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Novel operating theatre scheduling method based on estimation of distribution algorithm

Zhou Binghai Yin Meng

(School of Mechanical Engineering, Tongji University, Shanghai 201804, China)

Abstract: In order to improve the efficiency of operating rooms, reduce the costs for hospitals and improve the level of service qualities, a scheduling method was developed based on an estimation of distribution algorithm (EDA). First, a scheduling problem domain is described. Based on assignment constraints and resource capacity constraints, the mathematical programming models are set up with an objective function to minimize the system makespan. On the basis of the descriptions mentioned above, a solution policy of generating feasible scheduling solutions is established. Combined with the specific constraints of operating theatres, the EDA-based algorithm is put forward to solve scheduling problems. Finally, simulation experiments are designed to evaluate the scheduling method. The orthogonal table is chosen to determine the parameters in the proposed method. Then the genetic algorithm and the particle swarm optimization algorithm are chosen for comparison with the EDA-based algorithm, and the results indicate that the proposed method can decrease the makespan of the surgical system regardless of the size of operations. Moreover, the computation time of the EDA-based algorithm is only approximately 5 s when solving the large scale problems, which means that the proposed algorithm is suitable for carrying out an on-line scheduling optimization of the patients.

Key words: operating theatre scheduling; estimation of distribution algorithm; makespan

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On the basis of minimizing operational costs, how to maintain a high quality of health care becomes one of the most challenging issues for hospitals. An effective and efficient scheduling system of operating theatres provides an appealing solution to the challenging problem[1].

Currently, many researchers have tried to develop efficient models and heuristic algorithms for operating theatre scheduling problems. For example, Aringhieri et al.[1] studied the joint operating room planning and advanced scheduling problem. Choi et al.[2] provided an approach to optimize a block surgical schedule that adhered to the block scheduling policy. Vijayakumar et al.[3] introduced a mixed-integer programming model for a multi-period, multi-resource, patient-priority-based surgical case scheduling problem. Zhao et al.[4] studied how to schedule elective surgeries to multiple operating rooms in ambulatory surgical settings. Augusto et al.[5] considered that patients' recoveries were allowed in operating rooms, and presented a Lagrangian relaxation method for solving the operating theatre scheduling problem. Devi et al.[6] developed a general framework of algorithms to schedule operating rooms optimally by forecasting the surgery time. Wang et al.[7] focused on finding a satisfactory surgery scheduling to patients and efficiently managing scarce medical resources in laminar-flow operating theaters. Wang et al.[8] proposed a new method to solve the surgery scheduling problem with a downstream process. Xiang et al.[9] proposed a mathematical model to efficiently solve surgery scheduling problems. Souki et al.[10] proposed a set of dispatching rule-based heuristics and three meta-heuristics to solve a scheduling problem in two stages.

A review of the available literature indicates that there is a dearth of research that explicitly considers surgeons' availability. It cannot fully adapt to the practical applications. In this study, the availability of surgeons is inherent in operating rooms.

Moreover, some of those methods have been adopted for operating theatre scheduling problem such as the genetic algorithm, particle swarm optimization, and ant colony optimization approach. Population-based optimization algorithms have become popular for solving operating theatre scheduling problems. Therefore, this paper seeks to find an effective algorithm aimed at solving the above scheduling problems. As a relatively new population-based optimization algorithm, the EDA has been successfully developed to solve a variety of optimization problems in academic and engineering fields[11–12]. However, there has been no research concerning the EDA for solving the operating theatre scheduling problems so far. In this paper, the problem is explored with surgeons' availability constraint. An EDA is developed to solve the scheduling problem.

1 Model Description and Formulations

The operating theatre scheduling problem is concerned

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Biography: Zhou binghai (1965—), male, doctor, professor, bhzhou@tongji.edu.cn.

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with providing each surgical case with an operating room, a recovery bed and a starting time for the operation. It takes into account the constraint of surgeons' availability with the aim of minimizing the makespan.

According to Ref. [10], the assumptions are given as follows: 1) Each patient undergoes only one surgical operation in an operating room, and then he or she is transferred to an available recovery bed. 2) Each operating room is multifunctional, so that all surgical operations can be operated in any operating room. 3) There is no time needed for transferring a patient from an operating room to a recovery bed. 4) All surgical cases operated in the same time period are arranged successively in the same operating room. 5) One surgeon cannot perform two surgical cases in the same operating room at the same time. 6) Each patient occupies at most one available recovery bed at a time. 7) Not every surgeon is available all the time. 8) Operations can be performed by available surgeons.

Fig. 1 illustrates the process of a surgical case in an operating theatre. On a given day, Case A is scheduled to be operated. If the surgeon who is scheduled to operate Case A is available, Case A can be operated in an available operating room, and then can be transferred to an available recovery bed. Otherwise, Case A cannot be operated on that day.

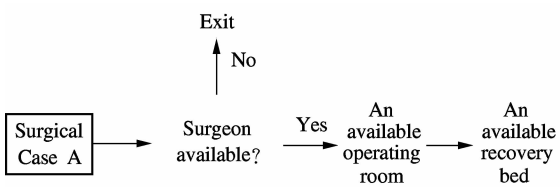

Fig. 1 Operating theatre scheduling problem

It is common expectation that a patient should receive treatment and recover as soon as possible. Also, most research has made efforts to minimize the makespan to increase the operating room's utilization. Let N be the number of patients, and the number of patients in the recovery room can be represented by N_{p}. Thus, the scheduling objective is to minimize the makespan of the surgical system, which is defined as follows:

$$\min_{1\leqslant k\leqslant N} \max_{1\leqslant l\leqslant N_{\mathrm{p}}} \left\{ \sum_{k=1}^{l} (O_k + E_k) \right\} \tag{1}$$

where O_i is the duration of surgical operation on patient i, and E_i is the duration of recovery on patient i.

According to assumption 1), an assignment constraint is needed. At any time, a patient can be assigned to at most one surgeon on a given day. In other words, a surgical case can be assigned only once. The following equation must be satisfied:

$$\sum_{m=1}^{P} x_{im} = 1 \qquad \forall\, i = 1, 2, \ldots, N \tag{2}$$

where $x_{im} = 1$ if patient i can be performed in operation room m and 0 otherwise. P is the number of operating rooms.

Based on assumption 3), the scheduling with no-wait constraint is considered. The starting time of each patient's recovery is the ending time of operation, which should satisfy the following requirement:

$$D_i - C_i = O_i \qquad \forall\, i = 1, 2, \ldots, N \tag{3}$$

where C_i and D_i indicate the operation starting time and recovery starting time of patient i, respectively.

According to assumption 4), to guarantee the continuity of operations, patients i and j do not overlap at one time. The following relationship must be satisfied:

$$\sum_{i=1}^{N} \sum_{m=1}^{P} y_{ijm} + \sum_{i=1}^{N} \sum_{m=1}^{P} y_{jim} \geqslant 1 \qquad \forall\, j = 1, 2, \ldots, N \tag{4}$$

where $y_{ijm} = 1$ if patient i is sequenced immediately before patient j in operating room m, and 0 otherwise.

Based on assumption 5), any surgeon cannot perform two surgeries on a given day simultaneously. Let S be the number of surgeons. The following inequality must be obeyed:

$$\begin{gathered} C_j \geqslant D_i + O_i - M(3 - \omega_{i,p} - \omega_{j,p} - y_{ijm}) \\ \forall\, i, j = 1, 2, \ldots, N, i \neq j; \;\; \forall\, m = 1, 2, \ldots, P \\ \forall\, p = 1, 2, \ldots, S \end{gathered} \tag{5}$$

where $\omega_{i,p} = 1$ if surgeon p perform patient i and 0 otherwise, and M is an infinity number.

According to assumption 6), to ensure that the number operations performed cannot exceed the maximum number of recovery beds on day t. Let R be the number of available recovery beds on day t. The following equation must be obeyed:

$$\sum_{b=1}^{R} f_{b,i} = 1 \qquad \forall\, i = 1, 2, \ldots, N \tag{6}$$

where $f_{b,i} = 1$ if patient i is assigned to the b-th recovery bed and 0 otherwise.

To deal with surgeons' availabilities, make the schedule fully adapt to the practical applications, the detail is described based on the mentioned assumptions 7) and 8) as follows:

$$\begin{gathered} C_i + O_i - M(1 - \omega_{i,p}) \leqslant F_q \\ \forall\, i = 1, 2, \ldots, N; \;\; \forall\, p = 1, 2, \ldots, S; \; \forall\, q = 1, 2, \ldots, Q \end{gathered} \tag{7}$$

where F_q is the completing time of time block q; Q is the number of surgeon time blocks and M is an infinity number.

We should ensure that a starting time of every surgical operation starts from $t = 0$. That is

$$D_i \geqslant O_i \qquad \forall\, i = 1, 2, \ldots, N \tag{8}$$

Consequently, the scheduling problem contains the objective function (1) and the constraints (2) to (8).

2 EDA-Based Scheduling Algorithm

As a relatively new paradigm in the field of evolutionary computation, the estimation of distribution algorithm employs explicit probability distributions in optimization[12-16]. A modified EDA algorithm is built for the operating theatre scheduling problem considering the availability of surgeons. Combined with the specific constraints of operating theatres, an adaption of the EDA is presented. The steps are introduced as follows.

Step 1 Determine availability. Determine whether a surgeon is available or not. If he or she is not available, exit the algorithm, otherwise go to Step 2.

Step 2 Encoding. Each individual of the population denotes a solution, which can be expressed by an integer number sequence with the dimension of L. $L = \sum_{j=1}^{N} i_j$, where i_j is the index of operation.

Step 3 Initialization. Determine the population size (PopSize). In order to guarantee diversification in the population, PopSize individuals in the L-dimensional search space are initialized randomly. To prune the search space and to remove the infeasible solutions in the range, the range of the L-dimensional vector is $[1, N]$.

Step 4 Generate feasible scheduling solutions. For any individual, an infeasible solution means that the total operation time exceeds the duration of all time blocks of the surgeon. Set $S_p = \sum_{q=1}^{Q} \sum_{i=1}^{N} (\omega_{i,p} O_i + D_q - F_q), \ \forall p$, where D_q is the starting time of time block q. If $S_p > 0$, go back to Step 3; otherwise, go to Step 5.

Step 5 Fitness value function. The objective is to minimize the makespan. To maintain its nonnegative and maximal, the reciprocal of the maximal makespan is selected as the fitness function, and the fitness of each individual is calculated according to fit $= 1 \Big/ \sum_{k=1}^{l} (O_k + E_k)$, $1 \leqslant l \leqslant N_p$.

Step 6 Probability model. The EDA produces new population by sampling a probability model. In this paper, the probability model is designed as a probability matrix $\boldsymbol{P}$. The element $p_{ti}(g)$ of $\boldsymbol{P}$ represents the probability that patient i appears before or in position t of the operation sequence at generation g. The value of p_{ti} refers to the importance of a patient when deciding the operations order[12]. First, select the superior sub-population with the best MP(MP $= \beta$PopSize, where $0 < \beta < 1$) solutions. Then, the probability matrix $\boldsymbol{P}$ is initialized according to the following equation:

$$p_{ti}(g = 1) = \frac{1}{i\mathrm{MP}} \sum_{s=1}^{\mathrm{MP}} I_{ti}^{(s)}(1) \qquad \forall i, j \in n$$

where

$$I_{ti}^{(s)}(g) = \begin{cases} 1 & \text{patient } i \text{ appears before or in position } t \\ 0 & \text{else} \end{cases}$$

Step 7 Updating mechanism. After generating a new population, it determines the superior sub-population with the best MP solutions. Then, the probability matrix $\boldsymbol{P}$ is updated according to the following equation:

$$p_{ti}(g+1) = (1-\gamma) p_{ti}(g) + \frac{\gamma}{i\mathrm{MP}} \sum_{s=1}^{\mathrm{MP}} I_{ti}^{(s)}(g+1)$$

where $\gamma \in (0, 1)$ is the learning rate of $\boldsymbol{P}$.

Step 8 Replacement. In each generation of the EDA, the new individuals are generated via sampling according to the probability matrix $\boldsymbol{P}$. For every position t, patient i is selected with probability p_{ti}. If patient i has already appeared, then $p_{ki}(k > t) = 0$ and all the elements of $\boldsymbol{P}$ will be normalized to maintain each row summing up to 1. An individual is constructed until all the patients appear in the sequence. In such a way, a population of PopSize individuals is generated.

3 Simulation and Analysis

To evaluate the presented algorithm performance, the computation times and makespan values as the performance measurements are chosen. The program is coded in Visual C++, on a 2.10-GHz portable computer with 2 GB of RAM running Windows 7. The results and analysis are given as follows.

To compare the system performance of proposed approach with two benchmarks which are the genetic algorithm (GA)[10] and the particle swarm optimization (PSO) algorithm[17] effectively, some variables are defined.

$R_T = \frac{\bar{T}_2 - \bar{T}_1}{\bar{T}_1} \times 100\%$ is defined as the decreased rate of results obtained by the EDA compared with the results obtained by the GA and PSO, where $\bar{T}_2$ and $\bar{T}_1$ represent the min(average makespan of the GA, average makespan of PSO) and average makespan of EDA, respectively. The larger the R_T value, the better the performance.

$R_{\mathrm{Tar}} = \frac{\bar{T}_{2\mathrm{Tar}} - \bar{T}_{1\mathrm{Tar}}}{\bar{T}_{1\mathrm{Tar}}} \times 100\%$ is defined as the decreased rate of results obtained by the EDA compared with the results obtained by the GA and PSO, where $\bar{T}_{2\mathrm{Tar}}$ and $\bar{T}_{1\mathrm{Tar}}$ represent the min(average delay time of the GA, average delay time of PSO) and average delay time of the EDA, respectively. The larger the R_{Tar} value, the better the performance.

The durations of surgical operation and recovery are randomly generated from a discrete uniform distribution in the range of $U[60, 1\,060]$, $U[2\,880, 4\,520]$, respectively. S and $Q = 4$, $N_p = 15$, $R = 25$, $P = 5$, and the regular capacity is equal to 12.

3.1 Parameter setting

The difficulty of solving the operating theatre scheduling problem is closely associated with the problem size.

The PopSize, the index of superior sub-population β and the learning rate γ need to be determined in the proposed method. Different combinations of these parameter values are listed in Tab. 1. The orthogonal table $L_{25}(5^3)$ is chosen; the EDA is run 20 times independently and the average values of objective function (AVOF) values are obtained by the EDA during 20 times. The orthogonal table and the obtained AVOF values are listed in Tab. 2.

Tab. 1 Parameter levels

Parameters	Factor levels				
	1	2	3	4	5
PopSize	30	40	50	60	70
β	0.2	0.3	0.4	0.5	0.6
γ	0.1	0.3	0.5	0.7	0.9

Tab. 2 Orthogonal table and AVOF values

Experiment number	Factor			AVOF
	PopSize	β	γ	
1	1	1	1	326.02
2	1	2	2	323.82
3	1	3	3	331.03
4	1	4	4	342.64
5	1	5	5	329.83
6	2	1	2	323.82
7	2	2	3	321.62
8	2	3	4	327.83
9	2	4	5	365.57
10	2	5	1	336.84
11	3	1	3	339.64
12	3	2	4	315.81
13	3	3	5	324.62
14	3	4	1	314.41
15	3	5	2	324.62
16	4	1	4	337.64
17	4	2	5	332.43
18	4	3	1	333.23
19	4	4	2	318.82
20	4	5	3	321.22
21	5	1	5	320.82
22	5	2	1	329.23
23	5	3	2	326.02
24	5	4	3	323.82
25	5	5	4	331.03

According to the orthogonal table and AVOF values, we can obtain the response values of each parameter which are listed in Tab. 3. According to the response values, we illustrate the trend of each factor level in Fig. 2.

According to the above analysis, a good choice of the parameter combination is suggested as PopSize = 40, β = 0.3, γ = 0.3.

Tab. 3 Response table

Level	PopSize	β	γ
1	330.67	329.59	327.95
2	315.13	324.58	320.02
3	323.82	325.14	327.47
4	328.67	333.05	329.99
5	321.78	327.71	335.53

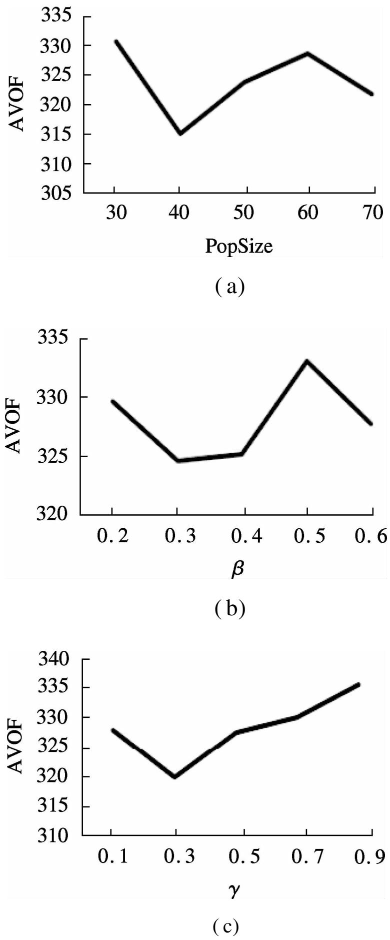

Fig. 2 Factor level trend of the parameters. (a) PopSize; (b) β; (c) γ

According to Ref. [10], the parameters of the GA are: PopSize = 80; the crossover probability P_c is 0.6; the mutation probability P_m is 0.001. According to Ref. [17], the parameters of the PSO are: PopSize = 80; c_1 = 2, c_2 = 2.

3.2 Solution quality analysis

According to the available research, the performance of heuristics can be examined by small, medium and large size. Therefore, three operation sizes (8, 20, 50) were used to test the algorithm. When the operation size is 8, the average outcomes of 10 repeated experiments of the PSO, GA and EDA are shown in Tab. 4 and Fig. 3, and the iteration is set to be 150.

Tab. 4 Performance comparison of small-scale surgery

Algorithm	CPU time/s	Operating time/min	Recovery time/min	Optimal solution/min	Iteration of optimal solution
GA	0.483	144.16	288.34	382.28	66
PSO	0.172	137.50	275.00	380.28	97
EDA	0.183	112.08	224.16	336.24	36

From Tab. 4 and Fig. 3, all the algorithms can find optimal solutions with the same number of iterations. However, it is clear that EDA outperforms the GA and PSO from the analysis of the makespan values and running times.

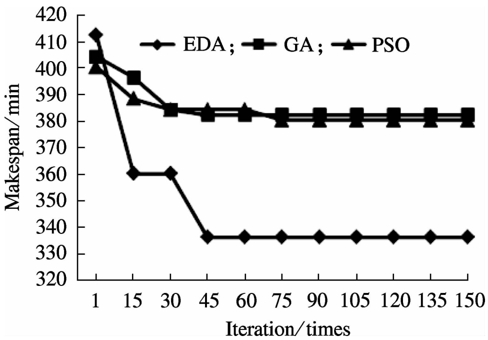

Fig. 3 Small size makespan trends over time

When the operation size is 20, the average outcomes of 10 repeated experiments of the EDA, PSO and GA are displayed in Tab. 5 and Fig. 4, and the iteration is set to be 200.

Tab. 5 Medial size operation performance comparison

Algorithm	CPU time/s	Operating time/min	Recovery time/min	Optimal solution/min	Iteration of optimal solution
GA	2.56	1 223.83	2 447.66	3 671.50	195
PSO	2.22	1 205.15	2 410.29	3 615.44	97
EDA	2.47	1 058.14	2 116.27	3 174.41	191

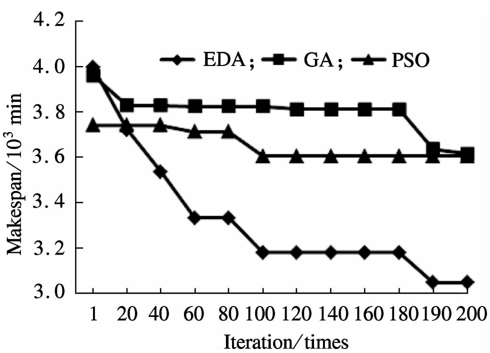

Fig. 4 Medial size makespan trends over time

Tab. 5 shows that the three algorithms have almost the same CPU time, while EDA has a smaller makespan compared to the others. Fig. 4 shows that although the EDA's makespan is larger than GA's and PSO's at the first iteration, as the iteration increases, EDA can find a better solution.

When the operation size is 50, the experiments are repeated 10 times and the average outcomes are illustrated in Tab. 6 and Fig. 5. The iteration is set to be 300.

From Tab. 4 to Tab. 6 and Fig. 2 to Fig. 5, regardless of size, the EDA, GA and PSO can find the optimal solutions in the limited iterations, and the CPU time is similar. As the iteration increases, the solution groups are changed. The EDA always finds better solutions than the GA and PSO.

Tab. 6 Large size operation performance comparison

Algorithm	CPU time/s	Operating time/min	Recovery time/min	Optimal solution/min	Iteration of optimal solution
GA	4.912	17 934.28	35 868.57	53 802.85	63
PSO	4.875	17 837.38	35 674.76	53 512.15	213
EDA	4.787	16 009.33	32 018.66	48 028.00	201

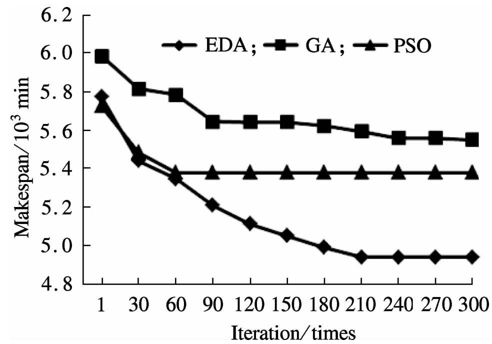

Fig. 5 Large size makespan trends over time

Tab. 7 illustrates that the makespans of EDA are better than that of the GA and PSO, regardless the size of the operations. The reason is that no genetic operators are necessary for EDA as compared with the GA which uses the operators like crossover and mutation for generations of new solutions. Instead, EDA explicitly obtains statistical information from the previous research and constructs a probability model of the best solutions, from which new solutions are sampled. Then, the probability model is updated in each generation with the elite individuals of the new population. In such an iterative procedure, the new population is built, and finally fitter solutions can be generated. Besides, the social cognition in the PSO is incomplete. The standard formula of PSO enables the particles to learn only from the best of the peers by their social cognition. Considering that the information can be exploited from the other non-global best peers, the social cognition in the PSO is incomplete. Then, the PSO may result in a premature convergence.

Tab. 7 Makespan value of different sizes

Size	Small	Medium	Large
GA	382.28	3 671.50	53 802.85
PSO	380.28	3 615.44	53 512.15
EDA	336.24	3 174.41	48 028.00

3.3 Computation time analysis

Fig. 6 shows the CPU time of the EDA, GA and PSO under different numbers of patients, which are 8, 20 and 50, respectively.

Fig. 6 indicates that all the three algorithms have almost the same CPU time, and the CPU time of the EDA increases with the increase of the number of patients. But it is clear that the CPU time of the EDA is very short. The

CPU time is only approximately 5 s when the number of patients is 50. The proposed algorithm is suitable for carrying out an on-line scheduling optimization of the patients.

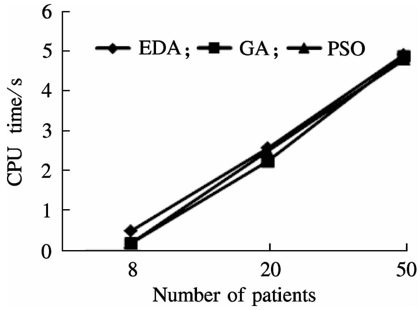

Fig. 6 CPU time of the algorithms

3.4 Impact of size of operations

Tabs. 4, 5 and 6 indicate that the PSO is better than the GA, thus $\overline{T}_2$ represents the average makespan of the PSO. Similarly, $\overline{T}_{2\,\mathrm{Tar}}$ represents the average delay time of the PSO.

The value of R_{T} and R_{Tar} varies with different numbers of patients, and the results are shown in Fig. 7. As shown in Fig. 7, both performance indices are positive. Average makespans and average delay time increase by using the proposed algorithm, which means that the proposed algorithm performs well in applications.

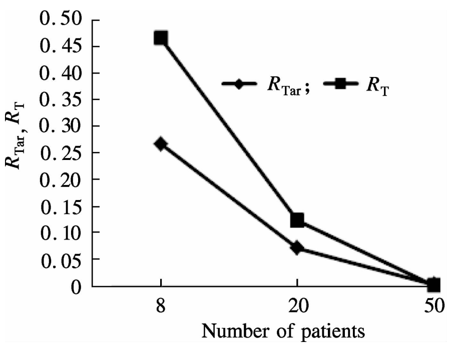

Fig. 7 Relationship with R_{T}, R_{Tar} and N

4 Conclusion

1) Compared with the GA and PSO, the proposed algorithm can effectively solve the operating theater scheduling problem by considering the availability of surgeons. It can also reduce the operation time and recovery time effectively.

2) The feasibility and availability of EDA is verified in Visual C + + language. Due to the short running time of the proposed algorithm, an on-line scheduling problem of patients can be carried out.

3) Compared with the GA and PSO, as the number of patients increases, the advantages of the proposed algorithm are revealed, but there is certain sensitivity to the number of patients. An optimal scope may exist, which can be further verified in practical applications.

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基于分布估计的新型手术室调度算法

周炳海　　殷　萌

(同济大学机械与能源工程学院，上海 201804)

摘要：为了提高手术室的利用率、降低医院的成本、提高服务质量的水平，提出了一种基于分布估计的调度算法(EDA). 首先，对问题域进行描述，以最大完成时间最小为优化目标，在考虑手术分配约束和资源能力约束的基础上，建立数学规划模型；在此基础上，建立可行调度解策略，结合手术室特有的约束条件，提出基于分布估计的手术室调度算法；最后，设计仿真实验，采用正交试验确定算法中的参数后，与遗传算法和粒子群算法进行对比，不同规模的实验结果表明该算法能够减少手术系统总完成时间，且在大规模情况下运行时间仅为 5 s，说明该算法适应大规模实际情况下的手术室调度.

关键词：手术室调度；分布估计算法；最大完成时间

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