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Simultaneous job scheduling and tool replacement based on tool reliability by proposed Tabu-SA algorithm

Farhad Kolahan* and Ahmad Sharifinya
Department of Mechanical Engineering, Ferdowsi University of Mashhad, PO Box 91775-111, Mashhad, Iran

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This paper addresses integrated job scheduling and tool replacement problems in a single machine environment with objectives to determine optimal job sequence, tool selection for operation, tool replacement schedule, and number of spares for each tool type, in such a way that total expected production cost is minimized. Since problem is NP-hard, a hybrid algorithm [Tabu-simulated annealing (SA)] is proposed to simultaneously provide job sequencing, tool replacement intervals and number of spare tools required. Tabu-SA is examined and results are compared by solving a real-sized example problem.

Keywords: Combinatorial optimization, Reliability, Scheduling, Tabu-SA algorithm, Tool replacement

Introduction

Under scheduling problems, performance measures include total completion time, makespan, number of tardy jobs, maximum earliness/ tardiness, number of tool changes, etc. Srinivas *et al*[1] proposed a lexicographic search algorithm to provide best possible changeover sequence in multi-component manufacturing environments. Sadfi *et al*[2] studied a single machine scheduling with availability constraints in order to minimize total completion time. Loukil *et al*[3] introduced scheduling models by seven possible objective functions (makespan, number of tardy jobs, maximum earliness and tardiness, mean weighted earliness and tardiness and, weighted completion time). Al-Fawzan & Al-Sultan[4] proposed a Tabu search algorithm to find a job sequence and tools to be loaded on machine such that the total number of tool switches is minimized. Lack of tool management considerations[5,6] in automated manufacturing systems is reported to result in a poor performance. A lack of tool availability hampers smooth flow of production and results in long work-in-process queues (inventory), an increased number of part groups, and frequent tool changes, which consumes time resulting in under utilization of the system[7].

Both deterministic and probabilistic techniques have been used to determine economic life of tools. Tool life is a random variable and should be described probabilistically. This has justified the use of tool reliability instead of deterministic tool life[8]. Standard distributions (Normal, Weibull, and Exponential) as well as their combinations can be utilized to describe tool life under certain machining conditions[9].

This paper aims to determine optimal job sequence, tool assignment to machining processes, tool replacement schedule, and number of spares for each tool type, in such a way that total expected production cost is minimized. This problem includes Just-In-Time (JIT) job scheduling and tool replacement with sequence-dependent setup times and probabilistic tool life. To provide an efficient solution procedure, a hybrid Tabu search (TS) /Simulated annealing (SA) approach is proposed for this multi-criteria planning problem.

Problem Statement

Problem Description

The system under consideration includes a flexible machining centre with an automated tool changer and a tool resource of unlimited capacity. All operations of various jobs can be processed on machining centre, provided that required tools are available in tool resource. Each job has a fixed operation sequence defined by a set of required tools. However, setup times between different jobs are sequence dependent. No preemption is allowed, or processing of a job cannot be interrupted until it is entirely

*Author for correspondence
Tel: +98-9153114112; Fax: +98-5118763304
E-mail: kolahan@um.ac.ir

completed. Every tool may have different tool life distributions when processing different jobs. By this specification, in some cases (lack of needed spare tools, tool cost considerations, etc.), one can choose an appropriate tool among tool alternatives. Each tool-job combination may have a different machining time and cost. In a machining process, tools may fail randomly. If a tool fails while processing a job, it is assumed that job also becomes defective. Therefore, probabilistic defective cost depends on tool replacement decisions. Defective cost is the sum of raw material cost and machining and tool costs added to the job, up to the point when in-process failure occurs.

Problem involves multiple tasks: i) to find best job sequence, ii) to determine best tool-operation combinations; and iii) to determine best tool replacement interval and number of required spares for each tool type. These tasks are done in such a way that total expected production cost is minimized. Total expected production cost consist of: 1) setup costs, machining costs and cost of deviation from jobs due dates, which are deterministic; and 2) tool replacement and defective costs, which depend on job sequence and previous tool replacement decisions and therefore are probabilistic in nature.

Tool replacement decisions are made at the beginning of each operation. If a used tool is replaced with a new spare tool before processing next job, new tool cost is added to production cost. Probability of in-process tool failure will increase in case of long-term usage of a tool. If a tool is replaced by a new one, processing cost is increased due to cost of new tool, although probability of in-process failure would decrease.

Problem Formulation

Integrated JIT job sequencing and tool replacement problem for minimizing total expected production cost can be formulated as follows:

$$\text{Min}\, Z = \left\{ \sum_{j=1}^{J} \sum_{l\in L_k} \sum_{i\in I_j} \min\,(\varphi,\psi) + \sum_{j=1}^{J} \left[y_j\ \bar{C}\tau_{kj} \right] (\forall k \notin j) \ + \right.$$

$$\left. \sum_{i\in I_j} \left[\bar{C}\,\bar{\tau}_{i-1,i} \right] (\forall j) + \sum_{j=1}^{J} \left[abs\left(x_j \omega_j T_j + (1-x_j)\gamma_j E_j \right) \right] \right\} \qquad ...(1)$$

Subject to

$$\sum_{j}^{J} \sum_{l\in L_k} m_{ijl} \le M_i \qquad \forall\ \text{i} \qquad ...(2)$$

$$\left[\sum_{k=1}^{j} \sum_{l\in L_k} \sum_{i\in I_k} \left(t_{ikl} + \bar{\tau}_i \right) + \sum_{k=1}^{j} y_k \tau_{hk} \right] - d_j \le T_j \quad (\forall\ h \notin k) \qquad (3)$$

$$d_j - \left[\sum_{k=1}^{j} \sum_{l\in L_k} \sum_{i\in I_k} \left(t_{ikl} + \bar{\tau}_i \right) + \sum_{k=1}^{j} y_k \tau_{hk} \right] \le E_j \quad (\forall\ h \notin k) \qquad ...(4)$$

$$E_j \ge 0 \qquad \forall\ j \qquad ...(5)$$

$$T_j \ge 0 \qquad \forall\ j \qquad ...(6)$$

where

$$\phi = \left(Q_i + W_j\right)\left(1 - r_{ijl}\right) + \left(C\ \ t_{ijl} r_{ijl}\right) \qquad ...(7)$$

$$\psi = \left(Q_i + W_j\right)\left(1 - R_{ijl}\right) + \left(C\ \ t_{ijl} R_{ijl}\right) + Q_i \qquad ...(8)$$

$$R_{ijl} = exp\left(-\int_0^{t_{ijl}} h_{ijl}(t)dt \right) \qquad ...(9)$$

$$r_{ijl} = \left(\prod_{q\in s_i} R_{iq} \right) R_{ijl} \qquad ...(10)$$

$$m_{ijl} = \begin{cases} 1 & If\ \ \psi < \varphi \\ 0 & Otherwise \end{cases} \qquad ...(11)$$

$$x_j = \begin{cases} 1 & If\ \ Tardiness\ \ Occur \\ 0 & Otherwise \end{cases} \qquad ...(12)$$

$$y_j = \begin{cases} 1 & If\ \ Job\ \ j\ \ processed\ \ immediately\ \ after\ \ job\ \ k \\ 0 & Otherwise \end{cases}$$
(13)

where, i, Tool type index, i=1,…,I; j, h, k, Job index, j, h, k=1,…,J; I_j, Set of tools needed for operating job j; L_j, Number of operations that should be done on job j; w_j, Penalty cost per unit time tardiness for job j; Y_j, Penalty cost per unit time earliness for job j; C, Machining cost per unit time; $\bar{C}$, Setup cost per unit time; Q_i, Cost of a tool type I; W_j, Value of job j; M_i, Maximum spares of tool type i available in tool magazine; d_j, Due date of job j; T_j, Tardiness of job j; E_j, Earliness of job j; τ_{kj}, Setup time required by job j if it is processed immediately after job k; $\bar{\tau}_i$, Setup time required by tool type I; t_{ijl}, Machining time required by tool type i for operation l of job j; h_{ijl}, Hazard rate when tool type i is used for operation l of job j; s_i, Set of operation done by tool type I; R_{ijl}, Reliability of tool type i at the end of operation l of job j if it is replaced immediately before processing operation l of job j; and r_{ijl}, Reliability of tool i at the end of the operation for job j if it is not replaced immediately before processing operation l of job j.

First term of objective function, $\min(\phi,\psi)$, consists of machining and defective costs, is probabilistic and is related to reliability of cutting tool. For any given sequence, tool replacement decision is made based on this part of objective function. Expected cost of in-process failure is calculated by Eqs (7) and (8), which show total machining and defective costs by utilizing a used or a new tool. Tool reliabilities for each tool-job combination are computed using Eqs (9) and (10). As reliability of a used tool is usually lower than a new one, $r_i < R_i$, keeping a used tool may result in a greater defective cost. On the other hand, when a tool is replaced with a new one, a term Q_i is added to reflect planned tool replacement cost. Therefore, decision regarding tool replacement is made based on the smaller cost.

Second and third terms of objective function show tool setup and job setup costs respectively. Tools switch times are usually small and considered to be equal for all tools; while jobs setup times are sequence-dependent. The last term of objective function is related to due dates of jobs. Constraints (3) and (4) respectively determine amount of tardiness or earliness of every job in the sequence. These two constraints along with constraints (5) and (6) also ensure that no job can be early and tardy at the same time. Constraint (2) limits number of spares for each tool type available on tool resource.

Proposed Heuristic Algorithm

Tabu Search (TS)

TS[10] is an optimization technique used to solve combinatorial optimization problems. TS involves exploration of problem's solution space through an iterative investigation of solution neighborhoods. Search process starts from a feasible solution and moves stepwise towards a neighboring solution so that after a number of moves an optimal or near-optimal solution is obtained.

Simulated Annealing (SA)

SA[11] is a method suitable for solving optimization problems of large scales. This algorithm is suitable for complicated problems where global optimum is hidden among many local optima. Method itself has a direct analogy with annealing, which is performed in order to relax the system to state with minimum free energy. A standard SA procedure begins by generating an initial solution at random. At each stage, a small random change is made to current solution. Then objective function value of new solution is calculated and compared with that of current solution. A move is then made to new solution if it has a better value. A non-improving solution is also accepted with the probability ($P_r = e^{-\Delta c / c_k}$). Acceptance probability of non-improving solutions decreases as different in costs (Δc) increases and as temperature (c_k) of the method decreases. This c_k, a positive number, gradually decreases from a relatively high value to near zero as the method progresses. Thus, at the start of SA, most worsening moves are accepted, but at the end only improving ones are likely to be accepted. This, to a large extend, helps algorithm to jump out of local optima.

Proposed Tabu-SA Algorithm

Since TS evaluates all or some of neighborhood, it takes longer time to make a move and to search entire solution space. Selecting first improving move may significantly increase speed of algorithm[12]. SA investigates just one neighbour for every move, and hence is faster than TS. However in SA, because of lower probabilities of accepting non-improving moves in final stages of the search, risk of being trapped in local optima increases as the number of moves increases. In recent years, to enhance efficiency of search algorithms, hybrid methods are increasingly being proposed[13-16]. Zhang *et al*[17] applied a hybrid TS/SA algorithm on several hypothetical job shop scheduling (JSP) problems, wherein SA was used to find a pre-specified number of promising elite solutions inside convex solution space of JSP problem. Such hybridizations are basically two-phase runs of TS and SA procedures used separately at different search stages.

Proposed solution procedure (Tabu-SA) is a modified SA algorithm (Fig. 1) equipped with a Tabu list and algorithm turns to a Tabu search as needed. In Tabu-SA algorithm, successive moves are put in Tabu list that gives it a better protection against cycling. A move is made based on TS procedure if number of non-improving neighbors goes behind a certain number, n. In other words,

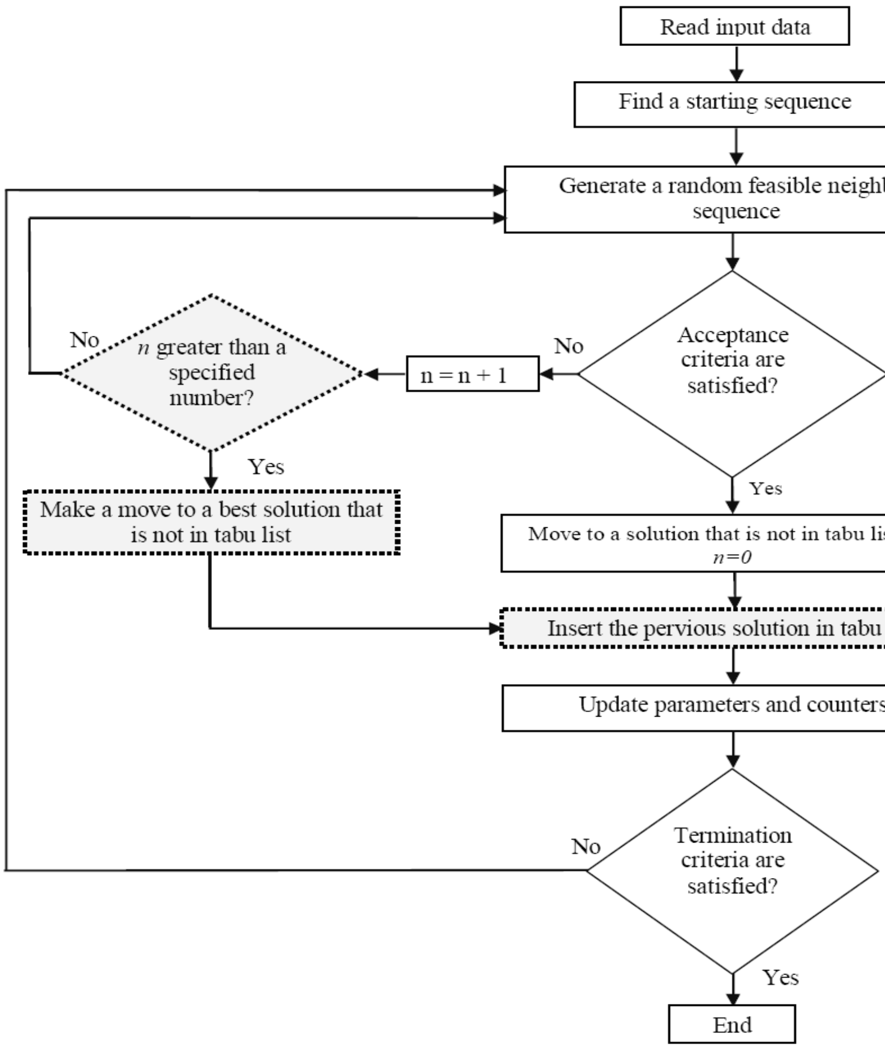


Fig. 1—Proposed Tabu-SA algorithm

after generating a feasible neighboring solution, if it is not in Tabu list and acceptance criteria of SA are satisfied, a move is made to it and previous move is stacked into Tabu list. However, if algorithm does not make a move in a pre-defined number of iterations, it makes a move to best neighborhood solution that is not in Tabu list. Thus, Tabu-SA algorithm has exploration speed of SA, as at each iteration only one neighbor solution is generated and evaluated.

A Numerical Example and Results

A numerical example is presented to illustrate performance of proposed model and heuristic algorithm. There are 30 jobs to be sequenced on a machining centre. A total of 15 tool types are needed to process these jobs. Each job has its own distinct due date and consists of several operations in a pre-defined order. Required machining time for every tool-operation combination is known. However, setup times for jobs are considered to be sequence-dependent. Weibull distribution is quite capable of predicting tool reliabilities and hence it is implemented in this research[18]. Therefore, tools lives are assumed to follow Weibull distribution.

Range of data related to jobs processing times, costs and due dates are as follows: processing times, 10-40 min; due dates, 40-820 min; tardiness penalties, 2.5-3.5 unit cost/h, earliness penalties, 1.0-2.0 unit cost/h; machining cost, 3 unit cost/min; setup cost, 2 unit cost/min; setup times, 1.5-4.0 min; raw material costs, 100-600 unit cost; and tool cost, 15-30 unit cost. These data may be obtained from machining tests. However, in this

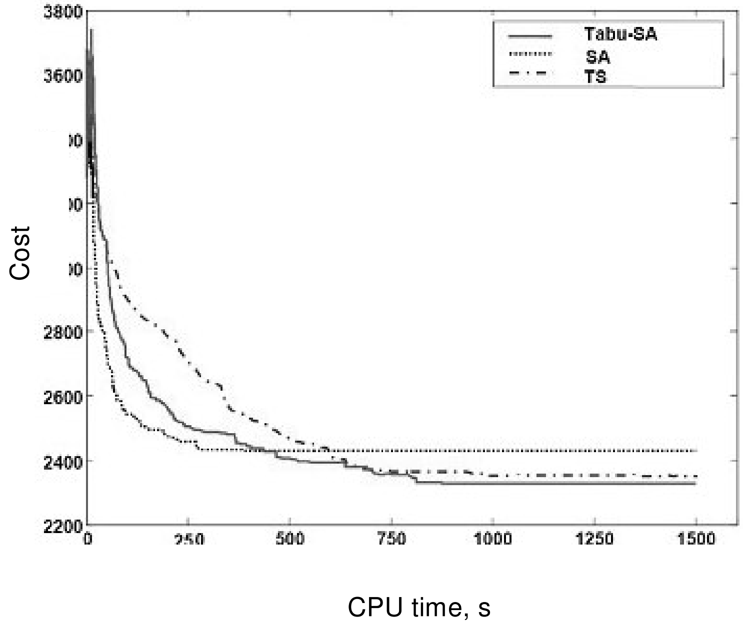


Fig. 2—Convergence rates for different algorithms

paper they are for illustrative purposes only. Weighting penalties are assigned to different cost components to show their relative importances in objective function. In this way, above multi-criteria scheduling problem can be treated as a single-objective optimization problem.

Algorithm was coded in MATLAB 7.0 software and executed on a Pentium 4 computer with 1.8 GHz processor. Best search parameters, obtained through several trial runs, are as follows: initial temperature (c_0), 5000; cooling schedule function, $c_{k+1}=ac_k$ ($a=0.98$); Tabu list size, 70; neighborhood generation, pairwise interchange; and termination criterion, 1500 s. Algorithm was run for following two scenarios: 1) non-restricted tool spare level; and 2) restricted tool spare level.

Non-Restricted Tool Spare Level

In this scenario, it is assumed that there is no restriction for number of available tool spares. Therefore, available tool copies for any tool type, M_i, were set at a high number (6 copies in this case). In this way, actual number of required tool spares for each tool type can be determined. It has been found that total production cost is improved (> 36%) from 3644 to 2327 unit cost (Table 1). It is noted that rate of improvement may be different for each item based on its importance in objective function. In this problem, defective cost is improved (> 44%) while improvement in setup cost is < 16%.

In order to compare performance of hybrid Tabu-SA procedure with pure SA and TS methods, above problem was solved by all three algorithms by using same starting points and computational times (Fig. 2). All three algorithms converge very quickly and most of the improvements are obtained within first 5 min of search time. Although SA has fastest improvement rate, it fails to find best solution. TS and Tabu-SA, on the other hand, perform same in terms of solution quality. TS has lower convergence rate and takes longer time to reach final solution because TS is a deterministic technique and needs to evaluate all neighboring solutions to make a move. This makes TS even more sluggish as problem size grows.

Table 1—Production costs obtained by Tabu-SA algorithm (no restrictions on tool spares)

Cost	Initial production schedule	Final production schedule	Improvement %
Total cost	3644	2327	36.1
Machining and tool spares costs	1554	987	36.5
Defective cost	1774	648	44.7
Earliness/tardiness cost	653	469	28.1
Setup cost	263	222	15.6

Table 2—Final job sequence and tool replacement intervals for non-restricted tool spares

Job	Tool type														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
10	—	—	—	0	0	0	—	—	0	—	—	—	—	—	—
5	0	0	—	0	0	—	—	0	—	—	—	—	—	—	—
4	0	0	—	—	—	—	—	—	1	0	0	—	—	—	—
3	0	0	—	0	0	—	—	—	—	—	—	0	—	—	—
21	0	1	—	—	—	0	—	—	—	0	—	0	—	—	—
2	1	—	—	—	—	—	—	—	—	1	—	0	—	—	0
1	—	—	0	1	—	—	0	—	—	0	0	—	—	—	—
7	—	0	—	—	—	—	0	—	0	0	—	1	—	—	—
9	1	0	0	—	—	—	—	—	0	—	0	—	—	—	—
14	—	—	1	—	—	1	1	—	—	1	—	—	—	—	—
15	0	—	—	0	—	0	0	—	—	—	—	—	0	—	—
6	—	1	—	—	1	—	1	—	1	—	—	0	—	—	—
13	0	0	—	—	0	—	—	1	—	—	—	—	0	—	—
19	—	—	—	—	1	1	—	—	—	—	0	—	1	—	—
25	—	0	0	—	—	0	—	—	—	—	—	—	—	—	0
16	—	0	1	—	—	1	—	—	0	—	—	—	—	—	—
17	0	0	—	—	0	—	—	—	—	—	1	—	—	—	—
18	0	—	—	—	0	—	0	—	—	0	—	—	—	—	—
20	—	0	—	—	—	—	1	0	—	—	—	—	—	—	0
12	—	0	—	—	—	—	1	—	—	—	—	—	—	0	—
22	1	1	—	—	—	—	0	—	—	—	—	0	—	0	—
8	—	0	0	0	1	—	—	—	—	—	—	—	—	—	1
23	0	—	0	1	0	—	—	—	—	—	—	—	—	—	0
24	1	—	—	0	—	—	—	—	0	—	—	—	—	—	0
11	0	—	—	—	—	—	—	—	—	—	0	—	1	—	1
27	—	—	—	0	—	—	—	0	1	0	—	1	—	—	—
26	—	—	—	1	0	—	—	1	0	—	0	—	—	—	—
29	0	—	0	—	—	—	—	—	—	0	—	0	—	—	0
28	—	0	—	—	—	0	—	—	—	—	—	—	0	0	0
30	—	—	—	0	—	—	0	0	0	—	—	—	0	—	—
spares	4	3	2	3	3	3	4	2	3	2	1	2	2	0	2

—, no operation is assigned; 0, no tool replacement required; 1, tool replacement required

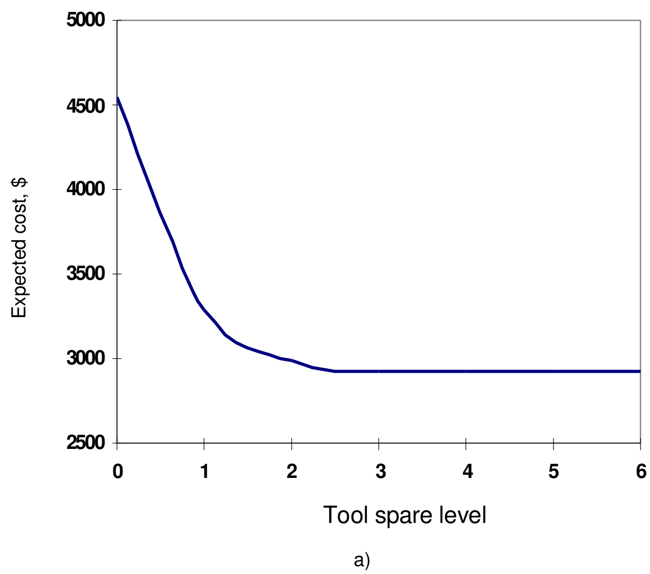
By hybridization of TS and SA, convergence speed and ability of escaping from local optima are improved (Fig. 2).

For non-restricted tool spare level, job sequence and tool replacement intervals are shown in Table 2. In first column, best job sequence is given. There are 15 tool types allocated to these jobs, for which replacement intervals are shown in associated columns. For example, to process first job in the sequence, job number 10, four tools are employed (tools number 4, 5, 6, and 9) and no replacement is required as this job is first one in the sequence. By same token, tool number 4 should be replaced by a new one at the beginning of operating jobs 1, 23, and 26. Therefore, a total of three copies of tool type 4 should be mounted on tool magazine. Last row of this table represents total number of required spares for each tool type. Tool replacement intervals are not fixed (Table 2). For instance, for tool type 1, which is required by 15 jobs, first replacement is required after processing 4 jobs but second replacement takes place after processing only one job. Irregular replacement intervals are because each tool is used for various jobs under different machining conditions and failure rates. This suggests that traditional tool replacement strategies (replacing tools after a pre-defined number of jobs or pre-specified machining times) may not be suitable for multi-tool and multi-job problems. Replacements should be according to different failure rates and machining conditions.

Table 3—Best job sequences for different tool spare levels

M_i	0		1		2		3		4	
	Seq.	Rel.	*Seq.*	Rel.	*Seq.*	Rel.	*Seq.*	Rel.	*Seq.*	Rel.
	20	97.31	*27*	98.45	*6*	98.45	*23*	98.45	*10*	96.94
	10	76.35	*1*	95.61	*1*	94.32	*1*	93.88	*5*	94.28
	16	83.94	*29*	86.02	*4*	91.93	*4*	95.02	*4*	96.56
	6	74.29	*15*	93.45	*29*	92.75	*2*	92.25	*3*	95.92
	26	89.74	*5*	93.13	*3*	95.63	*6*	94.89	*21*	96.16
	12	86.67	*7*	90.22	*11*	94.85	*5*	95.23	*2*	95.21
	15	70.06	*9*	88.37	*8*	91.11	*8*	90.66	*1*	87.62
	21	68.51	*6*	87.72	*7*	92.63	*7*	89.54	*7*	88.42
	25	67.46	*20*	84.14	*9*	87.41	*9*	87.86	*9*	93.44
	24	94.06	*21*	96.62	*20*	96.68	*10*	96.24	*14*	96.68
	3	75.98	*3*	90.03	*10*	87.60	*15*	91.62	*15*	90.71
	29	82.86	*12*	90.65	*5*	92.98	*14*	94.8	*6*	95.32
	2	64.63	*16*	80.32	*14*	87.63	*12*	87.68	*13*	90.38
	27	71.61	*14*	89.71	*28*	95.83	*11*	93.34	*19*	94.14
	5	91.84	*11*	94.80	*16*	95.86	*28*	96.3	*25*	96.17
	14	79.13	*19*	95.63	*2*	96.86	*17*	96.56	*16*	95.26
	4	78.45	*2*	93.09	*21*	91.30	*16*	95.1	*17*	98.26
	1	70.60	*10*	83.05	*17*	87.98	*29*	92.57	*18*	89.45
	11	61.54	*28*	79.94	*18*	84.97	*18*	89.27	*20*	91.38
	28	94.87	*22*	93.66	*12*	96.4	*20*	97.67	*12*	97.61
	7	78.66	*13*	85.30	*15*	94.59	*21*	92.36	*22*	93.53
	9	71.03	*24*	90.68	*25*	93.46	*26*	90.88	*8*	92.42
	8	82.21	*8*	89.36	*22*	90.12	*24*	92.84	*23*	91.4
	19	88.54	*25*	96.74	*24*	96.47	*3*	95.2	*24*	94.48
	22	89.01	*23*	92.92	*19*	95.40	*25*	95.98	*11*	94.28
	13	97.20	*26*	95.38	*26*	94.43	*22*	96.29	*27*	95.33
	17	76.89	*4*	89.52	*27*	92.45	*27*	91.76	*26*	93.51
	18	82	*17*	90.53	*23*	93.91	*13*	96.4	*29*	96.14
	30	89.72	*18*	94.71	*30*	95.84	*19*	95.84	*28*	95.79
	23	72.39	*30*	86.57	*13*	92.79	*30*	92.12	*30*	95.13
TSC, unit cost	0		132		199		233		239	
TC, unit cost	4542		3293		2985		2923		2920	
APR, %	80.8		90.5		93.1		93.6		\94	

TSC, Tool spare cost; TC, Total cost; APR, Average process reliability; M_i, Tool spare level



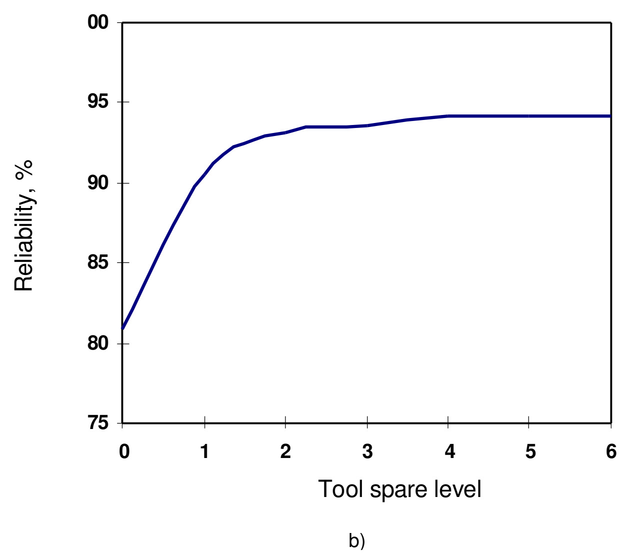


Fig. 3—Tool spare levels vs: a) Total production cost; b) Average process reliability

Restricted Tool Spare Level

For performance analysis of proposed model and solution procedure, under tool availability constraint, five tool spare levels (M_i = 0,1,2,3, and 4) were examined to evaluate impact of tool spare level on total expected production cost and system reliability. It has been observed that total production cost can be significantly reduced and a more reliable production process can be achieved by increasing tool spare level (Table 3). For instance, if there is no tool spares, M_i= 0, best expected production cost is 4542 and average process reliability is only 80%. As spare level is increased to 1, total cost is reduced to 3293, while average reliability reaches 90.5%. Although performance of machining centre may be improved by providing more spares, rate of improvement is reduced as more spare tools are added. Looking into saturation effect of tool spare level on total production cost (Fig. 3a) and average reliability (Fig. 3b), when tool spare level reaches a certain point (4 spares in this case), system is saturated and any extra spare become redundant.

Conclusions

In proposed model, cost components are weighted according to their relative importances. In this way, multi-criteria problem could be treated as a single objective model. Computational experiments demonstrate that hybrid Tabu-SA algorithm is superior to pure TS and SA methods, in terms of both convergence speed and solution quality. This proves effectiveness of proposed method towards solving large-size, multi-criteria planning problems. The results also show that job scheduling and tool replacement decisions should be considered simultaneously. In summery, computational results show: 1) tool replacement intervals are not fixed and depend on factors that affect tool reliability such as machining times and conditions; 2) performance of machining centre is directly affected by tool spare level; and 3) effect of tool spares on performance of machining centre has a saturation point. As the extension of this research, multi-objective optimization using Pareto-based approach may be considered. Developing more efficient hybrid optimization procedures can also be a promising area of research.

References

1 Srinivas J, Subbaiah K V & Chandra Mouli K V V, An optimal sequencing approach for job-shop production, *J Sc Ind Res*, **63** (2004) 458-461.

2 Sadfi C, Penz B & Rapine C, An improved approximation algorithm for the single machine total completion time scheduling problem with availability constraints, *Eur J Operat Res*, **161** (2005) 3-10.

3 Loukil T, Teghem J & Tuyltens D, Solving multi-objective production scheduling problems using methaheuristics, *Eur J Operat Res*, **161** (2005) 42-61.

4 Al-Fawzan M A & Al-Sultan K S, A tabu search based algorithm for minimizing the number of tool switches on a flexible machine, *Comp Ind Eng*, **44** (2002) 35-47.

5 Gray E, Seidmann A & Stecke K E, A synthesis of decision models for tool management in automated manufacturing, *Manage Sci*, **39** (1993) 549-567.

6 Crama Y, Kolen A W J, Oerlemans A G & Spieksma, F C R, Minimizing the number of tool switches on a flexible machine, *Int J Flexible Manuf Syst*, **6** (1994) 33-54.

7 Boyle C, Using group technology for tool inventory control, in *Proc 3rd Int Mach Tool Tech Conf* (National Machine Tool Builders Association, Chicago) 1986, 111-120.

8 Maccarini M, Production cost and tool reliabilities: The machining cost influence in flexible plans, *Int J Mach Tools and Manuf*, **31** (1991) 415-424.

9 Hitomi K, Nakamura N, & Inoue S, Reliability analysis of cutting tools, *J Eng Ind*, **101** (1979) 185-190.

10 Glover F, Tabu search — Part I, *ORSA J Comp*, **1** (1989) 190-206.

11 Kirkpatrik S, Gelatt C D & Vecchi M P, Optimization by Simulated Annealing, *IBM Res Rep RC* 9355, 1982.

12 Kolahan F & Tavakoli A, The effect of different neighborhood generation mechanisms on the performance of Tabu Search, *WSEAS Trans Math*, **6** (2007) 575-580.

13 Zolfaghari S & Liang M, Jointly solving the group scheduling and machine speed selection problems: A hybrid tabu simulated and simulated annealing approach, *Int J Prod Res*, **37** (1999) 2377-2397.

14 Shelokar P S, Jayaraman V K & Kulkarni B D, Multicanonical jump walk annealing assisted by Tabu or dynamic optimization of chemical engineering processes, *Eur J operat Res,* **185** (2008) 1213-1229.

15 Soke A & Bingul Z, Hybrid genetic algorithm and simulated annealing for two-dimensional non-guillotine rectangular packing problems, *Engg Appl Artific Intell*, **19** (2006) 557-567.

16 Anghinolfi D & Paolucci M, Parallel machine total tardiness scheduling with a new hybrid metaheuristic approach, *Comp Operat Res*, **34** (2007) 3471-3490.

17 Zhang CY, Li PG, Rao YQ & Guan ZL, A very fast TS/SA algorithm for the job shop scheduling problem, *Comp Oper Res*, **35** (2008) 282-294.

18 Ramalingam S, Peng Y & Waston J, Tool life distributions, Part 3: Mechanism of single injury tool failure and tool life distribution in interrupted cutting, *J Eng Ind*, **100** (1987) 193-200.