Available online at www.sciencedirect.com
SCIENCE DIRECT®
International Journal of Machine Tools & Manufacture 45 (2005) 949–957
INTERNATIONAL JOURNAL OF MACHINE TOOLS & MANUFACTURE DESIGN, RESEARCH AND APPLICATION
www.elsevier.com/locate/ijmactool

A novel approach to production planning of flexible manufacturing systems using an efficient multi-objective genetic algorithm

Jian-Hung Chen[a], Shinn-Ying Ho[b,*]

[a]Department of Information Engineering and Computer Science, Feng Chia University, 100 Wen-hwa Road, Taichung 407, Taiwan, ROC
[b]Department of Biological Science and Technology, Institute of Bioinformatics, National Chiao Tung University, Hsinchu 300, Taiwan, ROC

Received 11 May 2004; accepted 20 October 2004
Available online 19 December 2004

Abstract

In this paper, a novel approach using an efficient multi-objective genetic algorithm EMOGA is proposed to solve the problems of production planning of flexible manufacturing systems (FMSs) having four objectives: minimizing total flow time, machine workload unbalance, greatest machine workload and total tool cost. EMOGA makes use of Pareto dominance relationship to solve the problems without using relative preferences of multiple objectives. High efficiency of EMOGA arises from that multiple objectives can be optimized simultaneously without using heuristics and a set of good non-dominated solutions can be obtained providing additional degrees of freedom for the exploitation of resources of FMSs. Experimental results demonstrate effectiveness of the proposed approach using EMOGA for production planning of FMSs.

Keywords: Flexible manufacturing system; Multi-objective optimization; Genetic algorithm; Production planning

1. Introduction

A flexible manufacturing system (FMS) is a production system consisting of a set of identical and/or complementary numerically controlled machines which are connected through an automated guided vehicle (AGV) system. Since FMS is capable of producing a variety of part types and handling flexible routing of parts instead of running parts in a straight line through machines, FMS gives great advantages through its flexibility such as dealing with machine and tool breakdowns, changes in schedule, product mix, and alternative routes. Flexible manufacturing is of increasing importance in advancing factory automation that keeps a manufacturer in a competitive edge.

While FMS offers many strategic and operational benefits over conventional manufacturing systems, its efficient management requires solutions to complex product planning problems with multiple objectives and constraints. The aim of production planning is to develop a cost effective and operative production plan over planning phases. Decisions regarding production planning problems have to be made before the start of actual production, and consist of organizing the limited production resource constraints efficiently. Generally, production planning of FMSs consists of many optimization problems, such as routing optimization, equipment optimization and machine optimization [1].

During the past decades, a number of production planning approaches have been developed for automated planning and increased efficiency of production planning [1]. Many approaches usually optimize a single objective and treat other objectives as constraints [1,2]. However, it is known that many problems in production planning of FMSs are multi-objective optimization problems (MOOPs) in nature [1,2]. From a system designer's point of view, it is very desirable to obtain a set of non-dominated solutions providing the flexibility of reconfigurable manufacturing via simultaneously considering all the objectives. Recently, some approaches [3–9] have been proposed to deal with MOOPs in production planning. They can be classified into two categories:

* Corresponding author. Tel.: +886 3 5712121 ext. 56905; fax: +886 3 5729288.
E-mail address: syho@mail.nctu.edu.tw (S.-Y. Ho).

0890-6955/$ - see front matter © 2004 Elsevier Ltd. All rights reserved.
doi:10.1016/j.ijmachtools.2004.10.010

(1) *Decomposition approach* [3–6]. Problem is decomposed into several sub-problems according to its characteristics. Hereafter, the sub-problems are solved in multiple stages. A solution of a sub-problem is usually used as an initial solution of its succeeding sub-problem. The advantage of the decomposition approach is that heuristics of a specific objective can be utilized separately. However, the decomposition of problems requires prior domain knowledge, and the final solution is sensitive to the solution of previous stages. Chen and Askin [3] solved a multi-objective machine loading problem sequentially by heuristic algorithms. Kumar et al. [4] proposed a min–max approach to solving a grouping and loading problem in multiple stages. Liang [5] proposed a two-stage approach to jointly solving part selection, machine loading and machining speed selection problems. Lee et al. [6] proposed a two-stage approach to solving an operation sequence and tool selection problem.
(2) *Preference-based approach* [7–9]. Given relative preferences to each individual objective, the preference-based approach generally combines multiple objectives into a single objective function using a weighted linear combination of all objectives, and then a single-objective optimization algorithm is used to find a single solution at a time. The main advantage of the preference-based approach is that a suitable non-dominated solution can be easily obtained. However, relative preferences require prior domain knowledge and the solution quality is sensitive to the relative preferences used [10]. Liang and Dutta [7] proposed a mixed-integer programming approach to solving a machine loading and process planning problem by aggregating the makespan and manufacturing costs of the problems into a single objective function. Sodhi et al. [8] proposed a heuristic algorithm to solving a multi-period tool and production problem by aggregating the resource costs of the problems into an overall function. Swarnkar and Tiwari [9] aggregated two objective functions of a bicriteria machine loading problem into a single function and employed a hybrid algorithm based on tabu search and simulated annealing to solve the problem.

Multi-objective evolutionary algorithms (MOEAs) have been recognized to be well-suited for solving MOOPs because their abilities to exploit and explore multiple solutions in parallel and to find a widespread set of non-dominated solutions in a single run [10]. Several MOEAs based on Pareto dominance relationship [11] are proposed to solve MOOPs directly, and present more promising results than single-objective optimization techniques theoretically and empirically [10,12]. By making use of Pareto dominance relationship, MOEAs are capable of performing the fitness assignment of multiple objectives without using relative preferences of multiple objectives. Thus, all the objective functions can be optimized simultaneously. As a result, MOEA seems to be an alternative approach to solving production planning problems on the assumption that no prior domain knowledge is available.

In this paper, a novel approach using an efficient multi-objective genetic algorithm EMOGA is proposed to solve multi-objective production planning problems (MOPPPs) having four objectives: minimizing total flow time, machine workload unbalance, greatest machine workload and total tool cost. The fundamental difference of the proposed approach from the above-mentioned decomposition and preference-based approaches is that the problem decomposition and relative preferences are not necessary. In addition, the proposed approach can obtain a set of non-dominated solutions for decision makers in a single run. Decision makers can easily distinguish between the costs of different production plans and choose more than one satisfactory production plans at a time. Six benchmark problems with different complexities are derived to evaluate the performance of the proposed approach. An efficient multi-objective evolutionary algorithm SPEA [12], which outperforms many existing MOEAs, is used for performance comparisons. It is shown empirically that EMOGA can converge to better solutions than SPEA in solving MOPPPs.

This paper is organized as follows: Section 2 describes the investigated problem MOPPP. Section 3 presents the efficient multi-objective genetic algorithm EMOGA for solving MOPPPs. Section 4 gives the experimental results and analysis of the proposed algorithm. Section 5 summarizes our conclusions.

2. Problem statement

In this paper, we focus on *operation flexibility* in the production planning phase of FMSs. Operation flexibility is concerned with an operation which can be performed on alternative machines with different processing time, transportation time and resource costs [1]. Therefore, optimizations on routing, machine and equipment are essential for operation flexibility. With the assignment of operations to machines, four optimization objectives: minimizing total flow time, machine workload unbalance, greatest machine workload and total tool cost, are considered in our problems.

2.1. The FMS environment

An FMS consists of a set of identical and/or complementary numerically controlled machines and tool systems. All components are connected through an AGV system. Fig. 1 shows the layout of a simple FMS with several machines, AGVs and a tool system.

In order to design the production planning of FMSs, the environment within which the FMS under consideration operates can be described below.

(1) The term *machine* is to describe a machine cell. A machine cell consists of several identical