Risk-based Planning in Smart Supply Networks: The Merit of Multi-model Analytics

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Abstract. Extant approaches to supply network planning (SNP) are not capable of dealing with increasing requirements due to more volatile markets and the digital transformation of business. This paper proposes multi-model-based analytics approaches as a beneficial and promising avenue for further research in this field. Risk-based planning provides a suitable framework to this end.

Keywords: Risk-based Planning · Stochastic Models · Multi-model Approaches.

1 Introduction

Supply networks aim at providing superior value to the ultimate customer by integrating business processes across the boundaries of single organizational entities [1]. Advanced Planning and Scheduling (APS) systems are prevalent in business practice to support decision-making concerning the design and operation of such global networks [2]. For these purposes, APS systems use predictive and prescriptive analytics approaches to forecast, plan, and optimize integrated production and logistics systems.

However, the business environment has changed after the 2008/2009 financial crisis including persistent volatility and uncertainty of markets as well as increased competitive pressure in the course of the ongoing digital transformation [3]. This basically involves more demanding customer requirements concerning availability and customization of value offerings [4]. But high service levels, short lead-times, and product variety typically involve high costs to match supply network capabilities with customer demand.

At the same time, supply networks become more complex and interconnected driving exposure to various risks such as supplier failure or equipment breakdown [5]. As a consequence, operating models of supply networks need to become more responsive and need to manage the adverse effects of variability proactively while keeping operations cost-efficient. Ultimately, this mandates novel approaches to risk-based decision support in this field.

Due to their deterministic and simplified planning approach, APS systems are not qualified to support these aforementioned requirements. Integrating stochastic modeling into supply network planning (SNP) could be one way to overcome these deficiencies [6]. Most recently, multi-model approaches and predictive analytics are intensively discussed (or even hyped) for advanced decision support in this context [7]. This paper thus investigates the merit of multi-model-based analytics approaches using a risk-based planning perspective and outlines avenues for further research in this field

The paper is structured as follows: section 2 provides the research background and summarizes conceptual foundations. In Sections 3 and 4, a research framework for multi-model SNP approaches is developed and open research topics are discussed. The paper concludes in Section 4 with a summary of the findings.

2 Research background and conceptual foundations

Planning-related tasks within supply networks can be structured along the four value chain stages procurement, manufacturing, distribution, and sales and most fundamentally involve two hierarchical levels: (i) strategic design of the supply network in the long term, and (ii) mid- to short-term operations of the supply network [8] which is in focus of this paper.

Predictive and prescriptive analytics provide necessary approaches for decision support in supply networks. Prescriptive analytics approaches (esp. mathematical programming) have mostly dominated the discussion around APS systems [1] answering the questions 'what shall we do?' and 'why shall we do it?' [6]. In contrast, the questions 'what will happen?' and 'why will it happen?' fall within the scope of predictive analytics. Predictive analytics methods are mostly applied for time series analysis in the domain of demand forecasting [1].

The key deficit of APS systems refers to lacking decision support for managing variability [6]. Variability results from random demand and stochastic events in supply network processes such as supplier/equipment failure or variation in operating times. APS systems accommodate variability indirectly by implementing exogenous static buffers, i.e., safety stocks and/or safety capacity, or simply adjust parameters to arrive at more conservative plans [9]. However, inadequate buffers involve substantial potential for improvement.

Corresponding to the two fundamental principles of production planning and control (push vs. pull), there are two distinct approaches to manage the implications of variability directly: (i) lean planning [10] or demand-driven material requirements planning [11] that follow the pull paradigm aim at avoiding the adverse effects of variability, and (ii) push-oriented stochastic planning that uses predictive and/or prescriptive analytics methods such as discrete-event simulation (DES) or queuing models to anticipate variability [12]. Subsequently, this paper focuses on queuing model-related approaches. For an overview of simulation-based optimization, the reader is referred to [13].

Stochastic planning approaches also allow capturing non-linear system behavior which is mostly omitted in traditional SNP approaches [14]. This relates to the simplistic assumptions of APS systems that order lead times are independent of the capacity utilization. However, increasing the capacity utilization, i.e., releasing additional orders into the supply network, drives 'congestion' in the system and thus leads to longer lead times [12]. Early papers of Graves [16] and Karmarkar [17] have initiated the literature stream around *clearing functions* that aim at capturing this non-linear relationship within mathematical programming models. For these purposes, clearing functions can be derived from both theoretical queuing models or empirical shop floor data [14]. Summaries of related work can be found in [14] and [18].

Given that clearing functions need to be integrated into discrete-time (linear) mathematical programming models, this implies substantial modeling restrictions. Multi-model approaches that combine mathematical programming with DES have thus been proposed and are widely discussed [12]. DES provides extensive modeling flexibility with the drawback that numerical effort rises or even gets intractable. Keeping the concept of multi-model approaches that allows for additional modeling flexibility, this research aims at investigating alternative multi-model SNP approaches in this context.

3 Multi-model SNP approaches

3.1 Planning scope

The planning problem in focus is located at the mid- to short-term level of sales and operations planning (S&OP) [19]. Detailed characteristics and trade-offs in S&OP are summarized in Figure 1. The objective function involves maximizing (economic) profit for a planning horizon of 6 to 18 months [20]. S&OP covers the three perspectives of sales, operations, and finance and aims at aligning respective plans cross-functionally. These plans cover price ranges and sales volumes (*sales*), material flows, capacities, and production volumes (*operations*), and current assets and liabilities esp. accounts payable and receivable (*finance*).

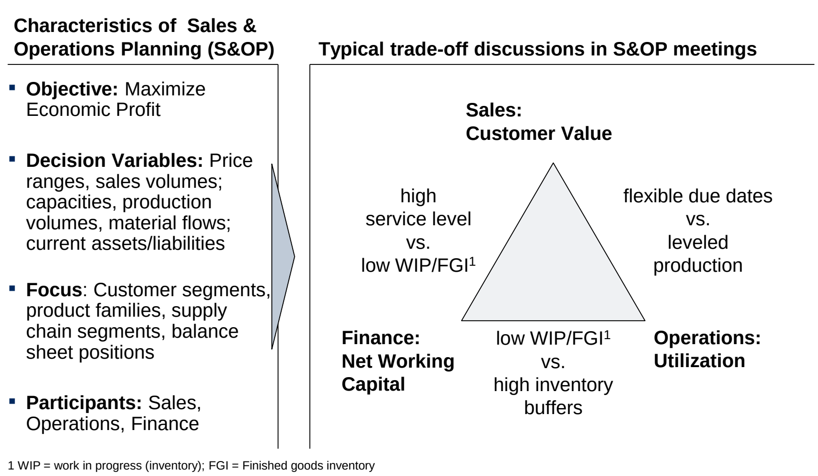

Fig. 1. Key characteristics and trade-offs in S&OP

While the sales function aims at improving customer value, operations is interested in maximizing utilization to reduce capacity-related costs. Net working capital and the reduction of costs of capital are in focus of the finance function. Consequently, three mutual trade-offs emerge that boil down to the strategic question of efficiency vs. responsiveness [21]. Notably, the trade-offs related to the operations function involve the non-linear clearing function relationship. More specifically, leveled production allows for higher utilization at the cost of longer lead times and increased inventory buffers due to larger batches.

There are two risk mitigation approaches that also foster responsiveness of supply networks: flexibility and redundancy [22]. Measures of flexibility can refer to the supply side (e.g. multi sourcing, flexible supply contracts), internal operations (e.g. multi-process equipment, postponement), or the demand side (responsive pricing). Responsive pricing represents the key lever at the operational level. Redundancy aims at finding the 'right' amount of buffer with respect to safety time, capacity, and inventories. Consequently, there are two major operational levers to manage the responsiveness of the supply network using a risk-based planning approach: responsive pricing and buffer management.

3.2 Conceptual framework

Capturing the stochastic and dynamic behavior of a supply network for planning purposes would require a stochastic non-linear programming approach [15]. However, one can use hierarchical decomposition [23] to simplify matters as follows: first, a deterministic linear programming (LP) model serves as the top level determining key sales, operations, and finance decisions given dynamic demand. An exemplary LP model for S&OP can be found in [20]. Second, an anticipated base level is implemented below that captures the stochastic and non-linear implications of the top-level decisions. Specific modeling approaches for the anticipated base level are discussed further below.

Capacity levels and production volumes serve as the top-down instructions for the anticipated base level. They basically determine inflow into the supply network and thus the workload in the system. Lead times or (WIP inventories) and capacity buffers in turn represent the bottom-up reaction and are incorporated as feedback at the top-level. The feedback can be implemented via 'hard' constraints or penalty costs in the objective function. Given that the overall approach aims at perfect anticipation [23] full coordination can be reached when applying an iterative algorithm. The hierarchical planning framework is summarized in Figure 2.

3.3 Methodological approaches

Modeling the anticipated base level involves two design decisions: scope/number of the model(s) and the analytics approaches. Both approaches of establishing one single model for the entire supply network and dividing the network into several sub-models can be found in the literature [24]. Here, the considerations for hierarchical decomposition also apply concerning the trade-off between modeling

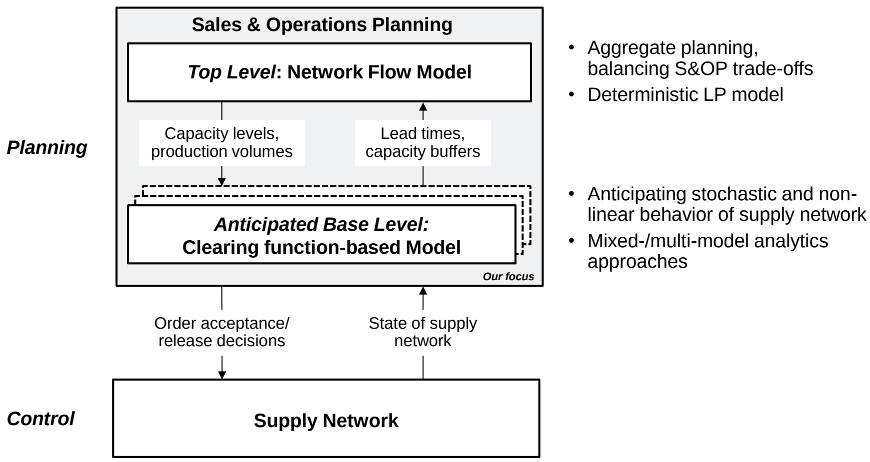

Fig. 2. Hierarchical planning framework (based on [24, 15])

accuracy and numerical tractability. Decomposition can also be required along the time dimension if parameters such as demand are time-dependent and the application of queuing theory requires steady state conditions [15].

Predictive and prescriptive analytics approaches or a combination of both can be applied. Predictive analytics approaches such as data mining have been proposed to estimate lead times in manufacturing systems [25]. [15] use a queuing networks-based approach to determine lead-time optimal batch sizes in a stochastic job shop setting (prescriptive analytics). Furthermore, one can find combined approaches: [24] use a moment-iteration algorithm to determine the workload in the system and apply a local smoothing algorithm to find a lead-time feasible schedule of planned order releases.

4 Avenues for further research

4.1 Planning scope

There are three avenues for further research concerning the planning problem: first, single-model approaches have been presented for supporting order acceptance decisions including workload considerations [26]. This could be further developed towards a responsive pricing approach to capture additional value from the customer. Second, the issue of multi-stage supply networks and especially the integration of production and logistics processes has not yet been considered and thus provides opportunities for further research.

Third, existing approaches for buffer management could be enhanced to arrive at more accurate predictions that would allow for the reduction of costly buffers while keeping supply network risk under control. This could involve more sophisticated approaches to modeling failure of technical equipment and corresponding repair activities [15] or approaches for predictive maintenance. Moreover, levers of manufacturing flexibility based on alternative routings in the job shop could be evaluated. [27] provide a corresponding approach for the process industries which could be extended to further domains of application.

4.2 Conceptual framework

The digitalization of the industrial sector – also known as *Industry 4.0* (i4.0) – envisions intelligent and interconnected 'things', i.e. smart products and machines, that operate autonomously and that can form self-coordinating smart supply networks [3]. Literature in this field mostly focuses on issues of operational scheduling and shop floor control [28]. Consequently, further research is warranted to develop novel planning frameworks and approaches that could support operational decision-making in smart supply networks.

Although the smart supply network paradigm proposes fully customized manufacturing using orders of 'lotsize 1' [29], component manufactures will still produce in small batch sizes for economic reasons. Given the volatile market environment, a dynamic batch planning approach could be one avenue for further research. Batch sizes need to be adjusted dynamically to support more flexible i4.0-like control approaches in supply networks. A corresponding comprehensive framework for integrated planning and control of supply networks should be developed to this end.

4.3 Methodological approaches

As outlined above, evaluating further predictive analytics approaches could yield novel approaches to risk-based SNP. There are two avenues that should be further considered: first, data-driven approaches could be applied extending extant concepts of data mining. This could involve determining relevant queuing-related statistics from empirical shop floor data to derive clearing function relationships. Related approaches are currently scant in the literature [30].

The second avenue relates to making more extensive use of data via predictive analytics which can inform prescriptive analytics approaches. [24] provide a corresponding example for the specific context of SNP. Further research in this direction would require investigation of existing methods and development of novel approaches considering both solution quality and numerical performance. Besides, the benefit of using a multi-model approach (compared to a single-model approach) should be evaluated for both aforementioned avenues.

5 Conclusion and outlook

Motivated by current developments in global supply networks due to more volatile markets and increasing customer requirements as well as shortcomings of extant APS systems, this paper investigated the merit of multi-model analytics approaches for risk-based SNP. For these purposes, current state of the art and avenues for further research have been identified along three lines: planning scope, conceptual framework, and methodological approaches.

From a business application perspective, this research area is closely related to Industry 4.0 and the smart factory paradigm. Especially component manufacturers that produce to order in small batches might represent an interesting industry for applications and case studies. Consequently, a design-oriented research approach should be pursued which could also yield managerial insights with respect to general rules for planning and decision support.

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