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Filtered-beam-search-based approach for operating theatre scheduling①

Zhou Binghai (周炳海)②, Yin Meng
(School of Mechanical Engineering, Tongji University, Shanghai 201804, P. R. China)

Abstract

To improve the efficiency of operating rooms, reduce the hospital's costs and improve the level of service qualities, a scheduling method is presented based on a filtered-beam-search-based algorithm. Firstly, a scheduling problem domain is described. Mathematical programming models are also set up with an objective function of minimizing related costs of the system. On the basis of the descriptions mentioned above, a solving policy of generating feasible scheduling solutions is established. Combining with the specific constraints of operation theatres, a filtered-beam-search-based algorithm is put forward to solve scheduling problems. Finally, simulation experiments are designed. The performance of the proposed algorithm is evaluated and compared with that of other approaches through simulations. Results indicate that the proposed algorithm can reduce costs, and are of practicality and effectiveness.

Key words: operating theatres, scheduling, algorithm, filtered beam search, costs

0 Introduction

In response to multiple challenges, hospitals have undergone the increasing pressure of providing high quality surgeries while minimizing operational related costs. An effective and efficient scheduling system of operating rooms provides an appealing solution to the challenging problem[1].

Scheduling problems of operating theatres were studied in last decades. Ref. [1] presented a simple heuristic scheduling algorithm. Ref. [2] addressed a problem which considered assigning operations to the time slots available in a planning horizon. Ref. [3] modeled a multi-period, multi-resource, patient-priority-based surgical case for scheduling problems as a mixed-integer programming model, and solved it using the first fit descending-based algorithm. Ref. [4] addressed a scheduling problem where patients with different priorities were scheduled for elective surgeries in a surgical facility, which had a limited capacity. Ref. [5] considered the patient's recovery was allowed in operating rooms, and the problem was modeled as a 4-stage hybrid flow shop problem with blocking constraints, and successfully solved thanks to the Lagrangian relaxation method. Ref. [6] focused on the scheduling problem of the ophthalmology department such that there was no overload on any of the beds, and the problem was solved by P||Cmax algorithm by forecast the surgery time, while in this method only the scheduling problem of time cost was considered. Focusing on the scheduling problem of the cardiothoracic department, Ref. [7] considered patients' stochastic durations for the stay in the intensive care unit (ICU) and in the medium care unit (MCU), and built a mixed integer linear programming model to determine a cyclic master operation schedule. Ref. [8] focused on generating an optimal surgery schedule of elective-patient in multiple operating theatres, which considered the intra-operative care and recovery phases. A scheduling method of two stages was described in Ref. [9]. The first stage was described as a set-partitioning integer-programming model and was solved by a column-generation-based heuristic procedure. The second stage was treated as a two-stage hybrid flow shop problem and solved by a hybrid genetic algorithm. Ref. [10] presented two-stage approach for planning and scheduling of operating theatres. However, it was possible that the efficiency of the final operating program would be influenced by a bad assignment of surgical cases in the first phase.

At present, most existing methods in literatures do not consider surgeons' availability in operating rooms and the postoperative period. It cannot fully adapt to the practical applications. Moreover, structural heuristic algorithms are rarely proposed. Here, on the basis

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② To whom correspondence should be addressed. E-mail: bhzhou@tongji.edu.cn
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of the mentioned literatures, the scheduling problem of operating theaters mentioned above is solved by using a novel filtered beam search approach.

1 Model description and formulations

The scheduling problem of elective surgeries is considered at hospital operating theatres over a finite horizon of D periods. The operating theatre is composed of several operating rooms and one or more recovery rooms where several beds will be available for patients to recuperate[11,12]. In order to describe the scheduling problem of operating theatres effectively, some basic assumptions are described as follows: (1) Each patient will get a recovery bed after his or her unique surgical operation in an operating room. (2) All surgical operations can be performed in any available operating rooms. (3) The surgeon for each elective case is determined in advance and cannot be changed. (4) All elective surgeries are hospitalized before surgeries. (5) Each operating room has an identical overtime hours. (6) One surgeon must perform only one surgical operation in the same operating room simultaneously. (7) A surgeon can carry out operations only when he or she is available.

To give a formal description of the scheduling problem, the parameters and variables are defined as follows.

D	Planning horizon
S	Number of operating rooms
N	Number of elective cases
t_n	Earliest period to perform elective case n
d_n	Duration of elective case n
fc_{nds}	Cost of performing elective case n in s^{th} operating room on d^{th} day
rc_{nd}	Cost of recovering elective case n in recovery room on d^{th} day
T_{OR}	Regular operation time
$T_{overtime}$	Regular overtime hours
c_{ds}	Beyond standard operation time cost in s^{th} operating room on d^{th} day
co_{ds}	Beyond standard overtime hours cost in s^{th} operating room on d^{th} day
u_{ds}	Underutilization cost in s^{th} operating room on d^{th} day
R_d	Number of recovery beds on d^{th} day
$x_{nsd} = 1$	If elective case n is performed in s^{th} operating room on d^{th} day, and 0 otherwise
$y_s = 1$	If surgeon p who perform operation n is available in s^{th} operating room on d^{th} day, and 0 otherwise
$\lambda_{nd} = 1$	After operation, patient n is assigned to the b^{th} recovery bed, or 0 otherwise
$\omega_{ns} = 1$	If surgical operation n is assigned to operating room s, or 0 otherwise

The scheduling objective is to minimize the sum of the expected operating room utilization costs and the elective-patient-related costs, which is defined as

$$\min\left\{\sum_{n=1}^{N}\sum_{d=1}^{D}\sum_{s=1}^{S}(fc_{nds}x_{nsd}+rc_{nd}x_{nsd}) + \sum_{d=1}^{D}\sum_{s=1}^{S}[c_{ds}A_{ds}+co_{ds}B_{ds}+u_{ds}C_{ds}]\right\} \quad (1)$$

where

$$A_{ds} = \max\{0,\sum_{n=1}^{N}x_{nsd}d_n - T_{OR}\},\quad \forall s=1,2,\cdots,S,\ \forall d=1,2,\cdots,D \quad (2)$$

Eq.(2) represents the time that the total operation time of all elective cases are assigned to the operating room s exceeds s's regular capacity on the d^{th} day.

$$B_{ds} = \max\{0,\sum_{n=1}^{N}x_{nsd}d_n - T_{OR} - T_{overtime}\},\quad \forall s=1,2,\cdots,S,\ \forall d=1,2,\cdots,D \quad (3)$$

Eq.(3) indicates the time that the total operation time of all elective cases assigned to the operating room s exceeds s's overtime capacity on the d^{th} day.

$$C_{ds} = \max\{0,T_{OR} - \sum_{n=1}^{N}x_{nsd}d_n\},\quad \forall s=1,2,\cdots,S,\ \forall d=1,2,\cdots,D \quad (4)$$

Eq.(4) shows the idle time of operating room s on the d^{th} day.

Based on assumption Eq.(1), it is a case assignment constraint. An operating room is given no more than one assigned elective case at any time on a given day. The following equation must be satisfied.

$$\sum_{s=1}^{S}\sum_{d}^{D}x_{nsd}\leqslant 1,\ \forall n=1,2,\cdots,N \quad (5)$$

To ensure the total operation time of all surgeries does not exceed the operating room's available capacity. It is a time constraint which should satisfy the following requirement.

$$\sum_{n=1}^{N}x_{nsd}\times y_s\times d_n - T_{OR}\leqslant T_{overtime},\quad \forall s=1,2,\cdots,S,\ \forall d=1,2,\cdots,D \quad (6)$$

It is a capacity constraint. To guarantee the number of patients transferred to the recovery room does not exceed the number of available recovery beds, the following inequality must be obeyed.

$$\sum_{n=1}^{N}\lambda_{nd}\sum_{s=1}^{S}x_{nsd}\leqslant R,\ \forall d=1,2,\cdots,D \quad (7)$$

According to assumption (6), each surgeon cannot perform two surgeries on a given day at the same time. The following relation must be followed.

$$t_j \geqslant t_i + d_i + M(3 - \omega_{is} - \omega_{js} - y_{ijs}), \quad i \neq j, \forall s = 1,2,\cdots,S \quad (8)$$

The schedule should be fully made according to the practical applications so that surgeons' availabilities could be assured. The following inequality must be obeyed.

$$t_n + d_n - M(1 - y_{ds}) \leqslant T_{OR} + T_{overtime}, \quad \forall n = 1,2,\cdots,N, \forall d = 1,2,\cdots,D \quad (9)$$

Consequently, the scheduling problem of operating theatres mentioned above can be transformed to a nonlinear programming problem with Eq. (1) as the objective function and Eqs (2) ~ (9) as the constraints.

2 Proposed scheduling algorithm

In this paper, the scheduling problem of operating theatres is analyzed on the basis of the operating theatre system considered elective patients as the primary resource. A filtered-beam-search (FBS)-based algorithm is developed to solve the scheduling problem.

Filtered beam search is an extension of beam search. Beam search is an adaptation of the branch and bound method in which it only explores the promising nodes level by level without backtracking[13,14]. A filtering mechanism is proposed to discard some nodes which do not satisfy constraints, and to evaluate some nodes which satisfy constraints. Generally, a successful FBS-based algorithm for a specific scheduling problem should solve four representation factors: (1) search tree representation for a solution space definition; (2) branching scheme; (3) determination of beam width and filter width; (4) local/global evaluation function selection[14,15].

(1) The solution space can be visualized as a search tree with each path in the tree representing a potential solution[15]. In the tree, each node generated by branching scheme represents a scheduling decision, involves in determining the starting time of the elective case n in the selected operating room, namely t_n. A line between two nodes represents the decision of adding a case to the existing partial schedule. In a finite horizon of D periods, according to the constraints, a complete schedule is composed of nodes and lines between nodes.

(2) The branching scheme is described as follows: let S_l be the set of schedulable operations at level l, $\partial^* = \min(\partial_s)$, where ∂_s is the earliest time of an operating room that can perform elective case s, $s \in S_l$. If $k \in S_l \wedge \partial_k = \partial^*$, then case k will be a node of level l.

(3) The selection of beam width and filter width appears to be very specific[16]. In general, the determination of beam width and filter width has a significant effect on the performance of FBS-based algorithms. Therefore, different combinations of beam width and filter width will be investigated to balance the computational time and the solution quality[14,15].

(4) The selection of evaluation functions will affect the solution quality. Here, dispatching rules are investigated as local and global evaluation functions. Since the local evaluation function is quick but may be poor, while global evaluation function is more accurate but more computationally demanding, and dispatching rules can make a trade-off between them.

On the basis of the descriptions mentioned above, the flow chart of the proposed algorithm is shown in Fig. 1.

The procedure steps of the proposed algorithm are described as follows:

Step 1: Initialization. Let $bn = 0$, $l = 0$; determine beam width b, filter width f; input planning horizon D, the number of operating rooms S; input the regular operation time T_{OR}, regular overtime hours $T_{overtime}$, the duration d_n of the elective case n, and let the partial schedule set PS be null.

Step 2: Determine availability. Determine whether a surgeon is available or not. If he or she is available, then go to step 3, otherwise exit the algorithm.

Step 3: According to D, S, T_{OR}, $T_{overtime}$, d_n to determine the number of elective cases T.

Step 4: Determining beam nodes:

Step 4.1: Generate nodes from the root node with the branching scheme. Check the total number of nodes N. Let $l = l + 1$, update PS with generated nodes.

Step 4.2: If $N > b$, compute the global evaluation function values for all nodes and select b of cases as initial beam nodes in terms of

$$G_t = \min \sum_{t=1}^{T-l} d_{t-1}, \quad i = 1,2,\cdots,b \quad (10)$$

At the same time, determine potential set PS.

Step 4.3: Form a set of candidate scheduling elective cases: $\Delta T = T - PS$.

Step 4.4: If $N \leqslant b$, move down to one more level, let $l = l + 1$, and generate new nodes by branching scheme with PS and update PS.

Step 5: $bn = bn + 1$

Step 5.1: If $bn \leqslant b$: let $l = l + 1$. If $l \leqslant T$, generate new nodes (the number of nodes is $N_{bn,l}$) from the beam node according to the branching scheme with PS_{bn}

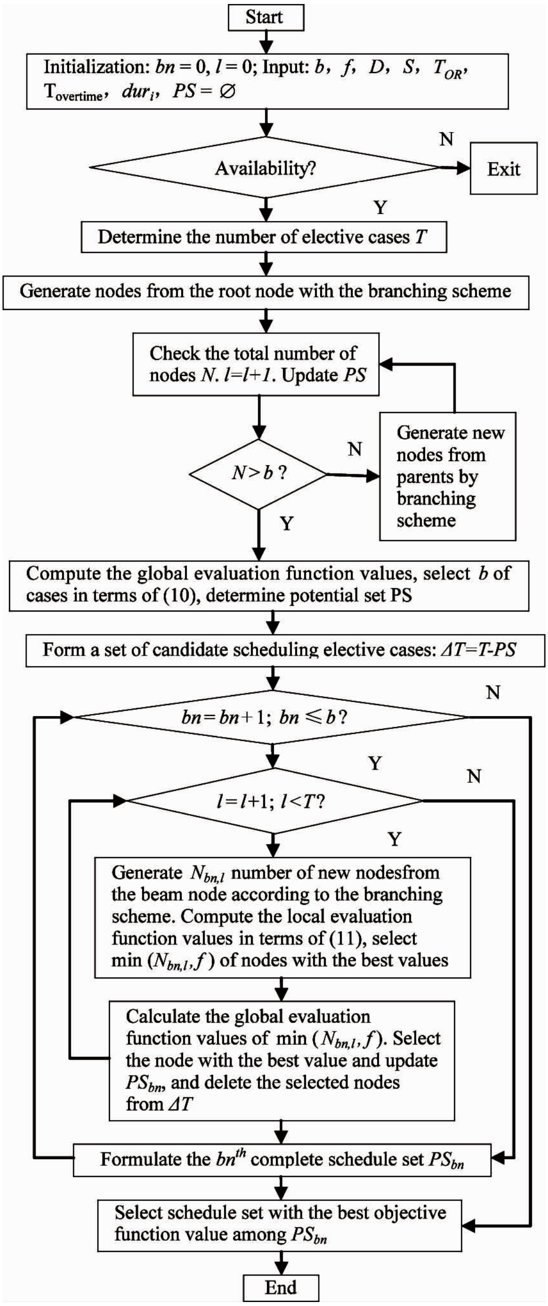

Fig. 1 The flow chart of the proposed algorithm

as the partial schedule represented by the beam node. Compute the local evaluation function values of all nodes generated in terms of

$$P_j = \min \sum_{t'}^{b} d_i, \quad j = 1, 2, \cdots, f \tag{11}$$

and select $\min(N_{bn.l}, f)$ of nodes with the best values for further evaluation. While if $l > T$, go to Step 5.3. If $bn > b$, then go to step 6.

Step 5.2: Calculate the global evaluation function values of $\min(N_{bn.l}, f)$ of nodes obtained by Step 5.1. Select the node with the best value and add the node into the partial schedule set PS_{bn}, and delete the selected nodes from ΔT. Go back to Step 5.1.

Step 5.3: Formulate the bn^{th} complete schedule set PS_{bn}.

Step 6: Generate the finishing time of each recovery bed in the recovery room, calculate A_{ds}, B_{ds} and C_{ds}, according to the objective function select schedule set with the best objective function value among PS_{bn}.

3 Simulation analysis

Under the precondition of the same objective function and branching scheme, the quality of the proposed algorithm is related to beam width b and filter width f. Different b and f are tested and evaluated.

3.1 Relationship between objective function value and *b*

During the same condition that the number of operating rooms is equal to 5, the regular operating time is equal to 14 hours, and the overtime is equal to 2 hours, the duration of elective cases is randomly generated from [60, 1000]. Set $b = 1, 2, \cdots, 10$, $f = 1, 2, 4, 6, 8, 10$, and the local/global evaluation functions are shortest processing time (SPT) rules. The average outcomes of 10 repeated experiments of the proposed algorithm are shown in Fig. 1.

Fig. 2 shows that average objective function value (AOFV) for each expected value f has similar tendency under the variations of b. When b increases beyond 10, AOFV almost keeps constant. Based on this experiment, it indicates that when f remains unchanged, as b increases, and $b < 10$, the proposed algorithm can get better scheduling results.

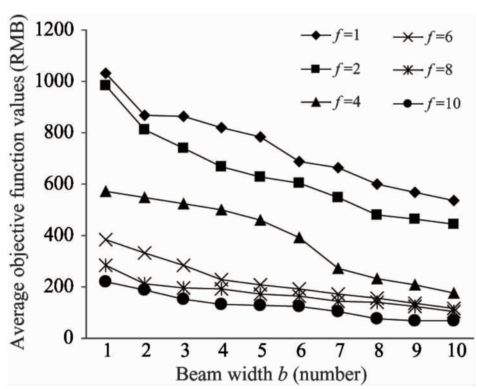

Fig. 2 The relationship between objective values and *b*

3.2 Relationship between objective function value and *f*

During the same condition that the number of operating rooms is equal to 5, the regular operating time is equal to 14 hours, and the overtime is equal to 2 hours, the duration of elective cases is randomly generated from [60,1000]. Set $f = 1, 2, \cdots, 10$, $b = 1, 2, 4, 6, 8, 10$, and the local/global evaluation functions are SPT rules. The average outcome of 10 repeated experiments of the proposed algorithm is shown in Fig. 3. The samples are different from the ones used in Section 3.1.

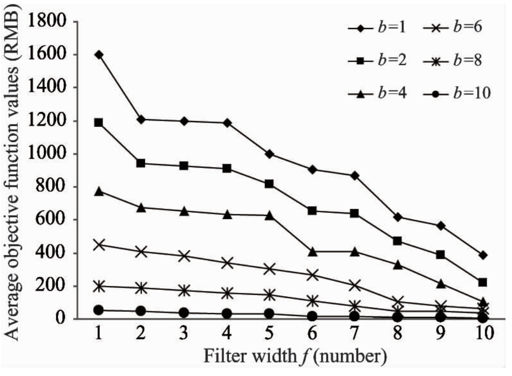

Fig. 3 The relationship between objective values and f

For individual b, Fig. 3 shows that AOFV decreases fast with the increase of f. Though the curves of AOFV are not identical, the general variation tendency of all curves is uniform.

Table 1 shows that when b keeps unchanged with f increasing from 1 to 10, the AOFV change rates are always larger than the case that f stays constant with b changing. Moreover, comparing Fig. 2 to Fig. 3, when b remains unchanged as f increases, the proposed algorithm can obtain better results than the cases when f remains unchanged as b increases. It is noticeable that both f and b play an important role in the good performance of the proposed algorithm, and f is more crucial than b.

Table 1 AOFV change rate

$f(1\sim10)$	AOFV change rate	$b(1\sim10)$	AOFV change rate
$b=1$	75.71%	$f=1$	47.84%
$b=2$	75.71%	$f=2$	54.61%
$b=4$	86.50%	$f=4$	69.39%
$b=6$	85.65%	$f=6$	70.06%
$b=8$	82.04%	$f=8$	64.21%
$b=10$	90.41%	$f=10$	69.80%
average	82.67%	average	62.65%

3.3 Comparison with other approaches

To compare the system performance of the proposed algorithm with other algorithms effectively, some variables are defined as follows.

$Dev = \dfrac{S_d - S_f}{S_d} \times 100\%$, where S_d is the optimal solution obtained by dispatching rules, and S_f is the optimal solution gained by the FBS-based heuristic algorithm.

$Dev' = \dfrac{S_m - S_f}{S_m} \times 100\%$, where S_m is the optimal solution obtained by genetic algorithm (GA[10]) and particle swarm optimization (PSO[17]) algorithm, and S_f is the optimal solution gained by the FBS-based algorithm.

To investigate the proposed FBS algorithm ($b = 2$, $f = 2$), its performance is compared with dispatching rules (first in first serve (FIFS), longest processing time (LPT), weighted due date (WDD), earliest due date (EDD)[18,19]) under the length of the different planning horizon, different elective cases and different operating rooms. And the results are shown in Table 2. Since solution times of the dispatching rules are very small, the CPU time of the rules is not included in Table 2. As expected, the performance of the proposed algorithm in terms of Dev is much better than the rules. The average Dev is 55.91%, 42.21%, 55.65%, 59.10% for FIFS, LPT, EDD, WDD, respectively. Even though beam search is a branch and bound based algorithm, the CPU time is not very long. The elective cases increase from 41 to 49, the CPU time rises from 0.002ns to 15000ns. The CPU time is small.

To further investigate the proposed algorithm ($b = 2$, $f = 2$), its performance is compared with GA and PSO algorithms (the population size = 80, the number of iteration = 300) under different sizes of elective cases and different number of operating rooms. And the results are shown in Table 3. Because there is no affection to the analysis of the algorithm performance for the days, the days are not involved in Table 3. Regardless of size, the solution quality of the FBS algorithm is better than the GA and PSO algorithms. The GA and PSO algorithms' running time reported for each problem is much larger than the CPU time requirement of the proposed algorithm. Therefore, the proposed algorithm has better performance on both CPU time and quality of solutions.

4 Conclusions

(1) The proposed algorithm can effectively solve the scheduling problem of operating theatres with the consideration of the availability of surgeons. It can also reduce the expected operating room utilization costs and the elective-patients-related costs effectively.

(2) Since the algorithm can solve the scheduling problem within a short period of running time, it can

Table 2 Comparison of simulation results with dispatching rules

Problem *	FBS		FIFS		LPT		WDD		EDD	
	Solution	CPU(ns)	Solution	Dev	Solution	Dev	Solution	Dev	Solution	Dev
1 * 9 * 5	1336.6	0.002	2522.2	47.01%	2409.4	44.53%	2172.6	38.48%	2103.8	36.47%
2 * 16 * 5	2388	0.002	4507.2	47.02%	2704.8	11.71%	4423.2	46.01%	4567.2	47.71%
3 * 22 * 5	2225.4	0.002	5089.4	56.27%	3371	33.98%	5188.6	57.11%	5188.6	57.11%
4 * 29 * 5	3963.6	0.002	7674	48.35%	4446	10.85%	6211.6	36.19%	6195.6	36.03%
5 * 35 * 5	3666.6	0.002	7189.8	49.00%	5224.2	29.82%	8328.8	55.98%	7690.6	52.32%
6 * 41 * 5	4786.2	0.002	8014.2	40.28%	5488.8	12.80%	9594.2	50.11%	9664.6	50.48%
7 * 49 * 5	5569.6	15000	10584	47.38%	6256.8	10.98%	11977.6	53.50%	9406.4	40.79%
8 * 56 * 5	3864.2	15000	6868.8	43.74%	33198.4	88.36%	13464.8	71.30%	12420.8	68.89%
9 * 63 * 5	7367.8	15000	72463.8	89.83%	67726.2	89.12%	44019	83.26%	43207	82.95%
10 * 72 * 5	7950.6	15000	81561.8	90.25%	79306.6	89.97%	864545	99.08%	48951.4	83.76%
Averages				55.91%		42.21%		59.10%		55.65%

Problem * : the number of days * the number of elective cases * the number of operating rooms

Table 3 Comparison of simulation results with improved meta heuristics

Problem **	FBS		GA			PSO		
	Solution	CPU(ns)	Solution	Dev'	CPU(ms)	Solution	Dev'	CPU(ms)
3 * 1	598	0.002	1306	54.21%	265	1306	54.21%	140
7 * 3	1412.4	2000	1475.6	4.28%	343	1458.8	3.18%	140
8 * 4	402.2	0.002	721.4	44.25%	374	627	35.85%	156
18 * 3	1866.4	0.002	3090.4	39.61%	249	3199.2	41.66%	202
20 * 2	2139.9	0.002	3409.2	37.23%	296	3077.2	30.46%	202
22 * 5	2225.4	0.002	3298.2	32.53%	280	3434.2	35.20%	218
48 * 2	5906.2	0.002	6866.6	13.99%	608	6740.2	12.37%	561
50 * 4	5517.2	15000	6629.2	16.77%	793	6266.8	11.96%	721
52 * 1	5780.2	15000	6771.4	14.64%	897	6575.4	12.09%	872
Averages				28.61%			26.33%	

Problem ** : the number of elective cases * the number of operating rooms

carry out an on-line scheduling problem of operations.

(3) Compared with dispatching rules, GA and PSO algorithms, the results show the proposed algorithm is more competitive.

(4) Not only the proposed algorithm can be used to solve static scheduling problem of operating theatres, but also it can be used to implement real-time scheduling problem of operating theatres in the future.

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Zhou Binghai, was born in 1965, He received M. S. and Ph. D degrees respectively from School of Mechanical Engineering, Shanghai Jiaotong University in 1992 and 2001. He is a professor, at Tongji University. He is the author of more than 140 scientific papers. His current research interests are scheduling, modeling, simulation and control for manufacturing systems, integrated manufacturing technology.