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Research Article

An Effective Meta-heuristic Algorithm for Solving Multi-criteria Job-shop Scheduling Problem with Maintenance Activities

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Abstract: In this study, a metaheuristic based on the Non-dominated Sorting Genetic Algorithm type II (NSGA-II) is proposed to solve the Multi-Criterions Job Shop Scheduling Problem (MCJSSP) under resources availability constraints. Availability periods and starting time of maintenance activities are supposed to be flexible. The MCJSSP requires, simultaneous minimization several antagonistic criteria, such as the maximum completion time of all jobs (Makespan), production cost and maintenance cost. To validate the proposed approach we tested it on forty-four instances references. The results show that our approach is experimentally promising to solve practical problems.

Keywords: Availability, job-shop scheduling, metaheuristic, multi-criteria optimization, Taguchi

INTRODUCTION

Scheduling is a form of decision making, which plays a vital role in manufacturing and service industries (Zhang *et al*., 2008). The establishment of an effective and efficient scheduling has become a necessity as to maintain competitive advantages in markets increasingly fickles. Indeed, many investigations have been deployed so far, according to the configurations workshops: single machine (Hfaiedh *et al*., 2014), Parallel machine (Liao *et al*., 2005), Flow shop (Gao *et al*., 2013), Job shop, open shop (Abdelmaguid, 2014) and hybrid (Wei-ling and Jing, 2013), the type or types of criteria to be optimized and the constraints to be considered (preemption, resumable, reentrant, etc.).

The majority, of the literature dedicated to the scheduling problem, suppose the constant availability of resources. But in reality they may be unavailable for reasons provided (preventive maintenance,) or unexpected (corrective maintenance,). Therefore, the consideration of the unavailability remains one of the decisive and acute factors, in manufacturing systems. In order to overcome the negative effects caused by the unavailability, three scheduling strategies of production and maintenance tasks have been proposed in the literature. The first one is said to separate strategy where the production and maintenance activities are considered independent, which can cause conflicts between the two services (Moradi *et al*., 2011). The second is the sequential strategy, consist to schedule one of the two activities and use the other as a further constraint (Benbouzid-Sitayeb *et al*., 2006). In spite of the drawbacks, this strategy, it is still much better than the separate strategy. The Last is a strategy of integration of the two activities, which must be done in a simultaneous, in order to increase productivity and reduce costs (Chung *et al*., 2009; Mohamed-Chahir and Mustapha, 2014). The major part of the research has focused on the single criterion optimization and mainly the makespan. In reality, they must expand to multi-criteria scheduling problems, since the objectives of the two services are complementary and contradictory (Bagchi, 1999, 2001; Garen, 2004). The Job-Shop Scheduling Problem (JSSP) is the most encountered in the industry. It is one of the most difficult problems of combinatorial optimization. Their complexity increases with the size of the search space, the number of constraints imposed and the number of targeted criteria. The membership of JSSP to NP-hard class is demonstrated (Garey *et al*., 1976; Garey and Johnson, 1979; Lawler *et al*., 1993; Ombuki and Ventresca, 2004; Al-Anzi *et al*., 2006).

The investigation dedicated to the scheduling problems under constraints availability was limited initially to single machine, Adiri *et al*. (1996) and Leon and Wu (1992) and parallel machines (Schmidt, 1988; Lee, 1996; Ayten, 1999). Later, it extended to flow shop scheduling problem. In besides, the job-shop problem under constraints of availability was also considered, Aggoune (2002) proposed a branch and bound algorithm with lower bound based on two-job decomposition for the job shop problem with heads and tails and unavailability periods. Zribi *et al*. (2008) for solving the .JSSP with Availability Constraints, they propose in the first part, a heuristic, based on priority

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rules to solve and improve the assignment problem. In the second part, they introduce a genetic algorithm to solve the sequencing problem. The integrated preventive maintenance scheduling and production planning was found in Ruiz and Stützle (2008). Integrated preventive maintenance and job shop scheduling problem for a single-machine discussed in Cassady and Kutangolu (2005) and Ping *et al*. (2014).

A number of papers discussed multi-objective scheduling problems; however, scheduling with multiple objectives is not investigated fully (Jian *et al*., 2013). This study addresses robust scheduling for a flexible job-shop scheduling problem with random machine breakdowns. Two objectives makespan and robustness are simultaneously considered. Robustness indicated by the expected value of the relative difference between the deterministic and actual makespan. Jun-Qing *et al*. (2014) presents a novel discrete artificial bee colony algorithm for solving the multi-objective flexible job shop scheduling problem with maintenance activities. Performance criteria considered are the maximum completion time, the total workload of machines and the workload of the critical machine. Deming (2013) Solve a scheduling problem with uncertainty, preventive maintenance and multiple objectives are rarely investigated. Interval job shop scheduling problem with non-resumable jobs and flexible maintenance is considered and an effective multi-objective artificial bee colony is proposed, in which an effective decoding procedure is used to build the schedule and handle preventive maintenance operation. The objective is to minimize interval makespan and a newly defined objective called total interval tardiness. Demion (2011) study a fuzzy job shop scheduling problem with n resumable jobs processed on m machines are considered and an efficient swarm-based neighborhood search is proposed, in which an ordered operation-based representation and the decoding procedure incorporating preventive maintenance are given. Karthikeyan *et al*. (2014) presented a hybrid discrete firefly algorithm to solve the multi-objective flexible job shop scheduling problem with limited resource constraints. The main constraint of this scheduling problem is that each operation of a job must follow a process sequence and each operation must be processed on an assigned machine. These constraints are used to balance between the resource limitation and machine flexibility. They considered simultaneously three minimization objectives: the maximum completion time, the workload of the critical machine and the total workload of all machines. Azadeh *et al*. (2015) proposes a novel hybrid algorithm based on computer simulation and adaptive neuro-fuzzy inference system to select optimal dispatching rule for each machine in job shop scheduling problems under uncertain conditions so that makespan is minimized. They contributes in two important ways. First, the inherent uncertainty of JSSP is reflected in fuzzy processing times. Second, this is the first study that develops an approach based on computer simulation. Tian and Tomohiro (2010) consider a multi-objective job-shop scheduling problem. The machines are subject to availability constraints that are due to preventive maintenance, machine breakdowns or tool replacement. Two optimization criteria were considered; the makespan for the jobs and the total cost for the maintenance activities.

To the present day, till now the MCJSSP under availability constraints, have been received considerable attention because of their importance both in the fields of manufacturing and combinatorial research. A vast number of these researches considers that availability duration and unavailability start time of machines, are known and fixed in advance. Sometimes, similar set of objectives are observed in more than ones. Although many researchers work in this field (Bahmani *et al*., 2015). However, this document has two important advantages, which makes it distinguished to our knowledge from the others. On the one hand, it provides a mathematical model to schedule simultaneously the production and maintenance activities within availability constraints, to minimize three different and antagonistic objective functions; Makespan (the maximum completion time of all jobs), production cost and maintenance cost, defined in the following. On the second hand, the availability duration considered variable, depending on the load of the engine. Likewise, the start date of unavailability may vary in a time window, limited by a lower time before which a penalty advance is imposed (the still usable is rejected) and an upper date after which a lateness penalty are approved (the machine may fail). The downtime is calculated and optimized via the probabilistic Weibull model (Fermin and Guardiola, 2014) where the systematic preventive Maintenance Purpose (MPS) and corrective Maintenance (TM) are considered. The meta-heuristic algorithm NSGA-II (Non-dominated Sorting Genetic Algorithm type II), has been proposed to find the optimal and near-optimal solutions for the formulated problem. Finally, 44 instances have been used to validate our approach. The results show that the proposed approach is experimentally promising to solve practical problems.

THE PROPOSED METAHEURISTIC METHOD

The JSP is the most difficult class of combinational optimization. Garey and *et al*. (1976) demonstrated that JSPs are Non-deterministic Polynomial-time hard (NP-hard). Hence, we cannot always find an exact solution in a reasonable computation time. The small size instances of the JSS problem can be solved with reasonable computational time by exact algorithms such as branch-and-bound (Carlier and Pison, 1989; Applegate and Cook, 1991) and the time orientation approach (Martin, 1996). However, when the problem size increases, the computational time of exact methods grows exponentially. Many approximate methods have been developed to overcome the limitations of exact enumeration techniques. The heuristic algorithm are usually resolved in a reasonable time and gives acceptable solutions, but do not guarantee optimality of the final solution, that is, a feasible solution is obtained which is likely to be either optimal or near-optimal. These algorithms can be broadly classified into two groups: local search type heuristics and meta-heuristics. The first one, include shifting bottleneck procedure (Adams *et al*., 1988; Huang and Yin, 2004), guided local search (Balas and Vazacopoulos, 1998), constraint propagation (Brinkkötter and Brucker, 2001; Dorndorf and Pesch, 1995) and parallel Greedy Randomized Adaptive Search Procedure (Aiex *et al*., 2003). The comprehensive survey of the JSS problem can be found in Aarts and Lenstra (1997), Blazewicz *et al*. (1996) and Jain and Meeran (1999). The latter consists of simulated annealing (Yamada and Nakano, 1996; Steinhöfel *et al*., 2002; Aydin and Fogarty, 2004), Tabu Search (Pezzella and Merelli, 2000; Murovec and Šuhel, 2004), Ant Colony Optimization (Colorni *et al*., 1994; Blum and Sampels, 2004), Neural Network (Satake *et al*., 1999; Jain and Meeran, 1998), Particle Swarm Optimization and Genetic Algorithm (Ye and Yan, 2010; Yu-Yan *et al*., 2014).

Since the early work of Schaffer (1985), a number of evolutionary multi-criteria optimization approaches have been proposed: MOGA, NPGA (Horn *et al*., 1994) and NSGA (Srinivas and Deb, 1994). The NSGA-II algorithm (Elitist Non-dominated sorting genetic algorithm) proposed by Deb (2001) and Nain *et al*. (2008) and described in Emmerich and Naujoks (2004) and Goal *et al*. (2007), appears as one of the most efficient algorithms to find the optimal set of Pareto with an excellent variety of solutions. It is based on the use of the principle of elitism, favoring non-dominated solutions and finally the use of a variety of explicit solutions. The application of NSGA-II starts with a random generation of an initial population P_0 of N individuals parents. Search for non-dominated solutions makes it possible to classify the individuals of Rt in several fronts of different ranks, provided that: $R = \{R_1, R_m\}$, where; $\bigcup_{1\le i\le m} R_i = P$ and $\bigcap_{1\le i\le m} R_i = \emptyset$. Each individual of R_t is compared to all the other individuals by the concept of predominance. The non-dominated individuals belong to the front of rank one, the Pareto front. Eliminating temporarily the individuals of all search, the algorithm is iterated to provide the front of rank 2 and so on. The new relative parent population P_{t+1} is then constructed with the N individuals belonging to the weakest fronts. For the last front, there are more solutions than remaining places in the new population P_{t+1}. Individuals are then sorted according to their crowding distance (Deb, 2001) and in ascending order. This choice will provide the best distribution of individuals in the front of the highest rank. The main steps of the NSGA-II algorithm are summarized by the following pseudo code:

Population Initialization P_0 and Q_0 of size N
While the stopping criteria is not met, do
Create $R_t = P_t \cup Q_t$
Calculate all Fi of the population R_t using a ranking algorithm
set $P_{t+1} = \phi$ and $i = 0$
While $|P_{t+1}| + |F_i| < N$ do
$P_{t+1} = P_t \cup F_i$
$i = i + 1$
End while
Put into P_{t+1} the $(N - |P_{t+1}|)$ individuals of F_i the best distributed according to the crowding distance.
Selection in P_{t+1} and creation of Q_{t+1} applying crossover and mutation operators
End while

Description of the problem: The considered scheduling problem MCJSSP is defined as a set of $n > 1$ different jobs $J = \{J_i\}_{i=1}^{i=n}$, that should be carried out over a set of $m > 1$ machines, $M = \{M_k\}_{k=1}^{k=m}$ critical, provided that we cannot affect simultaneously two jobs to a single machine. Every job $J_i = \{O_{ij}\}_{j=1}^{j=n_i} \in J$ is defined as a linear sequence of ni operations $\{n_i\}_{i=1}^{i=m}$, that can start at time ri (ri = 0 in this case) and should be terminated by the deadline di.

Operation O_{ij} represents the jth operation of the ith job, it requires machine M_k, to which is associated an operating time $p_{ij} \le c_{ij} - s_{ij}$ necessary for completing the operation, s_{ij} and c_{ij} represent the start and the end dates respectively.To every $M_k \in M$ a set of operation Φ_k with different jobs is affected Eq. (1):

$$\Phi_k = \bigcup_{\substack{1\le i\le n \\ 1\le j\le n_i}} \left(O_{ij} \times \alpha_{ijk}\right) \tag{1}$$

where, $\alpha_{ijk} = 1$ if O_{ij} is affected to M_k and $\alpha_{ijk} = 0$, for otherwise.

In order to be maintained according to the SPM, machines cannot be always available. The time of availability t_k of the machine is calculated on the basis of the historical of both the SPM and the CM, for this reason the Weibull probabilistic rule is chosen. This rule takes into account the preventive intervention time tp_k, the corrective intervention time tr_k, the statistical parameter like $\beta_k > 1$ and the scale η_k Eq. (2):

$$t_k = \eta_k \left[\frac{tp_k}{(\beta_k - 1)tr_k}\right]^{1/\beta_k} \tag{2}$$

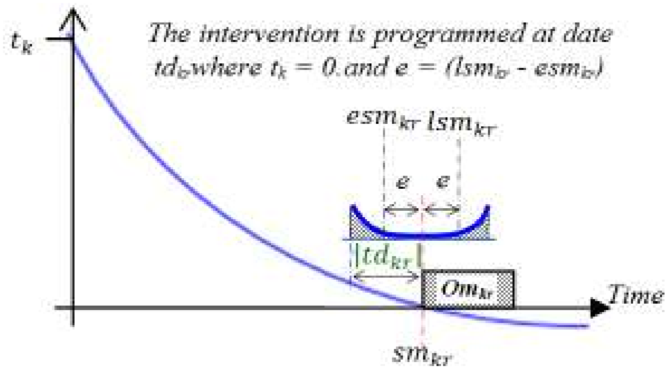

Fig. 1: Availability evolution with respect to machine load

The maintenance operation Om_{kr} is the rth intervention over the kth machine to which is associated a necessary operating time pm_{kr} to be accomplished. These operations are the maintenance job $J_m = \{Om_{kr}\}$, which is associated to the production jobs. The intervention can start at date $sm_{kr} \in [esm_{kr}, lsm_{kr}]$, without being a subject to penalties, or at date $sm_{kr} \notin [esm_{kr}, lsm_{kr}]$ with advance penalties am_kor delayed ones rm_k. dm_{kr} is the starting date of the desired intervention, to which the machine is normally not available. $esm_{kr} = dm_{kr} - e$ and $lsm_{kr} = dm_{kr} + e$, tolerance interval. dm_{kr} is determined according to machine $M_k$and values of t_k, Fig. 1.

During the scheduling the probable conflicts between the production operations and of those of the maintenance appear (1) according to the following pseudo code:

```
For every machine
    While the availability level tdkr>0;
        Upgrade the availability level;
        td_kr = tp_k − Σ_{l=1}^{l=j} p_il × α_ilk;
        If Tdkr<0
            Calculatet_kr = s_ij^[l] + |td_kr|
            Calculatethe limits of the time interval
            [lsm_kr, esm_kr];
            Calculatee = lsm_kr − esm_kr;
            Calculatethe threshold displacement time t_s:
            t_s = s_ij^[l] + ε_k × p_ij^[l] α_ijk;
            if t_kr − t_s ≥ 0
                sm_kr = c_ij^[l] α_ijk  : O_ij^[l] ∈ Φ_k;
                T_kr = max(0, sm_kr − lsm_kr);
            otherwise
                sm_kr = c_ij^[l−1] α_ijk : O_ij^[l−1] ∈ Φ_k;
                E_kr = max(0, esm_kr − s_ij^[l]);
                c_ij^[l] = sm_kr + t_k;
            End if
        End if
    End while
End For
```

The operations' scheduling over the various machines must be carried out in order to optimize certain "regular" criteria.

MATHEMATICAL FORMULATION

To address the MCJSSP; we started by modeling and optimizing three criteria: the makespan, the production cost and the maintenance cost:

- Makespan is the completion time of the last job. It is particularly interesting: it allows the determination of the critical path (bottleneck): Its minimization means the minimization of all the products' length of stay in the workshop, the outstanding and the idle Time. It is expressed by Eq. (1):

$$f_1 = min(C_{max}) = \min\left(max_{\substack{1\le j\le n \\ 1\le i\le n_j}} (c_{ij}) \right) \quad (3)$$

- Production cost is the sum of the costs of the raw material acquisition, launching, manufacturing, penalty and stocking. In this study we took into account neither the acquisition cost nor the launching cost (only the cost related to the operational time of the jobs is retained) (Bahmani *et al*., 2015).
- Manufacturing cost Cfab:

$$C_{Fab_i} = \sum_{1\le k\le m} \sum_{1\le j\le n_i} \left(C_{fu_k} \times p_{ij} \times \alpha_{ijk} \right) \quad (4)$$

C_{fu_k}: Manufacturing unit cost, $\alpha_{ijk} = \{0,1\}$.

- Stocking cost:

$$C_{sto_i} = ap_i \times E_i \quad (5)$$

$$E_i = \max_{1\le i\le n} \left(0, (d_i - c_{in_i}) \right)$$

ap_i : Advance unit penalty (of stocking).

- Penalty cost:

$C_{pen_i} = rp_i \times T_j (4)$

$T_j = \max_{1 \le j \le N} \left(0, \left(c_{n_j}^j - d_j\right)\right)$

rp_i : Delay penalty cost.
Equation (2) + (3) + (4) = Eq. (5):

$f_2 = min\left[\sum_{1 \le i \le n}\left(rp_i \times T_i + ap_i \times E_i + \right.\right.$
$1 \le k \le m 1 \le j \le ni Cfuk \times pij \times \alpha ijk$ (6)

- Maintenance cost is the sum of the spare parts' cost, the advance cost, the delay cost and the intervention cost. The acquisition cost of the spare parts is not taken into account:

$f_3 = min\left(\sum_{1 \le k \le m}\sum_{1 \le r \le n_i}(am_k . Em_{kr} + \right.$
$rmk.Tmkr + \mu kr.\sigma k.pmkr$ (7)

$Em_{kr} = max\left(0, (esm_{kr} - sm_{kr})\right)$

$Tm_{kr} = max\left(0, (sm_{kr} - lsm_{kr})\right)$

$am_k, rm_k\ et\ \sigma_k$: Advance unit cost, delay cost and the intervention cost over Mk.

The optimization of these criteria ($f_1, f_2 et f_3$) is subject to several constraints.

Execution uniqueness: The considered problem is without reentrant i.e., an operation cannot be carried out by more than one machine, Eq. (7):

$$c_{ij} - s_{ij} \ge \sum_{1 \le k \le m}\left(p_{ijk} \times \alpha_{ijk}\right) \quad (8)$$

Sequence constraints: Operations of the same job must be carried out on various machines in a preset order specified by an operational range of each job, $O_{ij} \prec O_{i,(j+1)}$ Eq. (8):

$$s_{i(j+1)} - c_{ij} \ge 0\ \forall i = 1, \dots, n, \quad \forall j = 1, \dots, (n_i - 1) \quad (9)$$

Resource constraints (without overlapping): Resources Mk cannot be affected to two operations at the same time. Operations which use the same resource must obey the following conditions: let $O_{ij}\ and\ O_{st} \in \Phi_k$ be the start dates s_{ij} and s_{st} respectively, if O_{st} is affected, then $s_{ij} \notin [s_{st}, s_{st} + p_{st}] \ge 0$. i.e.:

$$s_{ij} - s_{st} + G\left[\pi_{ijst} + \left(1 - \alpha_{ijk}\right) + (1 - \alpha_{stk})\right] \ge p_{stk}$$

$$s_{st} - s_{ij} + G\left[\left(1 - \pi_{ijst}\right) + \left(1 - \alpha_{ijk}\right) + (1 - \alpha_{stk})\right] \ge p_{ijk}$$

$$\forall i, s = \{1, \dots, n\}, \forall j, t = \{1, \dots, n_i\}, \forall k = \{1, \dots, m\}$$

$\forall O_{ij}\ and\ O_{st} \in \phi_k$, with $\pi_{ijst} = 1$ if $O_{ij} \prec O_{st}$ and $\pi_{ijst} = 0$ otherwise and G is a big number:

$$G = \sum_{1 \le i \le n}\sum_{1 \le j \le n_i} p_{ij}$$

Constraints on the resource's unavailability: Production operations can never been executed over an unavailable machine, i.e.:

$$\left[s_{ij}, s_{ij} + p_{ij}\right] \cap [sm_{kr}, sm_{kr} + tp_{kr}] = \emptyset$$

The SPM policy is adopted in order to reduce the failure rate of the machines; this is justified by the shape parameter $\beta_k > 1$. Assume that after every intervention, the machine is restored to its optimal performance.

EXPERIMENTS AND COMPARISON OF RESULTS

In this study, for ratified the obtained results, using NSGA-II metaheuristic algorithm during the benchmarking of the proposed approach (MCJSSP), we have used 44 instances that are taken from the OR-Library Beasley (1990), belonging to the three class of JSP instances: the class of Lawrence (1984) (from La01 to La32), the class of Fisher and Thompson (1963) (ft6, ft10 and ft20) and the class of Applegate and Cook (1991) (from orb1 à obr9). All the results were obtained using a PC with an Intel Pentium IV processor, 2 GHz CPU and 1 GB of RAM, with Windows XP 32 bits as an operating system. The algorithm was implemented using MATLAB programming language.

Mutation operator OX (Order operator crossover) proposed by Kumar *et al*. (2013) and of mutation PMX (Partially Mapped Crossover) Deep and Mebrahtu (2012) are chosen at the end of many trials on the proposed models. The population size is calculated using the empirical formula $Tp = m \times Nj + 100$ (where m: machines' number and Nj: jobs number) and the generation number is chosen between 200 et 400. Other trials set the crossover probability to 68% and mutation to 1.5%.

Ten independent experiments were carried out, on each instance. The majority of the 44 adopted instances require at least 300 iterations; the others can go up to 400 iterations.

Initially we have compared the makespan values obtained by our algorithm with those provided by the most recent specialized publications (Ziaee, 2014), in which sufficient information is offered to allow a more quantitative comparison. In Table 1: The first and the second column indicate respectively, the size and the name of each instance, the third column shows the Best Solution named (BKS) by other research works, the fourth column shows the best average solution obtained using our approach and the fifth column Presents the Relative variation (RPD) compared to BKS, which is calculated as follows: $RPD_1 = \frac{BSM - BKS}{BKS} \times 100$. The

Table 1: Experimental results

	Makespan			Without maintenance		With maintenance				
Instances	BKS	Our BSM	RPD_1	Makespan (M_1)	Prod. cost (PC_1)	Makespan (M_2)	Prod. cost (PC_2)	Maint. cost (MC_2)	RPD_2	RPD_3
FT06	55	55	00.00	68	273.5	71	277.3	62.4	4.41	1.39
LA01	666	666	00.00	851	3308.2	853	3311.3	706.1	0.24	0.09
LA02	655	655	00.00	894	3193.3	896	3201.6	755.5	0.22	0.26
LA03	597	597	00.00	842	2754.4	843	2756.0	662.4	0.12	0.06
LA04	590	595	00.85	731	2629.1	734	2634.7	589.8	0.41	0.21
LA05	593	593	00.00	749	2701.6	750	2705.9	565.6	0.13	0.16
LA06	926	928	00.22	1296	4259.9	1301	4263.8	945.0	0.39	0.09
LA07	890	890	00.00	1136	4228.1	1138	4231.9	1004.9	0.18	0.09
LA08	863	863	00.00	1147	4263.3	1148	4268.8	939.4	0.09	0.13
LA09	951	951	00.00	1209	4546.3	1214	4549.6	957.4	0.41	0.07
LA10	958	965	00.73	1213	4322.3	1219	4327.8	945.9	0.49	0.13
LA11	1222	1222	00.00	1556	5845.5	1561	5855.0	1386.3	0.32	0.16
LA12	1039	1040	00.10	1409	4824.4	1414	4830.2	1164.9	0.35	0.12
LA13	1150	1150	00.00	1413	5636.0	1417	5641.4	1323.6	0.28	0.10
LA14	1292	1292	00.00	1680	5852.0	1685	5859.2	1232.5	0.30	0.12
LA15	1207	1210	00.25	1503	5456.7	1509	5459.6	1274.9	0.40	0.05
FT20	1165	1201	03.09	1662	5591.9	1668	5596.5	1300.8	0.36	0.08
LA16	945	946	00.11	1160	4243.6	1166	4245.9	962.4	0.52	0.05
LA17	784	784	00.00	972	3629.6	980	3631.3	874.5	0.82	0.05
LA18	848	855	00.83	1186	4070.6	1189	4072.0	965.2	0.25	0.03
LA19	842	842	00.00	1142	4192.1	1149	4193.3	899.9	0.61	0.03
LA20	902	908	00.67	1165	4049.8	1170	4053.3	881.5	0.43	0.09
FT10	930	978	05.16	1371	4542.2	1378	4548.6	981.7	0.51	0.14
ORB01	1059	1156	09.16	1447	5479.0	1458	5492.1	1160.3	0.76	0.24
ORB02	888	924	04.05	1197	4411.1	1208	4418.4	960.8	0.92	0.17
ORB03	1005	1131	12.54	1557	5568.2	1572	5584.3	1329.3	0.96	0.29
ORB04	1005	1064	05.87	1446	4770.9	1453	4777.3	1119.3	0.48	0.13
ORB05	887	938	05.75	1249	4351.5	1258	4358.9	972.6	0.72	0.17
ORB06	1010	1058	04.75	1384	4994.4	1390	4999.0	1134.6	0.43	0.09
ORB07	397	421	06.05	558	2055.8	564	2064.0	496.8	1.08	0.40
ORB08	899	1016	13.01	1408	4809.7	1425	4824.4	1083.4	1.21	0.31
ORB09	934	991	06.10	1193	4602.7	1204	4611.1	1108.5	0.92	0.18
LA21	1046	1055	00.86	1273	5064.3	1277	5067.8	1130.6	0.31	0.07
LA22	927	927	00.00	1152	4625.6	1155	4632.9	1029.6	0.26	0.16
LA23	1032	1047	01.45	1377	5210.5	1386	5217.9	1113.4	0.65	0.14
LA24	935	941	00.64	1178	4486.7	1183	4492.5	1096.8	0.42	0.13
LA25	977	977	00.00	1368	4454.1	1376	4458.7	1059.4	0.58	0.10
LA26	1218	1218	00.00	1486	5577.2	1491	5582.1	1354.5	0.34	0.09
LA27	1235	1240	00.40	1519	6068.2	1523	6079.0	1342.7	0.26	0.18
LA28	1216	1216	00.00	1498	5799.7	1506	5803.1	1367.5	0.53	0.06
LA29	1152	1164	01.04	1627	5244.5	1636	5246.3	1094.0	0.55	0.03
LA30	1355	1355	00.00	1759	6337.0	1765	6344.4	1371.1	0.34	0.12
LA31	1784	1791	00.39	2514	8285.3	2521	8289.4	1760.4	0.28	0.05
LA32	1850	1850	00.00	2598	9196.8	2604	9207.7	2185.5	0.23	0.12

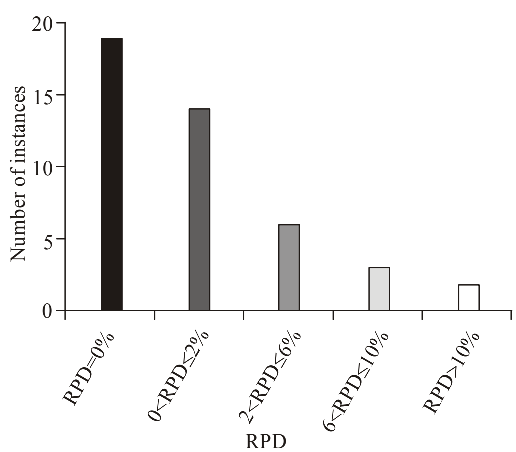

Fig. 2: Evolution of DPR

BKS values and the obtained results using our approach offer an average SPR equals to 1.91%. This means that our results are statistically satisfactory because if we observe Table 1, particularly columns 3 and 4, we notice that our metaheuristic have no difficulties in finding the BKS values for the instances of size 10×5, except the instance LA04, to which the obtained value is very close to the corresponding value of BKS. The behavior of our approach is similar to the majority of the other instances in spite of the increase in their size, Fig. 2.

The best known solutions as well as the solutions for which our algorithm has reached such values appear in bold characters. Figure 3, shows the solutions' distribution of the first, the second and the third rank in the vicinity of the first Pareto font.

Some experiments were carried out in order to compare the optimal values of three criteria (f1, f2 and f3). On Table 1, the results of the experiments without

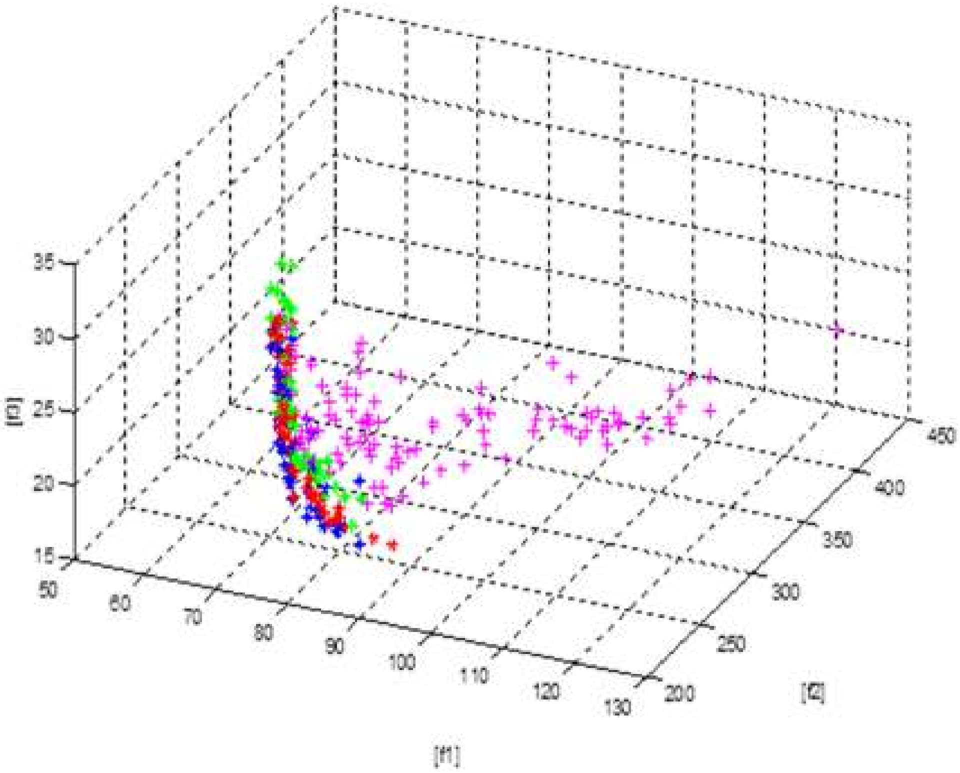

Fig. 3: Pareto front distribution of optimal solutions obtained by NSGA-II

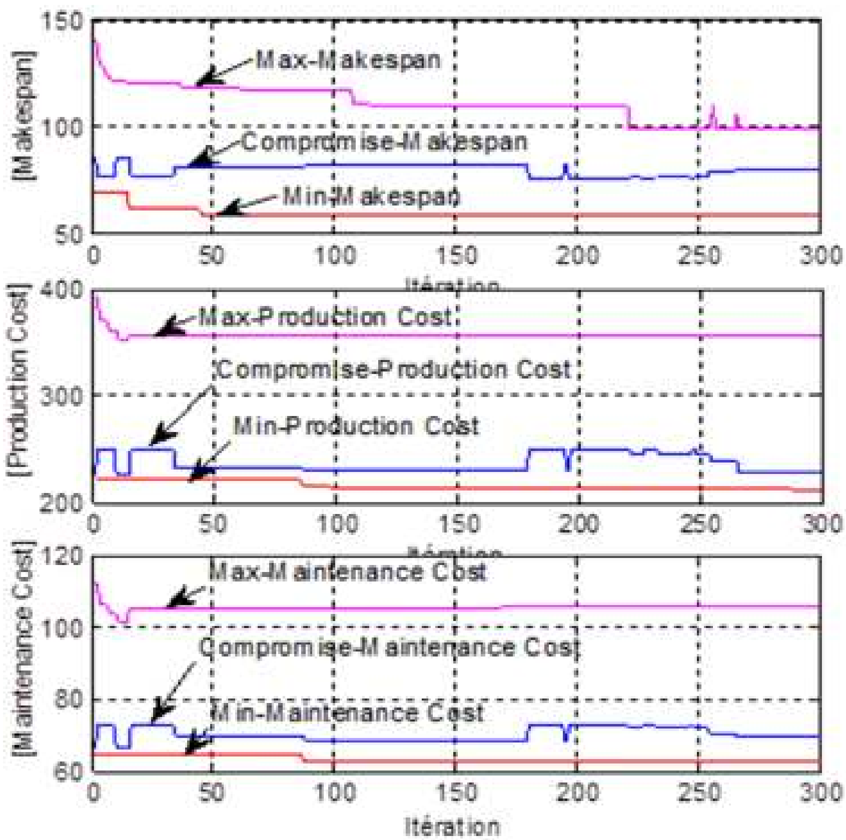

Fig. 4: Progress of the solutions found by NSGA-II

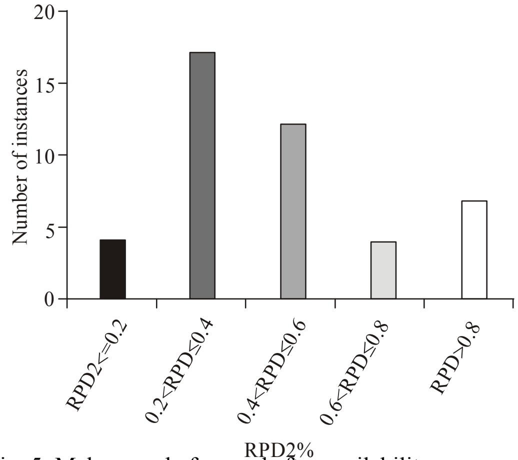

Fig. 5: Makespan, before and after availability

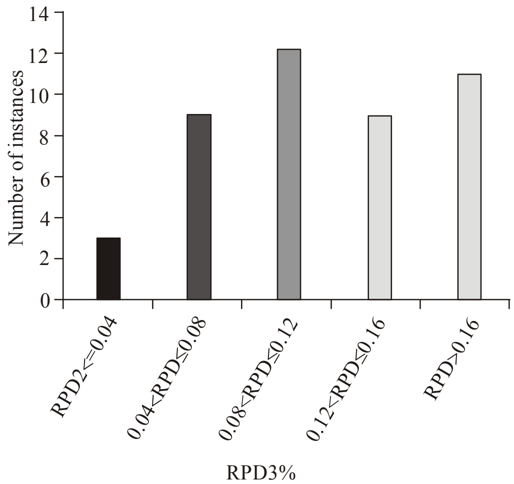

Fig. 6: Production cost, before and after availability

and with resources' unavailability constraints are represented respectively on the columns 6, 7, 8, 9 and 10, respectively. Comparison results are displayed on columns 11 and 12, where:

$$RPD_2 = \frac{M_2 - M_1}{M_1} \times 100$$

$$\text{and } RPD_3 = \frac{PC_2 - PC_1}{PC_1} \times 100$$

In Fig. 4, the instance Ft06 under the unavailability constraint is taken as an example to show the evolution of the compromise minimum values as well as the maximum values that can be taken by every retained criterion, Eq. (1), (5) et (6). The obtained curves show the correctness of the results and the insignificant gap between the compromised value and the minimal one of every criterion.

The experiment results presented in columns 11 and 12 of Table 1 are schematized in Fig. 5 and 6, where we can see that 38.64% of the instances offer an increase of the makespan from 0.2 to 0.4% and that the makespan of 75% of the instances do not evolve more than 0.6%. We can also notice that the production cost of 75% of the instances do not exceed 0.16%. These results are encouraging and proves the importance of the suggested approach.

Figure 7 shows the Gantt chart of the same instance for an optimal compromise solution of the three criteria, where the maintenance operations Om is scheduled according the pseudo-code of Description of the Problem section.

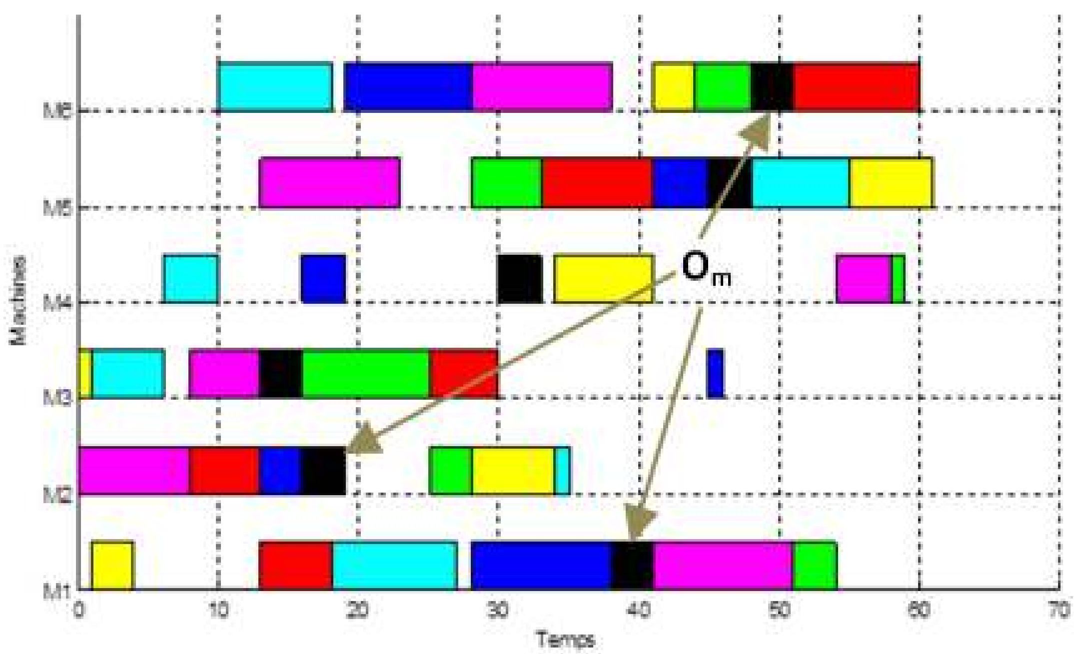

Fig. 7: Gantt chart of Ft06 instance under availability stress

CONCLUSION AND RECOMMENDATIONS

In this study we have studied the scheduling integration of production and maintenance in a job shop workshop, under resources unavailability constraint and to minimize simultaneously the makespan, the production costs and the cost of maintenance. The aim was to find a compromise solution of the three criteria in a reasonable computing time. A metaheuristic (NSGA-II) was used to solve the MCJSSP, where the maintenance operations are regarded as jobs associated with those of production with two characteristics: the flexibility of the start date and the flexibility of the availability duration.

This research field has a supreme interest in the resolution of the multi-criteria problems. For practical reasons in decision making domain, the search for a set of optimal Pareto solutions is just the first step to solve the MCJSSP, which must be followed by the choice of an appropriate solution among the obtained ones. For this reason, the TOPSIS sorting method is associated with our algorithm, at the level of optimal Pareto solutions of the first rank.

In order to validate the results of this approach, two comparisons were carried out. In the first one the makespan is compared with the BKS values and in the second one the makespan values are compared with the production costs without considering the maintenance cost.

The proposed algorithm is tested on several benchmarks. The primary obtained results show that the algorithm provides good quality solutions with little effort of calculation. The solution of the suggested problem can be regarded as an alternative to solve the MCJSSP. Other researches are under way to improve the quality of these solutions and to extend the range of this research to treat the case of pre-emption and breakability.

REFERENCES

Aarts, E. and J.K. Lenstra, 1997. Local Search and Combinatorial Optimization. Wiley, New York.

Abdelmaguid, T.F., 2014. A hybrid PSO-TS approach for proportionate multiprocessor open shop scheduling. Proceeding of the IEEE International Conference on Industrial Engineering and Engineering Management (IEEM, 2014). Bandar Sunway, pp: 107-111.

Adams, J., E. Balas and D. Zawack, 1988. The shifting bottleneck procedure for job shop scheduling. Manage. Sci., 34: 391-401.

Adiri, I., J. Bruno, E. Frostig and A.H.G. Rinnooy Kan, 1996. Single machine flow-time scheduling with a single breakdown. Acta Inform., 26: 679-696.

Aggoune, R., 2002. Ordonnancement d'ateliers sous contraintes de disponibilité des machines. Ph.D. Thèses, Université de Metz, Frane.

Aiex, R.M., S. Binato and M.G.C. Resende, 2003. Parallel GRASP with path-relinking for job shop scheduling. Parallel. Comput., 29: 393-430.

Al-Anzi, F.S., Y.N. Sotskov, A. Allahverdi and G.V. Andreev, 2006. Using mixed graph coloring to minimize total completion time in job shop scheduling problem. Appl. Math. Comput., 182: 1137-1148.

Applegate, D. and W. Cook, 1991. A computational study of job-shop scheduling. ORSA J. Comput., 3(2): 149-156.

Aydin, M.E. and T.C. Fogarty, 2004. A distributed evolutionary simulated annealing algorithm for combinatorial optimisation problems. J. Heuristics, 10: 269-292.

Ayten, T., 1999. Machine Scheduling with Availability Constraints. In Partial Fulfillment of the Requirements for the Course IE 672 Spring. Retrieved from: http://www.ie.bilkent.edu.tr/~ie672/docs/latex/turkcan.tex.

Azadeh, A., N. Hosseini, S.A. Zadeh and F. Jalalvand, 2015. A hybrid computer simulation-adaptive neuro-fuzzy inference system algorithm for optimization of dispatching rule selection in job shop scheduling problems under uncertainty. Int. J. Adv. Manuf. Tech., 79(1-4): 135-145.

Bagchi, T.P., 1999. Multi-Objective Scheduling by Genetic Algorithms. Kluwer Academic Publishers, Boston/Dordrecht/London.

Bagchi, T.P., 2001. Pareto-optimal solutions for multi-objective production scheduling problems. Proceeding of the 1st International Conference on Evolutionary Multi-criterion Optimization. Springer-Verlag, London, pp: 458-471.

Bahmani, Y., H. Smadi, F. Ghedjati, D. Bellala and M. Benzouai, 2015. Effective meta-heuristic algorithm for solving a multi-criteria job-shop scheduling problem with maintenance activities. Proceeding of the 5th International Conference on Information Systems and Technology (ICIST), Istanbul Turkey.

Balas, E. and A. Vazacopoulos, 1998. Guided local search with shifting bottleneck for job shop scheduling. Manage. Sci., 44(2): 262-275.

Beasley, J.E., 1990. OR-Library: Distributing test problems by electronic mail. J. Oper. Res. Soc., 41(11): 1069-1072. (website: http://people.brunel.ac. uk/~mastjjb/jeb/info.html).

Benbouzid-Sitayeb, F., C. Varnier and N. Zerhouni, 2006. Proposition of new genetic operator for so joint production and maintenance scheduling: Application to the flow shop problem. Proceeding of the International Conference on Service Systems and Service Management (ICSSSM). Troyes, France.

Blazewicz, J., W. Domschke and E. Pesch, 1996. The job shop scheduling problem: Conventional and new solution techniques. Eur. J. Oper. Res., 93: 1-33.

Blum, C. and M. Sampels, 2004. An ant colony optimization algorithm for shop scheduling problems. J. Math. Modell. Algorithm., 3: 285-308.

Brinkkötter, W. and P. Brucker, 2001. Solving open benchmark problems for the job shop problem. J. Sched., 4: 53-64.

Carlier, J. and E. Pison, 1989. An algorithm for solving the job-shop problem. Manage. Sci., 35: 164-176.

Cassady, C. and E. Kutangolu, 2005. Integrating preventive maintenance planning and production scheduling for a single machine. IEEE T. Reliab., 54(2): 304-310.

Chung, S., H. Lau, G. Ho and W. Ip, 2009. Optimization of system reliability in multi-factory networks by maintenance approach. Expert Syst. Appl., 36(6): 88-96.

Colorni, A., M. Dorigo, V. Maniezzo and M. Trubian, 1994. Ant system for job-shop scheduling. Belg. J. Oper. Res. Stat. Comput. Sci., 34(1): 39-53.

Deb, K., 2001. Multi-Objective Optimization Using Evolutionary. John Wiley & Sons, Chichester.

Deep, K. and H. Mebrahtu, 2012. Variant of partially mapped crossover for the travelling salesman problems. Int. J. Combinatorial Optim. Problem Inform., 3(1): 47-69.

Deming, L., 2013. Multi-objective artificial bee colony for interval job shop scheduling with flexible maintenance. Int. J. Adv. Manuf. Tech., 66(9-12): 1835-1843.

Demion, L., 2011. Scheduling fuzzy job shop with preventive maintenance through swarm-based neighborhood search. Int. J. Adv. Manuf. Tech., 54(9-12): 1121-1128.

Dorndorf, U. and E. Pesch, 1995. Evolution based learning in a job shop scheduling environment. Comput. Oper. Res., 22: 25-40.

Emmerich, M. and B. Naujoks, 2004. Metamodel Assisted Multiobjective Optimisation Strategies and their Application in Airfoil Design. In: Parmee, I.C. (Ed.), Adaptive Computing in Design and Manufacture VI. Springer, London, pp: 249-260.

Fermin, M. and I.G. Guardiola, 2014. The Weibull scheduling index for client driven manufacturing processes. Int. J. Prod. Econ., 150: 225-238.

Fisher, H. and G.L. Thompson, 1963. Probabilistic Learning Combinations of Local Job-shop Scheduling Rules. In: Muth, J.F. and G.L. Thompson (Eds.), Industrial Scheduling. Prentice Hall, Englewood Cliffs, New Jersey, pp: 225-251.

Gao, K.Z., P.N. Suganthan and T.J. Chua, 2013. An enhanced migrating birds optimization algorithm for no-wait flow shop scheduling problem. Proceeding of the IEEE Symposium on Computational Intelligence in Scheduling (SCIS). Singapore, pp: 9-13.

Garen, J., 2004. A Genetic algorithm for tackling multiobjective job-shop scheduling problems. In: Gangibleux, X. *et al.* (Eds.), Metaheuristics for Multiobjective Optimisation. Springer-Verlag, Berlin, Heidelberg, 535: 201-219.

Garey, M.R. and D.S. Johnson, 1979. Computers and Intractability: A Guide to the Theory of NP-completeness. W.H. Freeman and Co., New York, pp: 338.

Garey, M.R., D.S. Johnson and R. Sethi, 1976. The complexity of flow shop and job shop scheduling. Math. Oper. Res., 1: 117-129.

Goal, T., R. Vaidyanathan, R.T. Haftka, W. Shyy, N.V. Queipo and K. Tucker, 2007. Response surface approximation of Pareto optimal front in multi-objective optimization. Comput. Meth. Appl. Mech. Eng., 196: 879-893.

Hfaiedh, W., C. Sadfi, I. Kacem, A.B. Hadj-Alouane, 2014. An iterative lower bound algorithm for the single-machine scheduling problem under a non-availability constraint for maximum delivery time minimization. Proceeding of the International Conference on Control, Decision and Information Technologies (CoDIT). Metz, pp: 288-291.

Horn, J., N. Nafpliotis, and D.E. Goldberg, 1994. A niched Pareto genetic algorithm for multiobjective optimization. Proceeding of the 1st IEEE International Conference on Evolutionary Computation, 1: 82-87.

Huang, W. and A. Yin, 2004. An improved shifting bottleneck procedure for the job shop scheduling problem. Comput. Oper. Res., 31: 2093-2110.

Jain, A.S. and S. Meeran, 1998. Job-shop scheduling using neural networks. Int. J. Prod. Res., 36(5): 1249-1272.

Jain, A.S. and S. Meeran, 1999. Deterministic job-shop scheduling: Past, present and future. Eur. J. Oper. Res., 113: 390-434.

Jian, X., X. Li-Ning and C. Ying-Wu, 2013. Robust scheduling for multi-objective flexible job-shop problems with random machine breakdowns. Int. J. Prod. Econ., 141(1): 112-126.

Jun-Qing, L., P. Quan-Ke and M.F. Tasgetiren, 2014. A discrete artificial bee colony algorithm for the multi-objective flexible job-shop scheduling problem with maintenance activities. Appl. Math. Model., 38(3): 1111-1132.

Karthikeyan, S., P. Asokan and S. Nickolas, 2014. A hybrid discrete firefly algorithm for multi-objective flexible job shop scheduling problem with limited resource constraints. Int. J. Adv. Manuf. Technol., 72(9-12): 1567-1579.

Kumar, R., G. Gopal and R. Kumar, 2013. Novel crossover operator for genetic algorithm for permutation problems. Int. J. Soft Comput. Eng., 3(2): 252-258.

Lawler, E.L., J.K. Lenstra, A.H.G. Rinnooy Kan and D.B. Shmoys, 1993. Sequencing and Scheduling: Algorithms and Complexity. In: Graves, S., A.H.G. Rinnooy Kan and P. Zipkin (Eds.), Handbooks in Operations Research and Management Science. Logistics of Production and Inventory, North Holland, Amsterdam, 4: 445-522.

Lawrence, S. 1984. Supplement to resource constrained project scheduling: An experimental investigation of heuristic scheduling techniques. Technical Report, Graduate School of Industrial Administration, Carnegie-Mellon University, Pittsburgh.

Lee, C.Y., 1996. Machine scheduling with an availability constraint. J. Global Optim., 9: 395-416.

Leon, V.J. and S.D. Wu, 1992. On scheduling with ready-times, due-dates and vacations. Nav. Res. Log., 39: 53-65.

Liao, C.J., D.L. Shyur and C.H. Lin, 2005. Makespan minimization for two parallel machines with an availability constraint. Eur. J. Oper. Res., 160: 445-456.

Martin, P.D., 1996. A time-oriented approach to computing optimal schedules for the job-shop scheduling problem. Ph.D. Thesis, School of Operations Research and Industrial Engineering, Cornell University, Ithaca, New York 14853-3801, August.

Mohamed-Chahir, F. and N. Mustapha, 2014. Integrating noncyclical preventive maintenance scheduling and production planning for multi-state systems. Reliab. Eng. Syst. Safe., 121: 175-186.

Moradi, E., S.M.T. Fatemi Ghomi and M. Zandieh, 2011. Bi-objective optimization research on integrated fixed time interval preventive maintenance and production for scheduling flexible job-shop problem. Expert Syst. Appl., 38(6): 7169-7178.

Murovec, B. and P. Šuhel, 2004. A repairing technique for the local search of the job-shop problem. Eur. J. Oper. Res., 153: 220-238.

Nain, P.K.S., K. Deb and A. Geol, 2008. A multi-objective optimization procedure with successive approximate models. Proceeding of the International Conference on Systemics, Cybernetics and Informatics (ICSCI, 2008). Hyderabad, India, 1: 222-225.

Ombuki, B.M. and M. Ventresca, 2004. Local search genetic algorithms for the job shop scheduling problem. Appl. Intell., 21(1): 99-109.

Osman, I.H. and J.P. Kelly, 1996. Meta-Heuristics: Theory and Applications. Springer Science, Boston, MA, pp: 690, ISBN: 1461313619.

Pezzella, F. and E. Merelli, 2000. A tabu search method guided by shifting bottleneck for the job shop scheduling problem. Eur. J. Oper. Res., 120: 297-310.

Ping, C.M., T. Fei, L.L. Yi, Z. Lin, X.L. Hua *et al*., 2014. A hybrid particle swarm optimization and simulated annealing algorithm for job-shop scheduling. Proceeding of the IEEE International Conference on Automation Science and Engineering (CASE), pp: 125-130.

Ruiz, R. and T. Stützle, 2008. An iterated greedy heuristic for the sequence dependent setup times flow-shop problem with makespan and weighted tardiness objectives. Eur. J. Oper. Res., 187(3): 1143-1159.

Satake, T., K. Morikawa, K. Takahashi and N. Nakamura, 1999. Simulated annealing approach for minimizing the makespan of the general job-shop. Int. J. Prod. Econ., 60-61: 515-522.

Schaffer, J.D., 1985. Multiple objective optimization with vector evaluated genetic algorithms. In: Grefenstette, J.J. (Ed.), Proceeding of an International Conference on Genetic Algorithms and their Applications, pp: 93-100, sponsored by Texas Instruments and U.S. Navy Center for Applied Research in Artificial Intelligence (NCARAI).

Schmidt, G., 1988. Scheduling in dependent tasks with deadlines on semi-identical processors. J. Oper. Res. Soc., 39: 271-277.

Srinivas, N. and K. Deb, 1994. Multiobjective Optimization using Nondominated Sorting in Genetic Algorithms. Evol. Comput., 2(3): 221-248.

Steinhöfel, K., A. Albrecht and C.K. Wong, 2002. Fast parallel heuristics for the job shop scheduling problem. Comput. Oper. Res., 29: 151-169.

Tian, J. and M. Tomohiro, 2010. Multi-objective flexible job shop scheduling with uncertain processing time and machine available constraint based on hybrid optimization approach. Proceeding of the IEEE International Conference on Automation and Logistics (ICAL, 2010). Hong Kong and Macau, pp: 581-586.

Wei-Ling, W. and Y. Jing, 2013. A hybrid differential evolution algorithm for job shop scheduling problem to minimize the total weighted tardiness. Proceeding of the International Conference Management Science and Engineering (ICMSE), pp: 294-300.

Yamada, T. and R. Nakano, 1996. Job-shop Scheduling by Simulated Annealing Combined with Deterministic Local Search. In: Osman, I.H. and J.P. Kelly (Eds.), Meta-Heuristics: Theory and Applications. Kluwer Academic Publishers, Dordrecht, the Netherlands, pp: 237-248.

Ye, L. and C. Yan, 2010. A genetic algorithm for job-shop scheduling. J. Softw., 5(3): 269-274.

Yu-Yan, H., G. Dun-Wei, S. Xiao-Yan and P. Quan-Ke, 2014. An improved NSGA-II algorithm for multi-objective lot-streaming flow shop scheduling problem. Int. J. Prod. Res., 52(8): 2211-2231.

Zhang, G., L. Gao and Y. Shi, 2008. A genetic algorithm and taboo search for solving flexible job shop schedules. Proceeding of the International Symposium on Computational Intelligence and Design, pp: 369-372.

Ziaee, M., 2014. Job shop scheduling with makespan objective: A heuristic approach. Int. J. Ind. Eng. Comput., 5: 273-280.

Zribi, N., A.E. Kamel and P. Borne, 2008. Minimizing the makespan for the MPM job-shop with availability constraints. Int. J. Prod. Econ., 112(1): 151-160.

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Osman and Kelly (1996)