Machine learning based stochastic optimization methodology for production planning with uncertain demand and production capacity

Dan Luo[1], Simon Thevenin[1], Alexandre Dolgui[1]

IMT Atlantique, LS2N, France

dan.luo2@imt-atlantique.fr

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1 Introduction

Due to the manufacturing demand for mass customization and the widespread application of flexible automated production equipment, manufacturers tend to shorten their production cycle. This results in a loss of regularity in the production system, and it becomes difficult for manufacturers to control the product and process quality. In the meantime, the upgrading of the production system puts forward higher requirements for the decision-making of production planning. This means that production planning needs to be as precise as possible. However, with the loss of regularity in the production process, it becomes difficult to estimate the production capacity required to produce a given batch size. In this work, we consider the problem of planning production under demand and capacity uncertainty.

Production capacity is an important factor that affects the output when considering the production process within a manufacturing system. In a real manufacturing system, production capacity is always uncertain and can be affected by many factors, such as unexpected breakdowns of unreliable machinery, unplanned maintenance of uncertain duration, and rework of randomly defective items [1, 2]. Through the literature review, we found that the studies on production planning mainly focus on considering demand, yield, and lead time uncertainties, while few papers about production planning consider uncertain production capacity. Even fewer papers about production planning consider uncertain demand and production capacity at the same time. Our research aims to fill this gap and to provide a new solution for production planning considering uncertain demand and production capacity. The proposed stochastic optimization methodology is based on a machine learning (ML) method. On the one hand, we will apply ML to learn the distribution function of the demand and production capacity. On the other hand, we will improve the fix-and-optimize (F&O) algorithm to solve the mathematical model for production planning with the support of ML.

2 Problem description

The typical production planning problem considered in real manufacturing systems is a multi-echelon multi-item capacitated lot-sizing problem (MMCLP). The objective of the MMCLP is to determine the suggested production plan, including when to produce, how many items to produce, when to buy materials, how many items to buy, and the amount of extra capacity required. These decisions are made based on the demand, the bill of material (BOM), the production capacity, and the lead time.

The MMCLP can be formulated as a mixed-integer linear program. We choose a generic enough model for MMCLP that would fit in most manufacturing industries, which is a multi-stage stochastic programming model described in Luo et al [3]. In this model, we consider the flexible BOM, which leads to the flexibility and reactivity required in the Industry 4.0 era. In particular, we consider two uncertainties in the meantime. One uncertainty is uncertain demand D_{it}, which presents the quantity of product i required by the customer in period t. Another uncertainty is uncertain production capacity C_r, which presents the available production capacity of the resource r. Uncertain demand and production capacity both can be represented with the probability distribution. Based on these distributions, we will generate a set of scenarios with Quasi-Monte Carlo methods. For instance, uncertain demands can be represented by the set Ω of demand scenarios, where each scenario $\omega \in \Omega$ represents a possible realization of the demands over the planning horizon, and it has a probability p_ω.

We define three decision variables in the model. Y_{ot}, the binary decision variable, presents if a batch of operation o is performed in period t. Q_{ot} presents the quantity of operation o to perform in period t. w_{rt} presents the amount of extra capacity required for resource r in period t. The objective function is the expected total cost, and it includes inventory holding costs, setup costs, production costs, backlog costs, and extra capacity costs.

3 Machine learning based stochastic optimization methodology

We aim to provide a more general solution for large-scale MMCLPs. The proposed methodology mainly includes two parts. One is the ML-based forecast method for uncertain demand and production capacity, another one is the ML-based F&O heuristic algorithm.

In practice, these forecasts are always wrong, and the deviation of the actual value of the parameters from the forecast may have a large impact on the quality of the production plan. Therefore, rather than providing a point forecast, the proposed ML-based forecast method aims to learn the distribution function of uncertain demand and uncertain production capacity. For each uncertain parameter, ML-based uncertainty forecasting creates a Bayesian network using the data from the domain model or simulation model. The Bayesian network is built from the relations in the domain model, and we learn the conditional probability with the pair copula.

The target of the ML-based F&O heuristic algorithm is to use the ML method to improve the performance of the F&O algorithm for large instances. The core idea of the F&O algorithm is to separate MMCLP into several small sub-problems according to binary variables for faster iterative solutions. When we use the F&O algorithm to solve MMCLP with large instances, we should use the F&O algorithm in a smart way because of the limited computing time. The basic idea of our proposal is to use the ML method for learning the main parameters of the F&O algorithm, such as the ratio of free binary variables, the decomposition method, and the optimized route/sequence. Through learning the main parameters of the F&O algorithm, we want to provide a general F&O algorithm that can solve different large-scale MMCLPs.

Références

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