Computers & Industrial Engineering 111 (2017) 263–271

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

Shop floor lot-sizing and scheduling with a two-stage stochastic programming model considering uncertain demand and workforce efficiency

Yihua Li, Guiping Hu *

Department of Industrial and Manufacturing Systems Engineering, Iowa State University, IA 50011, USA

ARTICLE INFO

Article history:
Received 23 March 2017
Received in revised form 13 June 2017
Accepted 12 July 2017
Available online 14 July 2017

Keywords:
Manufacturing system
Production planning
Lot-sizing and scheduling
Automotive industry
Stochastic programming

ABSTRACT

Efficient and flexible production planning is necessary for the manufacturing industry to stay competitive in today's global market. Shop floor lot-sizing and scheduling is one of the most challenging and rewarding subjects for the management. In this study, a two-stage stochastic programming model is proposed to solve a single-machine, multi-product shop floor lot-sizing and scheduling problem. Two sources of uncertainties – product demand from the market, and workforce efficiency – are considered simultaneously, which is the major contribution of this study. The workforce efficiency affects the system productivity, and we propose different distributions to model its uncertainty given insufficient information. The model aims to determine optimal lot sizes and the production sequence that minimizes expected total system costs over the planning horizon, including setup, inventory, and production costs. A case study is performed on a supply chain producing brake equipment in the automotive industry. The numerical results illustrate the usefulness of the stochastic model under volatile environment, and the solution quality is analyzed.

1. Introduction

Production planning plays an essential role in the effective and economic operation of a manufacturing unit. In general, production planning aims to achieve effective utilization of resources; ensure steady flow of production and optimal inventory; improve labor productivity and product quality; enhance consumer satisfaction; reduce production costs; and thus capture the market when facing competition. Production planning is commonly adopted in scheduling, dispatch, capacity planning, quality management, inventory management, supply management, and equipment management (Chan & Prakash, 2012; Dal-Mas, Giarola, Zamboni, & Bezzo, 2011; Kanyalkar & Adil, 2008; Phan, Abdallah, & Matsui, 2011). Manufacturing firms consider three time ranges for decision-making: long-term (e.g., facility design and process choices), medium-term (e.g., capacity planning and material requirements planning), and short-term planning (e.g., day-to-day operations and job control) (Karimi, Ghomi, & Wilson, 2003). Lot-sizing and scheduling problem is applicable in medium- to short-term planning.

Lot-sizing and scheduling is one of the most challenging subjects in production planning (Almada-Lobo & James, 2010). The lot-sizing problem determines how much to produce of each product in each planning period. The scheduling problem determines the order of production lots to mitigate influences of setup time and costs in the manufacturing system. The decisions of lot-sizing and scheduling are made to meet the final product demand requirements and to minimize system costs, including setup, production, and holding costs. These operational strategies directly affect system performance, such as the utilization rate and the productivity of the shop floor, and thus are essential to enhancing a company's competitiveness in the market. The idea of incorporating uncertainty in mathematical models applied in lot-sizing and scheduling could significantly improve the decision-making, and provide more robust and stable scheduling decisions.

This paper focuses on the lot-sizing and scheduling decision-making in production planning considering uncertain demand and workforce efficiency data simultaneously, which could arise in many manufacturing companies. The uncertainty in demand is common and production plans usually rely on demand forecast, based on historical demand data, as well as the insight into market prospect. The uncertainty in workforce efficiency could be caused by different operational issues (e.g., proficiency of workers, parts availability). Both uncertain factors might cause a company not

* Corresponding author.
E-mail address: gphu@iastate.edu (G. Hu).

http://dx.doi.org/10.1016/j.cie.2017.07.014
0360-8352/

having sufficient production capability to meet the demand. To cope with volatile demand and production efficiency, we make it possible to deliver products later than their demand periods, and backorder costs will be incurred. A two-stage stochastic programming model is proposed to assist in the decision making to minimize total system costs.

A case study for a manufacturing company producing braking equipment in an automotive industry is conducted. Two sources of uncertainty are considered simultaneously. While demand uncertainty has fitted distributional representations based on historical data, uncertainty in workforce efficiency is modeled with insufficient information from experts' experiences. Given the circumstance, the impact of workforce efficiency is further discussed considering different choices of distributional models, with sensitivity analysis on distribution parameters. Computational experiments are implemented to demonstrate the effectiveness of the model compare to the deterministic model, and the solution qualities are analyzed. In particular, suggestions on scenario set cardinality is discussed, which is an important factor that balances the computational effort and solution quality.

The remainder of this paper is organized as follows. We review the related literature to lot-sizing and scheduling problem in Section 2. Section 3 formulates the scheduling and lot-sizing problem as a two-stage stochastic programming problem. The numerical results and discussions are included in Section 4. Section 5 concludes the paper and proposes directions of further research.

2. Related literature

Lot-sizing and scheduling problem has been studied extensively in the literature (Drexl & Kimms, 1997; Jans & Degraeve, 2008), and has been applied in many real-world industries, including a soft drink plant (Ferreira, Morabito, & Rangel, 2009), a diary company (Amorim, Antunes, & Almada-Lobo, 2011), a pharmaceutical company (Stadtler, 2011), and a metal foundry (Hans & Velde, 2011), to name a few.

According to Karimi et al. (2003), there are many variants of lot-sizing and scheduling problems. A simple economic order quantity (EOQ) model deals with single-level production without capacity constraints (Erlenkotter, 1990). Developed upon the EOQ model, the economic lot scheduling problem (ELSP) considers optimal sharing of scarce resources in a capacitated single-level, multi-item problem, while keeping the model with continuous time infinite planning horizon (Rogers, 1958); Wagner-Whitin (WW) problem assumes a discrete time finite planning horizon, while keeping the model without capacity limits (Wagner & Whitin, 1958). Extending the WW problem by including capacity constraints, we have the capacitated lot-sizing problem (CLSP or a large bucket problem), where multiple items may be produced per period. The following variants integrated lot-sizing with scheduling decision-making. Divide the macro-periods into several micro-periods, we have a discrete lot-sizing and scheduling problem (DLSP, or a small bucket problem) (Fleischmann, 1990). DLSP is developed with the so-called 'all-or-nothing' assumption, meaning only one item may be produced per micro-period, and, if so, full capacity will be applied. The continuous setup lot-sizing problem (CSLP) relaxed the 'all-or-nothing' assumption in DLSP, while still restricting that only one item could be produced in each period, i.e., the use of partial capacity is allowed, which is a shortcoming of CSLP. To fulfill the utilization of remaining capacity, the proportional lot-sizing and scheduling problem (PLSP) allows a second item being produced in one micro-period, i.e., the setup of a machine could change at most once in a micro-period (Kaczmarczyk, 2011). A further generalization is called the general lot-sizing and scheduling problem (GLSP), which allows multiple lots per period, where the maximum number of lots is user-defined (Fleischmann & Meyr, 1997).

Most scheduling problems in practice involve setup times and costs. In general, setup implies the activities that are required to prepare a machine to produce an item of a given type, including setting jigs and fixtures, adjusting tools, and acquiring materials. Shim, Kim, Doh, & Lee (2011) proposed an two-stage heuristic for the CLSP with sequence-dependent setup costs. Their heuristic suggests that after an initial solution is obtained, it is improved with a backward and forward improvement method with various priority rules to select the items to be moved among the periods.

Parallel machine setup is another type of extension that could complicate the model. Marinelli, Nenni, & Sforza (2007) illustrated a capacitated lot-sizing and scheduling problem with unrelated parallel machines with shared and capacitated buffers. The model was formulated as a hybrid continuous setup and capacitated lot-sizing problem, and solved with a two-stage heuristic approach. The model was applied in a yogurt packaging company. Quadt & Kuhn (2009) addressed a capacitated lot-sizing and scheduling problem with setup times, setup carry-over, and back-orders on identical parallel machines in a semiconductor assembly facility. The authors presented a MIP model and a solution procedure based on a novel "aggregate model." Afzalirad & Rezaeian (2016) addressed an unrelated parallel machine scheduling problem with resource constraints, sequence-dependent setup times, different release dates, machine eligibility, and precedence constraints. Two new meta-heuristic algorithms including genetic algorithm (GA) and artificial immune system (AIS) are developed to find optimal or near optimal solutions for this pure integer model.

Special modeling requirements should be taken into account given product characteristics. For example, Amorim et al. (2011) applied the lot-sizing and scheduling problem to perishable products (yogurt). To consider the trade-off between freshness of delivered product and total costs, the problem was extended to solving multi-objective models.

While the deterministic lot-sizing and scheduling assumes all the information that defines a problem instance is known with certainty in advance, in the real world, a production process can be affected by many forms of uncertainty. Ho (1989) categorized the uncertain factors into two groups: (1) environmental uncertainty, such as demand and supply uncertainty, and (2) system uncertainty, such as operation yield, quality, and system failure uncertainty. Therefore, a straightforward extension assumes that some of the problem data are subject to random fluctuations.

Brandimarte (2006) proposed a multi-stage stochastic programming approach for multi-item capacitated lot-sizing with uncertain demand; a time-sweep-based heuristic solution strategy is applied to solve the large-scale mixed integer linear programming model. Helber, Sahling, & Schimmelpfeng (2013) dealt with a multi-item stochastic capacitated lot-sizing problem under δ-service-level measure. The nonlinear functions of backlog and inventory are approximated with two different linear models, and the piecewise linear model is solved with a MIP-based heuristic. Lu, Cui, & Han (2015) addressed a problem of finding a robust and stable schedule for a single machine with availability constraints. A proactive approach generating a long-term initial schedule under failure uncertainty, which jointly determines the production planning and preventive maintenance (PM) is proposed.

To summarize the literature review, most of the previous researches deal with deterministic lot-sizing and scheduling problems, those consider stochasticity typically consider one uncertain factor. In our paper, two sources of uncertainties are taken into consideration simultaneously. The modeling of uncertainty with limited information is represented when modeling workforce efficiency uncertainty, and the impact from insufficient data is also discussed.