Study on disruption management approach for hot working scheduling problem in manufacturing supply chain

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Abstract

This research investigates a hot working scheduling problem for an anticipated machine disruption in manufacturing supply chain environment, a novel scheduling model and a heuristic hybrid algorithm based on disruption management is presented. The results of numerical experiments indicate that the scheduling model and algorithm is effective.

Keywords: Hot working scheduling, Disruption management, Hybrid PSO algorithm

Introduction

As one of the most important production processes in manufacturing supply chain especially in the steel industry, hot working connects upstream processes. Appropriate production planning and scheduling of hot working exerts a significant influence on steel plants under the manufacturing supply chain environment. Research results have shown that hot working scheduling problem is an NP-hard problem(Lopez et al.1988).

At present, the scheduling problem of hot working process has been extensively investigated from different angles by the research community, the method of solving this type of hot working scheduling including heuristic algorithms (Cowling 2003) and artificial intelligence search algorithms (Gao et al.2014). Bellabdaoui and Teghem(2006) establishment non-linear programming mode and mixed integer linear programming model for various disturbances in steelmaking and continuous casting process for hot working scheduling problem, and solved by software package. Zhao et al.(2009) propose a two-stage scheduling method as a VRPTW based on a modified PGA to solve a certain hot working scheduling problem in Shanghai operated by Baosteel Co. Ltd.. Additionally, Tang et al.(2002) presented an integer programming formulation with a separable structure for steel-making processes. A heuristic method based on Lagrangian relaxation and dynamic program- ming was developed to reduce the complexity of this scheduling model.

Although the researchers for the hot working scheduling problem made certain research, but these studies often focus only on a particular hot process, lack of reasonable cohesion and from the overall level of the system and to raise planning. And during the hot working process in the actual condition, because of the occurrence of random events, such as mechanical failure and others, managers must quickly set out rescheduling program based on the actual condition and degree of disruption.

Based on the above research, the following works has done in this paper: solve the hot working rescheduling problems by employ disruption management scheduling model. In this paper, A novel scheduling method based on disruption management is presented. The scheduling model is based on considering both the target to minimize total weighted completion time (the original objective) and the target to minimize total weighted delay time (the disruption repairing objective). Then a combining hybrid PSO algorithm which based on particle swarm optimization strategies and random neighborhood search mechanism is proposed. Finally, the numerical experiments show that the hybrid PSO algorithm is effective to solve the hot working disruption management scheduling model.

Formulation of the disruption management

Processing n jobs set $J=\{1,2,\cdots,j,\cdots,n\}\,(n>1)$ composed by different types need to through $L\,(L\geq 2)$ processes for production in the hot working processing system, the processing priority of each job is ω_j. The processing environment of the hot working system is: two production lines A and B, which have same function and resources configuration. Assume at the 0 moment, the processing system and the working set J are ready. It has been known that the processing time of job j is p_{ij} in the process i. When the job j through the step i, the start time of machine M_{ij}^1 and M_{ij}^2 on the flow shop A and B is s_{ij}^1 and s_{ij}^2, the completion time is C_{ij}^1 and C_{ij}^2. The completion time of job j in hot working system is C_j, and the feasible scheduling processing schedule is π.

Initial scheduling scheme. The n jobs' sum of weighted completion time give a inventory cost index (Pinedo 2012). Taking the minimizing sum of weighted completion time of all jobs $\sum_{j=1}^{n}\omega_j C_j$ as the initial scheduling optimization target, the initial scheduling problem can be described as $FF_L\left|nwt\right|\sum_{j=1}^{n}\omega_j C_j$. According to the first come first served rules, we can get the initial scheduling optimal processing times table for $\bar{\pi}$ (Figure 1 condition, Part I), the optimal objective function value is $f(\bar{\pi})=\sum_{j=1}^{n}\omega_j \bar{C}_j$.

Based on the initial scheduling, the random or an anticipated disruption event such as machine failure, machine maintenance and other machine disruption condition in the hot working system are recorded as ΔM. The effect of the machine disruption on the initial scheduling is shown in Figure 1 condition, Part II. In order to reduce the influence of machine disruption, we need to adjust the processing jobs' order to form a new production processing schedule π' which takes account of the initial scheduling objective and disruption repair objective.

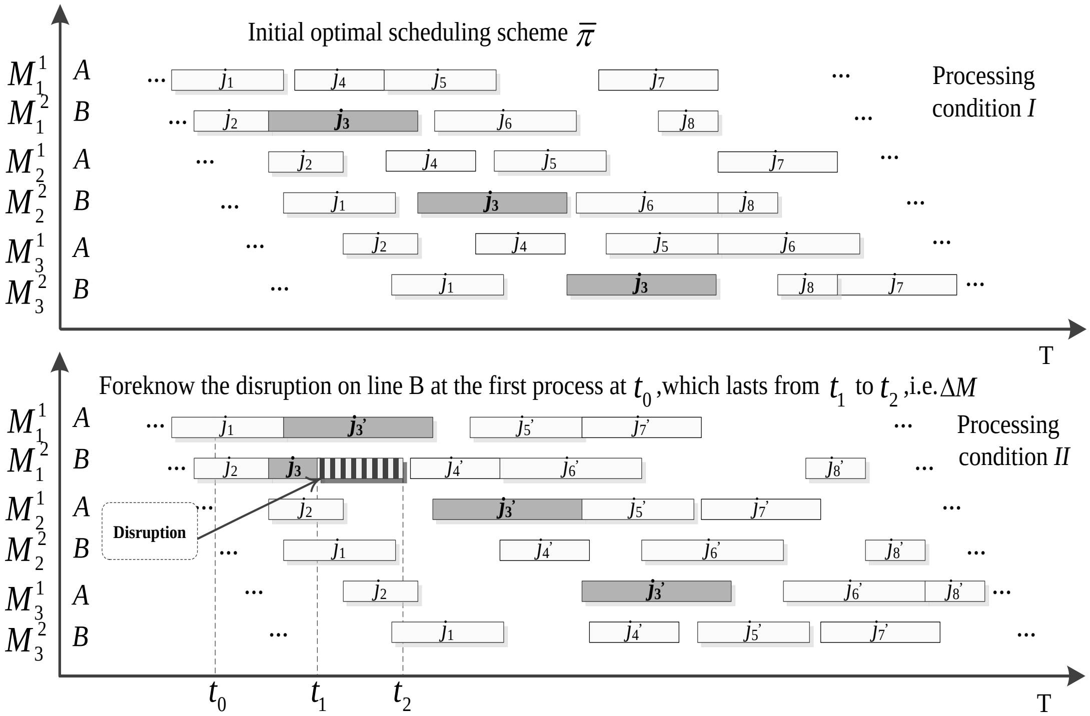

Fig. 1 Disruption management scheduling of FNWFS

Disruption management strategy. To reducing make span and ensuring the continuity and stability in the implement of every steps in hot working process, according to the basic principle of disruption management, disruption management scheme should be developed with fully consideration of the optimization objective in initial scheduling scheme. Disruption repair operation usually leads to a bias between the former scheduling and the latter scheduling. To reduce the deviation of the two schedules we ought to ensure the consistency of the two schemes in the scheduling as much as possible. Thus, two optimization objectives are described as:

(1)Initial scheduling objective: to minimize the weighted sum of completion time of the hot working processing jobs $f_{\mathrm{I}}(\pi')=\sum_{j=1}^{n'}\omega_j C_j$;

(2) Disruption repairing objective: to minimize the weighted sum of tardiness time of the hot working processing jobs $f_{\mathrm{II}}(\pi')=\sum_{j=1}^{n'}\omega_j T_j$.

In summary, this paper study the hot working scheduling disruption management problem can be described as $HWSP: FF_L \left| nwt\ , \Delta M \right| f_{\mathrm{I}}(\pi'), f_{\mathrm{II}}(\pi')$.

Disruption management scheduling model

In order to facilitate the description of this problem, we define the the job j on the machine i of the working procedure as $\sigma(ijk)$, define a variable x_{ij}^k indicating whether the job j is processed by the machine M_{ij}^k in the process i ($x_{ij}^k = 0 or 1$). The starting time s_{ij}^k of the x_{ij}^k and the job j in the process i of the machine M_{ij}^k ($k = 1 \mathrm{or} 2$) is a decision variable of the model. The time window for the emergence of the machine disruption ΔM is recorded as $[t_m, t_{m+1}]$, in which $m = 1, 3, 5, \cdots$ In this way, the hot working disruption management scheduling model can be described as follows:

$$\min_{i \in I, j \in J'} \{ f_{\mathrm{I}}(\pi') = \sum_{j=1}^{n'} \omega_j C_j ,\ f_{\mathrm{II}}(\pi') = \sum_{j=1}^{n'} \omega_j T_j \} \tag{1}$$

$$s.t. \quad s_{ij} = s_{ij}^k \cdot x_{ij}^k ,\ p_{ij} = p_{ij}^k \cdot x_{ij}^k \tag{2}$$

$$C_{ij} = s_{ij} + p_{ij} ,\ C_j = s_{1j} + \sum_{i=1}^{I} p_{ij} \tag{3}$$

$$s_{ij}, C_{ij} \notin [t_m, t_{m+1}] \tag{4}$$

$$s_{(i+1)j} = s_{ij} + p_{ij} ,\ i \in \{1, 2, \cdots, L-1\} \tag{5}$$

$$s_{i\sigma(ijk)}^k \cdot x_{ij}^k \geq s_{ij}^k \cdot x_{ij}^k + p_{ij}^k \cdot x_{ij}^k \tag{6}$$

$$(s_{ij}^k \cdot x_{ij}^k \geq C_{ij}^k \cdot x_{ij}^k \vee s_{ij}^k \cdot x_{ij}^k \geq C_{ij}^k \cdot x_{ij}^k) \vee (M_{ij}^k \neq M_{ij'}^k),\ \forall j, j' \in J' \tag{7}$$

$$(s_{i\sigma(ijk)} \geq C_{ij''}) \wedge (C_{i\min} = \min C_{ij''}) \wedge (x_{i\sigma(ijk)}^k = x_{i\min}^k), \forall j'' \in \{1, 2, \cdots, j-1, j\} \tag{8}$$

In the disruption management scheduling model, type (1) said the optimization target of the interference management scheduling problem; type (2) is the expression of the start time and processing time for the bogie in the process; type (3) is the completion time for the bogiein the process, and calculate the total completion time; type (4) that cannot arrange job processed within the time window where appear machine disruption; type (5) said the operating constraint of hot working system; type (6) said the same machine can start the process of the next job only after the completion of the first turning; type (7) means that if two jobs are arranged to produce on the same machine, it is banned for; type (8) said in the idle machine, job which come early are produced at first, i.e. FCFS scheduling rules.

Hybrid particle swarm optimization algorithm

Particle swarm optimization (PSO) algorithm, first proposed by Kennedy and Eberhart (1995), is an evolutionary metaheuristic based on swarm intelligent theory, which is inspired by bird predation [8]. Owing to the feature that PSO algorithm possesses fast global optimization and the stochastic neighborhood local search mechanism can improve the performance of local search algorithm significantly. In this paper, propose a hybrid PSO algorithm which is based on the tight combination of particle swarm optimization strategy and heuristic neighborhood search mechanism.

Algorithm initialization. To ensure that the coding strategy of scheduling scheme will not miss the possible global optimal solution, and the rationality and feasibility of PSO iteration evolutionary operation, remember position vector and velocity vector k in n' dimensional search space as $X_i=[x_{i,1},x_{i,2},\cdots,x_{i,n'}]$, $V_i=[v_{i,1},v_{i,2},\cdots,v_{i,n'}]$. At the t time, the best place for each particle record as $P_{i,best}^{n'}=[p_{i,1},p_{i,2},\cdots,p_{i,n'}]$. At the $t+1$ time, location and speed iterative update formula is:

$$v_{i,j}(t+1)=\omega v_{i,j}(t)+c_1r_1[p_{i,j}-x_{i,j}(t)]+c_2r_2[p_{g,j}-x_{i,j}(t)] \tag{9}$$

$$x_{i,j}(t+1)=x_{i,j}(t)+v_{i,j}(t+1),\ j\in\{1,2,\cdots,n'\} \tag{10}$$

Multi-target treatment strategies. To solve the multi-objective hot working disruption management scheduling problems, we build random weighted linear accumulation fitness function which support PSO algorithm search direction dynamic variable, namely $f(x)=\sum_{k=1}^{K}\lambda_k\cdot f_k(x)$. λ_k is the non-negative weighting factor. λ_k random generation as $\lambda_i=rand_k/\sum_{k'=1}^{K}rand_{k'}$, $rand_k$ is uniformly distributed random number between $(0,1)$. Therefore, the paper fitness function expression can be described as $rand()\cdot f_{\mathrm{I}}(\pi')+[1-rand()]\cdot f_{\mathrm{II}}(\pi')$.

Local search mechanism. To solve the problem of $HWSP:FF_L\left|nwt,\Delta M\right|f_{\mathrm{I}}(\pi'),f_{\mathrm{II}}(\pi')$ with the hybrid PSO algorithm, we design two local search neighborhood strategies, their structure is defined as HPSO-M algorithm and HPSO-R algorithm. The HPSO-M algorithm mainly uses the 3 kinds of neighborhood structure, as well as forms $swap(\pi,k_1,k_2)$, $forward\_insert(\pi,k_1,k_2)$ and $backward\_insert(\pi,k_1,k_2)$ neighborhood structure based on the structure $insert$.

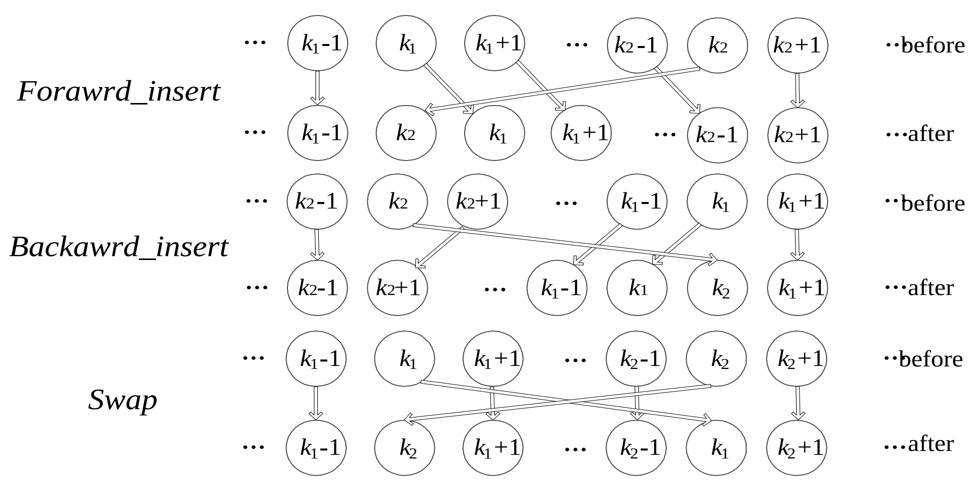

Figure. 2 *forward_insert*, *backward_insert* and *Swap* neighborhood structure

For the HPSO-R algorithm we designed a random neighborhood search mechanism by combining neighborhood structure $insert(\pi,k_1,k_2)$ and $swap(\pi,k_1,k_2)$ dynamically. The local search $insert-swap$ based on the hybrid operation of the insertion and swap is defined as $F(c_{P\mathrm{II}}\otimes X_{best}(g))$, representing execution local search of step is M for the best individual in each generation with probability $c_{P\mathrm{II}}$, the combination of two neighborhood operators is defined $COM\langle I,S\rangle$. For the overlapping probability distribution area, such as $\alpha_2<\beta_1$, i.e. it is overlapping area $[\alpha_2,\beta_1]$. If the random numbers meets the conditions $\alpha_2\le rand()\le\beta_1$, the combination neighborhood structure is formed, in which the $insert(\pi,k_1,k_2)$ operator and the $swap(\pi,k_1,k_2)$ operator are performed alternately according to the neighborhood operator priority.

The hybrid PSO algorithm flow for solving the hot working disruption management scheduling model is shown in Figure 3.

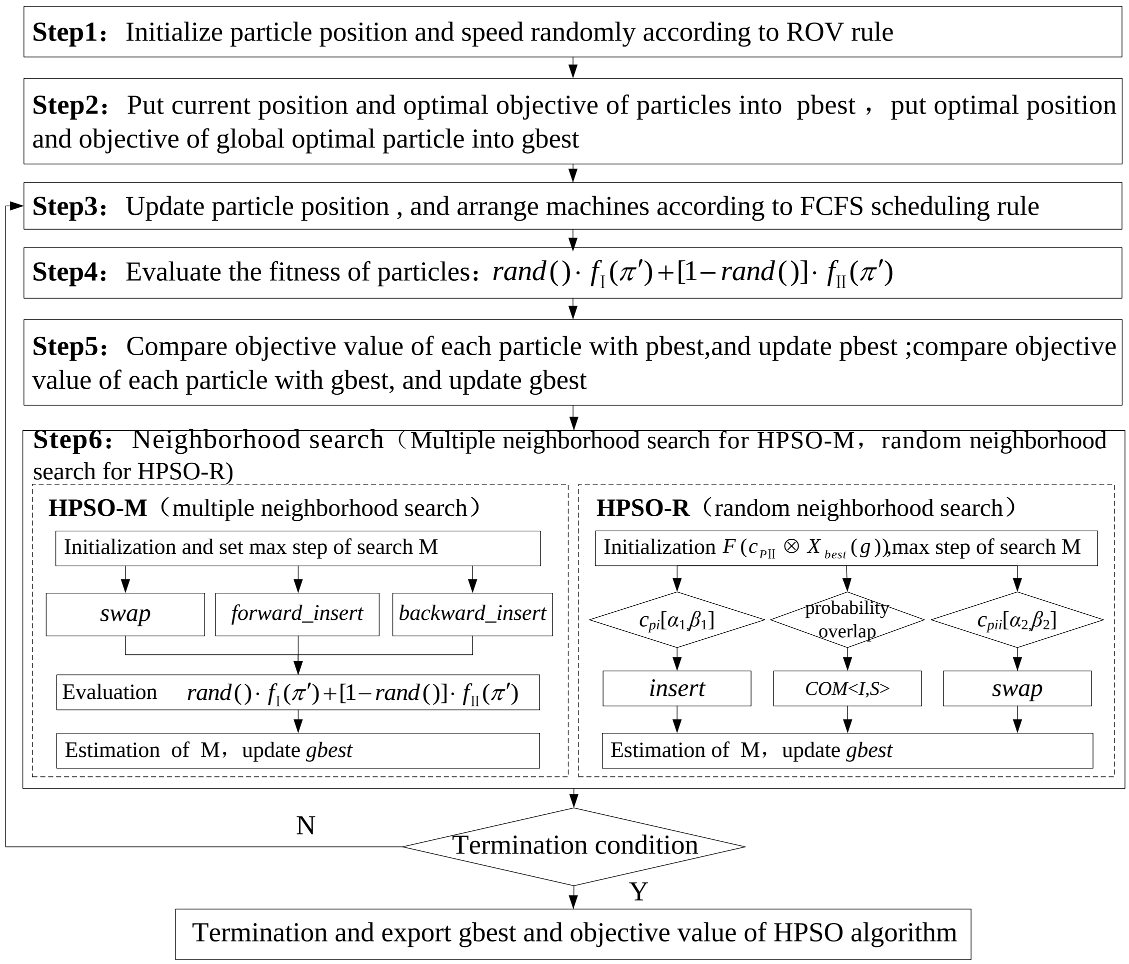

Figure. 3 The hybrid PSO algorithm flow chart

Example experiment

Experiment design. The numerical calculation example experiment scheme of hot working disruption management scheduling model for the job production is as follows: the production includes 3 processes: forging, annealing and sand blasting, and processing speed of 3 kinds of the homotype machine M_1^k, M_2^k and M_3^k ($k=1or2$) are v_1, v_2 and v_3. Assume $v_1:v_2:v_3=1:0.9:0.8$, the number of the job to be processed is 50. Sort encoding on all the job after reset the 0 time, the processing time of the job 1 in the process 1 is $p_{1,1}=10$, subsequent bogie 2 is $p_{1,2}=10.2$,......the processing time of the 50 jobs in the process 1 meet the arithmetic progression (tolerances is 0.2), that is $p_{1,3}=10.4$,......, $p_{1,50}=10+(50-1)\times 0.2=19.8$; according to the processing time on process 1 and the ratio relationship of the machine processing speed, we can obtain the process time of job set in the process 2 and process 3. Experimental hypothesis the weight coefficients of the 50 jobs are 1, and the earliest start time for the job set is $t_0 = 0$.

Result analysis. In this paper, we select the following 7 classic algorithm evaluation index: overall non-dominated vector generation(ONVG) and C-metric(CM) (Van 1999), the distance between the non-inferior solution and the optimal Pareto Frontier(Dav and Dmax) index (Czyak and Jaskiewica 1998), Tan's spacing (TS), maximum spread(MS), average quality(AQ) (Tan et al.2006). Comprehensive evaluating the non-dominated solution set obtained by HPSO-M and HPSO-R algorithm, further studying and comparing the performance of two hybrid PSO algorithms. The time window of the machine disruption is [140,170], conducting 10 separate experiments. The performance of the two algorithms is compared with the results shown in table 1, and the Pareto boundary of two hybrid PSO algorithms shown in figure 4.

Table 1 Comparison results of the algorithm performance under the time window [140,170]

Indicators	*ONVG*		*CM*		*Dav*		*Dmax*		*TS*		*MS*		*AQ*	
HPSO	M	R	M	R	M	R	M	R	M	R	M	R	M	R
1	8	9	0.444	0.125	0.027	0.039	0.214	0.180	0.989	1.000	1.159	0.437	5417	5411
2	10	6	0.333	0.800	0.207	0.102	2.067	0.285	0.227	0.913	1.154	0.949	5419	5413
3	8	9	0.333	0.250	0.040	0.025	0.187	0.106	0.984	1.000	0.599	1.411	5411	5408
4	11	8	0.625	0.364	0.009	0.015	0.083	0.056	1.000	0.512	1.812	1.258	5420	5415
5	5	9	0.222	0.667	0.073	0.000	0.151	0.000	0.572	1.000	0.760	0.619	5420	5416
6	9	10	0.100	0.444	0.047	0.006	0.124	0.057	0.417	1.000	0.653	0.360	5424	5401
7	7	7	0.286	0.143	0.069	0.006	0.166	0.044	0.599	1.000	0.922	0.209	5409	5421
8	9	12	0.500	0.667	0.039	0.006	0.148	0.057	0.6656	1.000	1.054	0.692	5417	5412
9	10	9	0.222	0.600	0.096	0.048	0.229	0.151	0.8153	1.000	0.946	0.859	5398	5410
10	6	7	0.571	0.167	0.012	0.035	0.071	0.077	0.6468	1.000	0.714	0.809	5418	5414
Max	11	12	0.667	0.800	0.207	0.102	2.067	0.285	1.000	1.000	1.812	1.411	5424	5421
Mean	8.3	8.6	0.392	0.423	0.062	0.028	0.344	0.101	0.692	0.943	0.977	0.760	5416	5412
Min	5	6	0.100	0.100	0.009	0.000	0.071	0.000	0.227	0.512	0.599	0.209	5398	5401

According to table 1 and figure 4, although the performance index of the two hybrid PSO algorithms is very close, it still can be found distinction: for ONVG, the HPSO-R algorithm can obtain more non dominated solutions in most cases; for CM, the non-dominated solutions obtained by the HPSO-M algorithm can be dominated by the HPSO-R algorithm; contrasting Dav and Dmax index values, the HPSO-R algorithm is closer to the ideal optimal Pareto frontier, and better than the results obtained from the HPSO-M algorithm in the sense of the mean value and minimum distance, the optimal Pareto frontier of two hybrid PSO algorithms as shown in Figure 3. Contrast MS index values, in the aspect of the non-dominated solutions, the coverage of the HPSO-R algorithm is more extensive. Contrast the TS index values, the results of the TS index by HPSO-R algorithm is smaller, that is, the distribution of the non-dominated solution of the HPSO-R algorithm is more uniform. Contrast the AQ index values, the difference between HPSO-M and HPSO-R is very small, this shows that the two algorithms are close to the non-dominated solution of the approximation and the dispersion, relatively speaking, the HPSO-R algorithm is better than the non-dominated solution.

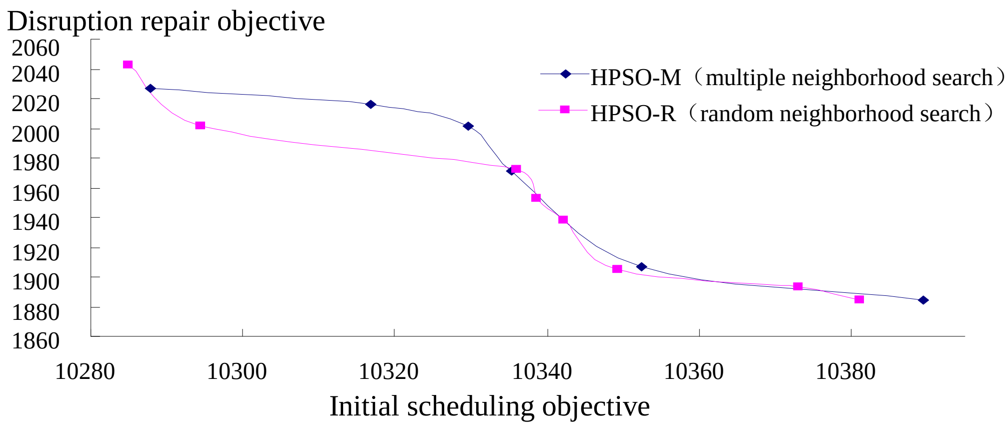

Figure. 4 Pareto boundary of two algorithms with the time widow of [140,170]

The analysis shows that HPSO-R algorithm is a more efficient hybrid algorithm for solving the problem, and can be effectively applied to the disruption management of hot working scheduling in manufacturing supply chain environment.

This research investigates a hot working scheduling problem for an anticipated machine disruption in manufacturing supply chain environment, a novel scheduling model and a heuristic hybrid algorithm based on disruption management is presented. The results of numerical experiments indicate that the scheduling model and algorithm is effective.

Conclusions

In this paper, the hot working scheduling model and algorithm of disruption management are studied, and the main results as follows:

1) Proposed the disruption management scheduling method of minimizing the weighted sum of completion time index and minimizing the sum of weighted tardiness time index, and construct multi-target disruption management scheduling model in machine disruption conditions during hot working process.

2) A hybrid algorithm which combines the dynamic local search mechanism and particle swarm optimization algorithm is proposed based on random neighborhood structure strategy, and its performance is compared with the classical multi neighborhood search operator. The numerical experiments show that the HPSO-R algorithm is effective to solve the hot working disruption management scheduling model.

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References

Lopez L, Carter M W, Gendreau M. 1998. The hot strip mill production scheduling problem: A tabu search approach. *European Journal of Operational Research* 106(2): 317-335.

Cowling P. 2003. A flexible decision support system for steel hot rolling mill scheduling. *Computers & Industrial Engineering* 45(2): 307-321.

Gao Y B, Ma N, Hu W J, et al. 2014. Scheduling Optimization of Hot Working Production Process. *Computer Simulation* 31(5): 355-358.

Bellabdaoui A, Teghem J. 2006. A mixed-integer linear programming model for the continuous casting planning. *International Journal of Production Economics* 104(2): 260-270.

Zhao J, Wang W, Liu Q, et al. 2009. A two-stage scheduling method for hot rolling and its application. *Control Engineering Practice* 17(6): 629-641.

Tang L, Luh P B, Liu J, et al. 2002. Steel-making process scheduling using Lagrangian relaxation. *International Journal of Production Research* 40(1): 55-70.

Pinedo M． 2012. *Scheduling theory, algorithm and systems*. Fourth edition.New York: Springer Science+Business Media, LLC.

Eberhart R C, Kennedy J. 1995. A new optimizer using particle swarm theory. *Proceedings of the sixth international symposium on micro machine and human science*., 1: 39-43.

Van Veldhuizen D A. 1999. Multiobjective evolutionary algorithms: classifications, analyses, and new innovations. *Ohio: Dept. of Electrical and Computer Engineering, GraduateSchool of Engineering, Air Force Institute of Technology*.

Czyak P, Jaskiewica A. 1998. Pareto simulated annealing—a metaheuristic technique for multiple-objective combinatorial optimization. *Journal of Multi-Criteria Decision Analysis* 7: 34-47.

Tan K C, Goh C K, Yang Y J. 2006. Evolving better population distribution and exploration in evolutionary multi-objective optimization. *European Journal of Operational Research* 171(1): 463-495.