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Intelligent multi-objective decision-making model with RFID technology for production planning

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ABSTRACT

A multi-objective production planning problem in the labor-intensive manufacturing industry is investigated. An intelligent and real-time multi-objective decision-making model is developed to provide timely and effective solutions for this problem by integrating RFID technology with intelligent optimization techniques, in which RFID technology is used to collect real-time production data, a novel $(\mu/\rho+\lambda)$-evolution strategy process with self-adaptive population size and novel recombination operation is proposed and integrated with effective non-dominated sorting and pruning techniques to generate Pareto optimal solutions for real-world production. Experiments based on industrial data were conducted to evaluate the effectiveness of the proposed model. Experimental results show that the proposed model can effectively solve the investigated problem by providing production planning solutions superior to industrial solutions.

1. Introduction

Effective production planning is crucial to delivering products on time to meet customer needs, which can greatly affect the overall performance of a manufacturing enterprise and thus the entire supply chain management. This paper investigates a real-world production planning problem, multi-objective order allocation (MOA), with the consideration of multiple plants and multiple production departments.

1.1. Difficulty in production decision-making practice

In today's labor-intensive manufacturing industries, production data are usually collected by using barcode technology or even manual input in an offline manner. The data collected are never real-time and their accuracy is questionable, which hinders the research and application of effective methodologies in production planning and control since the accuracy and real-timeness of production data are the premises of implementing effective production decision-making.

In recent years, radio-frequency identification (RFID) has attracted increasing industrial applications as an alternative to the barcode technology (Wyld, 2006), which utilizes electromagnetic wave communication to exchange data between a terminal and an electronic tag attached to an object for identification and tracking. As the application of RFID has become economically feasible, some commercial RFID-based data capture systems, such as ZymFactory system (Zymmetry Group, 2007) and GPRO system (GPROTechnologies, 2010), have been developed to obtain real-time and accurate production data and their effectiveness has been proved by various industrial applications and practices in labor-intensive manufacturing (Guo, 2008). However, these systems only focus on data collection and simple data reporting, and cannot provide decision-making solutions to assist production managers in performing production management. In today's labor-intensive manufacturing industries (such as apparel and footwear), manufacturing is characterized by short production lead-time, tight delivery due dates, small quantities with frequent product change, as well as the multi-plant and multi-production department nature. These phenomena and characteristics increase the complexity of making effective production decisions. Decision-making on production planning in these industries relies heavily on the production planners' experience and subjective assessments, which may not be consistent under similar conditions and is thus non-optimal.

1.2. Previous studies in production planning

In the production planning area, a great number of papers have been published and there exist some comprehensive review papers (Dolgui and Prodhon, 2007; Wang et al., 2009; Wazed et al., 2010). Research issues in this area mainly include master production

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schedule (Sahin et al., 2008), material requirements planning (Dolgui and Prodhon 2007), manufacturing resource planning (Wazed et al., 2010) and aggregate planning (Al-E-Hashem et al., 2011).

To assist manufacturers in assigning production processes of each order to appropriate plants, some researchers investigated order allocation and release problems in production planning stage, which are an important decision-making problems in labor-intensive industries because its performance greatly affects that of downstream production control and the entire supply chain. Ashby and Uzsoy (1995) proposed a set of heuristic rules to integrate order release, group scheduling and order sequencing into a single-stage production system. Chen et al. (2005) presented a decision support system to determine how to assign a particular order to the most appropriate manufacturing company from the global supply chain's perspective. Work by Axsater (2005) investigated the order release problem in a multi-stage assembly network by determining the starting time of different production operations. Chen and Pundoor (2006) investigated order allocation and scheduling at the supply chain level by assigning orders to different plants and exploring a schedule to perform the orders assigned in each plant. However, their study has not considered the effects of different production departments in each plant on production decision-making performance.

The order allocation problem in the production planning stage, with the consideration of multi-plant and multi-production department features, has not been addressed so far. Unfortunately, these features are typical in labor-intensive manufacturing, which significantly increases the complexity of production planning problems. The MOA problem investigated in this research is a computationally complex combinatorial optimization problem because it handles the assignments of production processes of multiple orders to production departments of multiple plants, which lead to a huge solution space.

1.3. Techniques for optimization problems in production decision-making

To obtain effective solutions to optimization problems in production decision-making, a wide variety of techniques have been developed (Guo, 2008; Guo et al., 2011), mainly including simulation-based techniques (Chan et al., 2002), priority-rule-based techniques (Weng and Ren, 2006), classical optimization techniques (Tanaka and Araki 2008; Tozkapan et al., 2003), and meta-heuristic techniques. The first three types of techniques cannot provide effective solutions to complex optimization problems in real-world production usually due to the high complexity of such problems. The meta-heuristic techniques have been proved to be very powerful in finding optimal or near-optimal solutions due to their heuristic nature (Blum and Roli 2003; Luna et al., 2010). The most commonly used meta-heuristic techniques are evolutionary algorithms, especially genetic algorithm (Holland 1975) and evolution strategy (ES) (Schwefel, 1995). Comparing with genetic algorithms, the applications of ES in production optimization problems have attracted relatively little attention.

It is usual that multiple optimization objectives, some of which are in conflict, need to be achieved simultaneously in many real-world optimization problems. Some researchers use the weighted sum method to turn the multi-objective problems to single-objective ones (Guo et al., 2008; Ishibuchi and Murata, 1998). However, it is impossible to have a single solution which can simultaneously optimize all objectives when multiple objectives are conflicting. To handle this problem, some researchers developed multi-objective optimization algorithms by introducing the Pareto optimality concept into the meta-heuristic techniques so as to provide more feasible solutions (i.e., Pareto optimal solutions). The most well-known ones include NSGA-II (Deb et al., 2002), PAES (Knowles and Corne, 2000), SPEA2 (Zitzler et al., 2001), IBEA (Zitzler and Kunzli, 2004), MSOPS (Hughes, 2005). However, these algorithms have not been reported to handle combinatorial optimization problems in production planning. The existing multi-objective optimization algorithms cannot be directly used to handle the MOA problem because different solution representations and evolutionary operators are probably required to handle various problem-dependent features. Moreover, Eiben et al. (2004) reported that self-adaptive population size adjustment has the potential to improve the evolutionary speed of single-objective optimization processes. However, its effectiveness on multi-objective optimization processes has not been investigated.

In this paper, an intelligent and real-time multi-objective decision-making (IRMD) model, which integrates an RFID-based production data capture (RPDC) submodel with a heuristic data extraction and analysis (HDEA) submodel and a novel ES-based Pareto optimization (ESPO) submodel, is developed to provide timely and effective solutions for the MOA problem investigated. To construct the ESPO submodel, the ES process with self-adaptive population size and novel recombination operation is proposed and integrated with effective non-dominated sorting and pruning techniques so as to generate Pareto optimal production planning solutions.

The rest of this paper is organized as follows. Section 2 formulates the investigated production planning problem. In Section 3, the IRMD model is presented to handle this problem. In Sections 4 and 5, experimental comparisons and analyses are conducted to validate the effectiveness of the proposed model. Finally, this paper is summarized and future research directions are suggested in Section 6.

2. Problem formulation

In this section, the MOA problem in the production planning stage of a labor-intensive manufacturing company with multiple production plants is formulated. The company receives various production orders from different customers. These orders need to be assigned to the company's n production plants located in different regions, including self-owned or collaborative plants, for production. These plants involve N production departments numbered as 1 to N, which perform, respectively, N types of different production processes denoted as process type 1 to process type N. That is, production process i can only be produced in production department $i (i = 1, \ldots, N)$. These production departments can be classified into two categories: ordinary category and special category. Each category involves multiple production departments. The departments of the ordinary category are fully contained in all plants but it is possible that those of the special category are only partly included (or not included) in some of plants. That is, it is possible that different production processes of an order need to be performed in different plants.

The manufacturer receives a group of production orders (called an order group) from the customers at a time. Each order group consists of multiple production orders. Each order consists of a maximum of N production processes. Each production process of an order is assigned to only one plant for processing. All finished products are delivered to a distribution center for product delivery and distribution. The transportation time between different production departments in a plant is included in the processing time of production processes.

Let G_h denote the hth production order group and P_{ij} denote the jth production process of the ith production order O_i $(1 \le i \le m)$.C_i and D_i represent the completion time and the due date of order O_i respectively. A_{ij}, B_{ij}, T_{ij} and C_{ij} indicate the arrival, beginning, processing and completion time of process P_{ij} respectively. X_{ij}^k indicates