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A Differential Evolution based Optimization for Master Production Scheduling Problems

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Abstract

Heuristic evolutionary optimization algorithms are the solutions to many engineering optimization problems. Differential evolution (DE) is a real stochastic evolutionary parameter optimization in current use.DE does not require more control parameters compared to other evolutionary algorithms. Master Production Scheduling (MPS) is posed as one of multi objective parameter optimization problems and often require an optimal solution for the success of a business organization by balancing demand and supply. This work reviews some of the fundamental theory of differential evolution, the methodology for master production scheduling calculation and most important results. The results available for the existing algorithms are compared with results obtained by the proposed evolutionary algorithm. The analysis reveals that the DE algorithm provides a better solution with reasonable computational time.

Keywords: *Master Production Schedule, Multi-objective Optimization, Differential Evolution*

1. Introduction

The current problem is a multi-objective nonlinear constrained optimization problem. The difficulty in optimization of engineering problems causes various optimization solutions. As a solution to these problems several heuristic algorithms have been developed for optimization of parameters. Among these one important group is evolutionary algorithms (EA) [16]. Genetic Algorithms (GA), Evolution Strategy (ES), Evolutionary Programming (EP) and Differential Evolution (DE) are some of the evolutionary algorithms. The most commonly used evolutionary optimization technique is the Genetic Algorithm (GA). Though, the GA provides a near optimal solution for complex problems, it requires a number of parameters in advance such as population size, crossover rate and mutation rate, which affect the effectiveness of the solution. Determining the optimum values for these controlling parameters is very difficult in practice [20]. Differential evolution (DE) is one of the most powerful stochastic real-parameter optimization algorithms in current use [6-8]. DE follows similar computational steps as in a standard evolutionary algorithm. Compared to other Evolutionary Algorithms DE is very simple to code. The recent studies on DE have shown that DE provides a better performance in terms of accuracy, robustness and convergence speed with its simplicity [9-11]. The number of control parameters in DE is very few compared to other algorithms [20].

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Master production scheduling has been extensively investigated over the last three decades and it continues to attract the interest of both the academic and industrial sectors. MPS is the declaration of what the company expects to manufacture in terms of configuration, quantities and specific dates that drives Materials Requirement Planning (MRP) and other subsequent activities of a manufacturing company [1]. Master Production Schedule 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. The master plan which is often mistaken as a sales forecast, along with the pending orders, availabilities of material and capacity, managerial policies and goals turns out as one of the most important information for the system.

The MPS acts as an instrument in the hands of top management in controlling over manufacture resources and becomes the input of the downstream planning levels such as Material Requirement Planning (MRP) and Capacity Requirement Planning (CRP). Hence, inappropriate decision on the MPS development may lead to infeasible execution, which ultimately causes poor delivery performance. One must ensure that the proposed MPS is valid and realistic for implementation before it is released to real manufacturing system [2]. In practice, where production environment is stochastic in nature, the development of the MPS is no longer a simple task. The MPS creation problem becomes even more sophisticated as decision makers try to consider multi-objectives; minimizing inventory, maximizing customer satisfaction and maximizing resource utilization.

In the present work, as in most industries worldwide, the creation of an MPS considers conflicting objectives, such as maximization of service levels, efficient use of resources and minimization of inventory levels. 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 present research illustrates that the use of differential evolution is a viable technique for MPS problems. However, its applicability is still heavily dependent on the size of the manufacturing scenario. As said by Higgins [3], Slack *et al.*, [4] and Tubino [5], the most important activity in any production planning and control of production is the master production schedule (MPS). From the literature one can figure out that a company's succession and malfunction of performance are apparently based on its master plan as it coordinates market demand with the internal resources of the company. The master plan whose creation depends on the management philosophy acts as a connection between the strategic planning and production scheduling. Just in time (JIT) and theory of constraints (TOC) are the two popular philosophies usually adopted [12]. Gaither and Fraizer [13] have portrayed the master production schedule process in a JIT environment at the Japanese Toyota car manufacturer. The company which adopts the TOC philosophy, should create the MPS concentrating on the final products that use the bottle neck resources and later on their components Spencer and Cox [1].

Pertaining to these issues, several studies have suggested an authentication process to check the validity of tentative MPS. Higgins *et al.*, [14] in order to ascertain an optimum and a realistic MPS have anticipated a simulation analysis to get executed on the tentative MPS. Kochhar *et al.*, [15] have introduced a knowledge-based system approach, which combines human proficiency with computer computation, to attain an accurate and realistic master schedule. Heizer *et al.*, [17] pooled a proposal about the iterative planning process that permits a planner to ensure the validity of each planning process.

In addition to the substitution of the verification process, researchers also employ various advanced optimization techniques in order to enhance MPS quality. For instance, Vieira *et al.*, [18] applied simulated annealing to solve MPS problem and the work reveals some drawbacks of simulated annealing such as overcoming local optimum. Soares *et al.*, [19] introduced new genetic algorithm structure for solving MPS problem and formulates the fitness function which aims to minimize inventory levels, maximize service level, minimize overtime and minimize inventory level below safety stock. At the end, Vieira *et al.*, [21] has compared genetic algorithms and simulated annealing for master production scheduling problems.

The next section describes how differential evolution can be used to solve the MPS problems.

2. Multi-objective optimization for MPS using differential evolution (MOMDE)

This section provides a solution for MPS problem using DE by proposing a three dimensional chromosome representation, criteria for initial population and for termination.

2.1. Chromosome representation

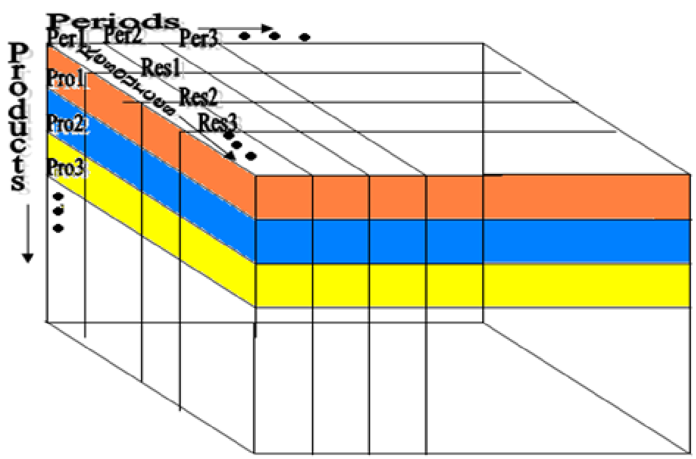

Figure 1. Structure of the Chromosome

The proposed MOMDE population contains several chromosomes. Each chromosome is in three dimensions to represent the individual solution. The conceptual model of the chromosome for the MOMDE for a scenario with products, resources, and periods is in the Figure 1. 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.

2.2. Basics of differential evolution

All evolutionary algorithms aim to improve the existing solution using the techniques of mutation, recombination and selection. The general paradigm is as follows:

2.2.1. Initialization: Creation of a population of individuals. The *i*th individual vector (chromosome) of the population at current generation t with d dimensions is as follows,

$$Z_i(t) = [Z_{i,1}(t), Z_{i,2}(t), \ldots, Z_{i,d}(t)] \qquad \text{---- (1)}$$

2.2.2. Mutation: A random change of the vector $\vec{x}$ components. It can be a single-point mutation, inversion, translocation, deletion, *etc.*

For each individual vector $Z_k(t)$ that belongs to the current population, a new individual, called the mutant individual is derived through the combination of randomly selected and pre-specified individuals.

$$U_{k,n}(t) = Z_{m,n}(t) + F * (Z_{i,n}(t) - Z_{j,n}(t)) \qquad \text{---- (2)}$$

the indices m, n, i, j are uniformly random integers mutually different and distinct from the current index k, and F > 0 is a real positive parameter, called mutation or scaling factor (usually€[0, 1])

2.2.3. Recombination (Crossover): merging the genetic information of two or more parent individuals for producing one or more descendants.

DE has two crossover schemes: the exponential and the binomial or uniform crossover. We have used the binomial crossover in this paper. The binomial or uniform crossover is performed on each component n (n= 1, 2, . . . , d) of the mutant individual $U_{k,n}(t)$. For each component a random number r in the interval [0, 1] is drawn and compared with the crossover rate or recombination factor (another DE control parameter), CR € [0, 1]. If r <=CR, then the n^{th} component of the mutant individual $U_{k,n}(t)$ will be selected, Otherwise, the nth component of the target vector $Z_{k,n}(t)$ becomes the nth component of the trial vector.

$$U_k,n(t + 1) = \begin{cases} Uk,n(t), \text{ if randn}(0, 1) < Cr \\ Zk,n(t), \text{ otherwise.} \end{cases} \qquad \text{-------------(3)}$$

2.2.4. Selection: choice of the best individuals for the next cycle.

If the new offspring yields a better value of the objective function, it replaces its parent in the next generation; otherwise, the parent is retained in the population, *i.e.*,

$$Z_k(t + 1) = \begin{cases} U_k(t + 1), \text{ if } f(U_k(t + 1)) > f(Z_k(t)) \\ Z_k(t), \text{ if } f(U_k(t + 1)) < f(Z_k(t)) \end{cases} \qquad \text{-------------(4)}$$

where f(·) is the objective function to be minimized.

2.3. Initial population criteria

In MOMDE the population individuals are filled up randomly, with values ranging from zero to the maximum Gross Requirement (GR) for the time period. These values always respect the standard batch (lot) size restriction (*i.e.*, they are always multiples of the standard lot size).

2.4. The stopping criteria

The stopping criteria in the present work is “Stop by convergence or stagnation”. The convergence of the algorithm is based on the fitness value of the fittest individual. The difference of fitness value of fittest individuals in any two successive generations is less than 0.0001, is the stopping criteria.

3. 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 (*Soares et al., 2008*)

$$fitness = \left[\frac{1}{1+Z_n}\right] --- (5)$$

Where $$Z_n = c_1 \frac{AIL}{AIL_{\max}} + c_2 \frac{RNM}{RNM_{\max}} + c_3 \frac{BSS}{BSS_{\max}} + c_4 OC -- (6)$$

EI_{max}, RNM_{max}, and BSS_{max}, are the biggest values found 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. Master Production schedule problem can be mathematically modeled as a mixed integer problem as follows [19]:

Minimize: $$Z = c_1 AIL + c_2 RNM + c_3 BSS + c_4 OC --- (7)$$

The constraints and the nomenclature used are taken from [19]. The subsequent section demonstrates the applicability of DE in finding a master schedule plan for a production scenario.

4. MPS problem considered

A manufacturing scenario is selected from *Soares et al.*, [19] to study the applicability of Differential Evolution algorithm 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

5. Results and discussion

The applicability of the proposed MOMDE was tested on the manufacturing scenario considered. The plot on figure2 shows the variations of fitness evolution in all the 50 independent runs. The best fitness value 0.867919601 is obtained in the 32nd run and the worst fitness value 0.866834744 is obtained in the 46 th 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.

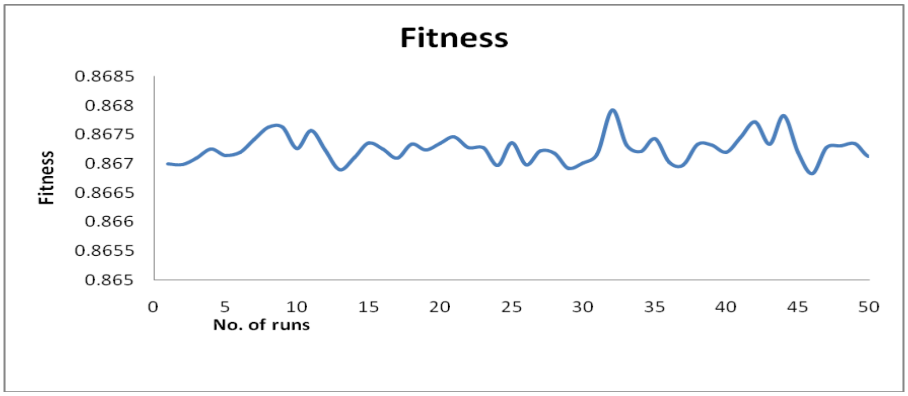

Figure 2. Evolution of fitness values

The best master production schedule found with respect to the 4 resources, 13 periods for all the 20 products along with the total MPS for each product is shown in the Table 1.

Table 1. 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

Figure 3 shows the evolution of the normalized performance measures considered in the multi objective fitness function which include: average ending inventory (EI), requirements not met (RNM), and inventory below safety stock (BSS).

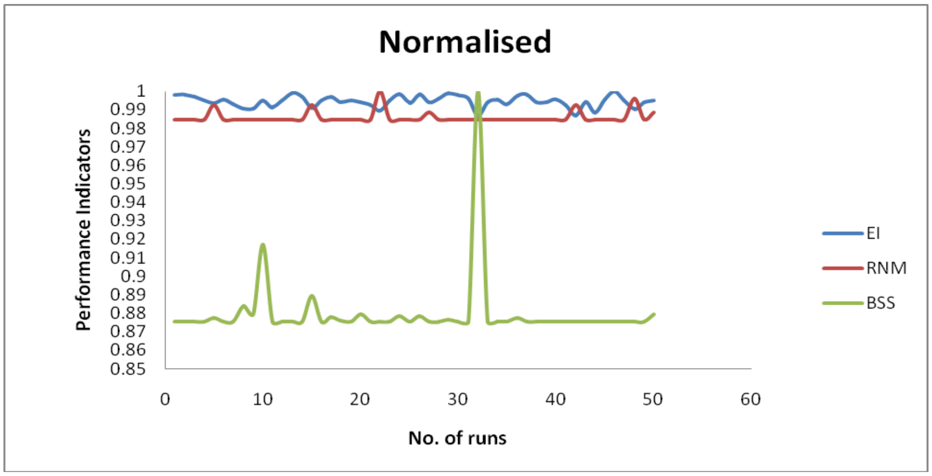

Figure 3. Normalized performance indicators in terms of number of runs

This work showed that master plan created with MOMDE presented low levels of ending inventory, low levels of requirements not met and efficiently met safety inventory levels. Also, the results show that the DE approach gives a better result when compared to the existing work with GE. Table 2 shows the comparison of the various parameters obtained through MOMDE with those of MPS GA [19].

Table 2. Comparison between the values of performance indicators

	GA	DE
Fitness	0.6679	0.867259
EI (units/hour)	4555.08	5363.246
RNM (units/hour)	321.42	200.2308
BSS (units/hour)	37.03	12.53789

6. Conclusions and Future Scope

The complexity of parameter optimization problems increases with the increase in the number of parameters. The present MOMDE model is useful for future research, to generate a more advanced model for improved reliability in MPS. The results demonstrate that the MOMDE produce more optimal values compared to GA. Application of the proposed MOMDE in a larger production scenario and testing its validity to an industry will be our upcoming work. Also Incorporation of self adaptation of parameters for DE for improved reliability is our future endeavor. Defining a more suitable fitness function by considering different weights to the coefficients and their influence may be analyzed.

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