SMOSA Optimization Approach to a Multi Objective Model for a Machine Tool Selection and Operation Allocation Problem in FMS

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Abstract
This paper considers a difficult of dynamic match inner-tool election and distribution of operation with part and tool movement policies in a flexible manufacturing system (FMS) environment. For this design, a novel 0-1 Non linear integer programming multi objective model is demonstrated in such a way that each tool and each part can move during the production phase. It is assumed that there are sets of tools and machines that can manufacture different kinds of orders (or part types). Therefore, in this study, we make use of one of the various objective decision-making methods, a global criterion approach, to improve a multi-objective model for find a solution FMS scheduling problems with payment of two performance measures, namely minimum machining cost, set up cost as first objective and minimum machining time, tools and parts transportation time and machines average idle time as second objective, at the same time. SMOSA algorithm approach is applied to optimize the model and the outcomes of the computational experiments are reported.

Keywords
SMOSA, Multi Objective model, Machine- tool selection, Operation allocation, Flexible manufacturing systems

1. Introduction and Literature review
Producing a given set of part types each one with many operations and different alternative machine-tool combinations is very significant in any flexible manufacturing system (FMS). A flexible manufacturing system (FMS) plans at attaining the efficiency of automated high-volume mass production while keep the flexibility of low-volume work shop production. In recent years, an increasing request for customized products has made an extreme increase in the number of options and product changes. Traditionally, the product different demanded by customers has been produced in a work shop or small batch activities. There are two great kinds of tool allocation in an FMS, namely part motion policy and tool motion policy. Scheduling in an FMS environment is more complicated and hard than in a conventional manufacturing environment. Production scheduling for an FMS can be treated as four sub-difficulties: (1) part type selection, (2) machine loading, (3) part input sequencing, and (4) operation scheduling (Sawik 1990). In this article, we focus the entire approach on the operation scheduling which evaluate the detailed schedule for processing the works in the system. Previous studies of operation scheduling problems related to FMSs can be organized into two categories: optimization procedure for an exact explanation and heuristic algorithms for near optimal solutions Adams et al. (1988); improved a model and a solution protocol for the machine loading and tool allocation problem in FMS. Kim and Yano (1993) offer a number of methods for loading problems in flexible manufacturing systems; Kim and Yano (1994), and displayed how an existing branch-and-bound algorithm for the workload balancing may be used to solve the model. Chan and Swarnkar (2006) improved a 0-1 mixed-integer target programming model and displayed ant colony optimization (ACO) for machine-tool selection and operation allocation in an FMS. Chan et al. (2005) demonstrated an artificial immune system (AIS) approach for the same previously mentioned problem. Buyurgan et al. (2004) showed a heuristic approach for tool selection in an FMS

based on the life over size ratio of each tool by allocating AGVs for tool (i.e., dynamic tool allocation). Their recommended method selects tool types with the defined criterion by considering tool alternatives for operations assigned to each machine. Chen and Ho (2005) displayed an approach for the multi-objective operation assignment to machines in production planning of an FMS that minimizes the total flow time, greatest machine workload, and machine workload unstable and total cost. Kumar et al. (2006) offer the machine-loading problem and tool allocation problem for an FMS. They recommended a constrained based genetic algorithm (CBGA) in order to consider variables and focuse the loading problem. Sujono and Lashkari (2007) offered a multi-objective model for the operation allocation and material handling system selection in an FMS. They offerd a 0-1 integer programming model with four objectives, namely minimization of machining cost, material handling cost, setup cost and maximization the compatibility of material handling equipment with part types. In fact, their model selects machines, apportions operations of part types to the selected machines, and assigns material handling equipment to handeling the part types from one machine to another machine. Law et al. (2006) improved a different kind of objective example and allocated a global standard approach to find a solution the FMS scheduling problem taking everything three performance measures, mean work tardiness, minimum mean work flow time, and minimum mean machine idle time, concurrently. In addition, a hybrid TS and SA method is also accepted for solving the given problem. Mahdavi et al. (2008) offer a 0-1 integer linear programming model for machine-tool selection and operation allotment together with real-world constraints, such as tool-life, available time of machines, tool slot, probability of machine-tool combination, tool magazine capacity of each machine, and feasibility of allotment of a machine-tool to a specific operation by considering a part movement policy. Moreover, they proposed a Pareto-ant colony optimization (P-ACO) approach to solve their presented model in a reasonable time. Konak et al. (2008) addressed the number of tool switching instants problem on a CNC machine in FMS environments. In fact, they deliberated the single machine difficulties of minimizing the number of tool switching instants. Besides, the flat research space of their difficulties and to find solutions with high quality, two different kind of TS approaches are recommended by them. Their computational conclusion display that both TS approaches produce optimal or near-optimal solutions. Zeballos et al. (2010) considered an integrated constraint programming sample to solve the problems of tool allocation, machine loading, part routing, and scheduling in an FMS. get into account some constraints. The most famous methods are simulated annealing (SA, Adenso-Diaz 1996; He et al. 1996; Low and Wu 1996), and tabu research (TS, Barnes and Chambers 1995; Brandimarte and Calderini 1995). Also, the genetic algorithm (GA) has also provided a good performance solution for scheduling problems in past research (Della Croce et al. 1995; Sakawa et al. 1996; Abazari etal.2012). Procedures according to these approaches are able to get away from local optima and get a near optimal solution.

2. Description of problem

The following suppositions are considered for the mentioned problem.

- The processing time for each operation in a batch is supposed to be identical.
- Each operation of a certain part type must be assigned on one machine only.
- Tool magazines of different kind of machines may have different number of tool slots of same shape and size.
- Operations to be carried out by a machine-tool combination are preemptive. In other words, there are precedence relations among the operations of each part type, in which this sequence is known in advance.
- A tool cannot be copied in the same tool magazine.
- Each tool has a special tool-life.
- Available time for each machine is restricted.
- Part types are moved among machines with AGV for parts. Transformation time of part type among machines is not gotten into account.
- Tools are transported via tool movement systems by handling system. Also, transformation time of tools among machines is not gotten into account.
- There is an adequate buffer space on each machine and after carry out the last operation of a part, it stays on the buffer beside the machine.
- The set of part types should be produced supposed to be unchanged in the given production period.
- Each operation must be processed with one machine-tool combination.

3. Multi-objective mathematical model

In this section, we expose one of the well-known multiple objective decision making (MODM) procedures, the global criterion method, and use it to solve the addressed FMS scheduling problem with two popular performance measures, namely minimum machining cost, set up cost as first objective and minimum machining time, tools and parts transportation time and machines average idle time as second objective, simultaneously.

3.1 Notations

The notations which are used to develop a mathematical model of the addressed FMS problem are defined and interpreted as follows:

P	$1 \le p \le P$, where P is the total number of part types
M	Machines; $1 \le m \le M$, where M is the number of machines
L	Tools; $1 \le l \le L$, where L is the number of tools
O	Operation for part type p; $1 \le o \le O_p$, where O_p is the number of operation for part p
T_{pmlo}	Machining time for operation o of part type p on machine m using tool l
C_{pmlo}	Machining Cost for operation o of part type p on machine m using tool l
SU_m	Set up cost for machine m
T_m	Maximum allowable machine time on machine m
TL_l	Tool life of tool l
B_p	Batch size for part type p
TS_m	Maximum number of tools slots available on machine m
T_{qm}	tool movement time for a tool from machine q to machine m
TK	Maximum allowable time on AGV
FT_{pmlo}	Finishing time for operation o of part type p on machine m using tool l
FT_p	Finishing time for part type p
ST_{pmlo}	Starting time for operation o of part type p on machine m using tool l
F_{pqm}	Moving Time for a part type p from machine q–m using AGV
d_p	Demand for part type p
s_m	Set up time for machine m
ST_{po}	Starting time for operation o of part type p

3.2. Decision variables

In the developed 0-1 integer programming, the following zero- one variables are determined.

x_m	if machine m is selected =1 ; otherwise=0
xt_l	if tools l is selected =1 ; otherwise=0
x_{pqmlo}	Equal to one if operation o of part p processed on machine m that this tool is came from machine q; otherwise, it is zero.
x_{pqmo}	Equal to one if operation o of part p is processed on machine m that the part is came from machine q; otherwise, it is zero.
x_{pmlo}	Equal to one if operation o of part type p is performed by tool l of machine m; otherwise, it is zero.
y_{ml}	if tool l is assigned to machine m =1 ; otherwise=0

3.3. Single objective mathematical models

Two single objective models concerned in this research are briefly described as follows:

$$Minimize\ z_1 = \sum_{p=1}^{P} B_p \sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{o=1}^{O_p} C_{pmlo} x_{pmlo} + \sum_{m=1}^{M} SU_m x_m$$

$$Minimize\ z_2 = \lambda_1 (\sum_{p=1}^{P} B_P \sum_{l=1}^{L}\sum_{o=1}^{O_p} T_{pmlo} x_{pmlo} + \sum_{p=1}^{P}\sum_{q=1}^{M}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{o=1}^{O_P} T_{qm} x_{pqmlo} + \sum_{p=1}^{P} B_P \sum_{q=1}^{M}\sum_{m=1}^{M}\sum_{o=1}^{O_P} F_{pqm} x_{pqmlo})$$

$$+\lambda_2 (C_{Max} - \frac{1}{m}\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{o=1}^{O_p} x_{pmlo}(S_m + T_{pmlo}))$$

Subject to the following constraints:

$$\sum_{m=1}^{M} y_{ml} = 1 \qquad \forall l \tag{1}$$

$$y_{ml} \geq x_m \qquad \forall m, l \tag{2}$$

$$y_{ml} \geq xt_l \qquad \forall m, l \tag{3}$$

$$\sum_{p=1}^{P}\sum_{o=1}^{O_p} x_{pmlo} \geq y_{ml} \qquad \forall m, l \tag{4}$$

$$\sum_{m=1}^{M}\sum_{l=1}^{L} x_{pmlo} = 1 \qquad \forall p, o \tag{5}$$

$$\sum_{q=1}^{M}\sum_{m=1}^{M} x_{pqmo} = 1 \qquad \forall p, o \tag{6}$$

$$\sum_{p=1}^{P} B_P \sum_{l=1}^{L}\sum_{o=1}^{O_p} T_{pmlo} x_{pmlo} \leq T_m \qquad \forall m \tag{7}$$

$$\sum_{p=1}^{P} B_P \sum_{m=1}^{M}\sum_{o=1}^{O_p} T_{pmlo} x_{pmlo} \leq T_l \qquad \forall l \tag{8}$$

$$\sum_{l=1}^{L} x_{pmlo} \leq x_m \qquad \forall p, m, o \tag{9}$$

$$\sum_{m=1}^{M} x_{pmlo} \leq xt_l \qquad \forall p, l, o \tag{10}$$

$$x_{pqmlo} = x_{pqlo-1} x_{pmlo} \qquad \forall p, q, m, l, o \tag{11}$$

$$\sum_{q=1}^{M}\sum_{l=1}^{L} x_{pqmlo} = \sum_{q=1}^{M} x_{pqmo} \qquad \forall p, m, o \tag{12}$$

$$\sum_{l=1}^{L} y_{ml} \leq TS_m \qquad \forall m \tag{13}$$

$$FT_{pqlo} + F_{pqm} x_{pqmlo+1} = ST_{pmlo+1}; \qquad \forall p, q, m, l, o \tag{14}$$

$$FT_{pmlo} = ST_{pmlo} + x_{pmlo}(S_m + T_{pmlo}); \qquad \forall p, m, l, o \tag{15}$$

$$\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{o=1}^{O_p} FT_{pmlo} = FT_p \qquad \forall p \tag{16}$$

$$FT_p \leq C_{Max} \qquad \forall p \tag{17}$$

$$\sum_{m=1}^{M}\sum_{l=1}^{L} (x_{pmlo-1} - x_{pmlo}) \geq 0 \qquad \forall p \in P, m \in M, l \in L, o = 2, ..., O \tag{18}$$

$$ST_{pmlo} = ST_{po} x_{pmlo} \qquad \forall p, m, l, o \tag{19}$$

$$ST_{po} + \sum_{m=1}^{M} x_{pmlo} (S_m + T_{pmlo}) \le ST_{po+1} + \sum_{m=1}^{M} x_{pmlo+1} (S_m + T_{pmlo+1}) \qquad \forall p, l, o \tag{20}$$

$$\sum_{p=1}^{P} B_p \sum_{q=1}^{M} \sum_{m=1}^{M} \sum_{l=1}^{L} \sum_{o=1}^{O_p} F_{pqm} x_{pqmlo} \le TK \tag{21}$$

$$b_p \times \sum_{l} \sum_{m} x_{pmlo} = d_p \qquad \forall p \in P \tag{22}$$

$$\lambda_1 + \lambda_2 = 1 \tag{23}$$

The multi objective function of the considered model is to minimize machining cost, set up cost, and transportation time, mean machine idle time, simultaneously. Constraint (1, 2, and 3) ensures that a tool can be assigned only to one machine, although it is not the same vice versa, i.e. a machine can be assigned more than one tool. Constraint (4) assures that once a machine–tool combination is selected properly, the operations can be assigned to it. Constraint (5) states that each operation o of each part type p is processed using one machine-tool combination m-l. Eq. (6) states that each operation o of each part type p is processed using one machine m that this part come from machine q. Constraint (7) ensures that once machine m is selected for the operation “o” of each part type p, the available time on the machine should be greater than or equal to the time required by that operation by considering its batch size. Constraint (8) ensures that the operation time for each tool l should be lesser than or equal to the tool-life by considering the batch size of all the operations that performed by this tool. Constraint (9) keeps the continuity of movement of each tool l with respect to its stages. For example, if there is a tool movement from machine q to machine m, then one operation should be perform in machine q in the previous stage of that tool. Eq. (9) states a specific machine is used in the production period or not. Also, this constraint states the relationship between two zero-one variables. Eq. (10) states that a specific tool is used in the production period or not. Also, this constraint states the relationship between two zero-one variables. Constraint (11) shows the relationship among decision variables. Eq. (12) states that operation o of part p should be processed on the machine m, in which this part coming from another machine q. This is also true for the related tool and shows the relationship among decision variables. Constraint (13) states that the tool magazine capacity if taken care in the following Constraint. Constraint (14, 15) is to calculate start and finish time of operation o of part p. Constraint (16) shows that how finish time of part p is calculated. Constraint (17) guarantees that finish time of part p is less than c max. Constraint (18, 19, and 20) guarantees the precedence relations among the operations of part types. Constraint (21) guarantees that the transportation time required by AGV should not exceed the available time on AGV. Constraint (22) guarantees that the summation of batch size of part p should not exceed the demand of part p and Constraint (23) shows that the summation of coefficients is equal one.

4. Solving the problem

4.1. Simulated annealing: an overview

Simulated annealing is a computational stochastic technique for finding near global optimum solutions to combinatorial and function optimization problems. The method is divined from the thermodynamic process of cooling (annealing) of liquefied metals to achieve the lowest free energy state (Kirkpatrick et al. 1983). When liquefied metal is cooled slowly enough it tends to solidify in a structure of minimum energy. This annealing process is copied by a search strategy. The key principle of the method is to allow occasional aggravating moves so that these can finally help locate the neighborhood to the true (global) minimum. The associated mechanism is given by the Boltzmann probability, viz.:

$$\text{probability } (P) = \exp\left(\frac{-\Delta E}{K_B T}\right) \tag{24}$$

where ΔE is the change in the energy value from one point to the next, K_B the Boltzmann’s constant and T the temperature (control parameter). Another variant of this acceptance criterion (for both improving and deteriorating moves) has been proposed by Galuber (1963) and can be written as:

probability $(P) = \dfrac{\exp(-\Delta E\ /T\ )}{1+\exp(-\Delta E\ /T\ )}$ (25)

4.2. Simulated annealing based multi objective algorithms

4.2.1. The method of Suppapitnarm and Parks (SMOSA)

As mentioned earlier, many simulated annealing based multi objective optimization algorithms have been proposed by many researchers. The concept of archiving the Pareto-optimal solutions coupled with return to base strategy has been used by Suppapitnarm et al. (2000) for solving multi objective problems with simulated annealing. An acceptance criterion uses objective function values after penalizing them and annealing temperature. Weight vector is not used in the acceptance criteria. It uses multiple annealing temperatures (one per objective). Hence, the key probability step can be given as:

$$P = \frac{\sum_{i=1}^{N} \exp(\frac{-\Delta s_i}{T_i})}{N} \tag{26}$$

where $\Delta s_i = (z_i(Y\ ) - z_i(X\ ))$, X is the current solution, Y the generated solution, z_i the objective function, T_i the annealing temperature and P the probability. A constrained problem is converted to an unconstrained one with the help of penalty function approach.

4.2.2. The SMOSA algorithm

The basic steps involved in the SMOSA algorithm for a problem having N objective functions and k decision variables are as follows:
1. Start with randomly generated initial solution vector, X, (a k×1 vector whose elements are decision variables) and evaluate all objective functions and put it into a Pareto set of solutions.
2. Give a random perturbation and generate a new solution vector, Y, in the neighborhood of current solution vector, X, revaluate the objective functions and apply penalty function approach to the corresponding objective functions, if necessary.
3. Compare the generated solution vector with all solutions in the Pareto set and update the Pareto set, if necessary.
4. If the generated solution vector is archived, make it the current solution vector by X = Y and go to step 7.
5. Accept the generated solution vector as the current solution vector, if it is not archived with the probability:

$$P = \frac{\sum_{i=1}^{N} \exp(\frac{-\Delta s_i}{T_i})}{N} \tag{27}$$

where $\Delta s_i = (z_i(Y\ ) - z_i(X\ ))$
If the generated solution is accepted, make it the current solution vector by X = Y and go to step 7.
6. If the generated solution vector is not accepted, retain the earlier solution vector as current solution vector by X = X and go to step 7.
7. Periodically, restart with a randomly selected solution from the Pareto set. While periodically restarting with the archived solutions, Suppapitnarm et al. (2000) have recommended biasing towards the extreme ends of the trade-off surface.
8. Periodically reduce the temperature using a problem dependent annealing schedule.
9. Repeat steps 2–8, until a predefined number of iterations is carried out.

5. Numerical examples and computational experience

To illustrate the application of the proposed approach, the shop floor of a random FMS is envisaged. Thirty sets of data pertaining to the shop floor and part order and associated goals are generated randomly. The different values in the data are uniformly distributed in the range shown in Table 1. A typical set of data is shown in Tables 2-4. Described in these table is an FMS consisting of eight multi-functional CNC machines, which are capable of performing several operations. The material handling and tools - Handling cost between the different machines are shown in Table 2. Table 3 shows the set-up costs associated with each of the machines and available machining time on them. A typical order consists of different part types having several operations. These operations can be done on different machine–tool combinations, however the machining time and cost of operations vary. There are three part types with batch sizes: 10, 20 and 30, respectively as shown in Table 4. These test problems has been addressed using the proposed multi objective model and optimized using the MOSA approach. The proposed algorithm was coded in MATLAB. The program was executed on the test problem using an IBM compatible PC with Pentium III processor running at 800MHz and 512MB of RAM. The values of the objective function and computational time taken for 30 problems can be seen in Fig. 1, 2 and 3. Results obtained for the example problem illustrated in Tables 2–4 are shown separately in Tables 5–7. Table 7 shows the operation allocation to machine–tool combinations while the details related to final costs/time and utilization of resources are enlisted in Table 6 and 7, respectively. As observed in the repeated runs, the fraction of ants choosing the best path increases with iterations, however it stabilizes at little over 70% (Fig. 4).

Table 1 : Parameters setting for the given problems

Parameter	Value
Number of machines	8
Number of tools	5
Machine’s magazine capacity	Rand(2,5)
Setup time for each machine(min)	Rand(1,20)
Number of parts	3
Number of operations	2,2,12
Tool life of each tool(min)	Rand(1,180)
Machine available time(min)	Rand(180,240)
AGV available time(min)	17

Table 2 : Material – Handling(AGV) and Tools - Handling Cost between the machines (F_{pqm}, T_{qm})

	8	7	6	5	4	3	2	1
1	30	20	10	40	30	20	10	-
2	20	10	20	30	20	10	-	
3	10	20	30	20	10	-		
4	20	30	40	10	-			
5	30	40	50	-				
6	20	10	-					
7	10	-						
8	-							

Table 3 : Details of the FMS

Machinne	Set - up cost	Available machining time
1	250	Rand(180,240)
2	250	Rand(180,240)
3	250	Rand(180,240)
4	250	Rand(180,240)
5	250	Rand(180,240)
6	250	Rand(180,240)
7	250	Rand(180,240)
8	250	Rand(180,240)

Table 4 : Details pertaining to machining time and cost of operations for part types

Part type	Batch size	Demand	Operation	Tool options	Machining time on different machines	Operation cost on different machines
1	10	10	1	4 5	RAND(1,100)(S)	RAND(1,20000)
			2	3 1		
2	20	20	1	4 5		
			2	3 1		
3	30	30	1	4 5		
			2	3 1		
			3	5 2		

Table 5 : Operation allocation to the machine tool combination

Part type p	Machine 1	2	3	4	5	6	7	8
1	1-3	3	1	-	1-3	-	-	1
2	1-2	-	1-3	1-5	-	2-5	2-3	3-5
3	3	3-4	3-5	4-5	4	-	-	

Element l–o at cell (p, m) of table shows operation "o" of part type p is performed by machine m using tool l.

Table 6 : Operational time and various costs associated with the solution

Part type	Operational cost for the part type	Operational time for the part type	set-up cost	set-up time	Material - handling costs (AGV)	tools - handling costs
1	601590	2590	1250	75	400	400
2	622800	6640	1500	90	180	180
3	1689770	5250	1500	90	80	80

Table 7 : Machine and tool utilization

Machine	1	2	3	4	5	6	7	8
Utilization (%)	25%	8%	33%	10%	6%	12%	9%	31%
Tool	1	2	3	4	5			
Time in use (%)	36%	18%	86%	7%	54%			

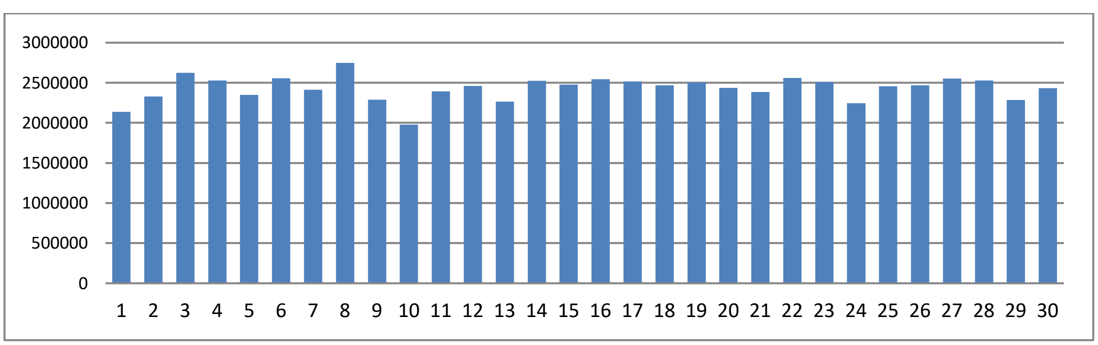

Fig. 1. Objective function value 1 based on problem set

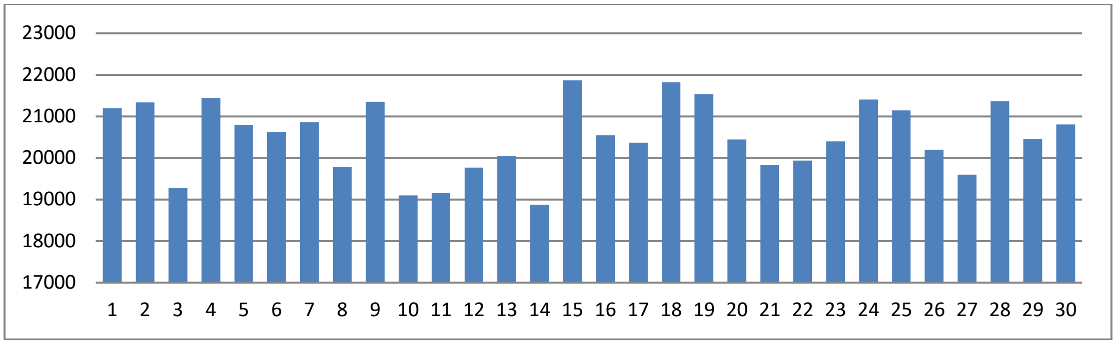

Fig. 2. Objective function value 2 based on Problem sets

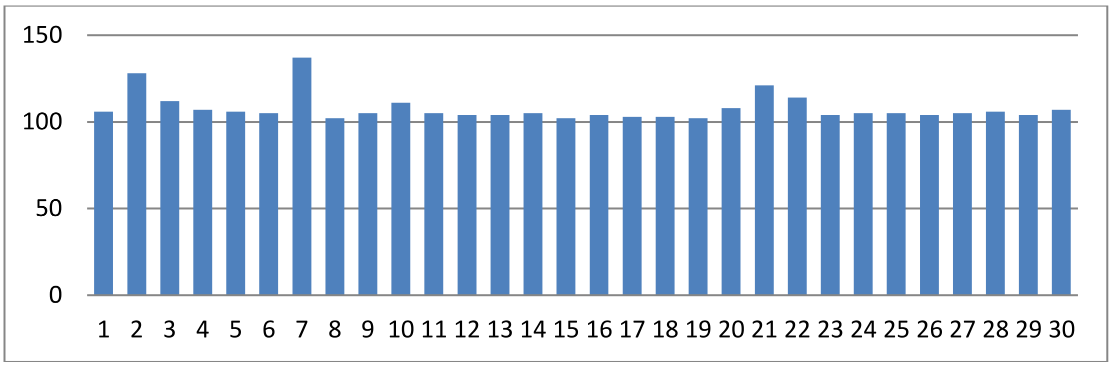

Fig. 3. computational time based on Problem sets

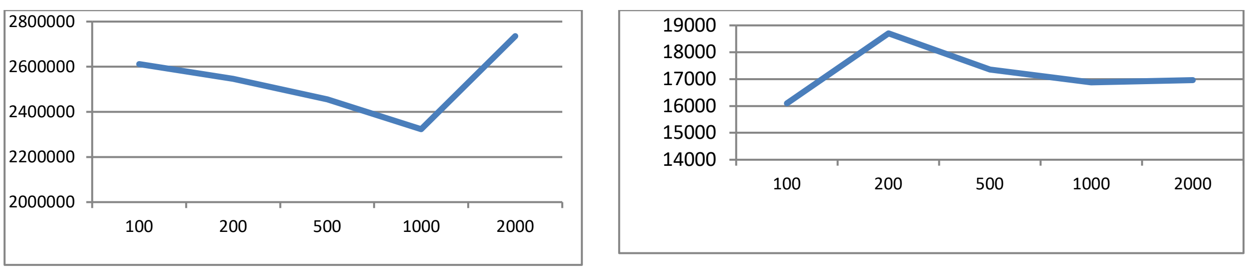

Fig.4. Best results obtained at different number of iterations.

5.1. Discussion

The number of variables and constraints increase manifolds in real-life industrial application of the model, owing to which the potentials of the integer programming software will be overrun. In the proposed approach, vagueness of information is mapped and the model is optimized the problem using MOSA algorithm. Following are some of the observations pertaining to application of this approach:

1. Being generic in nature, the proposed multi objective approach can be easily modified to suite the requirement of other specific problem.

2. In many cases, it is impossible to satisfy the all the goals at a time. The proposed fitness function exhibit the feature of controlling the extent to which the decision maker wants the goals to be satisfied. The fitness function directly related to the effectiveness for the given set of goals.

3. The MOSA parameters $\alpha = 0.98$, T0=15 and POP Size = should be chosen carefully as they might lead to poor performance of the algorithm.

Due to NP-hard nature of this problem, the computational time increases exponentially and finding optimal solution for large-size problems is so hard.

The parameters studied were α, T0, POP Size. The algorithm was tested on small test problems with default value set $\alpha = 0.98$, T0=15 and POP Size=200. With $\alpha = \{0.95, 0.96, 0.97, 0.98, 0.99\}$ and T0= {5,10,15,20}, the values of objective functions were observed to select the best combination of these values. The best value was found to be a $\alpha = 0.95$ for objective function 1 , $\alpha = 0.99$ for objective function 2 and T0=5 for OF 1 and T0=15 for OF 2 (Figs. 5 and 6). Another important parameter in the algorithm is POP Size. A too high value of parameter POP Size in the original algorithm results in a situation called stagnation. While a very low value of POP Size results in little information conveying rom previous solutions and the algorithm becomes a randomized greedy search procedure. A study of POP Size behavior is done with set of values {100,150,200,250,300}. A value of 100 for POP Size of objective function 1 and 300 for POP Size of objective function 2 rendered minimum computation time as shown in Fig. 7.

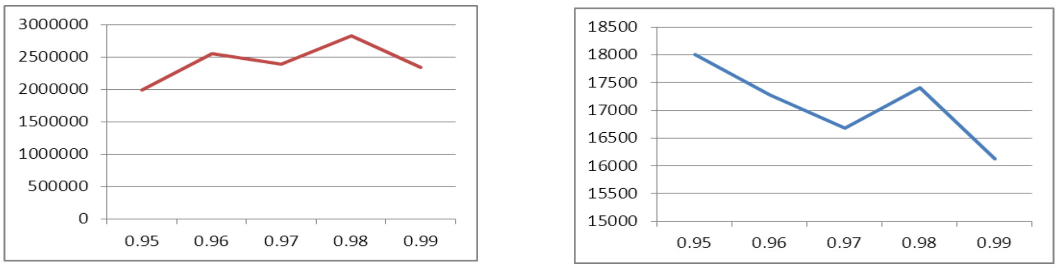

Fig. 5. Parameter α .

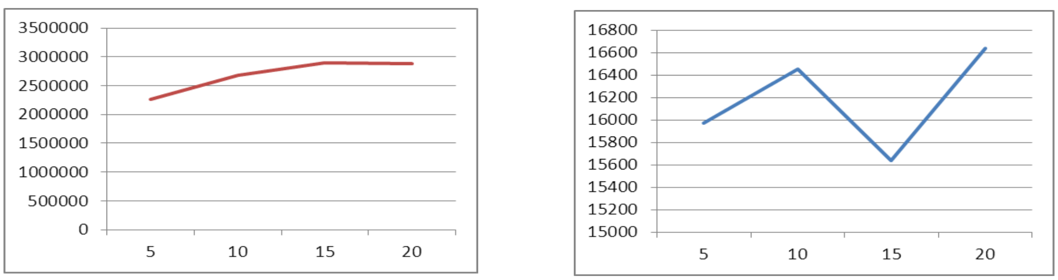

Fig. 6. Parameter T0.

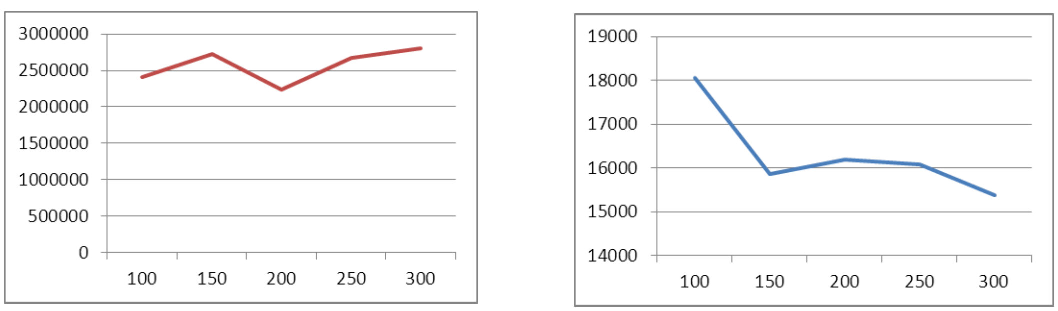

Fig. 7 . Parameter POP SIZE

6 . Conclusion

This paper considers the machine–tool selection and operation allocation problem and exhibits the effectiveness of the MOSA algorithm to address the same. The objective taken into account are to determine the optimal combinations for the machine and tool for operations keeping in mind the minimization of various costs; namely, machining cost, set-up cost ,part transportation cost between machines , tools handling cost and average machines idle time . The constraint posed by the system are pertaining to tool life, tool magazine capacity and machining time. The proposed model is optimized by MOSA algorithm. Some of the salient features of this work can be enlisted as follows:

1. This paper applies the concept of Multi objective to address problems close to real-life industrial scenarios.
2. The application of meta – heuristic proves be better than integer programming formulation in terms of solution quality for the real-life problems of large size.
3. The parameters for the MOSA-based approach have been selected in a manner that computational time and solution quality may remain optimal.

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