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A LITERATURE REVIEW FOR THE SIMULATED ANNEALING METHOD ON THE PARALLEL MACHINES SINCE 2003

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ABSTRACT
In this article, since the year 2003, many heuristic methods have been applied in parallel machine scheduling problem with the simulated annealing method in the literature review. Performing a detailed literature research has revealed that there are numerous heuristic methods applied to parallel machine problems. It is seen that, among these heuristics, simulated annealing yields the best solution in the shortest time, which is also the case with the other probabilistic approaches. Simulated annealing, which is inspired by the perfect atomic configurations of cooling solids, especially metals, and is the simpliest of all artificial intelligence algorithms, is a research area that is very open for further development. Creating this work we have benefited from the databases of many journals. Research results show that there is a little work which is the simulated annealing method with the implementation of the parallel machine has been noticed. Here, at this point, these studies reveal.
Keywords: Parallel machines, heuristic methods, scheduling, simulated annealing, optimization algorithm.

1. INTRODUCTION

Production scheduling seeks optimal combination of short manufacturing time, stable inventory, balanced human and machine utilization rate, and short average customer waiting time. Various heuristic and adaptive solutions have been proposed for miscellaneous production scheduling problems (Jou 2005). Of them, many scheduling algorithms for single machines with flow shop production have been proven effective. Achievements also have been gained in scheduling for single machine batch processing. However, the scheduling problem for parallel machines has been proven as NP-hard, mainly due to the additional choice of which machine a job should be assigned to (Lee et al.,2006; Li et al., 2008). Heuristics can be classified into three types: index-development, solution-construction, and solution-improvement. However, some heuristics may consist of one or more of these types. Meta-heuristics, such as tabu search and simulated annealing, can be regarded as a solution-improvement type (Chen and Chen 2009). Heuristic algorithms for the solution of NP-hard problem is recommended. In this article, since 1996 with the simulation annealing method is applied parallel machines has been the literature review. With the simulated annealing method, other probabilistic approaches (genetic algorithms, tabu search) as the best solution to be available as soon as possible provides. In the second part of our study with the simulated annealing method is described. Later in the third section, simulated annealing methodology is detailed. In the fourth part of this paper, parallel machine optimization constraints which are characterized in Tablo 1. Then, in the fifth chapter, simulated annealing method is prefered as a review of research literature for parallel machines. As a result, the findings is being concluded by the interpretation work.

2. SIMULATED ANNEALING METHOD

One of the techniques applied to scheduling in order to obtain solutions close to optimal is Simulated Annealing (SA). Simulated Annealing is basically a randomized local search method (Lee and Pinedo 1997). Simulated annealing is a stochastic heuristic algorithm, which searches the solution space using a stochastic hill climbing process (Aydın and Fogarty 2004). In general, the simulated annealing method, combined with a single optimum criteria are used in the solution of optimization problems. Simulated annealing procedure will continue until it achieved a stance position. This method is good for local optimum not inserted (Lee ve Pinedo 1997). Starting from an initial solution, SA as a neighbor of current solution *S* produces a new solution. In simulated annealing, even though the value of the objective function is higher than the values found previously, solutions leading to better results may still exist. In this way, simulated annealing prevents getting stuck at local minima by means of the processing algorithm. To explain better, let *S* be the current solution and *N(S)* be the neighborhood around *S*, which comprises the alternative solutions. Here, if S' is the objective function value of *S*, then S' is selected to be the new solution. This, in turn, means that downward movements resulting in better objective function values will always be accepted. A value is selected randomly and its difference is calculated. After that, the change in the cost function value, $\Delta = C(S') - C(S)$, is computed, where $C(*)$ denotes the cost function value of the solution *. In minimization problems, if $\Delta < 0$, then the transition to the new solution is accepted. This transition is called downhill movement. If $\Delta > 0$, the transition to the new solution is accepted with a probability that is generally determined by $\exp(-\Delta / T)$, where *T* is a control parameter called temperature. By allowing uphill movements (where transitions increase the objective function values), SA repeats this process L times at a given temperature. L is a control parameter called period length. The parameter T is decreased, with the advance of the SA, through a cooling function usually until a stopping criterion is satisfied. A typical simulated annealing method is as follows

Step 1. Determine an initial solution S

Step2. Choose a value $T_1 \rangle 0$ for the initial temperature. Set the period number as k=1.

Step3. Repeat the following L times:

* Form $S^{'}$ as a neighboring solution of S * $\Delta = C(S') - C(S)$ * If $\Delta < 0$, set S as $S^{'}$ (downhill movement)

* If $\Delta \geq 0$, let S be $S^{'}$ with probability $\exp(-\Delta / T_k)$ (uphill movement)

Step 4. Stop if a given stopping criterion is satisfied. Otherwise, let $T_{k+1} = F(T_k)$ and $k = k + 1$.

Go back to Step 3. (T_k and F denote the period and the temperature function at k, respectively(Park ve Kim 1997).

An SA algorithm for the implementation of a specific problem, a series of decisions should be created. For example, the code of a solution and a starting solution for the decision and the neighbors of a solution must be defined clearly. These decisions may be different if the problem is different.

On the other hand, for any implementation of SA, an annealing schedule or a cooling sequence should be decided to create. Simulated annealing algorithm can be used in the solution of electronic circuit design problems, image processing problems, path finding problems, travel problems, material physics simulation problems, cutting and packing problems, work flow scheduling problems (Hasteer ve Banerjee 1997). The notations of sequencing which is taken into consideration in this article are used:

i : Job index $i = 1,2,3,...,n$ j : Stage index $j = 1,2,3,...,m$

$C_{ij\max}$: Maximum completion time or makespan of job i at last stage j.

$F_{ij\max}$: Maximum flow time of job i at last stage j. S_t : Set up time. r : Release time. D : Due date.

T : Delaying time. L : Lateness time. (These notatitons will be showed in Table 1 with the researching papers).

3. LITERATURE REVIEW

First of all, simulated annealing (SA) method has been described in 1983 by S. Kirkpatrick, C. D. Gelatt and M. P. Vecchi and also in 1985 by V. Černý. To test the power of simulated annealing, Kirkpatrick et al.(1983) uses the algorithm on traveling salesman problems with as many as several thousand cities. Later, method has been developed by Metropolis in 1953 for outputting sample levels in a thermodynamic system, as an adaptation of Metropolis-Hastings algorithm and Monte Carlo method (Aarts and Laarhoven, 1987). The articles are then written about SA is belonged to Robusté, Daganzo and Souleyrette (1990) and Alfa, Heragu, and Chen (1991). In the first article, Robusté, Daganzo and Souleyrette (1990) has proposed an algorithm in which three types of routes are developed with customer movement. In the second article, Alfa, Heragu, and Chen have developed an algorithm for simulated annealing. (Aarts and Laarhoven 1987). The paper of Kim et al. (2007) considers the problem of determining the allocation and sequence of jobs on parallel machines for the objective of minimizing total tardiness. Each job may have a sequence-dependent set-up time that depends on the type of job just completed and on the job to be processed as well as distinct ready times at which the job is available for processing. These make the parallel machine scheduling problem more difficult than ordinary ones. Due to the complexity of the problem, two types of search heuristic, tabu search, and simulated annealing are suggested that incorporate new methods to generate the neighbourhood solutions. Jenabi et al. (2007) addressed the economic lot sizing and scheduling problem in flexible flow lines with unrelated parallel machines over a finite planning horizon. A new mixed zero–one nonlinear mathematical programming has been developed for the problem. Due to difficulty of obtaining the optimal solution especially for medium and large-sized problems, they have also proposed two algorithms: a hybrid genetic algorithm (HGA) and a simulated annealing (SA). Kashan et al. (2008) investigated the scheduling problem of parallel identical batch processing machines in which each machine could process a group of jobs simultaneously as a batch. The processing time of a batch was given by the longest processing time among all jobs in the batch. Based on developing heuristic approaches, they proposed a hybrid genetic heuristic (HGH) to minimize makespan objective. To verify the performance of their algorithm, comparisons were made through using a simulated annealing (SA) approach addressed in the literature as a comparator algorithm. In his paper, Figielska (2008) proposed a heuristic for solving the problem of scheduling in a two-stage flowshop with parallel unrelated machines and additional renewable resources at the first stage and a single machine at the second stage. The proposed heuristic combines column generation technique with a genetic algorithm (the heuristic algorithm HG) or a simulated annealing algorithm (the heuristic algorithm HS). In their paper, Li et al. (2008) study the problem of synchronized scheduling of assembly and air transportation to achieve accurate delivery with minimized cost in consumer electronics supply chain. The parallel machine assembly scheduling problem is shown to be NP-complete. Simulated annealing based heuristic algorithms are presented to solve the parallel machine problem. Damodaran and Chang (2008) proposed several heuristics in their article. The performance of the proposed heuristics is compared to a simulated annealing approach and a commercial solver. On the other hand, Li et al. (2008) study the problem of synchronized scheduling of assembly and air transportation to achieve accurate delivery with minimized cost in consumer electronics supply chain. The parallel machine assembly scheduling problem is formulated as a mixed integer programming model and proved to be NP-complete. SA based heuristic algorithms are developed to solve the scheduling problem. Jungwattanakit et al. (2009) investigated both constructive and iterative (GA-based) approaches for minimizing a convex combination of makespan and the number of tardy jobs for the flexible flow shop problem with unrelated parallel machines and setup times, which is often occurring in the textile industry in their paper. Simulated annealing, tabu search and GA-based metaheuristics were suggested to resolve the problem. Chang and Chen (2010) deal with an unrelated parallel machine scheduling problem with the objective of minimizing the makespan. According to the empirical results, the proposed Dominant Properties heuristic outperforms Genetic Algorithm and Simulated Annealing in effectiveness and efficiency.

5. CONCLUSION AND FUTURE RESEARCH

This paper presents a literature survey, from 1996 to the present, on simulated annealing (SA) which is one of the heuristic methods applied to the scheduling of parallel machines, one of the most important problems regarding production systems. Generally speaking, simulated annealing is deployed in the solution of hybrid optimization problems with a single optimization criterion. Simulated annealing is researched under the same category as heuristics like genetic algorithm and tabu search. From the literature review, it can be seen that simulated annealing is frequently used in the solution of single-criterion problems. It is also an area of research that can be expanded to include multi-criterion problems as well. In numerous papers, simulated annealing is compared with tabu search on scheduling problems and SA is observed to perform better than Tabu Search. However, as a result of its nature, SA forces the designer to either spend too much time or incur losses on the quality of solutions in scheduling problems. The parallelism of the applications of this kind provides the designer with a trade-off between saving time and lengthening the annealing, in order to improve quality. In spite of these drawbacks, simulated annealing is quite successful in minimizing the total weighted tardiness and solving release-time-based scheduling problems. Moreover, a traditional simulated annealing method arbitrarily chooses a neighbor with a high acceptation probability. For this reason, it requires time for computation over quite broad an interval, and hence providing the designer with flexibility. Although simulated annealing is a good explorer method, its “exploit” feature is rather weak. Therefore, it cannot by itself yield good results in scheduling problems, and in most studies, it appears to be used in hybrid methods. The actual purpose behind using this method with others in a hybrid fashion is to prevent these methods from getting stuck at a local optimum (sub-optimum) while searching for the optimal solution. This process is executed by incorporating new solution sets into the optimal solution search operation via randomly changing the annealing temperature. It can be seen from the papers in the literature review that studies purely based on this method are quite few in number. Nevertheless, we think that this area is open for further research. It can be readily stated that future research concerning this type of topics should be focused on improving this method either jointly or comparatively with other methods.

Table 1. Simulated annealing literature research chart since 2003

No	*Author, Publication Year*	*Optimization constraints*							*Hybrid*	*Solitary*
		$C_{ij\max}$	$F_{ij\max}$	S_t	r	D	T	L		
1	Chang and Chen (2010)	+							**	
2	Kashan and Karimi(2009)	+							**	
3	Behnamian (2009)	+		+					**	
4	Li and Yang (2009)	+							**	
5	Figielska (2009)	+							**	
6	Jungwattanakit et al. (2009)			+					**	
7	Li et al. (2008)						+			**
8	Kashan et al. (2008)	+							**	
9	Melouk et al. (2008)	+								**
10	Li et al. (2008)						+		**	
11	Damodaran and Chang (2008)	+							**	
12	Jenabi et al. (2007)			+					**	
13	Anghinolfi and Paolucci (2007)						+		**	
14	Raja et al. (2007)	+				+			**	
15	Kim et al. (2007)						+		**	
16	Arumugam et al. (2007)	+								**
17	Jin et al. (2006)	+							**	
18	Min and Cheng (2006)					+			**	
19	Chen and Wu (2006)						+		**	
20	Lee et al. (2006)	+								**
21	Kim et al (2006)						+			
22	Chen (2006)						+		**	
23	Gupta and Torres (2005)		+				+		**	
24	Low (2005)		+							**
25	Loukil et al. (2005)	+								**
26	Torres and Lopez (2004)	+					+		**	
27	Cochran et al. (2003)	+					+		**	
28	Kim et al. (2003)			+					**	
29	Kim and Shin (2003)						+		**	

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