Shortest route optimization of job-shop scheduling based on ant colony algorithm

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ABSTRACT. *This paper aims to design the best and versatile solution to job-shop scheduling problem (JSP). For this purpose, the ant colonly algorithm (ACA) was integrated to the shortest route optimization of the JSP, and a strategy was developed to solve the shortest scheduling route with the improved ACA (IACA). The proposed strategy was verified through case analysis and simulation experiment. The results show that the ACA is suitable to optimize the scheduling route of real-world JSP. With the increase of the pheromone residual coefficient, the route length of the ACA first increased and then decreased. The IACA worked out a better solution than the genetic algorithm with fewer iterations. The IACA is more adaptable and versatile than the genetic algorithm in shortest route optimization, as well as the IACA's relative advantage in the global optimization ability for JSP. The research findings shed new light on the optimization of dynamic JSP with multiple objectives.*

RÉSUMÉ. *Cet article vise à concevoir la solution la meilleure et la plus polyvalente au problème de séquençage de tâches (JSP, le sigle de « job-shop scheduling problem » en anglais). A cet égard, l' algorithme de colonies de fourmis (ACA, le sigle de « ant colonly algorithm » en anglais) a été intégré à l'optimisation de plus court chemin du JSP et une stratégie a été élaborée pour résoudre le chemin de planification la plus court avec l'ACA amélioré. La stratégie proposée a été vérifiée par une analyse de cas et un test de simulation. Les résultats montrent que l'ACA convient à l'optimisation de la planification des JSP dans le monde réel. Avec l'augmentation du coefficient résiduel de phéromone, la longueur de chemin de l'ACA a d'abord augmenté et puis diminué. L'ACA amélioré a élaboré une meilleure solution que l'algorithme génétique avec moins d'itérations. L'ACA amélioré est plus adaptable et polyvalent que l'algorithme génétique pour l'optimisation de plus court chemin, ainsi que l'avantage relatif de l'ACA amélioré dans la capacité d'optimisation globale de JSP. Les résultats de la recherche ont apporté un nouvel éclairage sur l'optimisation de la JSP dynamique avec des objectifs multiples.*

KEYWORDS: *Job-shop scheduling problem (JSP), shortest route optimization, ant colony algorithm (ACA), simulation, number of iterations.*

MOTS-CLÉS: *séquençage de tâches (JSP), optimisation de plus court chemin, algorithme de colonie de fourmis (ACA), simulation, nombre d'itérations.*

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1. Introduction

Recent years has seen a growing interest among production enterprises in efficient resource allocation and schedule planning, which gives birth to numerous innovative solutions and algorithms of the job-shop scheduling problem (JSP) (González *et al*., 2015). For example, many enterprises are competing to minimize the makespan and achieve an efficient output mode (Zhao *et al*., 2016, Zhai *et al*., 2014). The JSP is nonlinear, uncertain and largescale, often involving multiple objectives and constraints. The scheduling of a job-shop needs to determine the process line, machining time and thermodynamic operation, before minimizing the makespan, optimizing the resource utilization and maximizing the product qualification rate (Ling *et al*., 2013).

In actual production, lots of time is consumed by non-cutting processes. A reasonable route for the JSP may save the cost and promote the production efficiency (Hu, 2015). The shortest route optimization is an important solution to the JSP. It is constantly updated and improved. The relevant algorithms include the simulated annealing algorithm, the genetic algorithm, the ant colony algorithm (ACA), the neural network algorithms, and the chaos optimization algorithms. Among them, the ACA, an intelligent optimization algorithm, has lately been introduced to the shortest route optimization of the JSP (Saravanan and Haq, 2010).

Despite its proneness to the local optimal trap and slow convergence, the ACA, closely bound with the pheromone mechanism, has been found feasible to optimize the JSP solutions (Fnaiech *et al*., 2015). The relevant studies have proved that the ACA outperforms the other algorithms in positive feedback, self-organization and global search ability. Of course, these studies are still in their infancy, leaving an ample space for further application of the ACA in the JSP (Seidgar *et al*., 2016).

In light of the above, this paper applies the ACA to optimize the shortest route in job-shop scheduling, aiming to design the best and versatile solution to the JSP.

2. Basic theories of the ACA and the improved ACA (IACA)

2.1. The ACA

The traditional ACA involves the state transition strategy, global update rule and local pheromone update mechanism (Zhang *et al*., 2013), and supports self-organization and parallel operations. Thanks to the uncertainty of distributed computation, the ACA can approximate the optimal solution from many solutions without a central control (Azzi *et al*., 2012).

As a swarm intelligence algorithm, the ACA relies on the adaptation and cooperation processes. By the pheromone quantity released by ants, the models developed based on this algorithm fall into three categories: ant-density system, anti-quantity system and ant-cycle system. The first two categories use the local information while the last uses the global information to achieve good computing effect (Vinod and Sridharan, 2011). The three system models can be expressed as:

Ant-density system:

$$\nabla\tau_{ij}^{k}(t,t+1)=\begin{cases}Q, & (i,j)\in l_k\\ 0, & \text{otherwise}\end{cases} \tag{1}$$

Ant-quantity system:

$$\nabla\tau_{ij}^{k}(t,t+1)=\begin{cases}\frac{Q}{d_{ij}}, & (i,j)\in l_k\\ 0, & \text{otherwise}\end{cases} \tag{2}$$

Ant-cycle system:

$$\nabla\tau_{ij}^{k}(t,t+1)=\begin{cases}\frac{Q}{L_k}, & (i,j)\in l_k\\ 0, & \text{otherwise}\end{cases} \tag{3}$$

The three basic ant system models were respectively subjected to ten tests and the results were compared in Table 1 below.

Table 1. Test results of the three basic ant system models

Test no.	Ant-density system	Ant-quantity system	Ant-cycle system
1	27.282350	27.947872	25.734450
2	33.916369	28.198004	27.425817
3	31.813578	31.218422	26.764424
4	28.198004	28.198804	26.438203
5	29.950884	27.903925	28.198004
6	28.672368	32.925244	26.525410
7	27.900799	33.479480	26.935765
8	30.119585	27.947872	27.855764
9	28.198004	30.359064	26.327773
10	31.611845	28.241552	26.734450
Mean length route	29.78073	29.64202	26.87966

Here, the pheromone quantity of the ant is denoted as Q and the route length as Lk. It is obvious that the ant-cycle system has better computing effect than the other two systems.

2.2. The IACA

During the foraging process, each ant is guided by the relative importance of pheromone to the heuristic information, and tends to choose a route with relatively high pheromone concentration (Zhao and Tan, 2012).

Table 2. Effect of pheromone on ACA performance

Pheromones	Heuristic factor	Average value	Optimal path length	Worst path length	Iterations number
0	2	695.17	671.11	725.80	45
0.5	2	549.49	513.71	572.62	39
1	2	441.94	436.15	447.29	35
2	2	460.65	445.78	480.11	36

As shown in Table 2, the pheromone level directly bears on the ACA performance. The mean route length, the optimal route length and the number of iterations were all minimized at the pheromone level of 1.

With the elapse of the time, the pheromone level will gradually decline. Here, the pheromone volatilization coefficient ρ is introduced to disclose the relationship between ant movement and the decline amplitude, and the corresponding 1-ρ represents the pheromone residual coefficient.

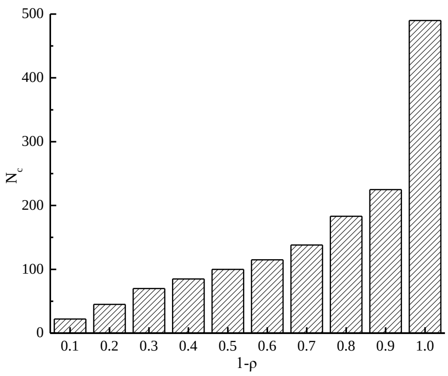

Figure 1. Relationship between 1-ρ and the convergence time

As shown in Figure 1, there is an obvious correlation between the pheromone residual coefficient and the convergence time Nc, indicating that the ACA convergence is greatly affected by the pheromone volatilization coefficient ρ. It can be seen the convergence time Nc clearly increased with the pheromone residual coefficient; the convergence time at 1-ρ=1 was twice that at 1-ρ=0.9. The relationship between 1-ρ and route length L is shown in Figure 2.

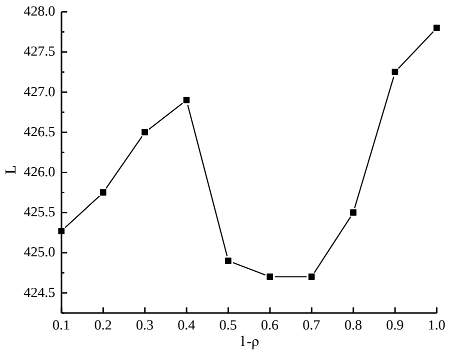

Figure 2. Relationship between 1-ρ and route length L

From Figure 2, it can be inferred that the route of the ACA first increased and then decreased with the growth of the pheromone residual coefficient, and reached the shortest length at 1-ρ=0.6 or 0.7.

3. ACA-Based shortest route optimization of static JSP

3.1. Shortest route optimization of single-objective static JSP

Our target is a static JSP, which leaves out such dynamic factors as sudden machine failure, order cancellation and emergency job insertion. The optimization aims to minimize the workspan, machine load, total machine load, lead time and total cost. The formulas of these objectives are as follows:

$$\text{Minimum completion time: } f_1=\min C_{max}=\min(\max(C_i)) \tag{4}$$

$$\text{Minimum machine load: } f_2=\min(\max(W_k)) \tag{5}$$

$$\text{Minimum gross machine loads: } f_3=\min(\textstyle\sum_{k=1}^{m} W_k) \tag{6}$$

$$\text{Minimum lead time: } f_4=\min(\max(\max(d_i-C_i))) \tag{7}$$

Minimum machining cost:

$$f_5=\min(Cost)=\min(\textstyle\sum_{i=1}^{n}\sum_{j=1}^{OperationNum}\sum_{k=1}^{MachineNum} Cost_{ijk}x_{ijk} \tag{8}$$

Where: $1\le i\le n$; $1\le k\le m$.

Based on the traditional ACA, the state transition, global pheromone update and local pheromone update were implemented on the ant colony system. Taking the job-shop of an engine enterprise for instance, there are six jobs to be produced, each of which needs to go through six processes, and ten machines for job production. With the aim to minimize the make span, the weight coefficient of selected pheromone was set to 2, the pheromone intensity was set to 120, and the number of iterations was set to 50. The traditional ACA, the genetic algorithm, the hybrid algorithm and the IACA were adopted for the simulation.

Figures 3 and 4 display the convergence time of the ACA to the optimal solution and the mean convergence time of the ACA to the optimal solution of each number of iteration. Figure 5 presents the solutions obtained by the four contrastive algorithms. It is obvious that the IACA consumed less time and achieved better solution than the other three algorithms, and realized the shortest JSP route.

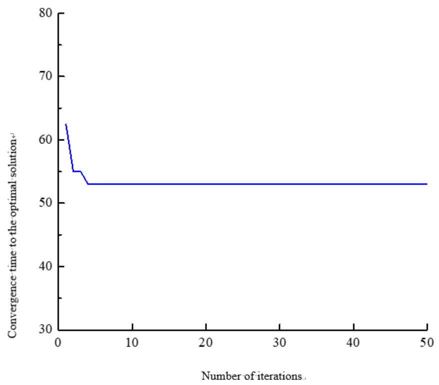

Figure 3. The convergence time of the ACA to the optimal solution

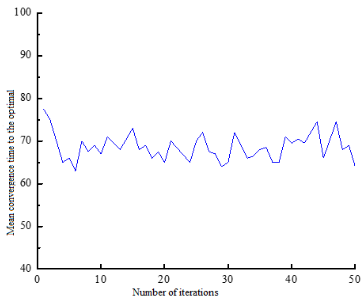

Figure 4. The mean convergence time of the ACA to the optimal solution in each iteration

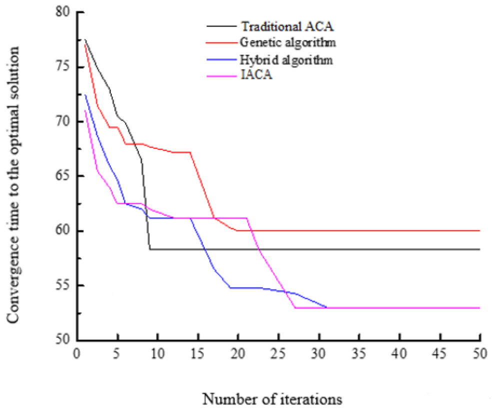

Figure 5. Solution results of four algorithms

3.2. Shortest route optimization of multi-objective static JSP

In real-world job-shops, there are more than one objective of scheduling optimization. The multi-objective JSP needs to strike a balance between the various objectives, such as the total makespan, the total cost and the lead time (Moradi et al., 2011, Calleja and Pastor, 2014). In light of these, the weighted sum method was employed to determine the objective weight λ_i based on the makespan f_1, the maximum machine load f_2, the total machine load f_3, the maximum lead time f_4 and the total cost f_5. Multiple scheduling plans were solved by the ACA to determine the optimal one. An overall optimization objective was derived from the single objectives and their corresponding objective weights:

$$\min(Y)=F=\lambda_1*f_1+\lambda_2*f_2+\lambda_3*f_3+\lambda_4*f_4+\lambda_5*f_5 \quad (9)$$

where $\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5=1$. After determining the overall optimization objective, the pheromone volatilization coefficient was set to 0.1, the pheromone intensity was set to 120, and the number of iterations was set to 100. Figure 6 provides the convergence time to the overall optimization objective of the IACA, and Figure 7 gives the mean convergence time to that objective in each iteration. It can be seen that the optimal solution of the multi-objective static JSP is not always consistent with that of all single objectives.

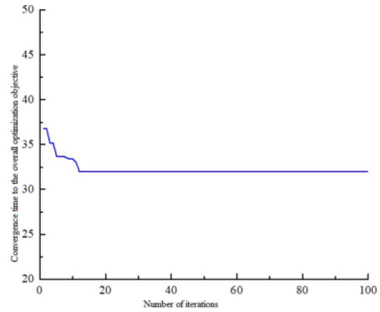

Figure 6. The convergence time of the IACA to the overall optimization objective

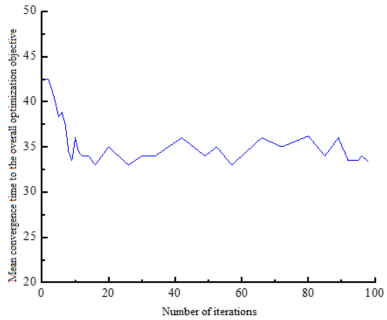

Figure 7. The mean convergence time of the IACA to the optimal solution in each iteration

4. IACA-Based shortest route optimization of dynamic JSP

4.1. Shortest route selection strategy

The static JSP described in the previous section adopts a constant scheduling plan, which is the optimal one for the production process. However, the JSP faces dynamic changes and various emergencies. The dynamic JSP requires constant rescheduling according to the latest conditions. In general, a dynamic JSP solution should optimize such core issues as the scheduling route and dynamic event processing. The popular rescheduling strategies are driven by cycle or event

The engine job-shop was still cited as the example. Taking the shortest scheduling route as the objective, the IACA was compared with the genetic algorithm through a performance test. The test results on the IACA and the genetic algorithm are listed in Tables 3 and 4, respectively. It is clear that the IACA worked out a better solution than the genetic algorithm with fewer iterations. The convergence curves of the IACA and the genetic algorithm are displayed in Figures 8 and 9, respectively. The figures demonstrate that the IACA is more adaptable and versatile than the genetic algorithm in shortest route optimization, as well as the IACA's relative advantage in the global optimization ability for JSP.

Table 3. Mixed ant colony algorithm test results

α	β	ρ	Shortest path value	Iterations number
1	5	0.8	765.5405	71
1	3	0.6	766.3511	58
2	5	0.8	729.5203	48
2	4	0.6	805.748	62
3	3	0.8	803.6245	32
3	5	0.6	729.7353	44

Note: α represents the pheromone heuristic factor; β represents the expected heuristic factor; ρ represents the pheromone volatilization coefficient.

Table 4. Test results of the genetic algorithm

Popnum	Pc	Pm	Shortest path value	Iterations number
60	0.5	0.06	755.1173	70
60	0.7	0.06	768.1229	48
60	0.8	0.12	744.8622	99
30	0.5	0.06	743.5381	33
30	0.7	0.06	818.8602	34
30	0.8	0.12	803.2614	96

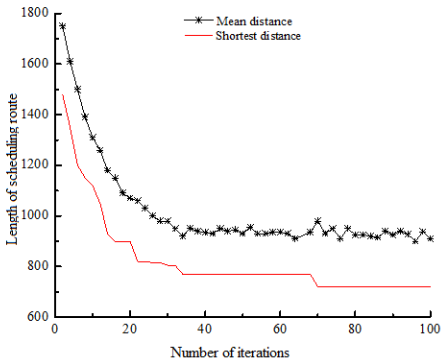

Figure 8. The convergence curves of the IACA

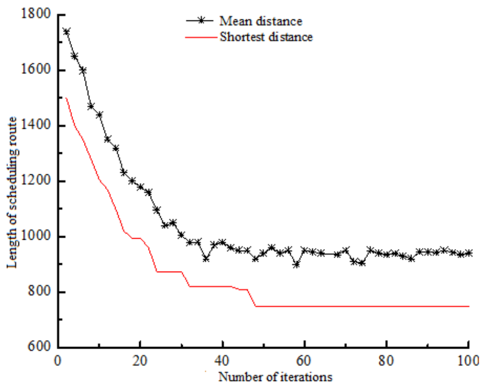

Figure 9. Genetic algorithm test results

4.2. Case study and results analysis

Our case has eight jobs, numbered as J1~J8, and ten machines, numbered as M1~M10. Each job requires different number of processes: 4 for J1, 3 for J2, 4 for J3, 5 for J4, 4 for J5, 5 for J6, 4 for J7 and 5 for J8. The rescheduling strategy is both cycle- and event-driven. The optimization objective was set as the minimal makespan. During the rescheduling, the job with higher priority should be processed first. If a machine fails, its processes should be terminated, and the unfinished jobs should also be scrapped. Under these conditions, the author conducted a simulation experiment on the IACA.

During the experiment, an emergency job J9 was added to the production queue at 20h. Then, the job was preferentially arranged into the production at 20h. In addition, machine M6 was assumed to fail at 7h, and all the jobs processed on it were suspended until the failure was eliminated. Moreover, job J5 was assumed to have a poor quality at 10h and should be scrapped. In this case, this job was removed from the production queue. The simulation of these three dynamic scheduling routes prove that the IACA can respond well to the changes induced by external uncertainties.

5. Conclusion

This paper integrates the ant colony algorithm into the shortest route optimization in job shop scheduling process. Here also gives the strategy for solving the shortest route of the job shop scheduling with improved ant colony algorithm. An example cited helps make the simulation experiment. The specific conclusions are drawn as follows:

With the increase of the pheromone residual coefficient, the route length of the ACA first increased and then decreased, and reached the shortest length when the pheromone residual coefficient was 0.6 or 0.7.

The multi-objective JSP needs to strike a balance between the various objectives, such as the total make span, the total cost and the lead time. Through simulation, it is learned that the optimal solution of the multi-objective static JSP is not always consistent with that of all single objectives.

The IACA is more adaptable and versatile than the genetic algorithm in shortest route optimization, as well as the IACA's relative advantage in the global optimization ability for JSP. The simulation analysis of three dynamic scheduling routes reveals that the IACA can respond well to the changes induced by external uncertainties.

Reference

Azzi A., Faccio M., Persona A., Sgarbossa F. (2012). Lot splitting scheduling procedure for makespan reduction and machine capacity increase in a hybrid flow shop with batch production. *International Journal of Advanced Manufacturing Technology*, Vol. 59, No. 5-8, pp. 775-786. https://doi.org/10.1007/s00170-011-3525-x

Calleja G., Pastor R. (2014). A dispatching algorithm for flexible job-shop scheduling with transfer batches: An industrial application. *Production Planning & Control*, Vol. 25, No. 2, pp. 93-109. https://doi.org/10.1080/09537287.2013.782846

Fnaiech N., Fitouri C., Varnier C., Fnaiech F., Zerhouni N. (2015). A new heuristic method for solving joint job shop scheduling of production and maintenance. *IfacPapersonline*, Vol. 48, No. 3, pp. 1802-1808. https://doi.org/10.1016/j.ifacol.2015.06.348

González M., Vela C., Varela R. (2015). Scatter search with path relinking for the flexible job shop scheduling problem. *European Journal of Operational Research*, Vol. 245, No. 1, pp. 35-45. https://doi.org/10.1016/j.ejor.2015.02.052

Hu R. S. (2015). A hybrid pso-ga algorithm for job shop scheduling in machine tool production. *International Journal of Production Research*, Vol. 53, No. 19, pp. 1-27. https://doi.org/10.1080/00207543.2014.994714

Wang L., Wang S. Y., Liu M. (2013). A pareto-based estimation of distribution algorithm for the multi-objective flexible job-shop scheduling problem. *International Journal of Production Research*, Vol. 51, No. 12, pp. 3574-3592. https://doi.org/10.1080/00207543.2012.752588

Moradi E., Ghomi S. M. T. F., Zandieh M. (2011). Bi-objective optimization research on integrated fixed time interval preventive maintenance and production for scheduling flexible job-shop problem. *Expert Systems with Applications*, Vol. 38, No. 6, pp. 7169-7178. https://doi.org/10.1016/j.eswa.2010.12.043

Saravanan M., Haq A. N. (2010). A scatter search algorithm for scheduling optimisation of job shop problems. *International Journal of Product Development*, Vol. 10, No. 1-2, pp. 259-272. https://doi.org/10.1504/IJPD.2010.029996

Seidgar H., Zandieh M., Mahdavi I. (2016). Bi-objective optimization for integrating production and preventive maintenance scheduling in two-stage assembly flow shop problem. *Journal of the Chinese Institute of Industrial Engineers*, Vol. 33, No. 6, pp. 404-425. https://doi.org/10.1080/21681015.2016.1173599

Vinod V., Sridharan R. (2011). Simulation modeling and analysis of due-date assignment methods and scheduling decision rules in a dynamic job shop production system.

International Journal of Production Economics, Vol. 129, No. 1, pp. 127-146. https://doi.org/10.1016/j.ijpe.2010.08.017

Zhai Y., Liu C., Chu W., Guo R., Liu C. (2014). A decomposition heuristics based on multi-bottleneck machines for large-scale job shop scheduling problems. *Journal of Industrial Engineering & Management*, Vol. 7, No. 5, pp. 1397-1414. https://doi.org/10.3926/jiem.1206

Zhang R., Chang P. C., Wu C. (2013). A hybrid genetic algorithm for the job shop scheduling problem with practical considerations for manufacturing costs: investigations motivated by vehicle production. *International Journal of Production Economics*, Vol. 145, No. 1, pp. 38-52. https://doi.org/10.1016/j.ijpe.2012.10.024

Zhao C., Tang H. (2012). Two-machine flow shop scheduling with deteriorating jobs and chain precedence constraints. *International Journal of Production Economics*, Vol. 136, No. 1, pp. 131-136. Retrieved from https://doi.org/10.1016/j.ijpe.2011.09.023

Zhao F., Shao Z., Wang J., Zhang C. (2016). A hybrid differential evolution and estimation of distribution algorithm based on neighbourhood search for job shop scheduling problems. *International Journal of Production Research*, Vol. 54, No. 4, pp. 1-22. https://doi.org/10.1080/00207543.2015.1041575