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Combining prospect theory with fuzzy theory to handle disruption in production scheduling

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Abstract. This paper focuses on revising a production scheduling that an unpredictable disruption happens after a subset of jobs has been processed. Under these circumstances, continuing with the original schedule will not be optimal. This paper combines prospect theory and fuzzy theory to present a recovery model to handle the disruption. The proposed model is different from most rescheduling approaches in that the difference between the original schedule and the recovery schedule is contained by taking human behavior into consideration. The computational result demonstrates that due to the tradeoff between all participators involved in production scheduling, our model is more effective than existing rescheduling approaches.

1. Introduction

How to provide consumers with the satisfactory service is the major consideration for modern production firms. Nevertheless, because of the complication of processing circumstances, random or unpredictable events constantly happen in production scheduling. Hence, following the original schedule may not be feasible, resulting in the failure of order fulfillment and consequent negative effects in customer services. In the paper, the jargon disruption is used to illustrate the reasons that cause a rescheduling process.

Disruption management tries to adjust the original schedule dynamically and generate a new schedule that reflects the changed environment while minimizing the deviation (Yu and Qi, 2004). In order to solve the disruption, Qi et al. (2006) put forward a recovery model where both the original objective and deviation cost were considered. Wang et al. (2011) studied parallel-machine scheduling problems with a deteriorating maintenance activity. They obtained the revised sequence of jobs by minimizing total completion time. Khedlekar et al. (2014) decided the production stage before and after disruption by solving the disruption analytically in production scheduling system. Paul et al. (2015) presented the rescheduling model and dynamic solution method to handle the disruption for production-inventory system.

Another stream of study relevant to our paper is rescheduling. Kasperski et al. (2012) dealt with the two machine permutation flow shop problem under the condition that job processing are uncertain. Shamshirband et al. (2015) proposed an improved genetic algorithm to cope with open-shop scheduling

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problem by considering the machine maintenance. Hosseinabadi et al. (2015) presented a new local search algorithm to solve the multi-objective dynamic job-shop scheduling problem. Fazayeli et al. (2016) put forward a hybrid algorithm to handle flowshop scheduling problem under machine breakdown.

The above researchers coped with disruptions by different ways. However, they assumed that humans were perfectly rational and emphasized on the optimization of material and financial resources. Since production scheduling system includes many participants, the existing researches overlooked these facts that people facing the changed condition have different perceptions and obtained solution may be unavailable.

In the paper, a recovery model by taking human behavior into consideration is demonstrated. The paper is organized as follows. Section 2 analyzes the effect of disruption and presents an approach combining prospect theory and fuzzy theory to measure the deviation. Sections 3 and 4 construct the model for original and recovery schedule. Section 5 presents an improved ant colony optimization (IACO) to generate recovery schedule effectively. Section 6 demonstrates the validity of our approach. Eventually, Section 7 provides the conclusions.

2. Approach of measuring deviation based on prospect theory and fuzzy theory

2.1 Impact of disruption

For the purpose of obtaining a recovery schedule to minimize the negative impact, the effect of disruption on different participators should be analyzed to measure the deviation.

As is known, the process of one schedule is as follows: ① managers of production enterprises generate an optimal schedule according to the requirements of customers, ② workers execute the schedule to process jobs, and then ③ customers receive their products within the required time. The impact of disruption on the above three participators (i.e., customers, managers, and workers) is analyzed below.

(1) Customers. The completion time of unprocessed jobs will be affected by the disruption, and a number of customers will not be served within the required time. Thus, the recovery schedule should reduce the deviation of completion time to improve the satisfaction and loyalty of customers.

(2) Managers. After disruption occurs, the processing sequence of unprocessed jobs will be changed, leading to the increase of makespan. Because the makespan is relevant to the operational cost, minimizing the makespan of unprocessed jobs is the key objective of managers when generating the recovery schedule.

(3) Workers. The original schedule may no longer be feasible after disruption occurs. Considering that many preparations have been made in advance, disruption leads to the increase of extra workload. Therefore, the recovery schedule should minimize sequence deviation to reduce negative impact on workers.

2.2 Approach of measuring deviation

Determining how to generate the recovery schedule is relevant to human perception because production scheduling is a typical human-machine system. Prospect theory is able to perfectly describe the decision making based on bounded rationality under the uncertainty condition. Hence, prospect theory is used to measure the subjective value of participators.

(1) Description of value function

The value function of the i-th participator is described as follows (Tversky and Kahneman, 1992):

$$V_i(x) = \begin{cases} x^{\alpha_i} & , \quad x \geqslant 0 \\ -\lambda_i(-x)^{\beta_i}, & x < 0 \end{cases} \quad i = 1, 2, \cdots, n \tag{1}$$

Where α_i, β_i, and λ_i are the parameters related to gains and losses.

(2) Formulation of unsatisfied membership function

Given that humans are subjective, the perception facing the disruption is fuzzy. Hence, we need to tackle the value function by fuzzy theory as follows.

Suppose the unsatisfied membership function of x_i is $\mu_i(x_i)$ and the reference point of the i-th participator is O_i. In particular, gains or losses are confirmed relative to the reference point. If humans maintain the status quo and do not make a decision facing a new situation, then the value will be zero. Therefore, the status quo is regarded as the reference point. According to Formula (1):

$$\mu_i(x_i) = -V_i(-x_i + O_i) = -[-\lambda_i(-(-x_i + O_i))^{\beta_i}] = \lambda_i(x_i - O_i)^{\beta_i} \tag{2}$$

$\mu_i(x_i) = 1$ denotes losses for human. When $\mu_i(x_i) = 1$, $x_i = O_i + (1/\lambda_i)^{1/\beta_i}$.

Suppose $R_i = O_i + (1/\lambda_i)^{1/\beta_i}$. $\mu_i(x_i)$ can be expressed as follows:

$$\mu_i(x_i) = \begin{cases} 1 & , \quad x_i \geqslant R_i \\ \lambda_i(x_i - O_i)^{\beta_i}, & O_i \leqslant x_i < R_i \quad i = 1, 2, \cdots, n \\ 0 & , \quad 0 \leqslant x_i < O_i \end{cases} \tag{3}$$

3. Model for original schedule

Considering its wide application in production and manufacturing industries, the Job-shop Scheduling Problem (JSP) is chosen as an example in the paper.

3.1 Problem definition

The problem is confined to the following conditions. Given n jobs, each job includes m operations and must be processed on m machines. The objective is to obtain a schedule of minimal time to complete all jobs, where

(1) one job can only be processed on the machine each time;

(2) every job is feasible for processing at time 0; and

(3) once processing is initiated, the operation must be completed on the machine without interruption.

3.2 Notations

n: the number of jobs;

m: the number of machines;

V: the set of jobs, $V=\{v_1, v_2, \ldots, v_n\}$;

U: the set of machines, $U=\{u_1, u_2, \ldots, u_m\}$;

c_{ik}: completion time of job i on machine k;

p_{ik}: processing time of job i on machine k;

d_i: due date of v_i;

M: a large positive number;

$a_{ihk} = \begin{cases} 1, & v_i \text{ is processed in } u_h \text{ before } u_k \\ 0, & \text{otherwise} \end{cases}$;

$x_{ijk} = \begin{cases} 1, & v_i \text{ is processed before } v_j \text{ in } u_k \\ 0, & \text{otherwise} \end{cases}$.

3.3 Mathematical model

The JSP model is constructed as follows:

$$\min \max_{1 \leqslant k \leqslant m} \{\max_{1 \leqslant i \leqslant n} c_{ik}\} \tag{4}$$

$$c_{jk} - p_{jk} + M(1 - x_{ijk}) \geqslant c_{ik} \quad i, j = 1, 2, \cdots, n; k = 1, 2, \cdots, m \tag{5}$$

$$c_{ik} - p_{ik} + M(1 - a_{ihk}) \geqslant c_{ih} \quad i = 1, 2, \cdots, n; h, k = 1, 2, \cdots, m \tag{6}$$

$$d_i \leqslant \max_{1 \leqslant k \leqslant m} c_{ik} \quad i = 1, 2, \cdots, n \tag{7}$$

The objective function (4) aims to minimize the makespan. Formulas (5) and (6) are the technological and processing constraints. Formula (7) ensures that all jobs are completed before their due date.

4. Recovery model for production scheduling

4.1 Problem hypothesis

This study hypothesizes that when disruption occurs in JSP:

(1) the original schedule is known,

(2) the time at the end of disruption is regarded as 0, and

(3) the processing job when disruption occurs has to be reprocessed after the disruption ends. That is to say, jobs are non-resumable.

4.2 Notations

w: the number of unprocessed jobs;

V': a subset of unprocessed jobs, $V'=\{v_1, v_2, \ldots, v_w\}$;

A_{ij}^1: the set of operations processed before operation j in the original schedule for machine i;

A_{ij}^2: the set of operations processed after operation j in the recovery schedule for machine i;

A_{ij}: the intersection of A_{ij}^1 and A_{ij}^2, $A_{ij} = A_{ij}^1 \bigcap A_{ij}^2$;

$\overline{\overline{A_{ij}}}$: the cardinality of subset A_{ij};

g: the sequence deviation between the original schedule and the recovery schedule, $g = \sum\limits_{i=1}^{m} \sum\limits_{j=1}^{w} \overline{\overline{A_{ij}}}$;

c_i^0: completion time of v_i in the original schedule, $c_i^0 = \max\limits_{1 \leqslant k \leqslant m} c_{ik}$;

c_i: completion time of v_i in the recovery schedule;

f^0: the makespan in the original schedule;

f: the makespan in the recovery schedule;

μ_1^i: unsatisfied degree of customer i for completion time deviation;

μ_2: unsatisfied degree of managers for operational cost deviation;

μ_3: unsatisfied degree of workers for sequence deviation;

α_1, α_2, α_3: parameters related to gains for customers, managers, and workers, respectively;

β_1, β_2, β_3: parameters related to losses for customers, managers, and workers, respectively;

λ_1, λ_2, λ_3: loss aversion coefficient for customers, managers, and workers, respectively.

The other notations are the same as the ones in above sections.

4.3 Function of measuring deviation

(1) Measuring the deviation of customers

As discussed in Section 3, the value function of customer i can be described as follows:

$$V_1^i(x) = \begin{cases} x^{\alpha_1} & , \quad x \geqslant 0 \\ -\lambda_1(-x)^{\beta_1}, & x < 0 \end{cases} \quad i = 1, 2, \cdots, w \tag{8}$$

Where the reference point is c_i^0. $c_i > c_i^0$ means losses ($x < 0$) for customer i; otherwise, it means gains ($x \geqslant 0$) for customer i.

According to Formula (3), the unsatisfied membership function of customers for completion time deviation can be given as follows:

$$\mu_1^i(c_i) = \begin{cases} 1 & , \quad c_i \geqslant R_{1i} \\ \lambda_1(c_i - c_i^0)^{\beta_1}, & c_i^0 \leqslant c_i < R_{1i} \\ 0 & , \quad 0 \leqslant c_i < c_i^0 \end{cases} \quad i = 1, 2, \cdots, w \tag{9}$$

Where $R_{1i} = [c_i^0 + (1/\lambda_1)^{1/\beta_1}](i = 1, 2, \cdots, w)$.

(2) Measuring the deviation of managers

As discussed in Section 3, the value function of managers can be constructed as follows:

$$V_2(x) = \begin{cases} x^{\alpha_2} & , \quad x \geqslant 0 \\ -\lambda_2(-x)^{\beta_2}, & x < 0 \end{cases} \tag{10}$$

Where the reference point is f^0. $f > f^0$ means losses ($x < 0$) for managers; otherwise, it means gains ($x \geqslant 0$) for managers.

According to Formula (3), the unsatisfied membership function of managers for operational cost deviation can be given as follows:

$$\mu_2(f) = \begin{cases} 1 & , \quad f \geqslant R_2 \\ \lambda_2(f - f^0)^{\beta_2}, & f^0 \leqslant f < R_2 \\ 0 & , \quad 0 \leqslant f < f^0 \end{cases} \tag{11}$$

Where $R_2 = f^0 + (1/\lambda_2)^{1/\beta_2}$.

(3) Measuring the deviation of workers

As discussed in Section 3, the value function of workers can be constructed as follows:

$$V_3(x) = -\lambda_3(-x)^{\beta_3}, \ x < 0 \tag{12}$$

Where the reference point is 0 because the sequence deviation does not exist in the original schedule. $g > 0$ means losses ($x < 0$) for workers.

According to Formula (3), the unsatisfied membership function of workers for sequence deviation can be given as follows:

$$\mu_3(g) = \begin{cases} 1 & , \quad g \geqslant R_3 \\ \lambda_3 g^{\beta_3}, & 0 \leqslant g < R_3 \end{cases} \tag{13}$$

Where $R_3 = (1/\lambda_3)^{1/\beta_3}$.

4.4 Recovery model

Lexicographic goal programming (LGP) is one of the important ways to handle multi-objective optimization problems (Farahani et al., 2010). The approach is suited for coping with the recovery model since the decision maker need to prioritize the objectives under different circumstances.

On the basis of the above functions of measuring deviation, the objective function of the recovery model is constructed through LGP as follows:

$$\min \quad Lex \quad = P_1 : \sum_{i=1}^{w} \mu_1^i(c_i) \quad P_2 : \mu_2(f) \quad P_3 : \mu_3(g) \tag{14}$$

Formula (14) aims to minimize the sum of the unsatisfied degrees of customers, managers, and workers. P_1, P_2, and P_3 represent the different priorities, which can be adjusted under different circumstances.

5. IACO for the recovery model

The proposed model is NP-hard, which has an optimal solution that is difficult to obtain. Ant colony optimization (ACO) is an efficient algorithm to solve NP-hard problems (Dorigo and Blum, 2005). However, the algorithm still has the weaknesses of premature convergence and low search speed. In this study, we illustrate an IACO to solve the recovery model.

5.1 Introduction of adjusting the pheromone trail

(1) In ACO, pheromone trails left by ants do not always show the evolutionary direction, and the pheromone deviating from the optimal solution has the probability of increasing, which leads to premature convergence. This study proposes an approach to enhance the global search capability of ACO by adjusting the pheromone trail adaptively with the evolutionary process. The proposed approach can search the solution space further when the search gets trapped in the local optimum.

(2) The updated pheromone trail in the path may reach the maximum value τ_{max} or minimum value τ_{min} after every search process is completed. τ_{max} will become trapped in the local optimal solution, and τ_{min} will increase the computational time. Thus, IACO limits the pheromone trail τ_{ij} in the interval (τ_{min}, τ_{max}). After the pheromone trails are updated, τ_{ij} is replaced by τ_{max} when $\tau_{ij} > \tau_{max}$, or by $(\tau_{min} + \tau_{max})/2$ when

$\tau_{ij} < \tau_{min}$. Moreover, the pheromone trail at the initial search is deliberately set to τ_{max}, which is subject to finding a better solution.

(3) ACO has difficulty obtaining the optimal solution because the trail persistence ρ is fixed. The smaller the ρ is, the better the global optimization will be. However, the computational time to search the solution space will increase. In contrast, increasing ρ can improve the computational time, but the probability of selecting unsearched paths will decrease, which is easily trapped in local optimum. Therefore, IACO uses a dynamic ρ rather than a fixed value.

5.2 Approach of the crossover and mutation

Crossover and mutation operations can increase the variance of the population and search the solution space completely in genetic algorithm (GA). Thus, they are adopted to avoid premature convergence.

(1) Crossover operation

In the paper, a schedule s is represented as follows:

$$s = \{s_1, s_2, \cdots, s_w\} = \{(solu_1, \cdots, solu_m), (solu_{m+1}, \cdots, solu_{2m}), \cdots, (solu_{(w-1)m+1}, \cdots, solu_{wm})\} \tag{15}$$

Where s_i denotes the sequence of operations of job $i = 1, 2, \cdots, w$. Each $solu$ in s_i is an unrepeated integer number in the interval $[1, w]$.

When the search is trapped in the local optimal solution, crossover operation is conducted as follows.

① Assume that encoding of schedule a is $\{a_1, a_2, \cdots, a_w\}$ and encoding of schedule b is $\{b_1, b_2, \cdots, b_w\}$.

② Randomly generate an integer number j in the interval $[1, w]$. Then, exchange a_j and b_j, and generate two new encodings, that is $\{a_1, a_2, \cdots, b_j, \cdots, a_w\}$ and $\{b_1, b_2, \cdots, a_j, \cdots, b_w\}$.

③ Update the encoding of optimal solution.

(2) Mutation operation

Mutation plays a significant part in improving the diversity of the population. Similar to GA, IACO is designed to avoid local optimization and obtain a better result by significantly decreasing pheromone trails in any path of the local optimization routing. These paths will also be selected by small probabilities because too many mutation operations can damage the distribution of pheromone trails in the previous solutions. Consequently, the search will be led to the wrong direction.

5.3 Combination with other heuristics

Exchange mechanism is originally applied in vehicle scheduling problem. It can obtain a new solution from the current solution by exchanging the nodes. We demonstrate that a neighborhood exchange mechanism based on the exchange mechanism can significantly improve the convergence speed of ACO.

(1) Operators of the neighborhood exchange mechanism

Two operators are included as follows.

① Random swaps of subsequences. The operator randomly selects i and j with $i \neq j$ and swaps s_i and s_j in the solution sequence.

② Random insertions of subsequences. The operator randomly selects i and j with $i \neq j$ and puts s_j in front of s_i.

(2) Rule of the neighborhood exchange mechanism

To avoid destroying the distribution of the previous pheromone trails, one neighborhood operator is chosen randomly from the above two operators and applied once to the current solution.

6. Numerical examples

We carry out experiments to illustrate the effectiveness of IACO and recovery model presented in the previous sections.

6.1 Computational experiment for IACO

(1) Computational results

The IACO is tested using the classical sets of JSP, which are TA (Taillard, 1994) and DMU (Demirkol et al., 1997). Five instances are selected randomly from each set. For each instance, the proposed algorithm is independently executed 10 times to compute the average value. We then conduct a performance comparison between IACO and other heuristics, including *i*-TSAB (Nowick and Smutnicki, 2005), GES (Pardalos and Shylo, 2006), and AlgFix (Pardalos et al., 2010). Table 1 shows the computational results.

Table 1 Computational results for different instances

Algorithm	TA05	TA11	TA20	TA37	TA43	DMU12	DMU26	DMU45	DMU61	DMU77
i-TSAB	1224	1361	1351	1778	1859	3519	4679	3321	5294	6930
GES	1224	1357	1348	1779	1870	3518	4667	3273	5293	7006
AlgFix	1224	1358	1348	1784	1869	3522	4688	3273	5310	6949
IACO	1224	1357	1348	1779	1858	3520	4665	3275	5277	6908

(2) Comparison among different heuristics

The comparisons obtained from the above results are demonstrated as follows.

① Compared with *i*-TSAB, IACO obtains better or close solutions in 8 out of 10 problems (80%).

② Compared with GES, IACO obtains better or close solutions in 8 out of 10 problems (80%).

③ Compared with AlgFix, IACO obtains better or close solutions in 9 out of 10 problems (90%).

The comparison shows that the IACO is competitive with the existing heuristics. Moreover, it can improve the best solutions known for a number of examples, especially for large size problems, such as DMU61 and DMU77.

6.2 Computational experiment for the recovery model

(1) Case description

In the given job shop, $n = 6$ and $m = 6$. The parameters of each job are shown in Table 2. The makespan of original schedule is 55h.

Table 2 Parameters of each job

	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6
Operation 1	M4:T1	M5:T8	M4:T5	M5:T5	M4:T9	M5:T3
Operation 2	M6:T3	M4:T5	M3:T4	M6:T5	M5:T3	M3:T3
Operation 3	M5:T6	M2:T10	M1:T8	M4:T5	M2:T5	M1:T9
Operation 4	M3:T7	M1:T10	M6:T9	M3:T3	M1:T4	M6:T10
Operation 5	M1:T3	M6:T10	M5:T1	M2:T8	M6:T3	M2:T4
Operation 6	M2:T6	M3:T4	M2:T7	M1:T9	M3:T1	M4:T1
Due date	60h	56h	60h	65h	55h	50h

Note: Mi:Tj means that the process time of the job's operation is j hours on machine i.

(2) Computational results

After 10h, the disruption suddenly occurs and the duration time is 3h. The remaining jobs, including the processing job when disruption occurs, must be reprocessed after the disruption ends.

Following Tversky and Kahneman (1992), we set $\beta = 0.88$ and $\lambda = 2.25$. Table 3 shows the results obtained by our model, total rescheduling, and right-shift rescheduling (Abumaizar and Svestka, 1997).

Table 3 Results from different approaches

	Customers' deviation	Managers' deviation	Workers' deviation
Our model	2	1	5
Total rescheduling	3	1	4
Right-shift rescheduling	6	1	0

(3) Comparison among different approaches

The results obtained from Table 3 can be demonstrated as follows.

① From the aspect of the deviation of customers, the result of our model is much better than the results of the other two approaches. In other words, our model plays an obvious role in reducing the unsatisfied degree of customers.

② From the aspect of the deviation of managers, our model, total rescheduling, and right-shift rescheduling obtain the same result. This is a valuable result, because our approach removes the perceived main advantage of total rescheduling.

③ From the aspect of the deviation of workers, right-shift rescheduling obtains the best result. This is because of the fact that it is a simple global shifting for original schedule. The results from our model and total rescheduling are relatively poor.

In summary, compared with the other two rescheduling approaches, our model increases the deviation of workers. By contrast, our model decreases the deviation of customers, and thus significantly improves customer satisfaction. Furthermore, the production enterprise is subject to improving the loyalty of customers to expand the influence and attract more new customers. Such improvement helps enhance the potential profit and promote the development of enterprise in the long run. Therefore, our model is more reasonable than the other two approaches.

7. Conclusions

Situations that cause deviation in human behavior may occur in production scheduling, which may fail to cope with the situation using the existing approach. This study provides a recovery model by combining prospect theory with fuzzy theory to effectively find a new schedule to minimize the negative impact of the disruption on the participators (customers, managers, and workers). Meanwhile, an IACO is presented to solve the above model. From a theoretical perspective, this study provides a useful tool to obtain the schedule that minimizes the negative impact by considering human behavior. From a practical perspective, the proposed model can be used in many other fields, such as flight scheduling and berth planning.

A limitation of this research is that we conducted the computational experiment for the recovery model by adopting the values of β and λ provided by Tversky and Kahneman (1992). Further research will concentrate on deriving the actual values of those parameters in production scheduling.

References

[1] R. J. Abumaizar, J. A. Svestka, Rescheduling job shops under random disruptions, International Journal of Production Research 35 (1997) 2065–2082.

[2] E. Demirkol, S. Mehta, R. Uzsoy, A computational study of shifting bottleneck procedures for shop scheduling problems, Journal of Heuristics 3 (1997) 111–137.

[3] M. Dorigo, C. Blum, Ant colony optimization theory: A survey, Theoretical Computer Science 344 (2005) 243–278.

[4] R. Z. Farahani, M. Steadieseifi, N. Asgari, Multiple criteria facility location problems: a survey, Applied Mathematical Modelling 34 (2010) 1689–1709.

[5] M. Fazayeli, M. R. Aleagha, R. Bashirzadeh, et al., A hybrid meta-heuristic algorithm for flowshop robust scheduling under machine breakdown uncertainty, International Journal of Computer Integrated Manufacturing 29 (2016) 709–719.

[6] A. A. R. Hosseinabadi, H. Siar, S. Shamshirband, et al., Using the gravitational emulation local search algorithm to solve the multi-objective flexible dynamic job shop scheduling problem in small and medium enterprises, Annals of Operations Research 229 (2015) 451–474.

[7] A. Kasperski, A. Kurpisz, P. Zieliński, Approximating a two-machine flow shop scheduling under discrete scenario uncertainty, European Journal of Operational Research 217 (2012) 36–43.

[8] U. K. Khedlekar, D. Shukla, C. Rps, Computational Study for Disruption Production System with Time Dependent Demand, Journal of Scientific & Industrial Research 73 (2014) 294–301.

[9] E. Nowicki, C. Smutnicki, An advanced tabu search algorithm for the job shop problem, Journal of Scheduling 8 (2005) 145–159.

[10] P. M. Pardalos, O. V. Shylo, An algorithm for the job shop scheduling problem based on global equilibrium search techniques, Computational Management Science 3 (2006) 331–348.

[11] P. M. Pardalos, O. V. Shylo, A. Vazacopoulos, Solving job shop scheduling problems utilizing the properties of backbone and "big valley", Computational Optimization and Applications 47 (2010) 61–76.

[12] S. K. Paul, R. Sarker, D. Essam, Managing disruption in an imperfect productionCinventory system, Computers & Industrial Engineering 84 (2015) 101–112.

[13] X. Qi, J. F. Bard, G. Yu, Disruption management for machine scheduling: the case of SPT schedules, International Journal of Production Economics 103 (2006) 166–184.

[14] S. Shamshirband, M. Shojafar, A. A. R. Hosseinabadi, et al., Osga: genetic-based open-shop scheduling with consideration of machine maintenance in small and medium enterprises, Annals of Operations Research 229 (2015) 1–16.

[15] A. Tversky, D. Kahneman, Advances in prospect theory: Cumulative representation of uncertainty, Journal of Risk and Uncertainty 5 (1992) 297–323.

[16] E. D. Taillard, Parallel taboo search techniques for the job shop scheduling problem, ORSA Journal on Computing 6 (1994) 108–117.

[17] J. J. Wang, J. B. Wang, F. Liu, Parallel machines scheduling with a deteriorating maintenance activity, Journal of the Operational Research Society 62 (2011) 1898–1902.

[18] G. Yu, X. Qi, Disruption Management: Framework, Models and Applications, World Scientific, Singapore, 2004.