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From process control to supply chain management: An overview of integrated decision making strategies

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ABSTRACT

Optimal decision-making in a process industry is fundamental in order to guarantee optimality of operations and increase profits and performance of a company. Decision-making occurs at different levels, from process control to supply chain management. Traditionally, these decisions have been considered individually, with little or no interaction between each other. However, an integrated decision-making framework can guarantee solutions closer to optimality. Such integration usually results in complex and large scale problems that are difficult to solve. We provide an overview of integrated decision-making strategies and review recent advances in the area, highlighting promising works as well as the main challenges that have yet to be overcome.

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1. Introduction

The process manufacturing industry has a tremendous significance to the US economy. It accounted for 12.1% of gross domestic product income (GDP) in the economy in 2015, and it is directly responsible for 12.3 million jobs in the US, according to the Bureau of Economic Analysis. However, this segment faces numerous challenges such as the constantly growing world-wide competition, increasing complexity of production process, fluctuating customer demand and expansion of supply chains, as well as huge structural cost disadvantages when compared to its major competitors, according to the Manufacturing Institute ("The Structural Cost of Manufacturing in the United States," 2011). In the field of operations research and process systems engineering, the main strategy to combat these emerging challenges and improve the efficiency of process industry is the pursue of optimal operation conditions through an enterprise-wide optimization.

Enterprise-wide optimization proposes to optimize the decision making process amongst the various levels that comprise the supply chain of a company. The decision making in the process industry ranges across different scales, from process control to supply chain management as shown in Fig. 1. The decisions taken at these levels vary in terms of time horizon, complexity and objectives. On one end of the spectrum, strategic decisions determine the configuration of the supply chain network and usually have time horizons of years. On the other end, process control decisions have time horizons of seconds and focus on transition periods when processes are subject to disturbances.

Traditionally, the decision making problems have been considered individually and solved in a sequential way. An upper level problem is often solved with few or none information from lower levels. Its result is then transmitted to the lower levels, which must be optimized given the conditions already set by upper level problems. Consequently, sequential approaches may result in sub-optimal and infeasible solutions that can be avoided by an appropriate integration of different decision layers. Driven by this possibility, many researchers have explored the problems of integrating two or more decision making process, and techniques to solve the complex resulting problems have been developed.

This paper provides an overview of state-of-the-art methods for integrating different levels of the decision making process. In particular, the problems of supply chain management, the integration of planning and scheduling and the integration of scheduling and control are addressed. An ideal framework capable of integrating all the decision levels, considering the complexities and dimensions of a real world enterprise has yet to be developed. The ultimate goal of an enterprise wide optimization will require efforts from both academia and industry communities. However, considerable advances in the past few years can be found in the literature. We review such advances, highlighting promising works as well as the main challenges that have yet to be overcome.

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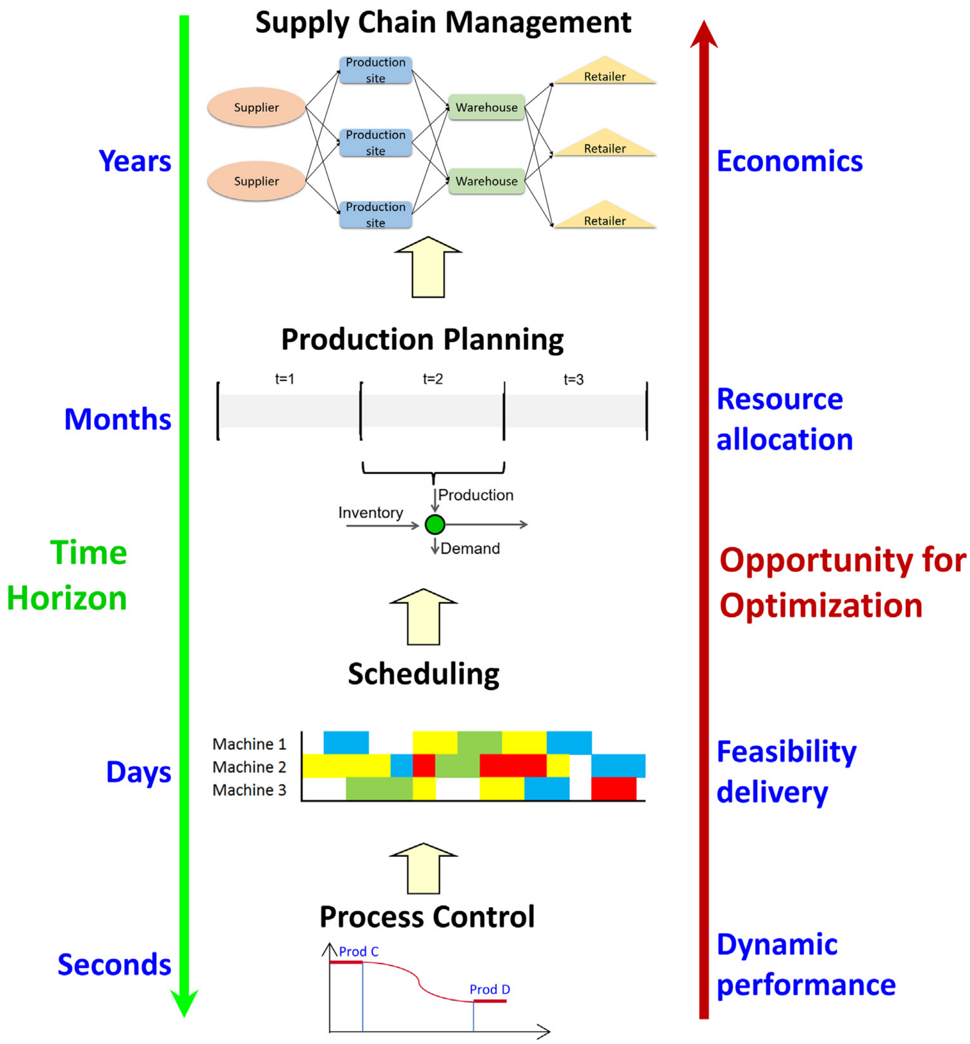

Fig. 1. Enterprise-wide decision making.

2. Supply chain management

A supply chain may be defined as an integrated process in which a group of various business entities, such as supplier, producers, distributors and retailers, work together in an effort to acquire raw materials, convert these raw materials into specified final products, and deliver these final products to retailers (Beamon, 1998). A supply chain schematic is shown in Fig. 2. Stadtler (2005) defines supply chain management as: '*the task of integrating organizational units along a supply chain and coordinating materials, information and financial flows in order to fulfil customer demands with the aim of improving competitiveness of the supply chain as a whole.*'

The planning tasks that support the decisions about material flows across a supply chain can be considered at different levels of aggregation and planning intervals ranging from "aggregated long term" to "detailed short term" planning (Fig. 3). At the strategic level (long-term), decisions related to number, capacities and location of manufacturing sites, warehouses and distributions centers are taken. Therefore, at this level, the design of the supply chain is defined. A comprehensive review focusing on methods to optimally design supply chains, as well as opportunities and challenges in this area has been recently published by Garcia and You (2015). At a tactical level (mid-term decisions), we look at problems which aim to define the most efficient way to fulfil demand forecasts over a medium-term planning interval. Tactical planning aims to balance demand forecasts with available capacities, and assign demands to production sites.

Traditionally, decision at strategic and tactical levels of a supply chain have been made individually by each entity in a network, based on their individual goals and objectives. However, greater efficiency and reduced costs can be achieved through proper coordination amongst the entities in terms of material, financial and information flow, which provides the motivation behind developing an integrated model for the whole supply chain. Due to increasing globalization of companies, integrated models must consider complex, large size global networks with different laws, taxes regimes, exchange rates and policies intrinsic to each country belonging to the supply chain. Hence, the first challenge in supply chain optimization is related to the modeling and accurate representation of detailed, complex interactions between global entities. A second challenge rises from the fact that strategic and tactical decisions usually involve a high level of uncertainty, such as uncertainties in demand, supply, process, resources availability and product returns. Such uncertainties must be dealt within the optimization frameworks, and risk management must be incorporated in solution strategies (Barbosa-Povoa, 2012, 2014). Additionally, the traditional supply chain paradigm where the goal was the maximization of profit while guaranteeing customer satisfaction is now changing, and aspects related to environmental and social concerns should be considered, leading to sustainable supply chains.

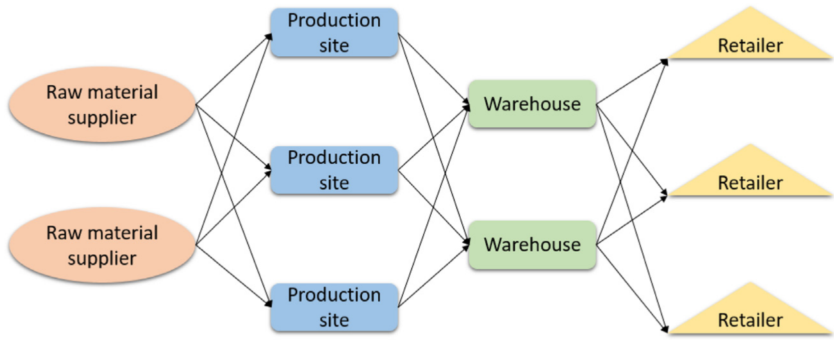

Fig. 2. A representation of a supply chain network.

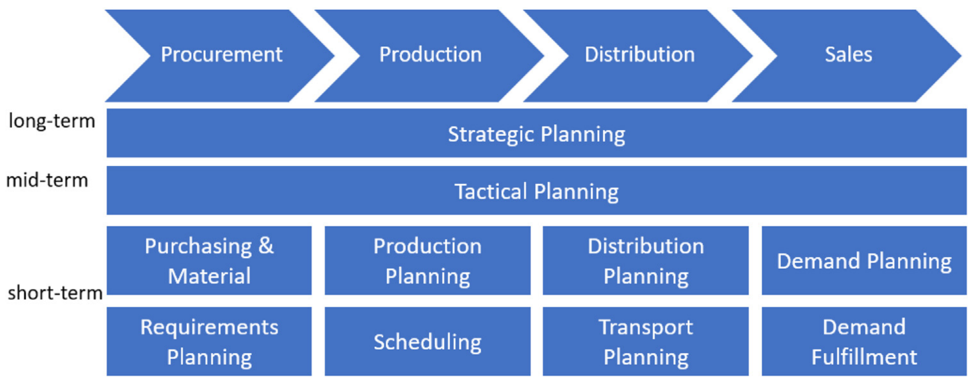

Fig. 3. Supply chain matrix.

Finally, business and financial aspects play an important role in multi-enterprise supply chains, and the particularities of interactions between different enterprises in the same supply chain must be considered in order to achieve optimal operation. The four mentioned challenges will be further discussed in the next sections.

2.1. Modelling a supply chain

Traditionally, supply chains have been modeled and optimized using mathematical programming techniques. Linear programming models (Kanyalkar and Adil, 2005; Martin et al., 1993; Ryu et al., 2004), mixed integer linear programming models (Jayaraman and Pirkul, 2001; Park, 2005; Timpe and Kallrath, 2000), nonlinear models (Benjamin, 1989), multi-objective programming models (Chen and Lee, 2004; Chen et al., 2003; Guillen-Gosalbez et al., 2010; You and Grossmann, 2011) and stochastic programming models (Gupta and Maranas, 2003; Sabri and Beamon, 2000) can be found in the literature to address various problems in supply chain management. Excellent reviews focusing on mathematical programming models for supply chain optimization problems were published by Mula et al. (2009) and Papageorgiou (2009). In Grossmann (2012), a brief overview of mathematical programming techniques, as well as decomposition methods, stochastic programming and modeling systems is provided. The author then addresses some of the major issues in the solution of these problems, and describes several applications of such techniques in enterprise wide optimization. However, mathematical models exhibit different shortcomings in representing the detailed behavior of each entity and their interactions in a supply chain, and are usually simplified versions of a complex system. Furthermore, the optimization of an entire supply chain considering decisions across multiple time-scales results in a large-scale problem that is usually computationally intractable.

Simulation based approaches have been proposed to tackle these challenges and contribute to more accurate representation of realistic supply chain systems. They can be used to represent the real world dynamics of the supply chain, and have been shown to be effective tools for analyzing supply chain dynamics and performance. Different simulation approaches have been used to model supply chains, including system dynamics (Georgiadis and Vlachos, 2004; Higuchi and Troutt, 2004), discrete event simulation (Angulo et al., 2004; Ganeshan et al., 2001; van der Vorst et al., 2000), and agent-based simulation (Garcia-Flores and Wang, 2002; Julka et al., 2002; Swaminathan et al., 1998).

In order to make use of advantages of both simulation and optimization models, hybrid approaches have been developed in recent years (Chen et al., 2012; Jung et al., 2004; Wan et al., 2005). Typically, these approaches tackle problems where the derivatives of the objective function and constraints are unavailable or difficult to compute and their values are obtained from simulations which are usually computationally expensive. Rios and Sahinidis (2013) and Amaran et al. (2014) provide good reviews of techniques that are used in these approaches. In Davidsson et al. (2007), a very good comparative discussion of the strengths and weakness of simulation based approaches and classical optimization techniques was provided. The authors concluded that the two approaches are complementary and thus, it was beneficial to use their combination.

In Sahay and Ierapetritou (2013), a hybrid based optimization approach was proposed to solve the problem of supply chain management with the aim of overcoming the computational complexity associated with pure optimization approaches. They assumed the design for the supply chain was predetermined, and therefore decisions such as location and capacities of the warehouses, production sites and products to be manufactured were taken as constraints in the optimization problem. An agent based simulation model was used to capture the dynamics of the supply chain where each supply chain entity was modeled as an autonomous body with its own behavior and policies. Market, production site, warehouse and raw material supplier agents were included in the model. On the other hand, the optimization model was formulated as a multi-objective mixed integer linear programming. The objective was to reduce the overall cost, which consisted in transportation costs, inventory costs and backorders costs while keeping the environmental impact within a predefined upper limit. With such framework, the authors propose to use the simulation model to capture the realistic conditions of a sustainable supply chain by incorporating the characteristic behavior of the entities, whereas the optimization model would guide the simulation toward optimality. Both simulation and optimization models were developed independently and further coupled together by a systematic exchange of information: the outputs from the simulation model were set as decision rules for the optimization model while the outputs from the optimization model were set as targets for the simulation model. It was shown that the objective function values from the simulation model and the optimization model converge to the same value as the iterative framework proceeds. The work was further extended by Sahay and Ierapetritou (2014a,b). In the first, the authors investigated how the supply chain behaved under different network and decision-making policies. In the former, the authors demonstrated the importance of capturing the synchronous and asynchronous decision-making strategies of different supply chain entities.

2.2. The uncertainty challenge

Whether by using simulation, optimization, hybrid or even heuristic approaches, many supply chains today are very efficiently designed and operate to maintain consistent low cost and high customer satisfaction. However, over the years, there have been tremendous advances in the field of information technology, and with it supply chains have become much more globalized, complex and subjected to uncertainties. Therefore, the need for flexible design and operation has gained attention as an approach to offset the uncertainties in supply chain environment. Supply chain flexibility has been studied for quite some time, and has been looked from very diverse perspectives (Chan and Chan, 2010; Garavelli, 2003; Graves and Tomlin, 2003; Tang and Tomlin, 2008). In addition, various strategies and models have been investigated to mitigate the supply chain disruptions and losses associated with different types of risks (Giannakis and Louis, 2011; Hahn and Kuhn, 2012; Talluri et al., 2013).

Comprehensive reviews on modeling approaches for the design of supply networks under uncertainties were presented by Peidro et al. (2009), Klibi and Martel (2012) and Heckmann et al. (2015). Recent publications in the field include the work by Rodriguez et al. (2014) and Yongheng et al. (2014), which proposed methodologies for the optimal supply chain design and management over a multi-period horizon. Uncertainties in demand were addressed by defining the optimal amount of safety stock that guarantees certain service level at a customer plant. Ye and You (2016) presented a simulation based optimization method with region-wise surrogate modeling for stochastic inventory management of supply chains, and Yue and You (2016) presented a framework for the optimal supply chain design and operations taking into account multi-scale uncertainties, and addressing uncertainties at each scale in a different manner. Cardoso et al. (2015) identified main supply chain characteristics that a decision maker should account for in order to design and plan a resilient framework for a complex supply chain operating under demand uncertainty.

In Sahay and Ierapetritou (2015), a hybrid simulation based optimization framework was presented for assessment of flexibility of supply chain operations and risk management. The authors considered uncertainty in the demand, and studied the trade-off between the economic performance and flexibility of the supply chain network. In this work, flexibility was defined in terms of the bound of uncertain demand within which the supply chain operation was feasible. The multiproduct supply chain planning problem under demand uncertainty gives rise to a stochastic optimization problem. A two-stage stochastic linear programming in a rolling horizon approach was proposed to solve the problem where hybrid simulation-based optimization approach was used to solve the first stage of the two-stage problem.

2.3. Sustainable supply chains

Over the past decades, environmental regulations and compliance costs resulted in efforts from industrial communities to minimize the environmental impact of process design and development. Focus on supply chain management has therefore moved from a specific cost perspective approach, to the broader adoption and development of sustainability. The importance of balancing social, environmental and economic objectives in companies' sustainable development has cultivated a growing awareness on sustainable optimal design. In particular, significant research effort has been devoted on developing sustainability analysis methods and measures and integrating them with supply chain design and management.

In the process systems engineering community, an excellent review of the area has been published by Nikolopoulou and Ierapetritou (2012). The authors review some of the relevant research on sustainable chemical supply chains extending from the process synthesis phase to the supply chain management. Recently, Garcia and You (2015) published a review on supply chain design and optimization. The authors believe that sustainability topics is one of the key areas of research opportunities for supply chain design. An overview of sustainable supply chain design is presented, and challenges in the area are described.

2.4. Multi-enterprise supply chains

It is important to notice that the different entities constituting a particular supply chain usually belong to more than one supply chain network. Multi-enterprise supply chains can have a lot of additional factors affecting their dynamics and performance compared to monolithic single enterprise supply chains. Factors related to competition, cooperation, negotiation, and so forth become more significant in such a scenario. However, most of the solution strategies mentioned so far are based on the consideration of centralized networks, and often ignored the effects of these factors. In multi-enterprise networks, the dynamics of the supply chain operations evolve as a result of the interactions among the different enterprises and therefore those should be taken into consideration while modeling such networks.

Initial studies discussing multi-enterprise networks were conducted by D'Amours et al. (1999), who proposed a network approach with multiple firms and showed that a collaborative approach between enterprises was more profitable. They suggested the implementation of electronic data exchange among firms in order to minimize costs. Recently, Yue and You (2014) proposed a bi-level MINLP model for the optimal design and planning of non-cooperative supply chains. Interactions among the supply chain participants were captured through a single-leader–multiple-follower Stackelberg game under the generalized Nash equilibrium assumption. In Hjaila et al. (2015), the issue of considering the supplier's competitive behavior and the uncertain behavior of other partners was addressed. They developed a scenario-based negotiation approach aiming to establish the best conditions for the coordination contract through quantitative negotiations built on win-to-win principles considering the uncertain behavior of the follower conditions when optimizing the leader supply chain. A Stackelberg-game model was also developed and the performance of both models was compared.

In Sahay and Ierapetritou (2016), a multi-enterprise supply chain network was studied. Raw material suppliers, production sites and warehouses were considered to belong to one particular enterprise while the retailers were different enterprises. An agent based simulation model was developed to represent the network. It was assumed that the transaction between warehouses and retailers happens through auctions. The auctioneer agent determined the auction mechanism and arranged the auctions. The agents participating in the auctions were able to adjust their behavior based on the outcome of the auctions. As the warehouse were directly participating in the auctions and their capacities have a significant effect on the performance of the supply chain network, an optimization methodology was used to find the optimal warehouse capacities in the network. The objective function was the minimization of total cost for the planning horizon, which includes transportation costs, inventory costs, production costs and backorder costs. The values of the objective function were obtained using the agent based simulation model. As the analytic derivatives were unavailable for the objective function, a derivative free optimization methodology was proposed to solve the supply chain problem.

Although some progress has been done in recent years, there is no model capable of capturing all the complexities of a multi-enterprise supply chain. Factors related to competition, cooperation, negotiation and so forth are significant in such networks, and therefore the representation of dynamics and performance of multi-enterprise supply chain is challenging. The literature provides some insights allowing a narrow understanding of some particular scenarios. Future work must be done to investigate higher dimensional problems incorporating a broader representation of negotiation aspects. A more precise representation of supply chains, as well as efficient algorithms to determine its optimal operation conditions is an essential step before the integration of decision making process in the lower levels of the decision-making hierarchy.

3. Integration of planning and scheduling

Although associated to different time horizons, production planning and scheduling are closely related problems. While production planning determines the optimal allocation of resources and production targets over a time horizon of weeks or months, scheduling of production determines assignment of tasks to units and the sequencing of tasks over a time horizon of days or weeks (Fig. 4). Traditionally, planning and scheduling problems are solved independently and in a sequential way. The planning model is solved first, and the output of the planning problem is set as the production target of the scheduling problem. In such approaches, there is no interaction between the two decision levels. However, sequential approaches often result in suboptimal or infeasible solutions, as they do not take into account the detailed production schedule information at the planning level. Therefore, the simultaneous consideration of planning and scheduling decision arises as an alternative that can guarantee solutions closer to the optimal.

The most intuitive way of addressing the integrated planning and scheduling problem is to use a detailed scheduling model as resource constraints and production costs in the planning model (full-space method). Standard mathematical programming methods can be used to solve the integrated problem (Kallrath, 2002; Papageorgiou and Pantelides, 1996a,b). However, the computational difficulty arising from the formulated complex model prohibits the application of such techniques when typical planning horizons are considered. Alternatively, decomposition approaches that exploits the structure of the integrated formulation and speed up the computation have been proposed in the literature. In particular, Lagrangian relaxation has been widely applied onto planning and scheduling problems for different applications including unit commitment in power industry (Padhy, 2004), midterm production planning (Gupta and Maranas, 1999), and combined transportation and scheduling (Equi et al., 1997). In Li and Ierapetritou (2009b), the drawbacks of Lagrangian relaxation methods are pointed, including the duality gap between the solution of the Lagrangian dual problem and the solution of original problem, and the need for recovering the feasibility of the solution through heuristic steps. The authors proposed to use an augmented Lagrangian relaxation (ALR) method in order to avoided the disadvantages of classical Lagrangian technique, and apply such method in the integrated planning and scheduling problem. The ALR problem is solved using a two-level optimization strategy. In the first level, the relaxation problem is solved only with respect to the planning decision variables. The second level involves solving a set of scheduling sub-problems with fixed planning decisions in every iteration. The main advantages of the augmented Lagrangian relaxation are that it is ensure convergence without solving the relaxation problem to optimality, it can be easily parallelized, and it is able to avoid the duality gap. In Shah and Ierapetritou (2012), augmented Lagrangian relaxation method was applied to a multisite production and distribution optimization problem.

An alternative to the full space models is the hierarchical decomposition approach. In hierarchical methods, the problem is decomposed into a master subproblem to determine production targets, and a slave subproblem with detailed scheduling. Information is passed from the master to the detailed scheduling problems, which are then solved separately. To ensure the feasibility and optimality of the solution, effective algorithms were developed in order to improve the solution using additional cuts in the planning level within an iterative solution framework (Bassett et al., 1996; Erdirik-Dogan and Grossmann, 2006; Kelly and Zyngier, 2008; Munawar and Gudi, 2005; Papageorgiou and Pantelides, 1996a,b). In Li and Ierapetritou (2009a), a hierarchical framework for the integration of planning and scheduling was proposed. A single planning problem and multiple scheduling sub-problems were formulated, and the equivalence between the bi-level model and a single level formulation was proved. Since the resulting model was computationally intractable because of the large size of the model, a decomposition approach was proposed. The production feasibility requirement was modeled through penalty terms on the objective function of the scheduling sub-problems, and a convex polyhedral underestimation of the production cost function was developed to improve the solution accuracy.

Recently, Chu et al. (2015) proposed a new integrated method based on bi-level model. They formulated the planning problem as a mixed integer linear program aiming to optimize the economic performance, while the scheduling problem was solved using an agent-based method. The agent-based method can solve a large-scale scheduling problem efficiently while capturing the process uncertainties. The problem was solved to minimize the total cost while meeting the customer order demands and satisfying service level. An iterative algorithm was proposed, in which the MILP planning problem was solved to determine the production quantities in the planning periods, while the agent-based simulation was conducted to schedule the production under uncertainties. Monte-Carlo simulations were performed to evaluate the service levels measured by probabilities. If the service levels were not satisfied, a cutting plane constraint was generated and appended to the MILP planning problem. The planning problem was solved again to determine new production quantities in the next iteration. The iterations between the MILP solver and the agent-based method were repeated until all service levels are satisfied.

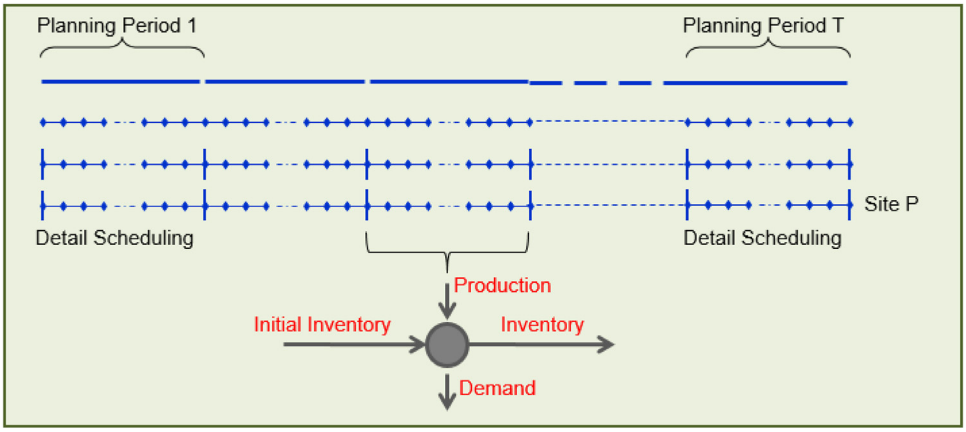

Fig. 4. Schematic for the integration of planning and scheduling.

Another alternative is to use hierarchical decomposition within a rolling horizon framework, where detailed scheduling models are used for a few early periods and aggregate models are used for later periods. The production targets for the early periods are directly implemented, while the production targets for the later periods are updated along with the rolling horizon. Such approaches were proposed by Dimitriadis et al. (1997), Sand et al. (2000), Van den Heever and Grossmann (2003) and Verderame and Floudas (2008). In Wu and Ierapetritou (2007), a hierarchical approach for production planning and scheduling under uncertainty was proposed. A multi-stage stochastic programming was formulated in which three stagers were considered with increasing level of uncertainty. The planning model included material balances and time horizon constraint which involved a sequence factor to reflect the recipe complexity. Using a rolling horizon strategy, the production for the current stage is provided to the scheduling problem, which was solved using a continuous-time formulation. An iterative framework was developed to converge the planning and scheduling results before solving for the next period.

For the cases where there is no plant and market variability, campaign mode can be applied to generate an easy to implement and profitable process operations plan. This results in big savings in operations due to effective management of frequent changes and the fact that it is easy to be implemented. In a periodic scheduling framework, the planning and scheduling integration problem is replaced by establishing an operation schedule and making it executed repeatedly (Castro et al., 2003; Schilling and Pantelides, 1999; Shah et al., 1993; Zhu and Majozi, 2001).

Finally, instead of using the detailed scheduling model in the integrated planning, surrogate models can also be used to represent scheduling feasibility and production cost within an aggregated planning problem. Parametric programming techniques can be used to derive the surrogate model of the scheduling problem which is represented by a set of critical regions and corresponding optimal production cost functions and feasibility boundary. In this direction, Sung and Maravelias (2007) proposed a model that uses offline computations based on a detailed scheduling model to generate the convex hull of feasible region of feasible production targets and a convex underestimation of total production cost. The common difficulty of this method is that both the feasible space and optimal objective function are non-convex functions of the planning decision parameters and the computational efforts for an accurate description of the surrogate model depends on the dimension of the decision space.

A significant number of studies have addressed the problem of integration of planning and scheduling. Now it is essential that these problems are integrated with the decision-making problem at control level, and by joining efforts with the industrial community, a realistic framework for the integration of planning, scheduling and control can be developed.

4. Integration of production scheduling and process control

Scheduling of production and process control are naturally related problems. Scheduling aims at maximizing profit by setting the optimal production sequence, batch sizes, unit assignments and timing of tasks while control maximizes performance by focusing on the dynamic behavior, such as the transition between products (Zhuge and Ierapetritou, 2015). The problem of integrating production scheduling and process control has gained increasing attention by academia and industrial communities as research shows the possibility of improving performance when the decision making processes across all the layers of the chemical supply chain are addressed simultaneously (Grossmann, 2005). Furthermore, such integration seems natural given the closer relation between scheduling and control problems, and the extensive exchange of information required for the solution of both problems.

Initial efforts towards the integration of scheduling and control followed the intuitive route of including the dynamic model of the process as an addition set of constraints in the scheduling problem. The result is a mixed-integer dynamic optimization problem (MIDO), and its solution provides the optimal production sequence and optimal control moves required to implement the schedule. The MIDO problem is then discretized into a Mixed Integer Nonlinear Programming (MINLP) using, for example, collocation point method or implicit Runge Kutta methods. This approach was proposed by Flores-Tlacuahuac and Grossmann (2006), and it was extended by Terrazas-Moreno et al. (2007) and Zhuge and Ierapetritou (2012). Alternatively, Pattison et al. (2016) proposed to solve the MIDO problem using sequential techniques, and decoupled modeling approaches were proposed by Nystrom et al. (2005) and Nystrom et al. (2006). The former consists of formulating the scheduling problem (master problem) as a Mixed Integer Linear Programming (MILP) and the control problem (primal problem) as Dynamic Optimization. The problem is solved through iterations between the master and primal problems.

These approaches, however, face considerable challenges associated to the use of high-fidelity representations of the process dynamics and the complexity, nonlinearities and discontinuities that this brings to the scheduling problem. The computational cost of performing the integrated scheduling/control calculations online and in real-time represent one of the main barriers in the deployment of an integrated scheduling and control framework in practical applications.

Recently, Zhuge and Ierapetritou (2014) proposed a framework for the integration of scheduling and control which facilitates its online implementation. To address the online computational burden, they incorporated multi-parametric Model Predictive Control (mp-MPC) in the integrated problem. The methodology involved using PWA approximations to linearize the original dynamic model of the process. Once this step was completed, the control problem for the derived PWA was solved using multi-parametric programming techniques to obtain explicit solutions for the control problem. The explicit solutions were then transformed to explicit linear constraints by introducing additional variables, and these constraints were incorporated to the scheduling problem. Case studies involving a batch process were presented, and the performance of the proposed model was compared to a model where a MIDO was built for the integrated problem and discretized into a MINLP using implicit Runge-Kutta method. The comparison showed that the proposed framework produced slightly lower profit while its solution time was nearly two orders of magnitude smaller. Nevertheless, the applicability of this model was limited to small and medium size control problems, provided that the number of critical regions in the multi-parametric problem increases exponentially as the problem size increases in terms of state dimension and prediction horizon.

Lagrangean and Benders Decomposition techniques applied to the scheduling and control problem have also been proposed in order to reduce computation complexity of the integrated problem, enabling online implementation of scheduling and control (Chu and You, 2013a,b; Terrazas-Moreno et al., 2008). However, in view of the difficulties these methods still face in practical implementation, a series of strategies to improve the computational efficiency of solving the integrated planning and scheduling problem was proposed by You and coworkers. In Chu and You (2014b), the integrated scheduling and control problem is formulated into a bi-level program. The problems are collaborated by a Stackelberg game, where the scheduling problem in the upper level acts as a leader and the dynamic optimization problems in the lower level acts as the followers. The follower problems have their own objectives, but the leader problem can coordinate the follower problems to pursue its objective. A decomposition algorithm is developed to efficiently solve the bi-level program, in which the lower level problems are solved first to determine the response functions, and the response functions are then represented by piecewise linear functions to solve the upper level problem. In Chu and You (2014a), the problem of integrating planning, scheduling and dynamic optimization for batch process is explored. The integrated problem is first formulated into a MIDO, discretized into a MINLP problem, and efficiently solved by separating it into sub-problems using surrogate models to represent the linking functions. In Shi et al. (2015) the integrated planning, scheduling and dynamic optimization problem of a continuous manufacturing process is studied. Again, the integrated problem is first formulated into a MIDO and further discretized into a MINLP problem. By using metamodeling to characterize the detailed linking information between different decision layers, an efficient solution method to decompose the integrated MINLP into a mixed integer linear program (MILP) is developed. A bi-level decomposition algorithm is also applied to further improve the computational efficiency.

Another challenge faced by the process industry today are the dynamic market conditions to which they are exposed, and the increasing uncertainties that such conditions bring to the process. Uncertainties can be associated to exogenous and endogenous factors, and can be effectively handled by the scheduling and control problems depending on its source. Disturbances such as flow and rate temperature variations, stream quality fluctuations, and dynamic model mismatches are associated to the control problem, while disturbances such as product demands, prices, processing times and equipment availability affect mainly scheduling solutions. The approaches for dealing with uncertainties can be classified as preventive or reactive. The first proposes to incorporate the model of uncertainty in the scheduling and control formulations and generate robust solutions prior to the occurrence of a disturbance. In the former, solutions for scheduling and control problems are based on nominal models, and are updated in response to the occurrence of uncertainties.

Most of the integrated approaches in the literature present models for continuous process operations and suggest to solve the problem offline for sequencing of production and control laws. Due to the large complexity, the online solution of these problems in impractical. However, the offline solution for control laws disregard disturbances at control levels and the advantages that modern process controls have in face of uncertainties. Handling disturbances at the scheduling level using an integrated framework is also difficult, and, so far, very few works in the literature attempted to address these problems.

Zhuge and Ierapetritou (2015) proposed a framework for the integrated problem using fast model predictive control. The framework was formed by two control loops. In the outer loop they approximated the original process dynamics using a piece-wise affine (PWA) model and incorporated it with the scheduling constraints, which resulted in a MINLP problem. The integrated problem at the outer loop generated the production scheduling and the state references for the inner loop. The inner loop tracked state references using fast Model Predictive Control, and the exact control solution was computed online. When disturbances at the control level were detected, information was feedback to the inner fast MPC or outer integrated problem based on a limiting value for deviations determined empirically. This way they avoided to resolve the full integrated problem when disturbances were small enough that could be handled efficiently in the control level.

Other attempts to address the problem of scheduling and control under uncertainties were presented by Chu and You (2013a,b,c), who formulated the integrated problem into a two-stage stochastic program;, who presented three approaches based on chance-constrained programming, fuzzy mathematical programming and robust optimization in order to analyze the impacts of uncertainties on the scheduling and control solutions; and Chu and You (2012), who proposed a fast computation of the integrated problem based on decomposition approaches.

In view of dynamic market conditions and uncertain scenarios, our future work includes the development of robust controls, the use of surrogate models to predict the closed-loop input-output behavior of systems governed by such controls, and the integration of robust control to the scheduling problem. We further aim to exploit the structure of the resulting integrated problem in order to reduce its computational complexity, enabling its online use and application to systems subject to uncertainties at control and scheduling levels.

5. Challenges in enterprise wide optimization

Due to its tremendous significance to the US economy, any efforts that increase the competitiveness of the process manufacturing industry are extremely valuable. The integration of different decision making processes of a company in the pursue of enterprise wide optimization is challenging, but it can clearly provide benefits and facilitate the achievement of optimal operation conditions. However, managing and designing such integrated schemes is a complex task and many issues remain unsolved.

5.1. Organizational challenges

First, organizational challenges related to corporations must be overcome. Currently, most companies use a variety of different tools including complex spreadsheets, enterprise resource planning, and supply chain management applications in order to manage their supply chains. However, such tools usually do not interact with each other and therefore are not appropriate to track and optimize the company's assets throughout the entire enterprise. Furthermore, information from different levels of the decision making process is usually gathered and kept in different departments within the company. Consequently, the different decision makers do not have access to all the information they need to make optimal decisions for the entire enterprise. Data integration across the different levels of a decision making process is a key issue that can be overcome by the implementation of modern IT tools which allow the sharing and instantaneous flow of information along the various organizations in a company (Grossmann, 2005).

5.2. Challenges at the supply chain level

Supply chain management is probably the most complex and challenging decision making process in an enterprise. The operations of a supply chain usually proceed as local interactions among the entities rather than a central entity coordinating all the operations. These interactions lead to flows of information, material and money which in turn result in subsequent interactions. Therefore, the overall operations of a supply chain develop as a network of feedback loops of interactions and information, material and money flows. We highlight some of the main issues faced by the decision makers at this level.

- Strategic, tactical and operations decisions must be taken into account when designing and operating a supply chain. Decisions at this level have a wide span of time scale and range from global in scope to the very localized. While these decisions are highly interdependent it is a challenge for individual decision makers to consider this interdependence. This results in outcomes that do not meet the expectations.
- The use of supply chain simulators has been employed by many companies, allowing the understanding of their enterprise state. However, very rarely the decision makers have the capacity to study different scenarios before a decision is due and moreover to understand what are the implications of different parameters in their supply chain state, as well as how far is their decision from the optimality.
- Being capital intensive, process industries have very long capital planning horizons that must deal with significant uncertainty and financial risk. It still is a tremendous challenge for companies to design supply chains that are responsive to market dynamics, changing energy availability, new regulations, and new technology.
- Extended supply chains involving raw material suppliers, manufacturing facilities, distribution centers, and final customers can be global and involve many transportation modes that are vulnerable to disruption. To be sustainable, supply chains need to be flexible and resilient. Quantifying supply chain resiliency so that it can be rigorously considered during design and operations is a difficult challenge.
- For a process industry, sustainability requires consideration of the potential environmental, social and economic impacts for all the company's activities and to improve not only what is in their direct control but also what they can influence in both upstream and downstream supply chains for their products and activities. Inclusion of additional dimensions greatly increases the complexity of the supply chain management, but companies must take on this challenge if they are to successfully find solutions that have farther-reaching and longer-lasting benefits.

5.3. Challenges in integrated decision-making strategies

Although the integrated decision making strategies can results in solutions closer to optimality, many challenges have yet to be overcome so its implementation can be possible. The different time scales to each planning, scheduling and control problems are associated creates difficulties to represent time in the integrated problem (Biegler et al., 2014). While it is desirable to use detailed representations so that events of small time scales can be accurately captured, the resulting integrated problems are usually complex and the computational time to solve such problems is intractable. Therefore, sequential methods, although no optimal, are still preferred by the industrial community.

Furthermore, the different objectives of planning, scheduling and control problems are often neglected in integrated frameworks. While the primary objective of the control problem is to achieve stability, robustness, safety and fast tracking, the objective of the scheduling problem is to ensure productivity and profitability. However, the integration of scheduling and control usually accounts only for the scheduling objective, and the advanced control methods and objectives which are widely and successfully applied by industries are not considered. Similarly, planning problems usually focus on economic criteria and customer service levels, neglecting the scheduling and control goals in integrated frameworks. Taking into account these different objectives in a single integrated problem is no trivial. However, in the long term, only the processes that simultaneously manage to optimize cost, quality, flexibility, operability, and sustainability will remain competitive (Chu and You, 2015).

Another critical issue in the integrated problems are the uncertainties related to different levels of the decision making hierarchy. While many efforts have been done in recent years, the problem of simultaneously accounting for uncertainties in planning, scheduling and control level remains unsolved. The reason for this is that the resulting optimization problems are extremely difficult to solve since they give rise to stochastic programming problems (Grossmann, 2005). The development of novel and effective stochastic programming tools will be essential for such challenges to be overcome.

Finally, an efficient solution algorithm for integrated problems that are able to represent complex and high-dimension supply chains, account for different objectives and goals of each decision layer in an enterprise, and simultaneously address the problem of uncertainties has yet to be developed. The development of novel computational algorithms and their implementation may be the solution, as well as the application of decomposition approaches to such complex and integrated frameworks.

6. Conclusions

This article has provided an overview of the research on integration of different decision-making stages. It is motivated by the growing need for improved and more efficient decision-making tools with the increasing size and complexity of enterprises. The multiple levels of decision-making in the process industry need to be integrated and efficient, parallelizable decomposition algorithms are required to address the integrated problems. Effective approaches have been proposed to solve problems with different levels of decision-making. However high dimensionality is an issue that still needs to addressed. Another challenge associated with the development of such advanced decision-making tools is data integration across the different levels. Seamless integration of data across these levels is essential. It is hoped that this article has conveyed the significance of integrated decision-making in the process industry as well as the opportunities for research in the area.

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