

Adaptive Hybrid Ant Colony Optimization for Solving Dual Resource Constrained Job Shop Scheduling Problem

Jingyao Li, Shudong Sun, Yuan Huang

School of Mechatronics, Northwestern Polytechnical University, Xi'an, China
Key Lab of Contemporary Design and Integrated Manufacturing Technology, MOE,
Northwestern Polytechnical University, Xi'an, China
Email: ljyao.6106@163.com; sdsun@nwpu.edu.cn; huangy@nwpu.edu.cn

Abstract—This paper presents a scheduling approach, based on Ant Colony Optimization (ACO), developed to address the scheduling problem in manufacturing systems constrained by both machines and heterogeneous workers called as Dual Resource Constrained Job Shop Scheduling Problem with Heterogeneous Workers. This hybrid algorithm utilizes the combination of ACO and Simulated Annealing (SA) algorithm and proposes an adaptive control mechanism based on ant flow of route choice to improve the global search ability. Two adaptive adjusting schemes of parameters based on iteration times and quality of solutions respectively are imposed to actualize the performance optimization by stages. Then the performances of different optimization methods with different resource allocation strategies are compared according to simulation experiments on both concrete instance and random benchmarks while related discussion are represented at last.

Index Terms—Dual Resource Constrained; Ant Colony Optimization; Adaptive Adjusting Parameters; Ant flow

I INTRODUCTION

The Job Shop Scheduling Problem (JSP) is one of the most important issues in current academia, however, most of the literature on JSP had considered only machine as a limiting resource and ignored the possible constraints imposed by the availability of workers with requisite skills to perform the operations. This type of problem, where both machines and workers represent potential capacity constraints, was referred to as Dual-Resource Constrained (DRC) JSP by Nelson[1] at 1967. Since then there had been considerable investigations of DRCJSP which can be clustered into two groups and are briefly surveyed below.

The first group investigated influences of different worker assignment rules using simulation method which forms the most investigated aspect of DRCJSP [2-4]. As machines in the DRC shop are not fully staffed where the operator can be reassigned from one machine to another as needed, decisions have to be made regarding when to consider transferring workers if they are eligible, and to

which areas. These were referred to as the "when" rule and "where" rules, respectively. Furthermore, another worker assignment rule, which was referred to as the "Push/Pull" rule [5-6] and initiated worker transfers based on need, was shown to provide good results in recent years. The other group of studies investigated a great variety of heuristic algorithms and intelligent algorithms in order to find optimal or near optimal solutions to DRCJSP problems (e.g., Genetic Algorithm(GA) [7-10] and Ant Colony Optimization(ACO) [11]).

In most of the researches about DRCJSP, all the workers were considered as the same resource. For example, if there were two workers A and B who were both able to operation machine C, then the process time of a same job on C operating by A and B respectively was considered to be the same. The affect of otherness among different workers on final scheduling results in DRCJSP, such as dexterity degree on equipment operation or working attitude, was usually ignored which violates the practice. Nelson[1] first announced to record the processing efficiency of different workers with the efficiency matrix, but he had not made a deep research on the DRCJSP with Heterogeneous Workers (DRCJSP-HW). Afterwards, a new worker transfer rule for DRCJSP-HW was proposed by Bokhorst [12-13]. However, there had been no reference on applying intelligent algorithm to solve DRCJSP-HW till now.

Ant Colony Optimization (ACO) is a constructed meta-heuristic algorithm based on swarm intelligence, in which artificial ants are created to solve problems by simulating the natural behavior of ant colony on three principal characteristics: (1) ants communicate with the others indirectly via releasing pheromone on passing routes; (2) pheromone of shorter paths accumulates faster; (3) ants prefer routes with higher pheromone level. Since the initial work of Dorigo [14] on the ACO algorithm, several scholars had developed different ACO algorithms that performed properly when solving combinatorial problems [15-17] such as the traveling salesman problem, the quadratic assignment problem, the sequential ordering

problem, the production scheduling, the project scheduling, the vehicle routing, the telecommunication routing, among others.

In the field of scheduling, ACO had been successfully applied to the single machine weighted tardiness problem [18], the flow-shop scheduling problem [19] and the resource constraint project scheduling [20]. Moreover, its application to JSP had been especially proven to be quite difficult. Colorni et al. [21] were the first group of researchers who applied ACO to solve JSP and their algorithm was far from reaching a state-of-the-art performance. The earliest competitive ACO approach for solving the JSP was imposed by Blum [22] when applying to the open shop scheduling problem. But up till now, the researches on applying ACO to solve JSP [23-24] and Flexible Job Shop Scheduling Problem (FJSP) [25-26] had made remarkable achievements in recent years.

Compared with the other intelligent algorithms that are always be used for solving JSP, such as Genetic Algorithm (GA) and Immune Algorithm (IA), ACO can efficiently avoid additional calculation consumption caused by illegal solution since its particular character of constructing solution by stages. A variety of constraints are actualized during the process of solution generation in ACO when applying to solve multi-constrained scheduling problem such as DRCJSP-HW. This paper presents the development of a hybrid algorithm which is the combination of ACO and Simulated Annealing (SA) algorithm for solving DRCJSP-HW. Based on the analysis of the influence of different parameter values on algorithm performance, two adaptive adjusting schemes of main parameters and another adaptive route choice control mechanism based on ant flow are proposed to further improve the convergence performance on the basis of guaranteeing the scheduling quality.

The paper is organized as follows. In the next section is the description and mathematical model about DRCJSP-HW. The construction process and step description of the hybrid algorithm (ACO-SA algorithm with adaptive parameters and route choice based on flow control which is short for A-FC-ACOSA) are presented in section 3. In section 4, the convergence of the algorithm is proved in theory based on Markov chain. Then the comparison experimental results of different resource allocating strategies and different intelligent algorithms are provided in section 5. Finally, some concluding remarks and proposals for future works are shown in section 6.

II MODEL RESEARCH

A. Problem Description

A DRCJSP-HW may be formulated as follows: given a $n \times m \times w$ manufacturing system, in which n parts must be processed exactly on m machines operating by w workers during the plan period. The set of n parts can be defined as $P = \{P_1, \dots, P_n\}$, each part has a certain delivery time $T_{P_i}^E$ and is constructed with an aggregate of pre-defined

order operations which can be processed with several combinations of machines and workers. The set of machines and workers are $W = \{W_1, \dots, W_w\}$ and $M = \{M_1, \dots, M_m\}$ respectively where must be $w < m$ and workers are capable of operating more than one machine. The practical process time $T_{P_{ij}M_kW_l}^P$ of P_{ij} on machine M_k operating by worker W_l is decided both by processing performance of machine and operating efficiency $e_{W_lM_k}$ of worker. Even if operating the same machine to process the same job, the otherness among workers results in different process time. Different workers and machines possess of different operating cost C_{M_k} and hiring wage C_{W_l} while resources with higher processing capacity are more expensive.

In this paper, once processing is initiated, an operation cannot be interrupted and concurrency is not allowed. That is, operation P_{ij} cannot begin processing until $P_{i(j-1)}$ has completed if $j > 1$. However, there is no constrain relationship between operations of different parts. The setup and release time is contained in the process time, the moving time of workers and parts and the accidents in production such as machine broken or worker absent are all ignored.

B. Mathematical Modeling

The following are the symbols and variables used in this model:

$$Tab_PM = \begin{cases} t_{P_{ij}M_k}^P & \text{standard processing time of job } P_{ij} \text{ with machine } M_k; \\ 0 & \text{machine } M_k \text{ cannot process job } P_{ij} \end{cases};$$

$$Tab_WM = \begin{cases} e_{W_lM_k} & \text{the efficiency when worker } W_l \text{ operating machine } M_k; \\ 0 & \text{worker } W_l \text{ cannot operate machine } M_k \end{cases};$$

$$H_{P_{ij}M_k} = \begin{cases} 1 & t_{P_{ij}M_k}^P > 0; \\ -1 & \text{else} \end{cases};$$

$$H_{P_{ij}M_kW_l} = \begin{cases} 1 & t_{P_{ij}M_k}^P > 0 \wedge e_{W_lM_k} > 0; \\ -1 & \text{else} \end{cases};$$

$T_{P_{ij}M_kW_l}^S$ —The start time of job P_{ij} with worker W_l and machine M_k ;

$T_{P_{ij}M_kW_l}^E$ —The end time of job P_{ij} with worker W_l and machine M_k ;

$T_{P_{in_j}M_kW_l}^E$ —The end time of the last operation P_{in_j} of part P_i with worker W_l and machine M_k ;

R_{M_k} —Available time sets of machine M_k ;

R_{W_l} —Available time sets of worker W_l ;

C_{P_i} —Material cost of P_i ;

$C_{P_i}^{early}$ —Punishment to early jobs;

$C_{P_i}^{late}$ —Punishment to tardy jobs;

C_{year} —annual interest;

According to the research of reference[27], let the discount rate of capital be zero and ignore the affect after interest deduction not only simplifies the computation process but also influences the scheduling decision remotely since the usually shorter scheduling period in DRCJSP system. Based on this hypothesis and the classical formula of production cost for JSP proposed by Shafei and Brunn [28-29], some factors of DRCJSP-HW problem, such as punishment to early and tardy jobs, flexible resources and heterogeneous workers, have been introduced to the definition of production cost, as shown in (1).

$$\begin{aligned}
 Cost = & C_{year} \times \sum_{i=1}^n (C_{P_i} \times (\max(T_{P_{in}j}^E, T_{P_i}^E) - T_{P_{i1}M_kW_l}^S)) + \\
 & C_{year} \times \sum_{i=1}^n \sum_{j=1}^{n_j} ((C_{M_k} + C_{W_l}) \times T_{P_{ij}M_kW_l}^P \times (T_{P_{i(j+1)M_kW_l}^S} - T_{P_{ij}M_kW_l}^S)) + \\
 & \sum_{i=1}^n \sum_{j=1}^{n_j} ((C_{M_k} + C_{W_l}) \times T_{P_{ij}M_kW_l}^P + \\
 & \sum_{i=1}^n (C_{P_i}^{early} \times \max(0, T_{P_i}^E - T_{P_{in}j}^E) + C_{P_i}^{late} \times \max(0, T_{P_{in}j}^E - T_{P_i}^E))
 \end{aligned}
 \tag{1}$$

The first two parts of this formula represents the inventory cost produced during the production process, the third part dedicates the resource operating cost while the last part is the punishment to early and tardy jobs. The objective of our DRCJSP-HW is to find a feasible schedule for a set of jobs such that the production cost is optimal or near-optimal, as shown in (2)

$$F = \min(Cost) \tag{2}$$

The DRCJSP-HW subjects to two constraints, known as the operation precedence constraint and resource capability constraint. In our DRCJSP-HW, each part is ready to be processed as soon as the scheduling started while the order of each operation is fixed, as shown in (3) and (4).

$$T_{P_iM_iW_i}^S \geq 0 \tag{3}$$

$$T_{P_{ij}M_iW_i}^E \leq T_{P_{i(j+1)M_iW_i}^S} \tag{4}$$

Considering delays in a job such as waiting time for resources during operations, we can obtain equation(5).

$$T_{P_iM_iW_i}^E \leq T_{P_iM_iW_i}^S + T_{P_iM_iW_i}^P \tag{5}$$

Compared to classical JSP, the practical process time of each operation is affected by both machine technical properties and worker efficiency as (6).

$$T_{P_iM_iW_i}^P = t_{P_iM_i}^P / e_{W_iM_i} \tag{6}$$

A job can be processed only if the machine and worker are both idled, as shown in (7-9).

$$H_{P_iM_iW_i} H_{P_{i+1}M_iW_i} (T_{P_iM_iW_i}^E - T_{P_{i+1}M_iW_i}^S) (T_{P_{i+1}M_iW_i}^S - T_{P_iM_iW_i}^E) \geq 0 \tag{7}$$

$$H_{P_iM_iW_i} H_{P_{i+1}M_iW_i} (T_{P_iM_iW_i}^E - T_{P_{i+1}M_iW_i}^S) (T_{P_iM_iW_i}^S - T_{P_{i+1}M_iW_i}^E) \geq 0 \tag{8}$$

$$R_{M_i} \cap R_{W_i} \cap [(T_{P_iM_iW_i}^S - T_{P_{i+1}M_iW_i}^E) \neq \Phi] \tag{9}$$

III ADAPTIVE HYBRID ANT COLONY ALGORITHM

The hybrid algorithm consists of two parts. We have the ACO part, where ants crawl over the search space trying to construct a feasible tour. After the fitness of each schedule defined by a tour is calculated, the SA part is operated as a neighborhood search method for the best solution and the pheromone updating process occurs only after the SA has finished.

A. ACOSA algorithm

a. Ant Map

Each artificial ant starts off from a virtual starting node to a virtual goal and routing randomly on a $N_j \times N_j$ network, in which N_j represents the number of all the operations and each node is corresponding to an actual operation, to construct a tour gradually. However, the number of actual destination nodes of each ant when routing is equal to the number of parts at most since the movement of ant is constrained by both operation precedence constraint and resources capacity constraint to guarantee a feasible tour. Each ant affects the route choice of the others by releasing pheromone on the chosen route while the pheromone level τ_{ij} , which expresses the expectation that operation j is scheduled following operation i, is set to 0 at the beginning if route (i,j) violates the operation precedence constraint. At last, the moving contrail of each ant directed by pheromone level τ_{ij} and local heuristic information η_{ij} seems to be an operation schedule.

b. Solution Construction

Generally speaking, the convergence performance of ACO is better than GA because of the guidance effect of pheromone, however, the performance of ACO is affected to a great extent by relatively optimal solution obtained at the early research stages which guide ant colony to local optimal at great probability and cause prematurely ACO. The best way to avoid it is to find the best balance between the exploration and utilization of existing information which not only guarantees large enough search space but also pays particular emphasis on solution space with higher fitness to accelerate the convergence speed.

Therefore, each ant uses the pseudo-random proportional state transition rule to select the destination in this hybrid algorithm. The state transition rule can be divided into exploitation and exploration, as shown in (10), where P_0 is an important parameter on balancing the relationship between information exploration and utilization, which is a random variable between 0 and 1, since each ant selects the currently optimal tour developed with the probability of P_0 and explores new

path with the probability of $(1 - P_0)$. When an ant at node i , P_{ij} means the probability of that the ant selects node j as destination node. η_{ij} is the heuristic information, also called visibility, and is the result of calculation according to corresponding strategy for resources allocation in our research.

$$P_{ij} = \begin{cases} 1 & P \leq P_0 \wedge \arg \max_{P_{ij} \in S_0} \{\tau_{ij}^\alpha \times \eta_{ij}^\beta\} \\ (\tau_{ij}^\alpha \times \eta_{ij}^\beta) / \sum_{(i,j) \in S_0} (\tau_{ij}^\alpha \times \eta_{ij}^\beta) & P > P_0 \end{cases} \quad (10)$$

c. Resources Allocation Strategy

Compared to JSP, it is need to allocate both machines and workers for each operation when solving DRCJSP-HW, capacity limited manufacturing resources have become the biggest bottleneck of the constraint for manufacturing system at this point. The often-used methods such as GA and IA get closer continuously to the global optimum solution through oriented neighborhood searching on a variety of initial scheduling solutions, which are easy to cause illegal solution and considerable reconfigurable time when applying to solve DRCJSP-HW due to the dual-resource capacity constraint. In contrast, ACO algorithm gradually allocates optimal combination of dual resources for each job based on heuristic allocating strategy library and available time sets of both machines and workers to ensure the feasible schedule. This research introduces five heuristic strategies in total:

- **Minimum Resource Cost (MRC):** Choose the combination with the minimum cost due to resources utilization which is calculated as(11).

$$Cost_{P_{ij}}^R = (C_{M_k} + C_{W_l}) \times T_{P_{ij}M_kW_l}^P \quad (11)$$

- **Minimum Additional Cost (MAC):** Choose the combination with the minimum additional cost including resources cost and punishment to early and tardy jobs is calculated as(12).

$$Cost_{P_{ij}}^A = (C_{M_k} + C_{W_l}) \times T_{P_{ij}M_kW_l}^P + [C_{P_i}^{early} \times \max(0, T_{P_i}^E - T_{P_{ij}M_kW_l}^E) + C_{P_i}^{late} \times \max(0, T_{P_{ij}M_kW_l}^E - T_{P_i}^E)] \quad (12)$$

- **Shortest Process Time-Most Urgent (SPT-MU):** The heuristic strategy used in reference [30-31] which first calculated the urgent degree of job based on its deadline, then a union criterion was built with the practical process time; at last the combination of resources with the minimum union criteria is chosen.
- **Earliest Finish Time-Minimum Additional Cost (EFT-MAC):** Choose the combination with the minimum additional cost from the sets of resources combinations with the earliest operation finish time.
- **Shortest Process Time- Minimum Additional Cost (SPT-MAC):** Choose the combination with the minimum additional cost from the sets of resources

combinations with the shortest practical process time.

d. SA Local Search

In order to avoid local optimal node being selected frequently caused by strongly deterministic resource allocating strategies, local search mechanism must be introduced to adjust resources combination after the routing process of ant colony. The local search mechanism of ACO was always the first advanced method with pruning or 2-opt exchange method in the past research [32], but the combination of ACO and local search intelligent algorithm often produce superior results according to researches [33-34] in recent years. This paper combines the ACO with the Simulated Annealing (SA) in the way of adjusting combination of resources of one operation in the optimal schedule randomly and utilizing the Metropolis rule as the decision criterion. The combination of both algorithms can jump out of local optimal at a certain probability as well as provide better initial solutions for SA with the fast search ability of ACO.

e. Pheromone Update

After each generation, the hybrid algorithm performs local updating to change the pheromone of each route as(13), Where ρ is pheromone evaporation parameter in the range of 0~1. The main purpose of local updating is to avoid producing a path that is too powerful to make algorithm fall into a local optimum, and hindering the ants from exploring new paths.

$$\tau_{ij} = (1 - \rho)\tau_{ij} \quad (\forall \tau_{ij} \neq 0) \quad (13)$$

Besides, the pheromone of global optimal solution is updated additionally according to the ASrank method of reference [35] : Sort all the solutions with fitness $Cost^i$ in descending order, then the pheromone on the routes participating in the solutions whose fitness at the top w is weighted updated as (14). The global updating not only accelerate convergence by increasing the differences between better solutions and worse ones, but also avoid fast pheromone accumulating on routes of relatively optimal solutions obtained at early stages.

$$\tau_{jk} = \tau_{jk} + \sum_{i=1}^w (\forall (j,k) \in L_i) (w-i+1) \frac{Q}{Cost_{max}^i} \quad (14)$$

B. Adaptive Adjusting Parameters

a. Case Study on Influence of Parameters

There are many parameters in ACO and different combinations of which lead to different results as well as convergence performance. A numerical example of DRCJSP-HW is proposed to test the influence of different combinations of parameters $\{\alpha, \beta, 1-\ell, P_0\}$ on performance of calculation and convergence. The concrete instance is constructed by introducing the factor of heterogeneous workers (workers with higher machine operating proficiency will be paid more) on the basis of the example in reference [9], as shown in table I~V.

In existent researching files, scholars usually represented convergence speed of algorithm by the least iteration times for obtaining global optimal solution[36], however, global optimal solution obtaining does not mean convergence but only represents the global search capability meets the requirement for the random search algorithm such as ACO and GA. This paper applies both the convergence times and the number of global optimal solutions obtained in total during the calculation process to denote the convergence performance.

TABLE I. TECHNOLOGICAL PROCESS

Part	Job	M1	M2	M3	M4	M5	M6
P1	1	2	3	4			
	2		3		2	4	
	3	1	4	5			
P2	1	3		5	2		
	2	4	3			6	
	3			4		7	11
P3	1	5	6				
	2		4		3	5	
	3			13		9	12
P4	1	9		7	9		
	2		6		4		5
	3	1			3		3

TABLE II. MACHINE OPERATING COST

M1	M2	M3	M4	M5	M6
60	40	30	60	30	10

TABLE III. WORKER SALARY

W1	W2	W3	W4	W5
20	15	15	20	15

TABLE IV. WORKER OPERATING PROFICIENCY

Worker	M1	M2	M3	M4	M5	M6
1	0.9	0.8				
2		0.7	0.9			
3			0.6	1		
4				0.9	0.8	
5					0.8	0.8

TABLE V. OTHER PARAMETERS

	P1	P2	P3	P4
Raw Material Cost	200	300	300	200
Delivery time	14	17	13	12
Punitive Cost of Early Part	20	20	20	20
Punitive Cost of Tardy Part	100	50	40	40

The values available of the four parameters are $\{0,0.5,1,1.5,2.5,3,3.5,4,4.5,5\}$, $\{0,0.5,1,1.5,2,2.5,3,3.5,4,4.5,5\}$, $\{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1\}$, $\{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1\}$ respectively according to the research of reference [34]. When one parameter are tested and changed its value, the others remains at their mean value. At last 42 combinations of parameters in total are applied to calculate the above example for 30 times respectively with ACOSA and EFT-MAC strategy. The results are drawn as shown in Fig.1~4.

- According to(10), α determines the relative influence of pheromone level on route choice. Each ant selects destination node mostly depend on heuristic information when α is lesser and the global

searching ability is so strong that the global optimal solution can be obtained earlier and lesser. The pheromone gradually plays a more important effect and strengthens convergence performance as α increases along with the decrease of average quality of solutions. Especially when α is too large, the choice of few ants has a tremendous influence upon the others and the pheromone of individual path accumulates so fast that the algorithm is easily to trap in local optima, as shown in Fig.1.

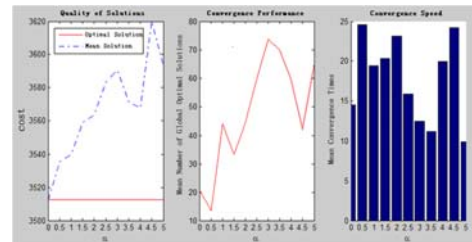


Figure 1. Performance of differnent α

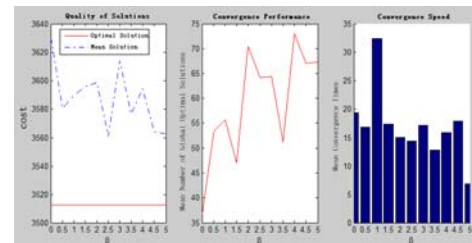


Figure 2. Performance of differnent β

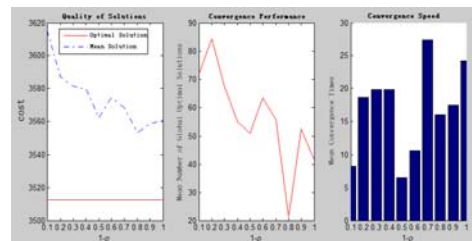


Figure 3. Performance of differnent l

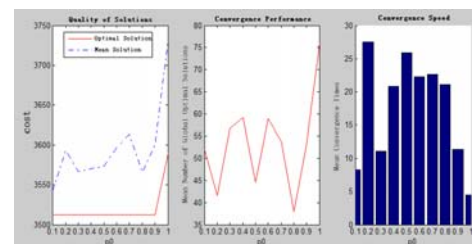


Figure 4. Performance of differnent P_0

- On the other hand, β determines the relative influence of heuristic information. The pheromone plays an important role in route choice and lead to worse schedule and better convergence performance when β is lesser. Then the certain factor guides choosing gradually and average result gets better and more global optimal results are obtained as β increases, as shown in Fig.2.

- 1- ℓ reflects the amount of pheromone residue after each evaporates. When 1- ℓ is lesser, pheromone evaporates so fast that the results are always been decided by first few iterations. At this time the algorithm can convergence quickly with worse results. Along with the increase of 1- ℓ , the average result becomes better and global optimal result is obtained faster and lesser due to higher global search ability, as shown in Fig.3.
- State transition probability P_0 reflects the possibility of selecting local optimal paths. Ants choose destination according to roulette selection when P_0 is lesser and the results are better. Along with the increase of P_0 , ants are gradually tended to select local optimal path which result in worse results and better convergence performance. Although the algorithm can convergence with smaller iteration times, the global optimal can't be obtained when P_0 is too high, as shown in Fig.4.

b. Adaptive Adjusting Schemes

Different parameter sets result in different direction of search as stated previously, however, up to now there lacks an efficiently and generality mathematic analysis method of parameter configuration. The researches of ACO generally find optimal parameter sets via amounts of simulate experiments which are only the “nearly optimal parameters” to concrete instance. For this problem scholars have proposed the ACO algorithm with adaptive adjusting parameter which obtains ideal experiment results in recent years which pay more attention to the parameters $1-\ell(t)$ [37] and P_0 [38] however. In addition, the parameters should be adjusted by stages in accordance with our experiment results: at the elementary stages of iteration, the lowest α , P_0 and highest β , 1- ℓ will lower the influence of pheromone on route choice and lead to larger search space; at the later period the lowest β , 1- ℓ and highest α , P_0 will accelerate the convergence due to the global pheromone updating mechanism.

Consequently, this paper proposes two synchronous adaptive adjusting schemes of the four parameters in ACOSA as below (only take the adjusting of α for example).

- Linear Adaptive (LA): Suppose α^{end} is the upper bound as the α increases gradually according to the analysis mentioned above while α^{start} is the lower bound and $\Delta\alpha$ is the delta of α . NC_{max} is the total times of iteration. Then each parameter is updated at a constant speed after each iteration step as(15).

$$\Delta\alpha = \frac{\alpha^{end} - \alpha^{start}}{NC_{max}} \quad (15)$$

- Adaptive based on Quality of Solution (QA): Each parameter is decided whether to be adjusted based on the quality of solutions at each iteration step. If the fitness R'_{best} of optimal solution at t_{th} iteration

is not worse than the fitness R_{Wbest} of currently global optimal which means currently combination of parameters is beneficial for global search and each parameter remains unchanged. Otherwise, each one is adjusted as(16) where α^t means the value of α at t_{th} iteration, R_{Gbest} and R_{Gworst} are the fitness of currently global optimal and worst solution, respectively. At the early iteration step, larger NC_{max}^{-t} results in smaller delta of parameters and enough ability of global search; the differences between global optimal and global worst is on the increase with iteration and parameters are adjusted to the status that are benefit for promoting algorithm convergence at latter stages (the more great the difference between R_{Gbest} and R_{Gworst} , the more approximation to the theoretical lower bound to a specific instance for the global optimal).

$$\Delta\alpha = (\alpha^{end} - \alpha^t) \times \exp\left(\frac{NC_{max}^{-t}}{R_{Gbest} - R_{Gworst}}\right) \quad (16)$$

From the adjusting formula of both schemes above, the scheduling performance of LA is stabler but weaker than QA since the adjusting of parameters is nothing to do with scheduling results which loses the learning ability on knowledge. Meanwhile, the performance of QA depends too much on the results of earlier stages because the parameters will be adjusted to promote convergence as long as the iteration results form an ascending sequence even without global optimal. Consequently, the performance of QA should be better than LA if the global search ability is enhanced at elementary stages, thus a route choice mechanism based on ant flow is proposed in this paper.

C. Adaptive Route Choice Control Based on Ant Flow

In the previous studies, ants choose destination mainly based on pheromone values and heuristic information. The research of Dussutour [39] about moving of ant colony on two symmetrical bridges with different width has revealed another impact factor—ant flow. Form his experiment, all the ants almost choose the same bridge when wider bridges and the numbers of ants become nearly equal on narrow bridges, as shown in Figure 5. It can be seen that pheromone can affect the path choice of the whole colony only if the ant flow of path is minor. It is caused by the method of ants on dealing with block: precedence ant will push the later to the branch road, as shown in figure 6, which means that the ACO is not a really parallel algorithm in fact since the precedence ants have priority on path choice.

Inspired by this result, a limit on the ant flow of each path during the search process will not only expand search scope of ants, but also avoid the fast accumulation of pheromone caused by abnormally attraction of local optimal path. However, too strict limitation on ant flow will bring about the “narrow bridge phenomena” as shown in figure 5 also, in which the positive effect of pheromone is weaken too much and the algorithm is hard

to convergence. Therefore, the route choice control based on ant flow should also be adjusted adaptively by stages: paying more attention on global search during the initial search stages while accelerating algorithm convergence later.



Figure 5. Double Bridge Experiment of Dussutour [39]

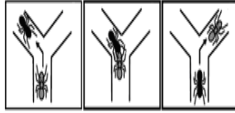


Figure 6. The method of ants on dealing with block [39]

Some variables have been introduced next:

$N_{ij}^r(t)$ —ant flow, reflects the number of ants selecting path (i,j) at t_{th} iteration.

$\theta_{ij}^r(t)$ —flow valve, reflects the number of ants that are admit to choose path (i,j) at the t_{th} iteration, which is adjusted adaptively as (17).

$$\theta_{ij}^r(t) = \theta_{ij}^r(t-1) + \frac{\theta_{ij}^r(\text{NC}_{\max}) - \theta_{ij}^r(1)}{\text{NC}_{\max}} \quad (17)$$

Let $\theta_{ij}^r(1)$ be $\left\lfloor \frac{\text{Num}_{\text{ant}}}{N_p} \right\rfloor$ and Num_{ant} reflects the total

number of ants in order to maximum the search space at the early stages since the maximum value of $|S_0|$ is n. Meanwhile, there is $\theta_{ij}^r(\text{NC}_{\max}) = \text{Num}_{\text{ant}}$ since all the ants may converge to the same tour at last.

According to the result of reference [39], precedence ants have the priority on route choice when the path is saturated which brings out $N_{ij}^r < \theta_{ij}^r(t) \Leftrightarrow P_{ij} > 0$. However, $|S_0|$ will decrease gradually from n to 0 along with the finish of each part in DRCJSP-HW and there will be $\text{Num}_{\text{ant}} > |S_0| \times \theta_{ij}^r(t)$ at the later period of scheduling which may result in super-saturated path. Therefore, $\theta_{ij}^r(t)$ should be adjusted dynamic along with $|S_0|$. Overall, the pseudo-random proportional state transition rule based on ant flow control should be improved as(18):

$$P_{ij} = \begin{cases} 1 & P \leq P_0 \wedge \arg \max_{j \in S_0 \wedge N_{ij}^r(t) \leq \left\lfloor \frac{n}{|S_0|} \times \theta_{ij}^r(t) \right\rfloor} \{ \tau_{ij}^\alpha \times \eta_{ij}^\beta \} \\ \frac{\tau_{ij}^\alpha \times \eta_{ij}^\beta}{\sum_{j \in S_0} (\tau_{ij}^\alpha \times \eta_{ij}^\beta)} & P > P_0 \wedge N_{ij}^r(t) \leq \left\lfloor \frac{n}{|S_0|} \times \theta_{ij}^r(t) \right\rfloor \end{cases} \quad (18)$$

IV SIMULATION AND ANALYSIS

The proposed A-FC-ACOSA is coded on Matlab 2006a with Inter Pentium 1.73 GHz and 512 RAM. In consideration of the fact that there is no classical

D. The description of A-FC-ACOSA

Step 1 Initial

Establish the ant map, assign initial pheromone value for each path, establish candidate solution set S_0 in which the destination node is the first operation of each part and the selected probability of them are all equal to $1/N_p$.

Step 2 Solution construction

For $t=1$ to NC_{\max}

For $a=1$ to Num_{ant}

While $S_0 \neq \phi$

Each ant selects destination node in accordance with the pseudo-random proportional state transition rule based on ant flow and record relative information of the selected operation in R.

Update the available time set of machines and workers.

Update S_0 : replace the selected node with the further operation; allocate optimal combination of resources for the new operation based on heuristic strategy.

End

Convert the tour to schedule and calculate its fitness.

End

Compare all the schedules and obtain the fitness R_{best}^C of the optimal solution at this iteration step.

Step 3 Local Search

Initial temperature T_0 ;

While $T_k \geq T_{\text{end}}$

Count=0;

While count < L_{\max}

Select an operation randomly and replace its resources combination with another one randomly.

Recalculate the new fitness $C_{\text{cost}}^{\text{new}}$ of the new schedule.

Decide whether to accept new solution according to Metropolis rule:

If accept

Replace the old solution by new one and turn to temperature update process.

Else

Count=count+1;

End

End

Temperature update: $T_k = T_0 \alpha^k$.

End

Step 4 Parameters Update

If LA

Update four parameters as(15).

Else if QA

Update four parameters as(16).

End

Step 5 Information Update

Local Pheromone Update;

Global Pheromone Update;

Ant Flow Update: The flow of path (i,j) plus 1 as soon as operation i is scheduled behind operation j for each solution of t_{th} iteration.

End

DRCJSP-HW benchmark in existing investigation and in order to avoid the influence on the credibility of A-FC-ACOSA algorithm caused by concrete instance, the simulation experiment of this paper not only utilizes the instance mentioned in section III, but also generates 10

benchmarks of different scales randomly which includes 3 parts of information as below:

- **Process Information:** the number of parts n is equal to 10 while the operation numbers of each part is a random number generated between 2 and 10, each operation can be operated with at least 2 kinds of machines and the standard process time obeys uniform distribution [2, 30]. Set the deadline of each part

$$\text{as } P_i^d = \sum_{j=1}^{n_i} \frac{\sum_{k=1}^m H_{P_i, M_k}}{\sum_{k=1}^m H_{P_i, M_k}} \times Rnd, \text{ in which Rnd is a random number in}$$

range from 1 to 1.5 for each part.

- **Resource Information:** resources utilization and scheduling result are best when staffing level is 70% according to the research of ElMaraghy [7] and Sun [8]. Therefore, the number of machines m obeys $U[5,10]$ and the number of workers w is set to $\lceil m \times 0.7 \rceil$, the amount of skills of each worker is generated randomly between 1 and 3 with the operating efficiency of each skill is generated randomly between 0.5 and 1, each machine is capable of being operated by one worker at least.

- **Cost Information:** The resource with more flexible or higher efficiency is more expensive, thus the process cost per hour of machine is set to $\left[\frac{(N_F^M)^2}{\text{Mean}_{\text{Time}}} \right]$ where N_F^M is the number of operations that can be processed on this machine while $\text{Mean}_{\text{Time}}$ represents the mean process time of them. The worker salary is set to $\text{sum}_e \times 10$ in which sum_e indicates the sum of the efficiency values of each worker. Material cost of each part is set to multiply the number of its operations by 100 and the punishment to early and tardy job is 20 and $P_i^d/2$, respectively.

A. Comparison on Resources Allocation Strategies

The combination of resources for each operation is recommended by resources allocation strategies which must affect the final schedules, so this paper applies a concrete instance and 10 random benchmarks to test the performance of different strategies.

a. Concrete instance

The computational results of simulation experiments of different strategies for the instance are given with QA-FC-ACOSA algorithm with the parameters $\{ \text{Num}_{ant} = 100, \text{NC}_{max} = 200, Q = 100, N_{cat} = 50 \}$, as shown in table VI.

TABLE VI. RESOURCES ALLOCATION STRATEGIES EXPERIMENTS

Resources Allocation Strategies	QA-FC-TACOSA				
	Global Optimal (GO)	Standard Error (SE)	Mean Result (MR)	Number of Global Optimal (NGO)	Convergence Times (CT)
MRC	3512.47	66.22	3571.09	18.7	10.2
MAC	3512.47	92.08	3623.75	16.5	21.5
EFT-MAC	3512.47	24.74	3519.60	41.6	6.7
SPT-MAC	3512.47	57.86	3541.18	18.3	24.4
SPT-MU	3532.03	102.11	3703.19	3.5	31.5

From the experiment results, the algorithm can obtain the global optimal solution with all strategies except SPT-MU which is nothing to do with the cost index. The scheduling results and convergence performance are better when using the EFT-MAC and SPT-MAC which

rely mainly on time index and secondarily on cost index than using MRC and MAC which only focus on cost index. Among them, EFT-MAC is the best and the most robustness strategy according to the table VI.

b. Random benchmark

Table VII is the Analysis of Variance (ANOVA) on the comparison results of calculating by QA-FC-ACOSA with 5 strategies to solve 10 benchmarks for 10 times respectively. The results represents that there are obvious otherness of scheduling results among different resources allocation strategies according to $\text{Sig.} < 0.05$ in the table.

TABLE VII. RESULTS OF ANOVA

	Sum of Squares	df	Mean Squares	F	Sig.
Contrast	6.706E9	4	1.676E9	41.059	.000
Error	1.984E10	486	4.083E7		

Then the Post Hoc is processed to analysis the crux of otherness specifically and find out the best strategy, as shown in table VIII. From which, the EFT-MAC is better than the others in 95% probability confidence interval.

TABLE VIII. RESULTS OF POST HOC

(I) Strategy	(J) Strategy	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
MRC	MAC	1229.52	903.66	.174	-546.04	3005.07
	EFT-MAC	8376.59*	903.66	.000	6601.03	10152.15
	SPT-MAC	765.55	903.66	.397	-1010.04	2541.11
	SPT-MU	-2613.56*	903.66	.004	-4389.12	-838.00
MAC	MRC	-1229.51	903.66	.174	-3005.07	546.04
	EFT-MAC	7147.07*	903.66	.000	5371.51	8922.63
	SPT-MAC	-463.95	903.66	.608	-2239.51	1311.60
	SPT-MU	-3843.07*	903.66	.000	-5618.64	-2067.51
EFT-MAC	MRC	-8376.59*	903.66	.000	-10152.15	-6601.03
	MAC	-7147.07*	903.66	.000	-8922.63	-5371.51
	SPT-MAC	-7611.03*	903.66	.000	-9386.59	-5835.47
	SPT-MU	-10990.15*	903.66	.000	-12765.71	-9214.59
SPT-MAC	MRC	-765.55	903.66	.397	-2541.11	1010.00
	MAC	463.95	903.66	.608	-1311.60	2239.51
	EFT-MAC	7611.03*	903.66	.000	5835.47	9386.59
	SPT-MU	-3379.12*	903.66	.000	-5154.68	-1603.56
SPT-MU	MRC	2613.56*	903.66	.004	838.00	4389.1251
	MAC	3843.07*	903.66	.000	2067.51	5618.6410
	EFT-MAC	10990.15*	903.66	.000	9214.59	12765.7193
	SPT-MAC	3379.12*	903.66	.000	1603.56	5154.6831

B. Comparison on Algorithm

a. Concrete instance

This paper utilizes the MAX-MIN Ant System(MMAS) in reference [36], ACOSA, and self-adaptive parameters ant colony algorithm without flow control(LS-ACOSA, QS-ACOSA), and ℓ -ACOSA which is constructed based on ACOSA and the adaptive adjusting parameter $\rho(t)$ proposed by reference [37] as the comparing algorithms. The parameters of them are $\alpha = 3, \beta = 1, 1 - \rho = 0.99, P_0 = 0.3, \text{Num}_{ant} = 50, \text{NC}_{max} = 100$. All algorithms are applied to calculate the concrete instance for 30 times and the results are compared, as shown in table IX.

In this table, only the MMAS couldn't obtain the global optimal result which shows that it's necessary to have local search mechanism when utilizing certain resources allocating strategy. On the other hand, although ACOSA has better result and more stable convergence performance, which is built on amounts of parameter configuration experiments. Meanwhile, compared to LS-ACOSA, the QS-ACOSA can accelerate the convergence speed, but it is easy to drop in local optimal which is in accord with the analysis above. After the introduction of adaptive route choice control mechanism based on ant flow, the average quality of results and the convergence performance of A-FC-ACOSA are improved greatly comparing to A-ACOSA. Moreover, the improvements of global search ability at the elementary stages makes the QA-FC-ACOSA better than LA-FC-ACOSA on both mean result and convergence performance.

TABLE IX. ALGORITHMS COMPARING

Comparing Algorithm	GO	GW	SE	MR	NGR	CT
LA-TACOSA	3512.47	3701.99	32.49	3552.45	20.4	20.1
QA-TACOSA	3512.47	3728.09	56.43	3567.36	27.0	14.1
LA-FC-TACOSA	3512.47	3611.92	23.95	3522.86	40.2	9.9
QA-FC-TACOSA	3512.47	3611.92	24.74	3519.60	41.6	6.7
ℓ -TACOSA	3512.47	3731.36	59.81	3559.28	26.8	25.7
TACOSA	3512.47	3780.28	64.63	3544.12	25.7	19.8
MMAS	3589.17	3701.40	22.45	3601.43	62.6	56.5

b. Random benchmark

10 groups of random benchmarks are solved by the mentioned algorithms above, the results of which has been shown in table X. Not all the algorithm can converge to the global optimal solution so that we only compare the fitness here. The performance of QA-FC-

ACOSA is improved obviously compared to QA-ACOSA and plays the best in most benchmarks while LA-FC-ACOSA is the most stable algorithm still.

V CONCLUSION

This paper has presented the application of Ant Colony Optimization with Simulated Annealing algorithm and adaptive adjusting parameters to solve dual resource constrained job shop scheduling problem with heterogeneous workers. The goal of the work was to gain some insight into the influence of resources allocation strategies on scheduling result and the improvement on convergence performance with adaptive adjusting parameters. According to the simulation experiments, the resources allocation strategy seems to play an important role in the construction of good solutions while EFT-MAC which replies mainly on time index and secondarily on cost index leads to the best performance. Two adaptive adjusting schemes of parameters have been proposed in accordance with the test experiments of different parameters. The ACOSA with adaptive adjusting parameters based on quality of solution plays better than the other competing algorithms when utilizing the proposed adaptive route choice control mechanism based on ant flow which strengthen the global search ability at the early stages, according to the comparison experiment on both concrete instance and random benchmark. However, this research only take cost index into account, time index is another important criterion for evaluation in practice. Hence, multi-object DRCJSP-HW would be deeply researched in future.

TABLE X. ALGORITHMS COMPARING

Comparing Algorithm	Index	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
LA-ACOSA	MR	174448.96	182837.03	323845.58	168913.41	390367.64	103933.45	292732.07	156661.75	343510.66	111165.96
	SE	2354.14	1988.50	8056.95	3129.60	3439.79	1516.74	5154.62	2801.62	7150.79	1234.28
QA-ACOSA	MR	174523.49	183962.82	335946.04	173562.58	400015.56	106257.47	296849.27	161657.05	359375.97	114964.03
	SE	5103.87	1997.83	8474.56	5155.57	6669.94	1818.71	6945.32	4882.05	9493.60	1917.33
LA-FC-ACOSA	MR	174695.33	181862.33	323732.16	166347.10	388941.77	102970.90	291505.95	155598.14	344408.85	111808.04
	SE	2418.22	1827.77	2606.23	2671.05	4478.87	1267.77	3104.25	2772.61	3568.07	1230.55
QA-FC-ACOSA	MR	174049.85	180768.15	323743.12	166899.90	387737.84	103177.32	290071.50	155308.75	337244.62	111568.42
	SE	2562.48	1874.27	2019.01	2619.39	6531.01	1356.94	2329.95	1508.76	8305.63	1512.84
ℓ -ACOSA	MR	175812.31	184227.56	331992.37	170978.40	394422.52	106037.42	295065.49	158346.19	353268.94	113430.95
	SE	3816.66	2447.32	5513.89	3061.85	3454.43	1327.92	6280.18	2944.62	12235.64	2457.00
ACOSA	MR	179347.90	182005.89	331297.68	169028.23	392535.16	104458.03	297418.65	157093.74	349188.99	113493.36
	SE	1995.28	2852.35	4810.59	4216.89	3400.90	1031.90	3388.16	2298.17	5535.86	1424.77
MMAS	MR	192230.14	194185.38	379203.56	190814.40	425263.46	111553.17	334307.97	175375.42	412487.60	120781.73
	SE	2959.18	2879.13	4839.47	2959.90	2843.20	1584.68	6764.61	3181.30	5805.11	2070.27

REFERENCES

- [1] R. T. Nelson, "Labor and Machine Limited Production Systems," Management Science, vol. 13, pp. 648-671, 1967.
- [2] M. Treleven, "A Review of the Dual Resource Constrained System Research," IIE Transactions, vol. 21, pp. 279-287, 1989.
- [3] H. V. Kher, "Examination of worker assignment and dispatching rules for managing vital customer priorities in dual resource constrained job shop environments," Computers & Operations Research, vol. 27, pp. 525-537, 2000.
- [4] O. Berman and R. C. Larson, "A queueing control model for retail services having back room operations and cross-trained workers," Computers & Operations Research, vol. 31, pp. 201-222, 2004.
- [5] M. Treleven, "THE TIMING OF LABOR TRANSFERS IN DUAL RESOURCE-CONSTRAINED SYSTEMS: "PUSH" VS. "PULL" RULES*," Decision Sciences, vol. 18, pp. 73-88, 1987.
- [6] L. Salum and Araz, "Using the when/where rules in dual resource constrained systems for a hybrid push-pull

- control," *International Journal of Production Research*, vol. 47, pp. 1661 - 1677, 2009.
- [7] H. ElMaraghy, et al., "Scheduling of manufacturing systems under dual-resource constraints using genetic algorithms," *Journal of Manufacturing Systems*, vol. 19, pp. 186-201, 2000.
- [8] Sun Zhijun, et al., "Intelligent optimization for job shop scheduling of dual-resources," *Journal of Southeast University(Natural Science Edition)*, vol. 35, pp. 376-381, 2005.
- [9] Li Shujuan, et al., "Mix optimization scheduling approach for multi-resource job-shop," *Journal of System Engineering*, vol. 22, pp.551-555, 2007.
- [10] Zhou Binghai, et al., "Scheduling Algorithm of Flexible Production System Based on Dual Resource," *Journal of South China University of Technology*, vol. 36, pp. 45-49, 2008.
- [11] Liu Zhigang, et al., "Multi-resource constrained job-shop optimization scheduling based on ant colony algorithm," *Journal of System Simulation*, vol 19, pp. 216-220, 2007.
- [12] J. A. C. Bokhorst, et al., "On the who-rule in Dual Resource Constrained (DRC) manufacturing systems," *International Journal of Production Research*, vol. 42, pp. 5049 - 5074, 2004.
- [13] J. A. C. Bokhorst and G. J. C. Gaalman, "Cross-training workers in Dual Resource Constrained systems with heterogeneous processing times," *International Journal of Production Research*, vol. 47, pp. 6333 - 6356, 2009.
- [14] M. Dorigo, "Optimization, learning and natural algorithms [in Italian]," PhD thesis, Dipartimento di Elettronica, Politecnico di Milano, Milan., 1992.
- [15] O. H. Cordon, Francisco ; Stützle, Thomas, "A review on the ant colony optimization metaheuristic: basis, models and new trends," *Mathware and Soft Computing*, vol. 9, pp. 141-175, 2002.
- [16] R. J. Mullen, et al., "A review of ant algorithms," *Expert Systems with Applications*, vol. 36, pp. 9608-9617, 2009.
- [17] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," *Theoretical Computer Science*, vol. 344, pp. 243-278, 2005.
- [18] C.-J. Liao and H.-C. Juan, "An ant colony optimization for single-machine tardiness scheduling with sequence-dependent setups," *Computers & Operations Research*, vol. 34, pp. 1899-1909, 2007.
- [19] B. Yagmahan and M. M. Yenisey, "Ant colony optimization for multi-objective flow shop scheduling problem," *Computers & Industrial Engineering*, vol. 54, pp. 411-420, 2008.
- [20] W. Chen, et al., "An efficient hybrid algorithm for resource-constrained project scheduling," *Information Sciences*, vol. 180, pp. 1031-1039, 2010.
- [21] A. Colomi, et al., "Heuristics from nature for hard combinatorial optimization problems," *International Transactions in Operational Research*, vol. 3, pp. 1-21, 1996.
- [22] C. Blum, "Beam-ACO--hybridizing ant colony optimization with beam search: an application to open shop scheduling," *Computers & Operations Research*, vol. 32, pp. 1565-1591, 2005.
- [23] K.-L. Huang and C.-J. Liao, "Ant colony optimization combined with taboo search for the job shop scheduling problem," *Computers & Operations Research*, vol. 35, pp. 1030-1046, 2008.
- [24] R.-H. Huang, "Multi-objective job-shop scheduling with lot-splitting production," *International Journal of Production Economics*, vol. 124, pp. 206-213, 2010.
- [25] L.-N. Xing, et al., "A Knowledge-Based Ant Colony Optimization for Flexible Job Shop Scheduling Problems," *Applied Soft Computing*, vol. 10, pp. 888-896, 2010.
- [26] A. Rossi and G. Dini, "Flexible job-shop scheduling with routing flexibility and separable setup times using ant colony optimisation method," *Robotics and Computer-Integrated Manufacturing*, vol. 23, pp. 503-516, 2007.
- [27] T. R. Rohleder and G. D. Scudder, "Comparing performance measures in dynamic job shops: economics vs. time," *International Journal of Production Economics*, vol. 32, pp. 169-183, 1993.
- [28] B. P. Shafaei R., "Workshop scheduling using practical (inaccurate) data Part 1: The performance of heuristic scheduling rules in a dynamic job shop environment using a rolling time horizon approach," *International Journal of Production Research*, vol. 37, pp. 3913-3925, 20 November 1999 1999.
- [29] B. P. Shafaei R., "Workshop scheduling using practical (inaccurate) data Part 2: An investigation of the robustness of scheduling rules in a dynamic and stochastic environment," *International Journal of Production Research*, vol. 37, pp. 4105-4117, 15 December 1999 1999.
- [30] Pan Quanke, et al., "Job Shop Scheduling for Decreasing Production Cost," *Journal of Nanjing University of Aeronautics & Astronautic*, vol. 36, pp. 121-124, 2004.
- [31] Liu Xiaoxia, et al., "Flexible Job Shop Scheduling for Decreasing Production Cost," *Journal of Northeastern University*, vol. 29, pp. 561-564, 2008.
- [32] ZHOU Hong, et al., "Hybrid ant colony optimization algorithm for unrelated parallel machine scheduling problem," *Computer Integrated Manufacturing Systems*, vol. 14, pp. 1733-1741, 2008.
- [33] V. Eswaramurthy and A. Tamilarasi, "Hybridizing tabu search with ant colony optimization for solving job shop scheduling problems," *The International Journal of Advanced Manufacturing Technology*, vol. 40, pp. 1004-1015, 2009.
- [34] S. T. Dorigo M, *Ant Colony Optimization*, 2004.
- [35] H. Bullnheimer B., Richard F., "A New Rank Based Version of the Ant System:A Computational Study," *Central European Journal for Operations Research and Economics*, vol. 7, pp. 25-38, 1999.
- [36] T. Stutzle and H. Hoos, "MIN-MAX Ant System," *Future Generation Computer Systems*, vol. 16, pp. 889-914, 2000.
- [37] CHEN Xiong, et al., "Novel ant colony optimization algorithm for robot path planning," *Systems Engineering and Electronic*, vol. 30, pp. 952-955, 2008.
- [38] Mu Feng, et al., "ACGA with adapting parameters based on cloud mode," *Systems Engineering and Electronic*, vol. 31, pp. 1763-1766, 2009.
- [39] A. Dussoutour, et al., "Optimal traffic organization in ants under crowded conditions," *Nature*, vol. 428, pp. 70-73, 2004.



Jingyao Li was born in Jiangxi, China, on April 10, 1984. He is currently pursuing the Ph.D. degree in Mechatronic Engineering at Key Lab of Contemporary Design and Integrated Manufacturing Technology, Northwestern Polytechnical University at Xi'an of China. His current research interests include studies of intelligent scheduling algorithms in dual-resource constrained job shop.



Shudong Sun was born in 1963. He is currently a Professor of Mechatronic Engineering at Northwestern Polytechnical University, Shan'xi, China.

He has authored or coauthored over 140 research papers in journals and conferences, a number of book chapters, and eight books, such as Genetic Algorithm Theory and Application (Beijing, China: National Defense

Industry Press, 1999), and so on. His current research interests are in the field of intelligent scheduling algorithms, manufacturing execution system and collaborative service system.

Yuan Huang was born in Shan'xi, China, on September 19, 1982. She received the M.S. degree in Engineering Management and Science also from Northwestern Polytechnical University at 2008.