A Digital Twin-Driven Methodology for Material Resource Planning Under Uncertainties

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Abstract. With the Industry 4.0 revolution currently underway, manufacturing companies are massively adopting new technologies to achieve the virtualization of their shop floor and the collaboration of their information systems. This process often leads to the construction of a real-time, collaborative, and intelligent virtual factory of their physical factory (so-called digital twin). The application of digital twins and frontier technologies in production planning still faces many challenges. But the research is still limited about how these frontier technologies can be applied to enhance production planning. This paper introduces how to enhance material resource planning (MRP) with digital twins and other frontier technologies, and presents a framework for the integration of MRP software with digital twin technologies. Indeed, the data collected from the shop floor can improve the accuracy of the optimization models used in the MRP software. First, several MRP parameters are unknown when planning, and some of these parameters may be accurately forecasted from the data with machine learning. Nevertheless, the forecast will never be perfect, and the variability of some parameters may have a critical impact on the resulting plan. Therefore, the optimization approach must properly account for these uncertainties, and some methods must allow building probability distribution from the data. Second, as the optimization models in MRP are based on aggregated data, the resulting plans are usually not implementable in practice. The capacity constraints may be acquired by communication with an accurate simulation of the execution of the plan on the shop floor.

Keywords: Digital twin, Industry 4.0, Material resource planning, Metaheuristics, Machining learning, Uncertainty.

1 Introduction

The current supply chain is characterized by high complexity, high flexibility, mass customization, dynamic conditions, and volatile markets [1]. The rapid industrial environmental changes motivate an evolutionary and integrative perspective for supply chain management in Industry 4.0 [2]. In recent years, due to the rapid development of network technology, the technologies in the era of Industry 4.0 have developed rapidly, including the digital twin (DT), internet of things (IoT), cyber-physical systems (CPS), big data (BDA) and analytics, artificial intelligence (AI), cloud manufacturing (CMg) [3,4]. Because smart manufacturing is the core of the Industry 4.0 concept, production planning would be crucial for the supply chain management of Industry 4.0 activities [5]. In production planning, the goal of material requirement planning (MRP) software is to decide the quantities to produce and purchase over a given planning horizon. In this context, companies must enhance MRP software to respond to dynamic and diversified market changes. Existing research mainly focuses on the technological framework and how to achieve the technology of Industry 4.0. However, the research is still limited about how these frontier technologies can be applied to enhance MRP software. Therefore, in this work, we present a methodology for the integration of MRP software with digital twin technologies. The resulting tools enhance MRP software with machine learning to forecast MRP parameters, stochastic optimization to properly account for parameter uncertainty, and automatic constraints learning by communication with a detailed simulation.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review for the production planning in the Industry 4.0 era. Section 3 introduces the optimization models used in MRP, and Section 4 presents the digital twin-driven methodology for MRP. Finally, the paper ends with the conclusion and some future research directions in Section 5.

2 A state of the art

In this section, we discuss the application and research status of the main technologies of Industry 4.0 used in MRP software, including the internet of things, big data and analytics/artificial intelligence, digital twin/cyber-physical systems, and cloud manufacturing.

The internet of things is the crucial basis for realizing cloud manufacturing, digital twin, and big data analysis [9]. The core functions of IoT for MRP include the digitalization of resources and information sharing from different software. Indeed, intelligent devices, such as sensors and radio frequency identification (RFID), embedded in products and resources allow real-time data collection and monitoring. With these intelligent devices, the MRP software can know the status of each resource (e.g., machine status, inventory levels, etc.) in real-time [2,10]. Besides, IoT facilitates the integration of information systems, such as enterprise resource planning (ERP) systems and manufacturing execution system (MES), to realize information sharing and collaboration [7]. Most of the research on IoT focuses on real-time collection, and application in scheduling [11]. Besides, most researchers consider a macroscopic view on IoT (e.g., the whole supply chain), and little work focuses on the application of IoT for the MRP in detail [12]. Therefore, there are still various problems that need to be studied and solved. For example, how to integrate information systems to achieve data-driven and dynamic planning, achieve distributed and collaborative planning for different workshops to support decision-making, and minimize the complexity of MRP systems.

MRP software is often used in an uncertain environment. That is, many parameters are not known when planning [6]. Therefore, big data and analytics/artificial intelligence are often used to forecast the parameters required for production planning [1]. Based on the massive data collected by IoT, BDA/AI tools can help MRP systems to predict the uncertain input parameters, such as the demand and capacity [13,14]. In this way, we can improve the accuracy and performance of forecasting. Furthermore, we can realize precise representation for the workshop and get more practicable and adaptable planning [15,16]. Existing research mainly focuses on demand forecasting, and only considers single uncertainty. The use of machine learning to predict the values of the parameters is not straightforward, since there exists a wide variety of predictive analytic approaches. The selection of the most appropriate approach depends on the context, usage, and volume of data [17,18]. Therefore, one research trend is to propose a general big data prediction method for MRP software.

The digital twin/cyber-physical systems can provide decision-making support, dynamic production planning, and real-time visualization by building the virtual duplicate for the physical system [19]. Based on the digital twin model, we can achieve automatic optimization, prediction, and re-planning for MRP [22], and extending MRP with real-time calculations, early reports, traceability, and visibility [21]. In this context, one challenge for MRP under the CPS environment is that enterprises must improve their adaptability, automation, and efficiency to deal with large-scale problems and more complex systems. Besides, because digital twins emphasize the integration and collaboration between systems, the implementation of cloud manufacturing (CMg) in MRP is also a critical process for constructing cyber-physical systems.

In summary, existing research mainly focuses on the technological framework and how to achieve the technology of Industry 4.0. However, the research is still limited about how these frontier technologies can be applied to upgrade the systems for production planning in detail. We summarize main challenges of frontier technologies in production planning as follows.

1) The relationships inside physical systems, the relationships inside virtual systems, and the relationships between physical systems and virtual systems, are complex to integrate.

2) The massive data creates new opportunities and challenges to make an effective production plan with frontier technologies.

3) How to use frontier technologies to provide the dynamic and automatic support of production planning for the managers is also an important challenge.

To address these challenges, we propose a vision and a methodology to enhance material resource planning with digital twins and other frontier technologies,

3 Optimization model for MRP

The problem solved by MRP software is a multi-echelon multi-item capacitated lot-sizing problem (MMCLP). The MMCLP is to decide when to produce as well as the sizes of the production lots to minimize the expected total cost (including inventory holding costs, fixed setup costs, unit production costs, extra capacity cost). These decisions are made based on the demand, the bill of material, the production capacity, and the lead time. We introduce below the optimization model used in current MRP software. Several models exist in the literature, and we provide a generic enough model that would fit in most of the manufacturing industries. In particular, we consider the flexible bill of material (BOM), which leads to the flexibility and reactivity required in the Industry 4.0 era.

The demand D_{it} for item i can be represented with a parameter or a probability distribution. We assume that all customer demand is for end items only. If there exists a demand for components, we can create a dummy end-item corresponding to components reserved for shipping.

The multi-echelon flexible bill of materials gives the production structure of each item in the set I of items. We denote I the set of all items, I_e the set of end items, and I_c the set of components, where $I = I_e \cup I_c$. Each item i can be acquired by alternative operations, and each operation o produces a_{oi} units of item i, it consumes b_{oi} units of component i, and consumes k_{or} units of resource r. Modelling operations leads to a very generic lot-sizing model that can include alternative production routing and make or purchase decisions (Begnaud et al 2009).

The requirement plan must account for the production capacity. Each resource r in the set of resources R has a given capacity C_r. In each period t, the capacity of resource r can be expended, and each unit of extra capacity costs o_r. The component i produced in period t is available in period $t + L_i$, where L_i denotes the lead time of item i. This lead time may correspond to the time between the placement of an order to a supplier and its delivery, or to the number of periods between an order is released to the scheduler, and the period where the item is produced. The inventory I_{it} will generate costs, and the backlog level B_{it} in period T corresponds to a lost sale. Besides, we define M as the big number.

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, and how many items to buy, and the amount of extra capacity required. We define the following decision variables:

Y_{ot} If a batch of operation o is performed in period t, and this is represented by a binary decision variable.
Q_{ot} The quantity of operation o to perform in period t
w_{rt} The amount w_{rt} of extra capacity required for resource r in period t.

The objective function is the expected total cost, and it includes inventory holding costs h_i, setup costs s_o, production costs v_o, backlog costs b_i, and the extra capacity cost o_r. The MMCLP can be formulated as the following mixed-integer linear program (MILP).

$$\min \sum_{t\in T}\sum_{i\in I_e}(h_i I_{it} + b_i B_{it}) + \sum_{t\in T}\sum_{o\in I_c}(s_o Y_{ot} + v_o Q_{ot}) + \sum_{t\in T}\sum_{r\in R} o_r w_{rt} \quad (1)$$

Subject to:

$$I_{it-1} - B_{it-1} + a_{oi} Q_{ot-L_i} - I_{it} + B_{it} = D_{it} \quad i \in I_e, o \in I_c, t \in T \quad (2)$$

$$I_{it-1} + a_{oi} Q_{ot-L_i} - \textstyle\sum_{o\in I_c} b_{oi} Q_{ot} - I_{it} = 0 \quad i, o \in I_c, t \in T \quad (3)$$

$$Q_{ot} - MY_{ot} \leq 0 \qquad o \in I_c, t \in T \tag{4}$$

$$\sum_{o \in I_c} k_{or} \cdot Q_{ot} \leq C_r + w_{rt} \qquad o \in I_c, t \in T \tag{5}$$

$$Y_{ot} = \{0,1\} \tag{6}$$

$$I_{it} \geq 0 \tag{7}$$

$$B_{it} \geq 0 \tag{8}$$

$$Q_{ot} \geq 0 \tag{9}$$

The objective function (1) is the expected total cost. Constraints (2) and (3) ensure the balance of flow for all items in each period. Constraints (4) set the production quantities to zero in periods without operations. Constraints (5) enforce limits on production capacity.

Based on this distribution, the tool will generate a set of scenarios with Monte Carlo or Quasi Monte Carlo methods. For instance, uncertain demands can be represented by the set Ω of demand scenarios, where each scenario ω ∈ Ω represent a possible realization of the demands over the planning horizon, and it has a probability p_ω.

4 The digital twin-driven material resource planning

In this section, we propose a digital twin-driven MRP software, before describing its main elements, including the machine learning based uncertainty forecasting, and the fix-and-optimize algorithm for two-stage stochastic optimization.

4.1 The digital twin-driven integration scheme

Figure 1 shows the digital twin-driven integration scheme for the MRP software, which describes how the physical system communicates with the virtual systems, and how to integrate the production planning with the simulator and the scheduler.

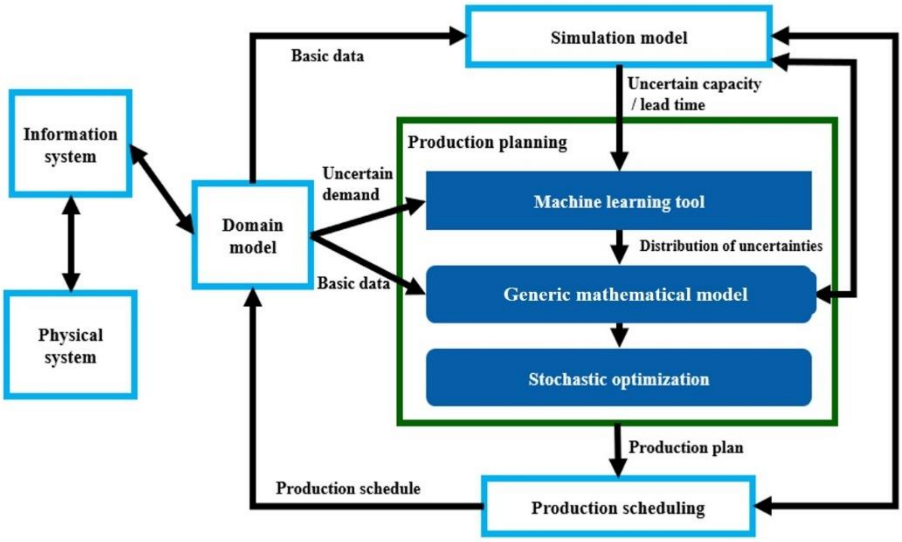

Figure 1 The digital twin-driven integration scheme

The domain model, one of the core components in the digital twin, is the bridge between the physical system and the visual systems. This domain model integrates data from heterogeneous sources (MES, ERP, IoT devices), and it provides the user with a rich data structure to understand this data. This data is then accessible to the simulation, the production planner, and the scheduler.

The simulation models help the user validate a production plan by providing a precise execution of the plan at a detailed level (with each machine, employee, transport between machines, etc.). The simulation gives a clear understanding of the performance of a production plan, since it can compute various KPIs relevant to the user. The simulation is also a valuable tool to enrich the optimization model. As explained in Section 4.3, the simulation can learn the capacity constraint from various simulation runs.

The production planner will provide the size of the production batches to the scheduler as well as a targeted production period. In the scheduler, the release date corresponds to the start of the period, and the due date corresponds to the end of the period. The due date in the scheduler is a soft due date, to ensure adherence to the production schedule, whereas the customer due date might be penalized strongly or even considered as hard deadlines.

4.2 Machine learning based uncertainty forecasting

The machine learning based uncertainty forecasting creates a Bayesian network using the data from the domain model or simulation model. The user will select the parameter to learn and the possible explanatory parameter. The Bayesian network is built from the relations in the domain model, and we learn the conditional probability with pair copula. The major sources of uncertainties in material resource planning include the demand, the production and delivery lead time, the process duration, and the production capacity. For instance, the capacity uncertainty can be inferred from the machine breakdown represented by the mean time between failures, and the mean failure duration.

To forecast the distribution of uncertain parameters, the input data for machine learning has two sources. For uncertain demand, the input data is from historical data, including the customer order and production plans implemented in the past. For uncertain lead time and production capacity, the input data can be generated by the simulation model.

4.3 Predictive analytics of capacity constraints

Tactical planning tools, such as MRP and APS (advanced planning and scheduling), decide the production amount over a long planning horizon (several months). In this context, the planning decisions are not based on a detailed model of the shop floor. The main reasons are that the resulting optimization problem would not be solvable, and it would lead to nervousness that aggregated data is more reliable than detailed one (e.g., determining the demand for the car is easier than for each specific car model). Consequently, we aggregate items, resources, and periods. The granularity of production planning is a day or a week. The items and resources are aggregated into families. Typically, a resource family is a group of resources (a work cell). This aggregation may lead to errors [24]. For instance, the resource consumption is computed for each resource group, but planning approaches allocate specific resources to each operation. More precisely, the capacity constraint is a linear function described as follows:

$$\sum_{(o\in O)} Q_{ot}\, k_{or} \leq C_{rt} + w_{rt} \qquad (10)$$

where k_{or} is an estimate of the processing time of an operation of family o on a resource of family r. In practice, the process duration may vary depending on the precise operation to perform, and on the specific resource that performs the operation. Besides, the production schedule may include idle time, and not all resources in a resource family can perform all operations.

Consequently, a production plan may not respect the production capacity once implemented in practice or the simulation. Some authors propose a rich model that integrates planning and scheduling [25], but the resulting model can only solve small scale instances. We aim to learn the capacity constraints in the mathematical model through machine learning based on the output of the simulation. The tool can run a simulation model to get the capacity consumption associated with given production quantities.

4.4 Fix-and-optimize algorithm for two-stage stochastic optimization

Mathematical optimization is the most appropriate tool for planning. The lot-sizing models have attracted a lot of work from the operation research community. Researchers propose several reformulations, cuts, and solution algorithms such as Lagrangian Relaxation, cutting planes. However, solving the complex lot-sizing problem under uncertainty is hard, especially in the dynamic decision framework, where the production setups are updated as the information unfolds. The existing works are limited to small-scale instances in a simple environment [27]. To solve large instances, with multi-echelon BOM in a long-term planning horizon, improved heuristic algorithms must be provided. For instance, Thevenin et al [23] showed that the two-stage approximation provides a good heuristic to the static-dynamic decision framework when the demand is uncertain. However, more research is needed to solve lot-sizing problems in a long-term planning horizon, and the use of the fix-and-optimize approach may be a possible research direction. Besides, more research should focus on developing methods to handle the dynamic decision framework. Based on the two-stage approximation proposed by Thevenin et al [23], more works required to do are listed as follows.

1) Evaluate the quality of this heuristic for other types of uncertainties (lead time/capacity/process duration/demand).

2) Extend the tool to a more generic lot-sizing model (with flexible BOM/possibility to add extra capacity).

3) Evaluate the quality of this heuristic for the dynamic type of uncertainties.

4) Improve the approach to solving large scale instances of the problem.

5 Conclusion and Perspectives

In this paper, we propose a digital twin-driven methodology for material resource planning software. The paper focuses on how to achieve the integration between the MRP system and other systems under the CPS environment. We also describe how to design a digital twin-based MRP system to solve planning problems in a dynamic and uncertain environment. First, the distribution of uncertainties can be predicted using machine learning. Then, with the distribution of uncertainties and basic data as the input of production planning, the generic mathematical model can represent the physical system precisely. Third, the fix-and-optimize algorithm can obtain the results for the MMCLP. Based on this, MRP systems can provide practicable and adaptable production plans and re-plans efficiently for large-scale planning problems.

For future research perspectives, we will conduct and implement the proposed method in a real factory. A comprehensive framework, which includes not only the production planning for MRP, but also a detailed description of the production scheduling and the connection protocols between them will be provided. Moreover, we are looking forward to improving the heuristic algorithm and machine learning method for the MMCLP. Finally, an interesting work direction is to study how to maximize efficiency and minimize the complexity of the MRP system when we integrate it with other systems under the CPS environment in Industry 4.0.

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