Robotics and Computer-Integrated Manufacturing 28 (2012) 113–131

Contents lists available at ScienceDirect

Robotics and Computer-Integrated Manufacturing

journal homepage: www.elsevier.com/locate/rcim

Simulated annealing with auxiliary knowledge for process planning optimization in reconfigurable manufacturing

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ARTICLE INFO

Article history:
Received 30 November 2009
Received in revised form
1 July 2011
Accepted 15 July 2011
Available online 16 September 2011

Keywords:
Simulated annealing (SA)
Auxiliary knowledge
Heuristic knowledge
Metaknowledge
Manufacturing process planning (MPP)
Reconfigurable manufacturing systems (RMS)

ABSTRACT

In this paper, three simulated annealing based algorithms that exploit auxiliary knowledge in different ways are devised and employed to handle a manufacturing process planning problem for reconfigurable manufacturing. These algorithms are configured based on a generic combination of the simulated annealing technique with; (a) heuristic knowledge, and (b) metaknowledge. Capabilities of the implemented algorithms are tested and their performances compared against a basic simulated annealing algorithm. Computational and optimization performances of the implemented algorithms are investigated and analyzed for two problem sizes. Each problem size consists of five different forms of a manufacturing process planning problem. The five forms are differentiated by five alternative objective functions. Experimental results show that the implemented simulated annealing algorithms are able to converge to good solutions in reasonable time. A computational analysis indicates that significant improvements towards a better optimal solution can be gained by implementing simulated annealing based algorithms that are supported by auxiliary knowledge.

1. Introduction

In the past years, simulated annealing (SA) has found many applications in solving difficult optimization problems. For example, SA has been implemented successfully in: travel salesmen problem [1,2]; the quadratic assignment problem [3,4]; multi-dimensional assignment problems [5,6]; scheduling problems of a wide variety and manufacturing process planning problems [7,8]. These examples show that the nature of the problems that have been solved through applications of SA is wide and cuts across the spectrum of combinatorial, N-P Hard and N-P Complete problems. Therefore, simulated annealing is a potential candidate for solving difficult optimization problem.

Simulated annealing (SA) is usually implemented as a trajectory-based search technique [9]. It was first introduced by Kirkpatrick et al. [10]. In most applications, simulated annealing has been utilized to locate a good approximation to an optimal solution for a given function in a large search space. Although a number of weaknesses of simulated annealing have been observed, variants of the standard simulated annealing algorithm have been developed to overcome the documented weaknesses [11]. In addition, current research has shown that search techniques that systematically exploit knowledge about the problem being solved are more effective than their corresponding counterparts [12]. Therefore, the contribution of this paper is in investigating the effects, on the quality of computed solutions, of exploiting auxiliary knowledge in simulated annealing implementations. The effects will be observed for implementations in which SA with auxiliary knowledge will be tasked to search for an optimal solution of a complex manufacturing process planning (MPP) problem in reconfigurable manufacturing.

In the public literature, most implementations of simulated annealing are based on the pseudocode template of the simulated annealing algorithm described in Algorithm 1 [13,14]. Algorithm 1 propagates iteratively keeping a tentative solution, S_α, at any time during implementation. At each iteration, a new solution, S_n, is generated from the previous one, S_α. This new solution will either replace the old one or not. The decision to replace or not to replace is based on an acceptance criterion. The acceptance criterion is described in Algorithm 2. The logic in the above algorithm lies in that if the new solution is better than the old one (tentative solution), then the new solution will replace the tentative solution. If it is worse, it replaces it with probability that depends on the difference between their quality values and a control parameter, T, usually named as temperature in the public literature [7]. This acceptance criterion provides a way for the algorithm to elude local optima. The mathematical expression for the probability, P, used in the acceptance criterion can be represented by the expression:

$$P = e^{-((E_n - E_\alpha)/T)} \quad (1)$$

Therefore, with more iterations, the value of the control parameter, T, is changed according to a predefined schedule, thus

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doi:10.1016/j.rcim.2011.07.003

enforcing the SA algorithm towards accepting only better solutions.

Algorithm 1.

Steps	Pseudocode
1.	$T \leftarrow 0$;
2.	Initialize (T, S_α)
3.	Evaluate (S_α)
4.	While not endCondition (T, S_α) DO
5.	While not coolingCondition (T) DO
6.	$S_n \leftarrow$ chooseNeighbor (S_α)
7.	Evaluate (S_n)
8.	IF accept (S_α, S_n, T) THEN
9.	$S_\alpha \leftarrow S_n$
10.	END IF
11.	$T \leftarrow T+1$
12.	END While
13.	coolDown (T)
14.	END While

Algorithm 2.

Steps	Pseudocode	
1.	Calculate the quality values; E_α, E_n	// (i.e. the tentative solution, S_α, and the new solution, S_n, are each associated with quality values, E_α, and E_n, respectively. These values are determined by a predefined an objective function—sometimes called fitness function)
2.	IF $E_\alpha > E_n$ accept the change	//(let the solution be the tentative solution)
3.	ELSE	
4.	Generate a random number, X $(0 < X < 1)$	
5.	IF $X < e^{\frac{E_\alpha - E_n}{T}}$	//Accept the change (i.e. let the solution be the new solution)
6.	ELSE	//Reject the change
7.	END IF	
8.	END IF	

Unlike most implementations of SA that are based on the theories described in the previous paragraphs, this paper proposes an innovative incorporation of auxiliary knowledge in the implementation of the simulated annealing algorithm. Two forms of auxiliary knowledge; i.e. (i) heuristic process planning knowledge, and (ii) process planning metaknowledge, will be configured to support the simulated annealing algorithm. The former involves heuristic additions to the simulated annealing template, while the latter involves coupling the simulated annealing template with metaknowledge. Since heuristic knowledge is derived from process planning experience, its role towards guiding a search technique to an optimal solution is essential. On the other hand, process planning metaknowledge is knowledge derived from process planning methods hence; availability of process planning metaknowledge may contribute to the effectiveness of the search process. The effects and impacts of deploying auxiliary knowledge in the two proposed ways will be evaluated and compared in this paper.

In light of the discussions above, the objective of this paper is to investigate the capabilities of simulated annealing with auxiliary knowledge when tasked to generate process plans for reconfigurable manufacturing. This objective is achieved by seeking optimality in process selection and process sequencing, with respect to processing constraints and manufacturing conditions. For experimental purposes, capabilities of basic simulated annealing algorithms with auxiliary knowledge are investigated under four cases namely; the standard simulated annealing algorithm, which is included as a control experiment, and three variations of the simulated annealing algorithm that incorporate auxiliary knowledge in different ways. A computational study is carried out to: (a) determine the capabilities of the simulated annealing algorithms in tackling a manufacturing process planning optimization problem for reconfigurable manufacturing; (b) determine whether the solution methods based on exploitation of auxiliary knowledge are more effective than the basic simulated annealing technique in solving an instance of the manufacturing process planning optimization problem.

The remainder of the paper is organized as follows: Section 2 presents the process planning optimization problem in reconfigurable manufacturing. A simple illustrative example is also included. The proposed solution methodology and the configurations of the implemented simulated annealing algorithms are described in Section 3. Applications of the simulated annealing algorithms and computational results are presented in Section 4. Finally, concluding remarks are given in Section 5.

2. Process planning optimization in reconfigurable manufacturing

Reconfigurable manufacturing environments are often associated with large information flows that help and support the operations of the manufacturing system. In addition to supporting process planning decisions, availability of information also facilitates decision making processes for reconfiguration of the manufacturing system. Due to the need to manipulate and communicate large amounts of relevant process planning knowledge and information, an optimization perspective is inevitable.

One of the key features in manufacturing process planning problems in reconfigurable manufacturing is the need to generate reconfigurable process plans that facilitate logical reconfiguration of the manufacturing system [15]. When a manufacturing system is required to undergo reconfiguration, there is a change in production requirements due to changes in either manufacturing system functionality, capacity or production mix. In such a case, the current process plans are rendered invalid. Therefore, if reconfiguration actions are to be implemented in response to changes in production requirements, it is necessary to generate, evaluate and implement alternative process plans that can accommodate changes to production requirements. In addition to being feasible, such process plans should be optimal to avoid degrading overall manufacturing performance. In this paper we adopt an optimization perspective to manufacturing process planning for reconfigurable manufacturing. The optimization solution method is based on a generic combination of the simulated annealing technique with auxiliary knowledge. The auxiliary knowledge supplies guidelines for; appropriate process planning methods, processing characteristics, process capabilities and cost considerations. Such guidelines assist process planners in meeting the production requirements of specified operations.

2.1. Background

Usually, the process planning problem involves finding optimal processing conditions and/or optimal processing parameters that minimize a desired objective function. The specific process planning activities depend on the type of the manufacturing