

A selective survey on multi-objective meta-heuristic methods for optimization of master production scheduling using evolutionary approaches

Review Article

Radhika Sajja^{1*}, Srinivasa Rao Chalamalasetti²

¹Department of Mechanical Engineering, R. V. R. & J. C. College of Engineering, Guntur, AP, India

²Department of Mechanical Engineering, Andhra University, Andhra Pradesh, India

Received 24 November 2013; accepted (in revised version) 21 February 2014

Abstract: Evolutionary approach based meta-heuristics have gained prominence in recent years for solving multi objective optimization problems (MOP). Multi Objective Evolutionary Approaches (MOEA) has substantial success across a variety of real-world engineering applications. Master Production Scheduling (MPS) is a plan that determines optimal values of products to be produced. As an MPS can effectively and efficiently synchronize the operations in any organization, it can be posed as one of multi objective parameter optimization problems. The present selective survey attempts to provide a general overview of the work that has been done in the last two decades in MOEAs in line with Master Production Scheduling problems.

MSC: MSC 2010 codes: 68M20,90B05,90B30,90C31

Keywords: Master Production Scheduling, Multi Objective Optimization, Evolutionary Algorithms, Meta-Heuristics

© 2014 IJAAMM all rights reserved.

1. Introduction

Being the highest level of operational production planning in the integrated structure, the Master production scheduling (MPS) model focuses on individual products and deals with weekly production, inventory levels and workforce usage under the constraints of the manufacturing operation. As per the APICS, master production schedule (MPS) is "the anticipated build schedule for those items assigned to the master schedule". The MPS provides a link between planning and actual manufacturing stages by reconciling with the resource constraints. An effective MPS helps in keeping the priorities valid and also allows making promises which can be kept. MPS forms the basis and drives MRP [1]. MPS has been extensively investigated over the last three decades and it continues to attract the interest of both the academic and

* Corresponding author. E-mail: sajjar99@yahoo.com

industrial sectors. The most general OR-optimization methods are mathematical programming formulations [2]. Several mathematical programming models have been developed for solving MPS problems. However, the computational effort required makes such an approach impractical for real-time control in most applications. Recently, as the computation power of available computers has rapidly improved, several meta heuristic approaches based on iterative improvement procedures have been applied to the scheduling problems.

Meta-heuristic techniques comprise a variety of methods including optimization paradigms that are based on evolutionary mechanisms such as biological genetics and natural selections. A meta-heuristic is described as an iterative master process that guides and modifies the operations of subordinate heuristics to efficiently produce high quality solutions. It may manipulate a complete or incomplete, single or a collection of solutions for every iteration. The subordinate heuristics may be high or low level procedures, or a simple local search or just a construction method. The meta-heuristics are not designed specifically for a particular problem but are considered general approaches that can be tuned for any problem.

This survey provides a selective overview that is fully devoted to meta-heuristic evolutionary algorithms for Master Production Scheduling (MPS) problems. The rest of the paper is organized as follows.

Section 2 introduces relevant Multi Objective Evolutionary Algorithms (MOEA) classification scheme along with Pareto Optimality and briefly addresses the basic framework, algorithms, design, recent developments and applications in this field. Section 3 provides a taxonomy that highlights some important aspects in the context of MPS optimization. Section 4 summarizes the survey paper by addressing some important issues of MOEAs and MPS and set most hopeful paths for future research.

2. Multi objective evolutionary algorithms (MOEA)

MOEAs ([3] [4]) 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 ECs. The first generation of MOEA [5] was characterized by use of selection mechanism based on Pareto ranking. Fitness sharing was the most common approach to maintain diversity of the same. The second generation of MOEA can be characterized by an emphasis on efficiency and by the use of elitism [6] which is a technique to preserve and use previously found best solutions in subsequent generations of EA. Maintaining archives of non-dominated solutions is an important issue in elitism EA. The final contents of archive represent usually the result returned by optimization process [7].

While solving optimization problems, single-solution based meta-heuristics improves a single solution in different domains. They could be viewed as walk through neighborhoods or search trajectories through the search space of the problem. The walks are performed by iterative procedures that move from the current solution to another one in the search space. Population based meta-heuristics [8] share the same concepts and viewed as an iterative improvement in a population of solutions. First, the population is initialized. Then, a new population of solutions is generated. Finally, this new population is integrated into the current one using some selection procedures. The search process is stopped

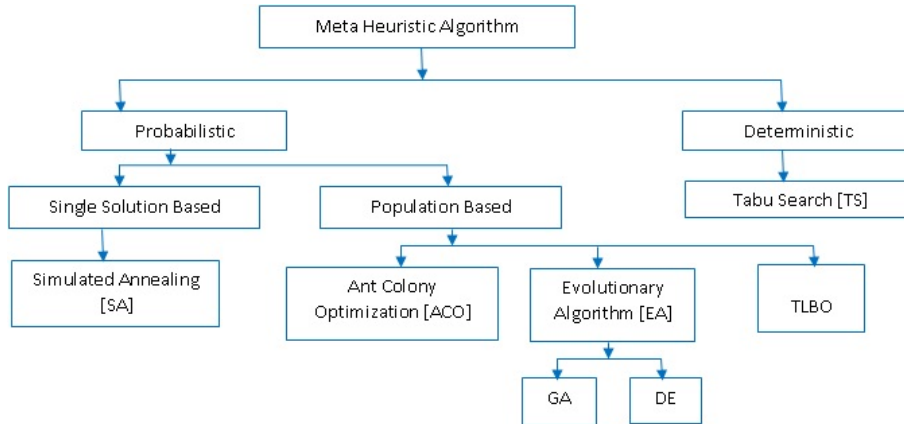


Figure 1. Taxonomy of the meta-heuristic approaches for solving MPS problems

when a given condition is satisfied (stopping criterion).

There are several possible classifications of meta-heuristics but one is commonly used in single solution approaches and population based approaches. Single solution methods are Basic local search, Tabu search, simulated annealing, Variable neighbourhood search and others. Population based methods include Genetic algorithm, Particle swarm optimization, Ant colony optimization, Scatter search, Memetic algorithm etc. Fig. (1) provides the taxonomy frameworks of Multi-objective Meta-heuristics for solving MPS problems so far found in the literature.

2.1. Probabilistic meta-heuristics

This can be further divided into single solution based and population based heuristics. Simulated Annealing(SA) comes under the single solution category and as shown in the Fig. (1), Ant Colony Optimization (ACO), Genetic Algorithms(GA), Differential Evolution (DE) and the recently developed Teaching-Learning based Optimization (TLBO) are all a part of the population based meta-heuristic approaches.

2.1.1. Simulated Annealing (SA)

Simulated annealing (SA) is applied on cell formation problems and is the oldest among meta-heuristic methods. SA was proposed by [9]. It was motivated by simulating the physical process of annealing solids. The process can be described as follows. First, a solid is heated to a high temperature and then cooled slowly so that the system at any time is approximately in thermodynamic equilibrium. At equilibrium, there may be many configurations with each one corresponding to a specific energy level. The chance of accepting a change from the current configuration to a new configuration is related to the difference in energy between the two states. Kirkpatrick et. al. [10] were the first to introduce simulated annealing to optimization problems. Since then, simulated annealing has been widely used in combinatorial optimization problems and has achieved good results on a variety of problem instances. The pseudo code 1 demonstrates the working procedure of SA.

Pseudo code 1: Simulated Annealing (SA)

Step1:	Initialize	
Step2:	Repeat	
Step3:		Generate a candidate solution.
Step4:		Evaluate the candidate.
Step5:		Determine the current solution
Step6:		Reduce the temperature.
Step7:	Until	Termination condition is met.

2.1.2. Ant Colony Optimization (ACO)

The first ACO algorithm appeared in early 90s by Dorigo [11] widely studied meta-heuristic for combinatorial optimization problems. The concept is based on the observation of foraging behavior of ants; when walking on routes from the nest to a source of food, ants seem to find not just a simple random route, but a quite 'good' one, in terms of shortness, or equivalently, in terms of time of travel; thus, their behavior allows them to solve an optimization problem [12]. The pseudo code 2 demonstrates the working procedure of ACO.

Pseudo code 2: Ant Colony Optimization (ACO)

Step1:	Initialize
Step2:	Set I to 0
Step3:	Repeat
Step4:	Generate a feasible solution
Step5:	Evaluate goodness η
Step6:	If $\eta > \eta_{max}$ then
Step7:	Begin update Elite list.
Step8:	Shift the bounds End.
Step9:	If $I \bmod \alpha = 0$ then alter the solution.
Step10:	If $I \bmod \beta = 0$ then intensify elite pheromone traces.
Step11:	Update pheromone trails.
Step12:	Increment I
Step13:	Until $i = \sigma$

2.1.3. Genetic Algorithms (GA)

Genetic algorithms (GA) are randomized search and optimization techniques guided by the principles of evolution and natural genetics, having a large amount of implicit parallelism [13]. GAs perform search in complex, large and multimodal landscapes, and provide near optimal solutions for objective or fitness function of an optimization problem. The canonical GA encodes the problem within binary string individuals. Evolutionary pressure is applied with a stochastic technique of roulette wheel in step 3; parent selection is used to pick parents for the new population. The pseudo code 3

demonstrates the working procedure of GA. While selection is random any individual has the choice to become a parent, selection is clearly biased towards fitted individuals. Parents are not required to be distinctive for any iteration; fit individuals may produce many offspring's the crossover is selected at random and mutation is applied to all individuals in the new population. With probability P_m , each bit on every string is inverted. The new population then becomes the current population and the cycle is repeated until some termination criteria satisfied [14]. The algorithm typically runs for some fixed number of iterations, or until convergence is detected within the population. The probabilities of mutation and crossover, P_m and P_c are parameters of the algorithm and must be set by the user [15].

Pseudo code 3: Genetic Algorithm (GA)

Step1:	A population of \hat{N} random individuals is initialized.
Step2:	Fitness scores are assigned to each individual.
Step3:	Using roulette wheel parent selection $\frac{\mu}{2}$ pairs of parents are chosen From the current population to form a new population.
Step4:	With probability P_c , children are formed by performing crossover on the $\frac{\mu}{2}$ pairs of parents. The children replace the parents in the new population.
Step5:	With probability P_m , mutation is performed on the new population.
Step6:	The new population becomes the current population.
Step7:	If the termination conditions are satisfied exit, otherwise go to step 3.

2.1.4. Differential Evolution (DE)

DE [16] 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 to multiobjective, constrained, large scale, and uncertain optimization problems [17]. They are solved a kind of objective function by twisting and tuning the various constituents of DE, i.e., initialization, mutation, diversity enhancement, and selection of DE as well as by the choice of the control variables etc. The pseudo code 4 demonstrates the working procedure of DE.

Pseudo code 4: Differential Evolution (DE)

Step1:	Begin
Step2:	Generate randomly an initial population of solutions
Step3:	Calculate the fitness of the initial population
Step4:	Repeat
Step5:	For each parent, select three solutions at random
Step6:	Create one offspring using the DE operators
Step7:	Do this a number of times equal to the population size
Step8:	For each member of the next generation
Step9:	If offspring (x) is more fit than parent (x)
Step10:	Parent (x) is replaced
Step11:	Until a stop condition is satisfied
Step12:	End

2.1.5. Teaching Learning Based Optimization (TLBO)

Teaching Learning Based Optimization (TLBO) is an optimized method used to obtain global solutions for continuous non-linear functions with less computational effort and high consistency [18]. The TLBO method works on the philosophy of teaching and learning. The TLBO method is based on the effect of the influence of a teacher on the output of learners in a class. The quality of a teacher affects the outcome of learners. It is obvious that a good teacher trains learners such that they can have better results in terms of their marks or grades. Moreover, learners also learn from interaction among themselves, which also helps in improving their results. Fig. (2) provides the flow chart for the TLBO.

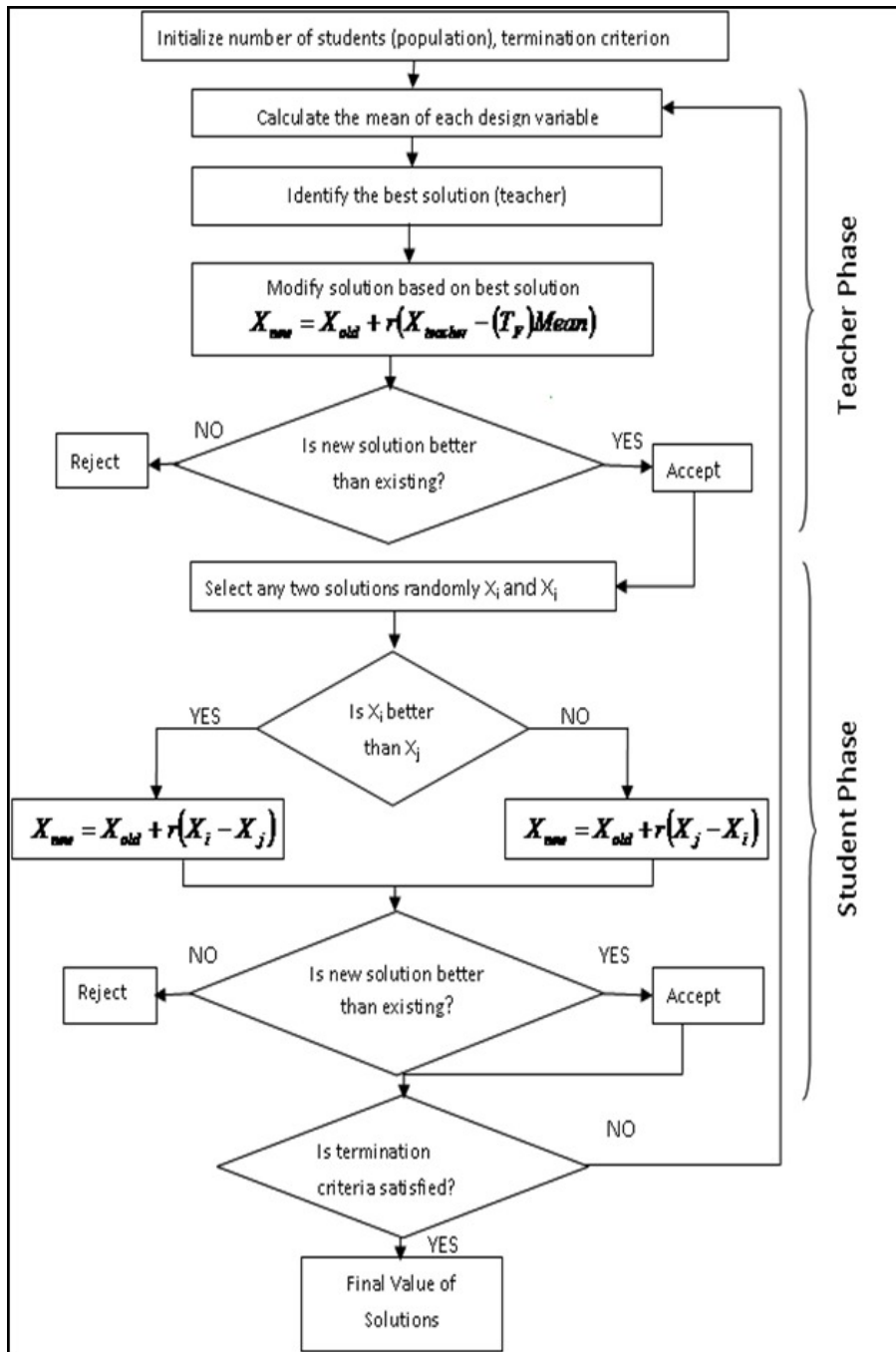


Figure 2. Flow chart for the TLBO

2.2. Tabu Search (TS)

Tabu search [19], also known as Hill Climbing is essentially a sophisticated and improved type of local search, the algorithm works as follows: Consider a starting current solution, evaluate its neighboring solutions based on a given neigh-

neighborhood structure, and set the best or the first found neighbor which is better than the current solution as new current solution and repeat the procedure until an improved solution is detected in the neighborhood of the current solution. The local search stops when the current solution is better than all its neighbors, that is, when the current solution is the local optimum. The pseudo code 5 demonstrates the working procedure of Tabu Search.

Pseudo code 5 : Tabu Search (TS)

Step1:	Initialize
Step2:	Repeat
Step3:	Generate all of the acceptable neighborhood solutions.
Step4:	Evaluate the generated solutions.
Step5:	Choose the best one as the candidate solution
Step6:	If there is no suitable candidate then
Step7:	Choose the best of forbidden solutions as the candidate.
Step8:	Update the tabu list
Step9:	Move to candidate solution
Step10:	If the number of generated solutions are sufficient, diversify
Step11:	Until Termination condition is met.

3. Master Production Scheduling

According to Proud [20], the real challenge of MPS development is to effectively balance product supply with product demand (Fig. 3). The demand can consist of a forecast, customer orders (which may or may not be part of that forecast), contracts or long-term agreements, engineering prototypes, branch warehouse requirements (i.e. replenishing a distribution center), or orders from another division within the company if the product in question is, in turn, a component of that division's product. Demand can also originate in the need for specials (industry shows, sample), service parts or spares, increase in safety stock requirements, or lot sizes. All those demands commonly refer to "Gross Requirement".

Few works in line with the meta-heuristic techniques applied to the mps problems can be briefly summarized as follows: Simulated annealing technique was used by [21]. The work considered four objectives, minimization of inventory costs, costs for not meeting requirements, overtime costs and costs for operating below recommended safety stock levels (all taken to the common scale by normalization). The main advantage of SA is that, unlike the other artificial intelligence techniques which have many parameters to be set; SA has only one influencing parameter i.e., temperature. If this parameter is correctly set, results will likely be good. The limitation of the work was overcoming the local optimum. Vieira et al have concluded that future should consider an objective function with actual cost instead of relative values like production inventory and overtime cost and losses for not meeting demand.

Ant colony optimization (ACO) algorithm which shows its good performance in combinatorial optimization solution was used by Zhengjia et al [22]. The objectives considered are the maximization of equipment utilization inventory and the

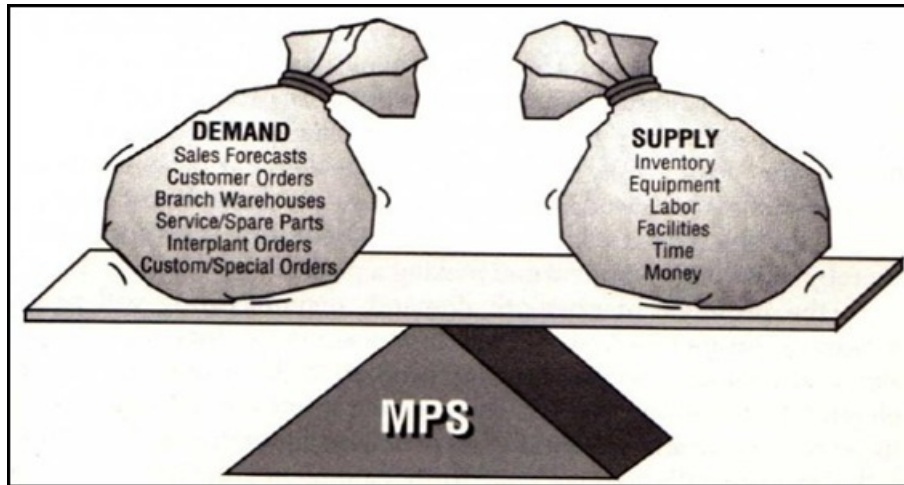


Figure 3. Balancing Supply and Demand

minimization of tardiness penalties. Zhengjia et al [22] showed that, being the most important input, in the process of formulation of MPS, demand forecast has played a great role. By the influence of the diversity and randomness of demand and hysteresis nature compared with production, demand forecast is particularly important in the process of enterprise formulate MPS. MPS Scheduling problems contain numerous constraints, difficult to solve non-polynomial complex optimization problems. The results in the work assured production high efficient, playing important guide role in practice.

The works of [23]; Chern and Hsieh [24] also have proposed heuristic algorithms. The former have suggested five performance measures were suggested: service level, inventory level, overtime, chance of occurring stock outs, and setup times, along with an easy way to normalize these. The later have considered three objectives: minimization of delay penalties; use of outsourcing capacity, and the minimization of the materials, production, processing, transportation and inventory holding costs. Both the works have proved that the proposed heuristic was efficient in solving mps problems and often generates the same solution as the LP model.

Genetic algorithm (GA) was used in the work of [25]. A new GA structure for MPS was developed and a software based on C++ programming language and objective oriented modeling was also tested. Although the work could not guarantee optimality, the proposed GA presented low levels of ending inventory efficiently met and had a very little need for overtime. Soares and Vieira [25] have suggested the implementation of other adaptive techniques for the determination of convergence points.

Differential evolution (DE) for solving mps problems was first used by the author herself, in [26]. DE does not require more control parameters compared to other evolutionary algorithms. The work presented solution for Multi Objective MPS problem using DE (MOMDE) by proposing a three dimensional chromosome representation (which was first of its kind). The results demonstrated that the MOMDE have produced more optimal values compared to GA. It was found that there was nearly 22% improvement in fitness value when compared to the one done with GA.

The very recently developed powerful population based meta-heuristic Teaching Learning Based Optimization (TLBO) was applied to the MPS problem by Radhika et al [27]. Although the DE could produce better results when compared to GA, it requires few parameters. To reduce this influence of parameters on the solution, Radhika et al (2013b), have demonstrated the use of TLBO which does not require any algorithm specific parameters. The results obtained could show improvement even over that done with DE. The authors have concluded that, TLBO is the most viable technique for solving a multi objective MPS problem.

4. Conclusions

The present selective survey attempts to provide a general overview of the work that has been done in the last two decades in MOEAs in line with Master Production Scheduling. The survey includes basic historical framework of MOEAs, algorithms, benchmark problems, methodological issues, applications and research inclinations. As EAs can process multiple solutions in parallel they can cope with different objectives more naturally. Like most randomized search algorithms, evolutionary algorithms are easy to describe and implement, but hard to analyze theoretically. Despite much empirical knowledge and successful application, only few theoretical results concerning their effectiveness and efficiency are available.

Master Production Schedule (MPS) is a plan that determines optimal values of products to be produced. As an MPS can effectively and efficiently synchronize the operations in any organization, it can be posed as one of multi objective parameter optimization problems. For many engineering optimization problems, more competitive and optimal solutions can be obtained by using Heuristic evolutionary optimization algorithms. Few works in which the MPS problem is solved using meta-heuristic approaches are discussed in brief. One can infer that, the repeated evaluations of MOEA's yield very similar results. This can help in achieving high overall gains in quality (or reductions in cost).

The authors also observed that similar mathematical models are being used in formulating the multi-objectives of MPS problems. The concepts of earliness, tardiness and even uncertainties may also be considered in future works. The survey also shows the need for new algorithms which might be treated as a potential area of future research.

References

- [1] M. S. Spenser, J. F. Cox III, Master production scheduling development in a theory of constraints environment, *Prod. Inv. Manage. J.* 1(36) (1995) 8-14.
- [2] H. B. Nanvala, Use of Genetic algorithm based approaches in scheduling of FMS: A Review. *Int. J. of Engg. Sci.* 3(2) (2011) 621-626.
- [3] I. H. Osman, G. Laporte, Metaheuristics: a bibliography, *Annals of Operations Research* 63 (1996) 513-623.
- [4] C. Dimopoulos, Multi-objective optimization of manufacturing cell design. *Int. J. Prod. Research* 44(22) (2006) 4855-4875.

- [5] K. Deb, Multi-objective Optimization Using Evolutionary Algorithms, England: John Wiley & Sons Ltd, 2001.
- [6] Q. Zhang, H. Li, Multiobjective evolutionary algorithm based on decomposition, IEEE Tran. on Evolutionary Compu. 11 (6)(2007) 712-731.
- [7] R. R. Kurada, K. K. Pavan, A.V.D. Rao, A preliminary survey on optimized Multiobjective metaheuristic methods for Data clustering using evolutionary Approaches, Int. J. of Computer Sci.& Info. Tech. 5(5) (2013).
- [8] T. Ghosha, S. Senguptaa, M. Chattopadhyayb, P. K. Dana, Meta-heuristics in cellular manufacturing: A state-of-the-art review Tamal, Int. J. of Ind. Engg. Compu. 2 (2011) 87-122.
- [9] A. Metropolis, M. Rosenbluth, A. Rosenbluth, A. Teller, E. Teller, Equation of State Calculations by Fast Computing Machines, J. Chem. Phys.21(6) (1953) 1087-1092.
- [10] E. Kirkpatrick, E. Aarts, J. Korst, Simulated Annealing and the Boltzmann Machine. John Wiley & Sons, New York, 1991.
- [11] M. Dorigo, Optimization, Learning and Natural Algorithms, Ph.D. Thesis, Politecnico di Milano, Italy 1992.
- [12] M. Dorigo, T. Stutzle, Ant Colony Optimization. MIT Press, Cambridge, MA, USA, 2004.
- [13] D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning. New York: Addison-Wesley,1989.
- [14] J. Koza, Genetic programming: on the programming of computers by means of natural selection. MIT Press, Cambridge, 1992.
- [15] J. Liu, L. Tang, A modified genetic algorithm for single machine scheduling, Computers & Industrial Engineering 37 (1999) 43-46.
- [16] R. Storn, K. Price, Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces, J.of Global Optimization 11 (1997) 341-359.
- [17] S. Das, P. N. Suganthan, Differential Evolution: A Survey of the State-of-the-Art, IEEE Transactions On Evolutionary Computation 15(1) (2011) 4-11.
- [18] P. J. Pawar, R. V. Rao, Parameter optimization of machining processes using teaching-learning-based optimization algorithm, Int. J. Adv. Manuf. Tech. (2012) 1-12.
- [19] F. Glover, M. Laguna, Tabu Search. Kluwer Academic Publishers, Norwell, MA, USA, 1997.
- [20] J. F. Proud, Master Scheduling-2nd Edition, John-Wile-Sons Inc. 1999.
- [21] G. E. Vieira, C. P. Ribas, A new multi-objective optimization method for master production scheduling problems using simulated annealing. Int. J. of Prod. Research 42(21) (2004) 4609-4622.
- [22] W. Zhengjia, C. Zhang, Z. Xiaoqin, An ant colony algorithm for Master production scheduling optimization, Proceedings of the IEEE 16th International Conference on Computer Supported Cooperative Work in Design, 2012.
- [23] G. E. Vieira, F. Favaretto, A new and practical heuristic for master production scheduling creation. Int. J. of Prod. Research 44(18-19) (2006) 3607-3625.
- [24] C. C. Chern, J. S. Hsieh, A heuristic algorithm for master planning that satisfies multiple objectives, Computers & Operations Research 34 (2007) 3491-3513.
- [25] M. M. Soares, G. E. Vieira, A New multi-objective optimization method for master production scheduling problems

based on genetic algorithm, *Int. J. of Adv. Manuf. Tech.* 39 (2008) 656-668.

- [26] S. Radhika, C. S. Rao, K. K. Pavan, A Differential Evolution based Optimization for Master Production Scheduling Problems, *Int. J. Hybrid Info. Tech.* 6(5) (2013) 163-170.
- [27] S. Radhika, C. S. Rao, K. K. Pavan, A study and performance evaluation of evolutionary optimization techniques for multi-objective master production scheduling problems, *J. of Prod. Research and Management*, 3(2) (2013) 12-22.
- [28] M. Garey, D. Johnson, *Computer, complexity and intractability. A guide to theory of NP-Completeness.* Freeman, San Francisco, USA, 1979.