduling the admission directly. The algorithm is thus to be run only once for an appropriate strategy, and every day all the scheduling work is done according to the optimized strategy.

III. GA for the Optimization of Admission Scheduling Strategy

A. Coding of Strategies

The proposed GA is designed for the optimization of admission scheduling strategies. However, coding all possible scheduling strategies in chromosomes would be infeasible. Thus, here we only handle one class of strategies, which is specialized for the considered problem. This class of strategies has a number of parameters, which are to be optimized by GA.

Patients with ocular trauma do not need admission scheduling, as they would be admitted as long as there are vacant beds. There are still three categories of patients except ocular trauma. Among the three, patients with cataract can be divided into two groups according to the number of eyes that need surgery. Thus the patients for admission scheduling can be grouped into four categories: patients with cataract on one eye, patients with cataract on two eyes, patients with retinal diseases, and patients with glaucoma. In the following paragraphs, we number them from 1 to 4.

There is a period of T days for the timetable of the surgeries. Cataract surgeries can only be scheduled to the 1^{st}, 3^{rd}, …, $(2*v-1)^{th}$ day of a period. Every day, when admitting the patients, the ith category of patient can be admitted only if the surgery can be scheduled to at most G_i days later. Generally, smaller G_i promises less time of stage 2 for the i^{th} category of patients, but the average length of stage 2 for all patients may increase.

A coefficient k_i is defined for the i^{th} category of patients, and k_i is a real number for deciding the proportion for the i^{th} category of patients in all the admitted patients. When admitting patients, the number admitted for the i^{th} category of patients is

$$a_i = \left\lfloor a_0 \cdot \frac{k_i}{\sum_{j=1}^{4} t_j \cdot k_j} \right\rfloor \tag{1}$$

where a_0 is the total number of vacant beds; t_j is assigned 0 or 1. The value of t_j is 1 only when the i^{th} category is admitted according to G_i.

In the strategy, the period T, the integers v and G_1-G_4, and the real coefficients k_1-k_4 are all parameters. The structure of a chromosome is illustrated in Fig. 2. All the parameters are optimized by GA to form an efficient and unbiased strategy.

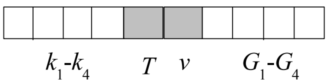


Fig. 2. The structure of a chromosome.

B. Objective Function

The optimization of a strategy has two objectives: (a) minimization of the waste of resources; (b) maximization of the fairness of the system. Both of the objectives are associated with long-term performance of a strategy. Thus the evaluation of a strategy should consider its effect over a period of d days. In this paper, the calculation of the value of objective functions are based on simulation and historical data, thus the value of d is decided by the length of available data.

For objective (a), there are two cases where the bed resource is wasted: the vacant beds without assigning patients and the beds that are in stage 2 as mentioned in the previous section. Thus the first objective can be defined as the average number of vacant beds and beds in stage 2:

$$\min f_1 = \frac{\sum_{i=1}^{d} w_i}{d} \tag{2}$$

where d is the number of days for simulation; w_i is the number of beds that is vacant or in stage 2 in the i-th day. The value of f_1 is calculated through simulation.

For objective (b), we denote the total number of the i^{th} category of patients n_i, and the total admitted number of the ith category of patients n_i'. The system is relatively fair if the ratio between n_i and n_i' are almost the same for all i. Thus we define the second objective to be the standard deviation of n_i'/n_i as shown in (3)

$$\min f_2 = \sqrt{\frac{\sum_{i=1}^{i=4} \left(\frac{n_i'}{n_i} - U\right)^2}{4}} \quad U = \frac{1}{4}\sum_{i=1}^{i=4} \frac{n_i'}{n_i} \tag{3}$$

where U is the average value of n_i'/n_i.

When evaluating a chromosome, the values of f_1 and f_2 are calculated though simulation. All of the constraints described in Section II-*A* are handled in the process of simulation. Thus the constraints can be changed without modifying the coding strategy and the framework of the algorithm.

C. Description of the Algorithm

The GA for optimization of scheduling strategies has the same framework as the classical GA, except that a local search operator is added to refine solutions. The flowchart of the algorithm is presented in Fig. 3.

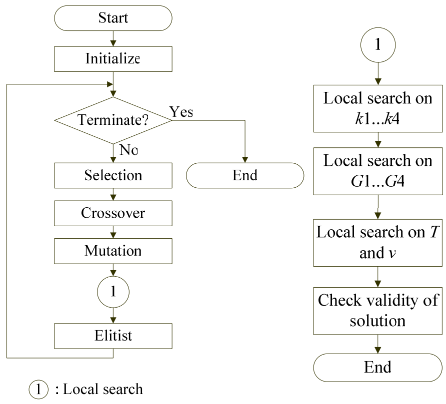


Fig. 3. Flow chart of the proposed GA.

The detailed description of the algorithm in Fig. 3 is as follows:

1) Initialization. In a population of size N, all chromosomes are initialized to be the random strategy with all variables within the legal range. The counter of function evaluations is set to 0.

2) Selection. The algorithm employs the tournament selection, where the scale of tournament is K. When selecting a new population, the algorithm selects K chromosomes randomly for tournament. Then it adds the winner of the tournament to the new population repeatedly until there is a new population of size N. When comparing two chromosomes, the following strategy is applied: chromosomes with both better f_1 and better f_2 definitely win, whereas chromosomes with better f_1 but worse f_2 (or with better f_2 but worse f_1) win with a probability of 0.5.

3) Crossover and mutation. Each chromosome goes through the crossover process with a probability of px. In the proposed algorithm, we choose the traditional single-point crossover for simplicity. The single-point crossover exchanges the variables after a randomly selected position for two chromosomes. Also, for each chromosome, every variable is mutated with a probability of pm. The mutation sets the variable to a random value within the legal range.

After crossover and mutation, every chromosome is checked to guarantee that it is a legal strategy, i.e. the value of T is no less than twice the value of v. Illegal strategies are reset to a legal one by modifying v to be $\lfloor T/2 \rfloor$.

4) Local search. The local search process includes three parts: local search on coefficients k_1-k_4, local search on G_1-G_4, and local search on period T. The three parts are described as follows:

(a) For local search on k_1-k_4, the algorithm selects a variable from k_1-k_4 randomly, and add a random real number to the variable within the range [-r, r], where r is the radius of local search, and is set to $(U_k-L_k)/N$, U_k is the upper bound for k_i, L_k is the lower bound, and N is the population size. We set $U_k = 0$ and $L_k = 10$.

(b) For local search on G_1-G_4, the algorithm randomly selects a variable from G_1-G_4, and adds a random integer within [-1, 1] to the variable. Then the algorithm checks G_1-G_4 to be within the range [L_g, U_g]. Here we set L_g=1 and U_g=10.

(c) For local search on T, add a random integer within [-1, 1] to T. The algorithm first checks whether T is within the range [L_T, U_T] (in this paper we set L_T=5, U_T=20), then it checks the validity of chromosome as in 3).

IV. Experiments and Discussions

A. Experimental Settings

In this section, experiments are conducted to compare the performance of strategies optimized by GA, the FCFS strategy, and the greedy strategy. Here the FCFS strategy simply admits the patients according to the order of their arrival. The greedy strategy admits patients according to the expected number of days of stage 2, and also to the order of arrival if the expected length of stage 2 is the same.

The setting of parameters for GA are shown in Table I, where N is the population size, px is the probability of crossover, and pm is the probability of mutation.

TABLE I
Parameter Setting for GA

Parameter	N	px	pm
Value	30	0.1	0.7

Experiments are conducted on three cases, and the descriptions of the test cases are presented in Table II. In Table II, there are four columns that describe the test cases. The first column shows the total number of available beds. The next column presents the average number of days for the preparation of surgery, and the numbers are listed for all the five categories of patients, i.e. patients with cataract on one eye, with cataract on two eyes, with retinal diseases, with glaucoma, and with ocular trauma, respectively. The third column shows the average number of patients that arrive every day, and the last column is the average days required for resumption. The data for case 1 and case 2 are generated, while the data for case 3 are from a hospital.

TABLE II
Description of Test Cases

	Beds	Preparation	Arrival	Resumption
Case1	56	1,1,2,2,0	2.5, 3,3, 1.5, 1.5	2, 2.5, 6, 4.5, 5
Case2	79	1,1,2,2,0	3.5, 4.5, 5.5, 3, 2	4, 5, 8, 8, 7
Case3	79	1,2,3,2,0	3.5, 4, 3, 2.5, 1.5	3, 3.5, 7, 5.5, 6

B. Experimental Results

On each case, both FCFS strategy and greedy strategy need only one run, whereas GA runs 30 independent times. In each run, the GA terminates after 40000 function evaluations. The average and best values of f_1, f_2 are shown in Table III.

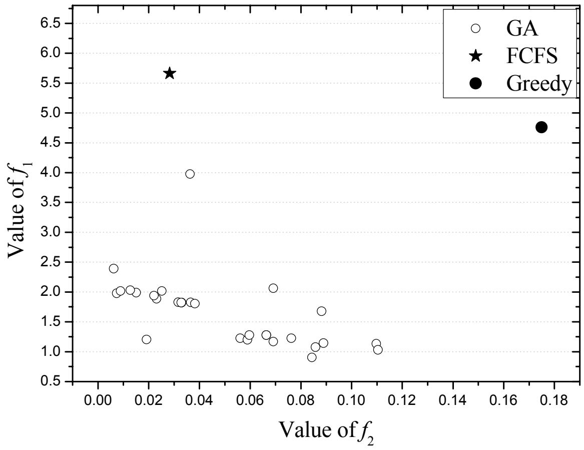
TABLE III
Experimental Results

Case	Algorithm	Avg f_1	Avg f_2	Best f_1	Best f_2
Case1	GA	1.6534	0.04712	0.94256	0.00621
	FCFS	5.6615	0.028285	5.6615	0.028285
	Greedy	4.7589	0.17495	4.7589	0.17495
Case2	GA	2.4653	0.03312	0.82455	0.00134
	FCFS	7.5777	0.029135	7.5777	0.029135
	Greedy	5.3852	0.17100	5.3852	0.17100
Case3	GA	4.4345	0.053445	3.6465	0.04325
	FCFS	6.0444	0.057735	6.0444	0.057735
	Greedy	5.8666	0.080979	5.8666	0.080979

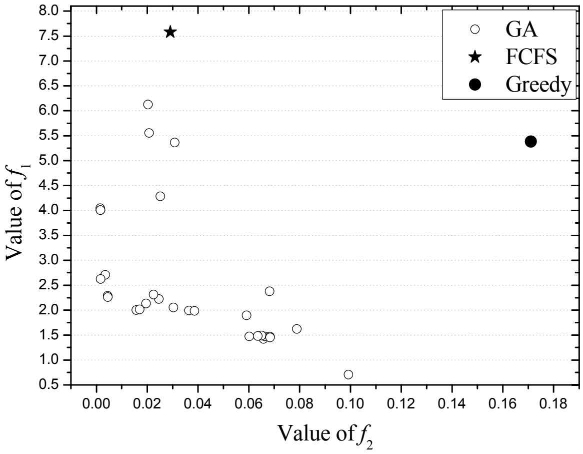
From Table III, strategies optimized by GA outperform the FCFS strategy and the greedy strategy on f_1 in all the three cases. On f_2 the proposed GA outperforms the greedy strategy but performs slightly worse than the FCFS strategy. However, the FCFS strategy is not competitive for its poor performance on f_1. The results are consistent with the idea that the FCFS strategy only guarantees the fairness of the system but does not consider the utilization of recourses. The results for the greedy strategy on f_1 is due to the fact that it admits patients only based on the expected length of stage 2 but pays no attention to the balance among the admission of different categories of patients.

Case 3 is from a hospital, and the data are relatively odd compared with case 1 and case 2. Thus in this case an optimal strategy is hard to achieve. GA still outperforms FCFS strategy and the greedy strategy in case 3, although its superiority is not so obvious as in case 1 and case 2.

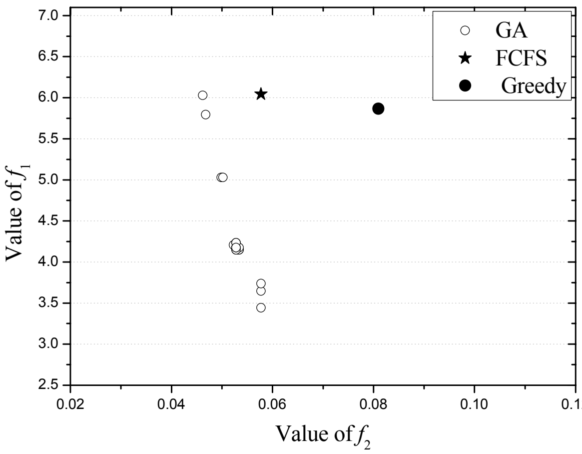
Fig. 4(a)-(c) illustrate the distribution of the values of f_1 and f_2 on case 1 to case 3. The objective function values of solutions found by GA, the FCFS strategy and the greedy strategy are plotted. It is shown in Fig. 4(a)-(c) that almost half of the points that represent solutions found by GA have both better f_1 and better f_2 than the FCFS strategy and greedy strategy, and that almost all of the points representing solutions found by GA have better f_1.



(a) Case 1



(b) Case 2



(c) Case 3

Fig. 4. Distribution of the objective function values on Case 1, Case 2, and Case 3.

V. CONCLUSION

This paper proposes a GA designed for the optimization of patient admission strategies in the eye disease department. For the optimization of admission strategies, we devise a coding scheme of chromosomes and define the evaluation functions for two objectives: efficiency and fairness. The proposed algorithm utilizes historical data from the hospital for evaluation of chromosomes. Although only one class of medical systems is considered in this paper, the proposed algorithm can solve other problems with modified constraints without changing the coding strategy and the framework of algorithm. Experiments are conducted on three cases, and the strategies optimized by the proposed GA are compared with the FCFS strategy and greedy strategy. Experimental results show that the strategies optimized by the proposed algorithm outperform both the FCFS and the greedy strategies.

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