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Hierarchical stochastic production planning for the highest business benefit

Hong-Sen Yan

Research Institute of Automation, Southeast University, Nanjing, Jiangsu 210096, People's Republic of China

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Abstract

This paper addresses the hierarchical stochastic production planning (HSPP) problem of flexible automated workshops (FAWs), each with a number of flexible manufacturing systems (FMSs) the part-transfer between which is a delay of a time period. The problem not only includes uncertainties in the demand, capacities, material supply, processing times, necessity for rework, and scrap, but also considers multiple products and multiple time periods. The objective is to develop a production plan which tells each FMS how many parts to produce and when to produce them so as to obtain the highest business benefit. Herein, the HSPP problem is formulated by a stochastic nonlinear programming model whose constraints are linear but whose objective function is piecewise linear. For the convenience of solving the stochastic nonlinear programming model above, it is approximately transformed into a deterministic nonlinear programming model and further into a linear programming model. Because the scale of the model for a general workshop is too large to be solved by the simplex method on a personal computer within acceptable time, Karmarkar's algorithm and an interaction/prediction algorithm, respectively, are used to solve the model, the former for the medium or small scale problems and the latter for the large scale problems. By the implementation of the above-mentioned algorithms and through many HSPP examples, Karmarkar's algorithm, the interaction/prediction algorithm and the linear programming method in Matlab 5.0 are compared, the result of which shows that the proposed approaches are very effective and suitable for not only "push" production but also "pull" production. © 2001 Elsevier Science Ltd. All rights reserved.

Keywords: Flexible automated workshops; Flexible manufacturing systems; Hierarchical stochastic production planning; Karmarkar's algorithm; Interaction/prediction method

1. Introduction

A manufacturing department of a manufacturer in China usually consists of several workshops or sub-factories, each with some workshop-sections. Thus, the manufacturing department of the computer integrated manufacturing system (CIMS) in such a manufacturing department also consists of several shops, each of them with some manufacturing cells or flexible manufacturing systems. Secondly, in theory, the workpiece-transfer time and charges can be decreased by the reconfiguration of manufacturing cells [1,2]. However, because the main machines in cells (or FMSs) are NC machines and machining centers that cannot be arbitrarily moved, the physical reconfiguration of cells cannot be realized and the logical reconfiguration of cells cannot obviously decrease the workpiece-transfer time and charges. Thirdly, although the commercial software of enterprise resource planning (ERP) or manufacturing resource planning (MRP II) can directly assign manufacturing orders to manufacturing cells, these orders usually are not optimal. It is better for ERP/MRP II to assign shop manufacturing orders (i.e., medium-term plans) that are to be optimally decomposed into short-term plans to be executed by manufacturing cells or FMSs in the shop, about which little has been written in the literature on production planning (PP). Fourthly, the solutions of PP problems in workshops will provide the theoretical basis for implementing manufacturing execution systems [3]. Fifthly, with the increasingly keen competition for markets, there will be no manufacturer that has all the resources to win a victory in the "battle". Thus, several manufacturers, whose resources are complementary, will temporarily form themselves into an agile virtual enterprise [4] to take advantage of a transient market opportunity and to win a victory in the keen competition. To reduce the number of participating manufacturers for easy coordination, each of them will supply

E-mail address: hsyan@seu.edu.cn (H.-S. Yan).

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the agile virtual enterprise with as many required resources as possible. Hence, a participating manufacturer will probably supply the agile virtual enterprise with shops which are taken as manufacturing resources. In such a manufacturing environment, a shop is empowered to organize production autonomously, according to manufacturing orders (product demand plans) not only from the manufacturer (which it belongs to) but also from the agile virtual enterprise (which it belongs to), which generates more uncertainty in the product demand than the traditional production. Besides, the equipment capacity in the shop is uncertain because of unplanned maintenance and the material supply for the shop is also uncertain because of the supplier's capacity and the material quality. Thus, the shop can be taken, to some extent, as a stochastic manufacturing system. On the other hand, the production planning in a manufacturing setting is essential to efficient resource allocation over time while satisfying demands for finished products [5]. Therefore, the problem of stochastic production planning (SPP) for a flexible automated workshop (FAW) consisting of FMSs (or cells) is important and worth studying.

Since the scope of PP problems generally prohibits a monolithic modeling approach, a hierarchical production planning approach has been widely advocated in the PP literature [5]. To model PP problems, the existing hierarchical approaches usually employ the following concepts: (1) product disaggregation [5–7], (2) temporal decomposition [8], (3) process decomposition [9–11], and (4) event-frequency decomposition [12]. However, these articles are focused on deterministic HPP problems and little has been written about the HSPP problems in the existing HPP literature. By way of exception, an integrated stochastic decision-making approach of integrating the techniques of mathematical programming and Monte Carlo simulation is employed within each implemented generic controller to rigorously address the uncertainties that are inherent to PP problems [5].

The existing articles on the PP problems with uncertainties are mostly focused on uncertainties of the demand, capacity and material supply in the single period or infinite-horizon setting [13–17]. However, Bitran et al. examine deterministic approximations to multi-period multi-item production planning problems in environments with stochastic process yields and substitutable demands [18]. Schmidt presents a Markov decision process model that combines features of engineering design models and aggregate production planning models to obtain a hybrid model that links biological and engineering parameters to optimize operation performance in biopharmaceutical production processes [19]. Stecke et al. [20] use an open queueing network model of a flexible manufacturing system to determine the optimal configurations and machine workload assignments for the no grouping and total grouping cases. Bonissone et al. [21] propose a new approach to planning in the financial domain of mergers and acquisitions and in dynamic and uncertain environments. The planning is viewed as a process in which an agent's long term goals are transformed into short term tasks and objectives, given the agent's strategy and the context of planning [21]. Yan proposes two new approaches [22,23] respectively, to the optimal decomposition of stochastic production plans for FAWs with or without respect to delay interaction. By building up linear quadratic models of SPP problems and using interaction/prediction, the proposed approaches optimally decompose FAW's medium-term stochastic product demand plans into short-term stochastic plans (to be executed by FMSs in the FAW) at a high speed. These approaches aim to combine the principles of both a temporal decomposition and a process one with the organizational structure of the FAW and are capable of solving very big HSPP problems. However, the overproduction penalty and the underproduction penalty in the objective function are the same, and so are the overload penalty and the underload penalty. In practice, the penalty for underproduction is usually heavy and the overproduction only leads to the increase in the finished-product inventory, so the underproduction penalty should be much greater than the overproduction penalty. As with the overproduction and underproduction, the wages for overtime are several times as many as those for the usual hours and the underload only leads to the decrease in the utilization of resources (such as men and equipment), so the overload penalty should be much greater than the underload penalty. Besides, in many factories, any job which needs processing on more than one manufacturing cell (or FMS, or workshop section) usually cannot be transferred directly from one cell to the next. Instead, a semi-finished product completed in one period (shift or day) usually must be put into shop storage until the next period when it can be transferred to the next cell for further processing.

Thus, a HSPP model with the nonlinear objective function and linear constraints and with delay interaction should be built up. The HSPP problem here involves not only the three kinds of uncertainties (demands, capacities and material supply) in the existent PP literature, but also the uncertainties of processing times, rework and waste products. Besides, the system under consideration is very complicated (an FAW consists of some FMSs, each with several work centers), and the problem is a multi-period multi-product stochastic nonlinear programming one. It is thus clear that there exists a challenge. Since most stochastic programming problems in the literature are solved for the single-period or infinite-horizon [18,24,25] and because the solution of multistage stochastic optimization problems requires the tree-like decision-making