International Journal of Applied Science and Engineering
2014. 12, 1: 75-86

A New Multi-Objective Optimization of Master Production Scheduling Problems Using Differential Evolution

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Abstract: Master Production Schedule (MPS) plays an important role in the specifications of optimization levels of resources for production. MPS describes what is to be produced and also refers to the time in which the production is scheduled to be completed. The creation of MPS becomes complex when objectives like maximization of service level, resource utilization and minimization of inventory levels, overtime, chance of occurring stock outs, setup times etc. are considered. Such multi objective parameter optimization problems can effectively be solved using the nature inspired population based algorithms. Differential Evolution (DE) is one such most powerful parameter optimization algorithm, which doesn't require many control parameters. This work proposes a new Multi-objective Optimization for MPS using Differential Evolution (MOOMDE). The MOOMDE is applied to a benchmark problem and the results demonstrate that the use of DE yields the most optimal solution for MPS problems.

Keywords: Master production scheduling; multi-objective optimization; differential evolution; mutation schemes.

1. Introduction

Multi Objective Evolutionary Algorithms (MOEA) [1, 2, 3] have attracted a lot of research effort during the last three decades, and they are still one of the hottest research areas in the field of Evolutionary Computations (EC). All evolutionary algorithms share the same basic concepts, but differ in the way they encode the solutions and on the operators they use to create the next generation. Evolutionary algorithms are controlled by several inputs, such as the size of the population, the rates that control how often mutation and crossover are used etc. In general, there is no guarantee that any evolutionary algorithm will find the optimal solution to an arbitrary problem, but a careful manipulation of the inputs and choosing a representation that is adequate to the problem increase the chances of success [4].

As the current problem is a multi-objective, linear constrained optimization problem, Differential evolution (DE) which is one of the most powerful stochastic real-parameter optimization algorithms, is applied in the present work. DE [5, 6] emerged as a simple and efficient scheme for global optimization over continuous spaces more than a decade ago. DE operates through similar computational steps as employed by a standard evolutionist application

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Received 17 April 2013
Revised 17 December 2013
Accepted 20 December 2013

to multi-objective, constrained, large scale, and uncertain optimization problems [7]. Master Production Schedule (MPS) facilitates us to perceive what is needed, anticipating changes as well as potential shortages or surpluses that may possibly have a negative impact on any phase of an enterprise. Few works reported in the literature based on the type of MPS environment can be summarized as follows.

Yi wu et al [8] analyzed the characteristics of production line with both assembly and processing. The work proposed a new production planning method using GA, compared the proposed GA with a pseudo heuristic. But, Earlier to the work of James A Hill et al [9] changeovers are assumed to be either negligible or sequence independent. A make to stock process industry environment is considered. Hill et al have shown that manufacturing performance can be improved by adjusting the timing of production orders and sequence dependent process.

Tadeusz Sawik [10] applied simple mixed integer programs to find the optimal value of the maximum earliness and has shown the way to optimize long-term production schedules. in make-to-order manufacturing. The work of E. Powell Robinson Jr et al [11] considered MPS policy design in a two-stage rolling schedule environment with a particular focus on the policy governing schedule flexibility in the non-frozen time interval. G. I. Zobolas et al [12] have shown that when demand exceeds available resource capacity, Rough Cut Capacity Planning (RCCP) extended by positive lead times can be used as an intermediate tool to determine resource utilization. Chee-Chong Teo [13] proposed a non-linear optimization program to find the optimal values of the planning parameters and have suggested incorporation of dynamics of the MPS and its impact on the production flow.

Different researchers have applied various heuristics for obtaining a valid and realistic MPS [23]. Few of these that can be mentioned here are Guilhereme E Vieira et al [14] considered simulated annealing where overcoming the local optimum is the limitation. Guilhereme E Vieira and F. Favaretto [15] proposes a practical heuristic for the MPS creation which strongly impacts final product costs, a decisive measure for being competitive. C.C.Chern, J.S.Hsieh [16] proposed multi-objective master planning algorithm (MOMPA), for a supply chain network with multiple finished products. Though S.k.Chahrsooghi and N.Jafari [17] have shown that TOC fails in the case of encountering multiple constraints. Kamran Rezaie et al [18] used Particle Swarm optimization considering Theory of Constraints approach using through output, operating expenses and inventory as performance measures. Lotfi Gaafar [19] compared GA with the traditional modified silver Meal (MSM) and has shown that the GA performs at its best when the planning horizon is short, whereas the MSM performs at its best when the ratio of the ordering cost to the carrying cost is small which shows that a better GA performance can be obtained by using an adaptive approach.

Marico M Soares et al [20] developed and proposed GA structure for MPS and a software based on C++ programming language and objective oriented modeling is also tested. The proposed GA presented low levels of ending inventory efficiently met and had a very little need for overtime. But this does not guarantee optimality. According to Chee-Chong Teo et al [21] one of the options to complete the production in-time is to increase the planned lead time to buffer against uncertainty in lead time which may lead to a longer delivery lead time and thus obtain production smoothing. Zhengjia Wu et al [22] proposed an ant colony algorithm that assured high efficient production, but only two objectives have been considered.

From the brief review of the relevant literature, one can make out that, but for the works of [14, 20] and [23] none considered the creation of MPS with conflicting objectives, such as maximization of service levels, efficient use of resources and minimization of inventory levels.

This study attempts to develop more recent and efficient methodology in solving MPS problems with the said conflicting objectives. The work presents the development and use of Differential Evolution (DE) to MPS problems, something that does not seem to have been done so far.

The rest of the paper is organized as follows: the next section reviews mathematical modeling of parameters involved in the MPS creation, along with the constraints. Section 3 proposes a DE based solution for the MPS problem along with the procedural steps of its creation. Section 4 illustrates the benchmark manufacturing problem. Important results and discussions are given in the section 5. The last section presents conclusions and suggestions for future researches in this area.

2. Mathematical model

The present mps problem is to find optimal values for number of units of the product to be produced for a resource in a given time period, by minimizing Inventory levels, safety stock and requirements not met. The master Production schedule problem can be mathematically modeled as a mixed integer problem as follows [20]:

Minimize:

$$Z = c_1 AIL + c_2 RNM + c_3 BSS + c_4 OC \tag{1}$$

where,

$$AIL = \sum_{k=1}^{K} \left(\frac{\sum_{p=1}^{P} AIL_{kp}}{TH} \right) \tag{2}$$

$$RNM = \frac{\sum_{k=1}^{K} \sum_{p=1}^{P} RNM_{kp}}{TH} \tag{3}$$

$$BSS = \frac{\sum_{k=1}^{K} \sum_{p=1}^{P} BSS_{kp}}{TH} \tag{4}$$

$$OC = \sum_{r=1}^{R} \sum_{p=1}^{P} OC_{rp} \tag{5}$$

$$TH = \sum_{r=1}^{P} TH_p \tag{6}$$

$$BI_{kp} = \begin{cases} OH_k se(p=1) \\ EI_{k(p-1)} se(p>1) \end{cases} \tag{7}$$

$$EI_{kp} = max[0,((MPS_{kp} + BI_{kp}) - GR_{kp})] \tag{8}$$

$$MPST_{kp} = \sum_{r=1}^{R} MPS_{kpr} \tag{9}$$

$$MPS_{kpr} = BN_{kpr} \times BS_{kpr} \tag{10}$$

$$RNM_{kp} = max[0,(GR_{kp} - (MPST_{kp} + BI_{kp}))] \tag{11}$$

$$BSS_{kp} = max[0,(SS_{kp} - EI_{kp})] \tag{12}$$

$$CUH_{rp} = \sum_{k=1}^{K} \frac{(BS_{kp} \times BN_{kp})}{UR_{kr}} \tag{13}$$

$$CUH_{rp} \leq AC_{rp} \tag{14}$$

$$OC_{rp} = max\left[0, \left(\frac{CUH_{rp}}{AC_{rp}} - 1\right)\right] \tag{15}$$

3. Multi-objective optimization for MPS using differential evolution (MOOMDE)

DE is a real valued parameter optimization technique which can be used to solve a kind of objective function using specific mutation and cross over schemes. DE attracted many researchers with its simplicity and improved efficiency compared to other optimization algorithms. Unlike other evolutionary algorithms, DE uses very limited number of control parameters namely the mutation rate and the cross over rate which have a negligible impact on the output solution.

3.1. Chromosome representation

The proposed MOOMDE population contains several chromosomes. Each chromosome is in three dimensions to represent the individual solution. The conceptual model of the chromosome for the MOOMDE for a scenario with products, resources, and periods is shown in the Figure 1 (b). An example of a chromosome is given in Figure 1 (a). A set of genes makes a chromosome, which represents the distribution of quantities to be made at the various available resources for a given product at a specific time period. A set of chromosomes composing the chromosome group represents the total distribution of quantities to be made of all the products at every resource, in a given time period.

That is, if Z is a chromosome, then Z(i, j, k) is the value of number of units of i^{th} product for j^{th} resource at k^{th} period.

3.2. The fitness function

MPS problem is posed as a multi-objective optimization problem. For the optimization of the selected parameters, the following multi-objective criteria is selected as the fitness function

$$fitness = \left[\frac{1}{1 + Z_n}\right] \tag{16}$$

where

$$Z_n = c_1 \frac{AIL}{AIL_{max}} + c_2 \frac{RNM}{RNM_{max}} + c_3 \frac{BSS}{BSS_{max}} + c_4 OC \tag{17}$$

EI_{max}, RNM_{max}, and BSS_{max}, are the biggest values found during ‘warm-up’ from the initial population created. Unit values are used for the fitness coefficients c_1, c_2, c_3 and c_4-which indicate equal importance among the objectives to be minimized.

The new MOOMDE is to find optimal production values for the selected scenario. Equation (16) is selected as fitness function. The algorithm is as follows.

Step 1. Initialize each chromosome, Z_i, to contain random values ranging from zero to the maximum Gross Requirement (GR) for the given time period. These values always respect the standard batch (lot) size restriction (i.e., they are always multiples of the standard lot size).

Step 2. For $t = 1$ to $t_{\max}$ do

a) Evaluate each chromosome or candidate solution quality using fitness function.

b) Find new off springs by applying the following mutation formula.

$$U_k\ (t+1) = Z_m\ (t) + F * (Z_i(t) - Z_j(t)) \tag{18}$$

where F, is mutation factor in the range [0, 1]. Mutation operation on selected MPS problem chromosomes is described in detail in Figure 1 (c).

c) Apply crossover operation according to the following equation

$$U_k(t+1) = \begin{cases} U_k(t), & if\ \ rand\ \ (0,1) < CR \\ Z_k\ (t), & otherwise \end{cases} \tag{19}$$

where rand is a random value between value 0 and 1. Application on MPS chromosome is presented in Figure 2.

d) Apply selection using

$$Z_k(t+1) = \begin{cases} U_k(t+1), & if\ \ f(U_k(t+1)) > f(Z_k(t)) \\ Z_k(t), & if\ \ f(U_k(t+1)) < f(Z_k(t)) \end{cases} \tag{20}$$

Step 3. Report the final solution obtained by the globally best learner (one yielding the lowest value of the fitness function) at time $t = t_{\max}$.

4. MPS problem considered

To study the applicability and to evaluate the relative performance of the proposed MOOMDE, a manufacturing scenario is selected from [20] for the MPS problem as follows.

The scenario is with a planning horizon of 13 periods, four productive resources, and 20 different products. The scenario also considered (a) different period lengths (b) different initial inventory quantity for each product and (c) different safety inventory levels and different standard production lot sizes.

Table 1. Details of scenario

	Periods												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Prod. lot size	10	10	10	10	10	1000	10	100	1000	10	100	100	1000
Safety Stock	300	500	100	300	500	100	300	500	100	300	500	300	500
No.of Hours	8	8	8	8	40	40	160	160	160	160	160	160	160

Table 2. Production rate (units/hour) for scenario

Products	Resources			
	Resource1	Resource2	Resource3	Resouce4
Product1	100	120	140	0
Product2	100	0	140	0
Product3	120	0	0	100
Product4	0	100	140	100
Product5	120	80	120	0
Product6	120	0	100	0
Product7	120	0	0	100
Product8	0	100	140	100
Product9	120	80	100	0
Product10	100	0	140	0
Product11	100	120	140	0
Product12	100	0	140	0
Product13	120	0	0	100
Product14	0	100	140	100
Product15	120	80	120	0
Product16	120	0	100	0
Product17	120	0	0	100
Product18	0	100	140	100
Product19	120	80	100	0
Product20	100	0	140	0

Table 3. Initial inventory and gross requirements for scenario

Products	Init. Inventory	Gross Requirements												
		Periods												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Product1	100	150	70	70	130	70	600	11400	700	7000	14000	700	7000	14000
Product2	0	70	50	70	60	40	700	700	400	7000	7000	400	7000	7000
Product3	300	70	100	0	70	100	0	600	1000	0	6000	1000	0	6000
Product4	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product5	100	150	70	70	150	60	700	400	2000	6000	14000	600	6000	14000
Product6	0	70	50	70	70	40	600	700	400	7000	7000	400	7000	7000
Product7	300	70	100	0	60	100	0	600	1000	0	6000	1000	0	6000
Product8	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product9	100	100	50	60	140	70	600	1400	700	7000	14000	700	7000	14000
Product10	50	60	40	70	60	40	700	700	400	7000	6000	400	7000	6000
Product11	100	150	70	70	130	70	600	1400	700	7000	14000	700	7000	14000
Product12	0	70	50	70	60	40	700	700	400	7000	7000	400	7000	7000
Product13	300	70	100	0	70	100	0	600	1000	0	6000	1000	0	6000
Product14	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product15	100	150	70	70	150	60	700	400	2000	6000	14000	600	6000	14000
Product16	0	70	50	70	70	40	600	700	400	7000	7000	400	7000	7000
Product17	300	70	100	0	60	100	0	600	1000	0	6000	1000	0	6000
Product18	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product19	100	100	50	60	140	70	600	1400	700	7000	14000	700	7000	14000
Product20	50	60	40	70	60	40	700	700	400	7000	6000	400	7000	6000

Chromosome X1, with 2 products , 2 resources and 2 periods

X1(1,:,:) =

50	15	200
150	40	90

X1(2,:,:) =

100	50	10
20	10	0

Figure 1. (a)

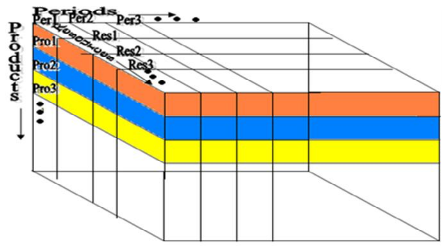

Figure 1. (b) Structure of the chromosome

Mutation using X1, X2, X3 candidate solutions or chromosomes

X1

X1(1,:,:) =

50	15	200
150	40	90

X1(2,:,:) =

100	50	10
20	10	0

X2

X2(1,:,:) =

50	150	20
10	50	90

X2(2,:,:) =

10	25	10
20	100	0

X3

X3(1,:,:) =

5	10	20
100	30	9

X3(2,:,:) =

110	2	100
30	10	20

Let V=X1+rand*(X2-X3) , Assume rand value is 0.4

V(1,1,:)=X1(1,1,:)+0.4*(X2(1,1, :)-X3(1,1,:)

V(1,1,:)= [50 15 200] + 0.4 * ([50 150 20] -- [5 10 20])

V(1,1,:)= [50 15 200] + 0.4 * ([45 140 0])

V(1,1,:)= [50 15 200] + [18 56 0]

V(1,1,:)= [68 71 200] , similarly V(1,2,:) and V(2,:,:), then V is

V

V(1,:,:) =

68	71	200
114	48	1124

V(2,:,:) =

60	59.2	-26
20	10	0

Figure 1. (c)

Mutation for X1 with trial solution V, for the assumed Cr=0.6 , is as follows:

Assume the 6 rand values in sequence are 0.4, 0.9, 0.3, 0.8, 0.71, 0.1 then target solution contains either X1 (if rand is <=Cr) or V (if rand < Cr)values. The sample first product is as follows

68	15	200
150	40	1124

Figure 1. (d)

Figures 1. Creation of chromosome and its application to mps using mutation

5. Results and discussion

The applicability of the proposed MOOMDE was tested on the manufacturing scenario considered. The plot on Figure 2 shows the variations of fitness evolution in all the 50 independent runs. The best fitness value 0.86791 is obtained in the 32nd run and the worst fitness value 0.86683 is obtained in the 46th run. The fitness is increased by nearly 20% to that when done with GA and the average number of iterations taken for the convergence is 4.

For further analysis, two cases are considered by varying the weights allotted to the performance measures. This also gives a chance of knowing as to which measure greatly influences the fitness value. In case 1, more weight is assigned to RNM (ie trying to provide more efficient service level) and in case2, more weight is assigned to the EI levels.

Results in Table 4 shows that the improvement of achievement level in one objective must be balanced with poor performance on other objectives, which reminds us of the conflicting objectives in the creation of MPS. Figure 3 shows the comparison of the fitness values obtained in the three cases considered.ie, with equal weights and that with the two cases (unequal weights).

When equal weights are given to the performance measures, although the MOOMDE have produced more levels of EI when compared to that with MPSGA, it could produce low levels when more weights are assigned. In case1, the improvement of EI over MPSGA is 12.1% and that in case2 is 29.1%. This could be achieved with better RNM levels (51.2% and 14.6% respectively) and a much better fitness (almost 42% improvement in both the cases)

As there isn't much change in the levels of BSS obtained, we can conclude that the value of fitness is greatly affected by the RNM & EI values. The average values obtained in line with the existing values are shown in the Figures 4 and 5. The best master production schedule found with respect to the 4 resources, 13 periods for all the 20 products along with the total mps (TT. MPS) for each product is shown in the Table 5.

The work showed that master plan created with MOOMDE presented low levels of ending inventory; low levels of requirements not met and efficiently met safety inventory levels. Also, the results show that DE approach gives a better result when compared to the existing work with GE. Table 6 shows the improvisation of the various parameters obtained through MOOMDE with those of MPS GA [20].

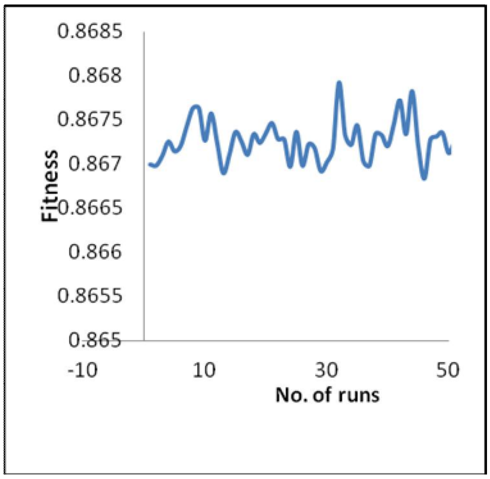

Figure 2. Evolution of fitness values

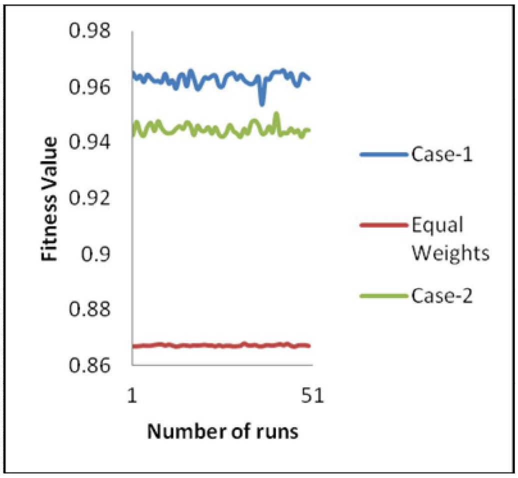

Figure 3. Comparison of fitness values

Table 4. Comparison between the average values of performance indicators

	MPS GA	MOOMDE		
		Equal weights	Case1	Case2
FITNESS	0.6679	0.867259	0.96276	0.94473
EI (units/hour)	4555.08	5363.246	4005.49	3227.7
RNM (units/hour)	321.42	200.2308	156.94	274.4
BSS (units/hour)	37.03	12.53789	6.25	7.88

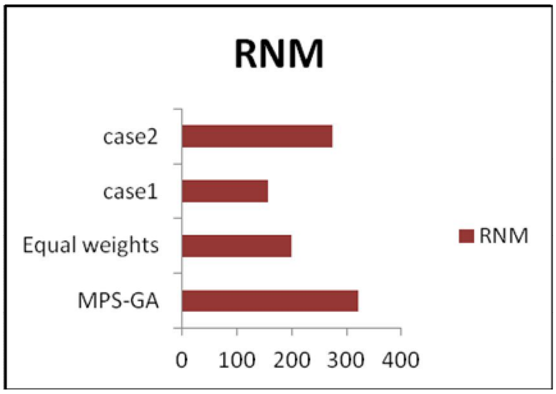

Figure 4. Comparison of RNM values

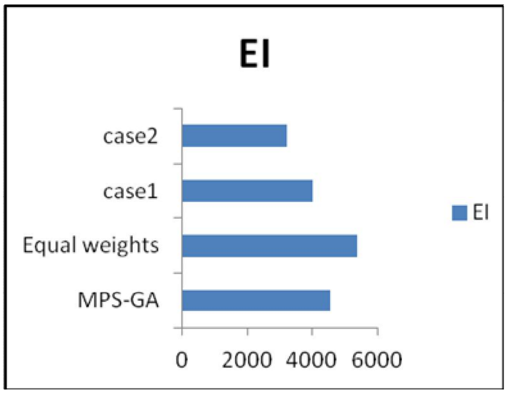

Figure 5. Comparison of EI values

Table 5. Best mps obtained

	Resources	Periods											
		1	2	3	4	5	6	7	8	9	10	11	12	13
Product1	Res1	20	40	20	30	20	0	3480	200	2000	3500	200	1700	2000
	Res2	40	0	0	30	0	0	3480	200	1000	3500	200	1700	4000
	Res3	50	10	20	30	20	0	950	200	2000	3500	100	1800	3000
	Res4	40	20	30	40	30	0	3490	100	2000	3500	200	1800	5000
	TT. MPS	150	70	70	130	70	0	11400	700	7000	14000	700	7000	14000
Product2	Res1	20	10	10	10	10	0	60	100	2000	1750	100	1800	2000
	Res2	0	0	20	10	10	0	20	100	2000	1750	100	1400	2000
	Res3	10	30	20	20	10	0	40	100	1000	1750	200	1900	1000
	Res4	40	10	20	20	10	0	580	100	2000	1750	0	1900	2000
	TT. MPS	70	50	70	60	40	0	700	400	7000	7000	400	7000	7000
(For conciseness, MPS for products 3 thru 18 are not shown)														
Product19	Res1	30	10	10	40	30	0	550	200	2000	2160	200	500	5000
	Res2	30	10	10	40	0	0	440	0	2000	3940	0	2100	1000
	Res3	40	20	20	40	10	0	10	300	1000	3950	200	2200	2000
	Res4	0	10	20	20	30	0	180	200	2000	3950	300	2200	6000
	TT. MPS	100	50	60	140	70	0	1180	700	7000	14000	700	7000	14000
Product20	Res1	20	0	10	10	10	0	210	100	3000	1500	100	1900	2000
	Res2	20	20	20	10	10	0	210	200	1000	1500	100	2000	1000
	Res3	20	20	20	20	10	0	220	0	3000	1500	100	2000	0
	Res4	0	0	20	20	10	0	60	100	0	1500	100	1100	3000
	TT. MPS	60	40	70	60	40	0	700	400	7000	6000	400	7000	6000

Table 6. Improvement of performance indicators

Performance Measure	%Improvement over MPS GA		
	EQUAL WEIGHTS	CASE-1	CASE-2
FITNESS	29.85	44.1	41.4
EI (units/hour)	17.7 (decline)	12.1	29.1
RNM (units/hour)	37.7	51.1	14.6
BSS (units/hour)	66.1	83.1	78.7

6. Conclusions and future scope

Optimization [24] is the process of obtaining the best outcome under a given set of circumstances. Business decisions are made ultimately by maximizing/minimizing a goal while also balancing, or controlling the use of, limited resources and meeting zero or more constraints. The size and complexity of optimization problems that can be solved in a reasonable time has been advanced by the advent of modern computing technologies. Master scheduling calculates the quantity required to meet demand requirements from all sources. A good MPS enables the efficient use of resources which in turn paves way for reduced production costs, leading to increased savings in inventory levels and thus contributing to a consistent raise in company's profit margins.

In any production planning, master schedules include only key elements like, inventory and production costs, forecast demand, plant capacity, lead time etc that have proven their control affectivity. The present work considered conflicting objectives, such as maximization of service levels, efficient use of resources and minimization of inventory levels in the creation of MPS. The work proposes a Differential Evolution based multi-objective optimization for MPS problems. The proposed MOOMDE have proved the efficiency of DE in providing solution to MPS problem. Based on fitness function, the algorithm could determine more optimal solutions for the production planning with respect to given scenario. Experimental results demonstrate that the proposed algorithm produced nearly 30% of improved quality than MPS GA in terms of fitness, 37% of improved performance in the case of RNM and 66% of increased efficiency with respect to BSS.

Experimental results are conducted further to study the impact of the EI, RNM and BSS on the fitness function by assigning different weights. From the results, one can figure out that the EI and RNM are the highly influencing parameter which is true in practice too. Much more reduced levels of EI and RNM could be achieved by assigning more weightage to them. The best value for fitness function is observed when more weightage is given to RNM, which is the first preferred parameter in real world. Thus the results meet the real world preferences also. Application of the proposed MOOMDE in a larger production scenario and testing its validity to an industry will be our upcoming work.

7. Nomenclature used

AC_{rp}	Available capacity, in hours, at the resource is at period p
AIL_{kp}	average inventory level generated for product k at period p
BI_{kp}	Initial inventory level of the product k at period p
BN_{kpr}	Quantity of standard lot sizes needed for the production of the product k at resource r, at period p
BS_{kp}	Standard lot size for product k at period p
CUH_{rp}	Capacity used from the resource r at period p
CUP_{rp}	Percent rate obtained from the relation of the number of hours consumed from the resource r at the period p, and the available number of hours to the same resource and period
GR_{kp}	Gross requirements for product k at period p
K	Total quantity of different products (SKU)
MPS_{kpr}	Total quantity to be manufactured of the product k at resource r, at period p

$MPST_{kp}$	Total quantity to be manufactured of the product k at resource r, at period p; (considering all available resources r)
NR_{kp}	Net requirements for product k at period p, considering infinite capacity
OH_k	Initial available inventory (on-hand), at the first scheduling period
P	Total number of planning periods
R	Total quantity of different productive resources
RM_{kp}	Total requirements met for product k at period p
RM_{kpr}	Total requirements met for product k at period p, at resource r
RNM_{kp}	Requirements not met for product k at period p
SL_{kp}	Service level, the relation of the requirements met
SS_{kp}	Safety inventory level for product k at period p
TH	Total planning horizon
TH_p	Available time at each period p
UR_{kr}	Production rate for product k at resource r (units per hour)

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