Novel Approaches for the Integration of Planning and Scheduling

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Abstract

The problem of integrating planning and scheduling models is addressed. Many of the previous models proposed in the literature assume that both models need to be solved over the same time horizon, leading to intractable models. Integrated models with shorter scheduling horizons are considered. To maintain the trade-off balance between the decision levels, the objective functions are appropriately scaled. The second modeling aspect explored is the communication between planners and schedulers. Communication through inventory policies is explored as an alternative to the traditional communication through production and inventory targets. The resulting models are evaluated in a tailored simulation framework. Models with a shorter scheduling horizon, which cover the decision horizon of the planning, obtain similar profits as the full space models. The communication through inventory policies leads to lower inventories, while maintaining similar profit levels. The proposed models and the modular modeling methodology used are contributions to bring decision support systems closer to practice.

1 Introduction

Supply chain decisions are hierarchically organized in strategic, tactical, and operational decisions (Fig. 1). In practice, these planning processes are often conducted independently in practice with limited exchange of information between them. Achieving a better coordination between these processes allows companies to capture benefits that are currently out of their reach and improve the communication among their functional areas (Brunaud and Grossmann, 2017). Optimization methods for the integration of strategic and tactical decisions are well established (Barbosa-Póvoa, 2012). Nevertheless, the integration of tactical

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and operational decisions remains a challenge (Bassett et al., 1996; Maravelias and Sung, 2009; Garcia and You, 2015; Dias and Ierapetritou, 2017; Castro et al., 2018). In previous models for the integration of planning and scheduling reported in the literature, two assumptions have been frequently made: (1) planning and scheduling models need to be solved in the same time horizon, and (2) the communication is done through inventory and production targets. We propose alternatives to these assumptions in order to improve the underlying models.

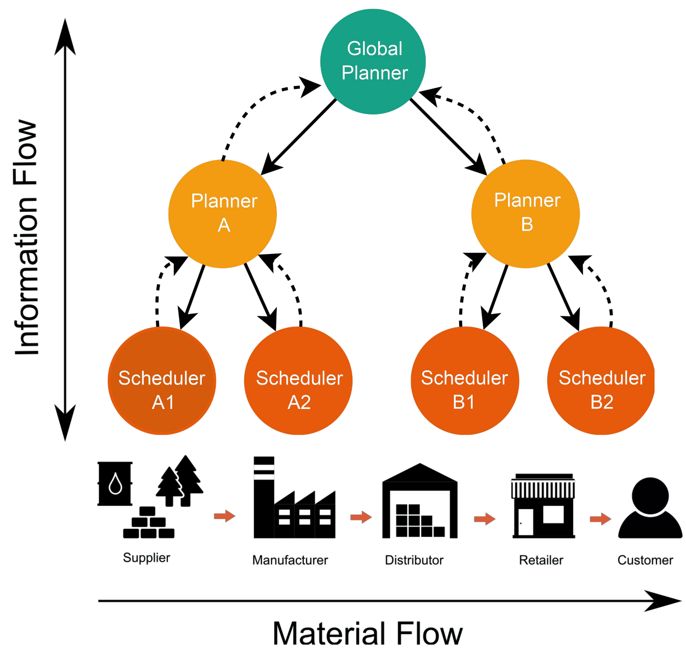


Figure 1. Supply chain decision network structure

For the first assumption addressed—the matching of optimization horizons for planning and scheduling—solving the scheduling problem in a shorter horizon is explored. The trade-off between both levels is maintained by scaling the objective functions. When the scheduling models are solved separately from the planning, the horizon considered is shorter. Decisions associated to optimal scheduling of processes are not required for several weeks in advance. Defining models with shorter horizon can reduce the computational complexity, facilitating the implementation of decision support systems based on these models. Assessing the effects of decreasing the scheduling horizon is not straightforward. For this task a tailored simulation framework is designed to evaluate the models in the same setting they are meant to be used, including planning and scheduling agents that run optimization models to make their decisions.

The second aspect studied is the effect of establishing a communication between planners and schedulers through inventory policies. The traditional approach has been to assume that the planner defines production and inventory targets, which are followed by the scheduler. The alternative proposed is to optimize an (s,S) policy (Vrat et al., 2016) at the planning level using the models proposed by Brunaud et al. (2019) and pass the policy parameters to the scheduling level. In order to be able to enforce the policy, the scheduling model also needs to consider inventory policy constraints. The inclusion of these constraints leads to novel integrated planning and scheduling models (IPSM) with simultaneous optimization of inventory policies. The performance of the alternative communication mode is evaluated in the same simulation framework that is proposed.

The proposed models bring the IPSM closer to the application. The reduction of complexity obtained from decreasing the scheduling horizon can reduce the implementation barriers in decision support systems, while the communication through inventory policies offers an alternative with the potential to improve the communication between planners and schedulers. The proposed models represent an advance in IPSM. Nevertheless, the integration challenge still remains an important problem to be solved in Enterprise-wise Optimization (Grossmann, 2005). The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the problem statement. Section 4 develop in detail the modeling alternatives proposed. Section 6 describes the simulation framework proposed. The planning and scheduling models considered are presented in Section 5. Section 6 describes the simulation framework proposed. Finally, a case study and its results are discussed in Section 7, to conclude in Section 8 with the most relevant contributions of the paper.

2 Literature review

The importance of hierarchical approaches for the integration of planning and scheduling has been recognized for many decades (Hax and Meal, 1975). In the early approach by Bitran and Hax (1977), the levels are defined by aggregation of products into families and types. A multiperiod model is only solved at the top level, while the next levels are disaggregation models.

In the process industry several authors have considered the hierarchical approach. Birewar and Grossmann (1990) propose a planning model that incorporates an aggregated scheduling model, which determines the number of batches to be produced for each product, and then used to solve the detailed scheduling. The model is extended by Petkov and Maranas (1997) to consider demand uncertainty. van den Heever and Grossmann (2003) address a hydrogen supply chain problem in which the planning determines production targets and energy prices, while the scheduling manages the pipeline operation. They propose a heuristic solution based on Lagrangean decomposition (Guignard and Kim, 1987). Lagrangean decomposition is also employed by Terrazas-Moreno and Grossmann (2011) to solve an integrated problem with continuous time scheduling.

Other solution methods proposed are based on Benders decomposition (Benders, 1962). The planning and scheduling models are solved iteratively adding cuts in the planning model at each iteration until ϵ-convergence is achieved. The downside of these methods is that the scheduling model usually includes discrete variables (Grossmann et al., 2002) that do not allow to obtain dual information to generate standard Benders cuts. Therefore, ad-hoc cuts or convexification strategies are required. For example, Erdirik-Dogan and Grossmann (2006) consider a planning model that determines production and inventory targets. They add integer and logic cuts to the upper level to propose a rigorous decomposition algorithm. Recent advances in these solution strategies come from the stochastic programming community in their attempts to solve stochastic mixed-integer problems (Laporte and Louveaux, 1993; Sherali and Fraticelli, 2002; Gade et al., 2014; Zou et al., 2017). These problems share the same structure with IPSM. A third group of solution strategies comes from projecting the feasible space of the scheduling model into the planning model (Sung and Maravelias, 2007; Li and Ierapetritou, 2009).

The large number of publications and frequent review papers in the topic of IPSM are an indicator that the problem is relevant for the process industry, and that it is still a challenging problem that needs to be solved. Since the decrease in the scheduling horizon and the incorporation of inventory policies are not considered in any of the papers reviewed, the proposed models in this paper are contributions to address this difficult problem.

3 Problem statement

In every supply chain there is a hierarchy of decisions that needs to be coordinated in order to deliver products in the right amount, with the required quality, in a timely manner. The customer satisfaction strongly depends on consistently achieving these three targets. Several employees are tasked with making planning decisions to ensure the highest customer satisfaction. The paper considers the integration of tactical and operational decisions, in which a single planner must coordinate with one or more schedulers. The planner receives a demand forecast for the next 3-6 months, and must decide the allocation of demand to each plant under his area of responsibility. The allocation of demand comes in the form of aggregated production and inventory targets for each plant, or alternatively, in the form of an inventory policy. At each plant there is a scheduler responsible for short-term production planning to meet the requests from the planner and satisfy the delivery orders occurring in the next 2-4 weeks. The decision processes are executed periodically. The planning is done every month, while the scheduling is done on a weekly basis. These periods are referred to as decision horizons in the paper. When the time in which these processes must be executed matches, an integrated decision must be obtained. The decisions made remain unchanged until the next time the decision processes are updated. For example, if the planning process is due every 4 weeks, and the scheduling process is executed every week, every time the planning process must be executed the scheduling process also would need to be updated. In these periods when both processes are due, an integrated decision is obtained by coordinating both processes. The planning decisions remain unchanged until the next time the planning process is due.

Given a set of manufacturing plants serving demand for a set of customers of a set of products, the planner needs to determine the optimal monthly delivery flows to customers, production plan at each manufacturing plant, and inventory levels, to maximize the profit from satisfying demand, while minimizing production, inventory, and transportation costs. At the same time, the planner must determine the optimal parameters for an (s,S) inventory policy for each product at each manufacturing plant.

At each plant, there is ~~scheduler responsible of~~ a scheduler responsible for determining the optimum production plan for the short term. The scheduler is given a set of processing units and storage tanks with their connectivity, capacities, initial inventory levels, batch processing tasks that can be performed at each unit, and their respective recipes and processing times. The scheduler must determine the amount and timing for every batch produced at each processing unit, the inventory level at each storage tank to satisfy the inputs from the planner, and a list of delivery orders that need to be satisfied. The optimal schedule maximizes the satisfaction of orders, while meeting the planning inputs, and minimizing inventory and backlogs. Both the planning and inventory models are described in detail in Section 5.

4 Novel modeling approaches in IPSMs

Alternatives for two traditional assumptions in IPSMs are considered. The shortening of the scheduling horizon, and the communication between decision levels using inventory policies. In this section the current assumptions and the proposed methods are described.

4.1 Alternative optimization horizons for IPSMs

The first assumption, the matching of optimization horizon for planning and scheduling, stems from the timescale difference between both processes. Planning is usually conducted to make decisions for a horizon ranging from one month to one year, which leads to discrete time optimization models with weekly or monthly time periods. On the other hand, the decision horizon for scheduling is much shorter, ranging from days to several weeks. In discrete time scheduling models the time discretization is of the order of hours or even shorter. Furthermore, the optimization models are longer than the decision horizons to ensure the stability of the plan at the end of the horizon (Fig. 2). This extra horizon considered is called look-ahead horizon (Harmonosky, 1990), also sometimes called terminal constraints.

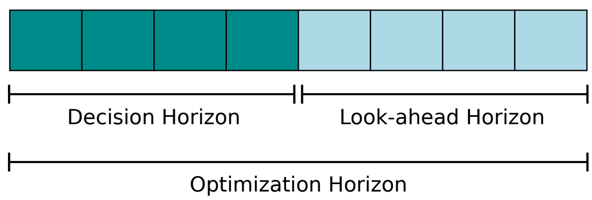


Figure 2. Time horizons in optimization models

The most common approach in integrated planning and scheduling models (IPSMs), has been to formulate a single large scale model using the largest of the two optimization horizons (the planning and the scheduling horizon), and the smallest time discretization (Bassett et al., 1996). The resulting models have an horizon of several months divided in hours (Fig. 3). Because of the intractability of these models, the research has been focused on proposing algorithms to deal with the model, and also on approximation strategies to reduce the model complexity, such as representative day approaches. These strategies also allow to work around the lack of information available to schedule production far into the future. Scheduling models are driven by delivery orders, which are only available for 2-4 weeks in the future. When optimizing scheduling models with a longer horizon, the order information needs to be extrapolated. Representative day approaches are also used to extrapolate this information further (Heuberger et al., 2017; Lara et al., 2018). Both the large scale of the integrated models, and the need for extrapolating information, complicates their optimization and implementation.

In scheduling model with a long optimization horizon, the ~~optimum~~ solution of the problem prescribes decisions that include a detailed schedule for several months in the future. As mentioned before, there is a high level of uncertainty in these decisions because the required information to determine these decisions

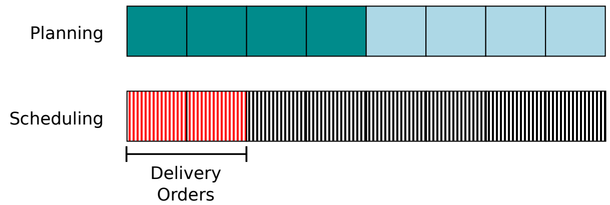


Figure 3. Integration of timescales in planning and scheduling

is estimated through extrapolation of information for the short term, namely the delivery orders for the upcoming weeks. Even if the decision obtained is the optimal for the model, it may not be the optimal decision for the system, considering that there is a dynamic aspect of the implementation in which both information and decisions are frequently updated.

When the scheduling is not coupled with planning, the optimization horizon for the scheduling models is shorter than the horizon for the integrated models. We investigate the possibility to decrease the scheduling look-ahead horizon in an integrated model and still obtain good decisions for the system. That is, designing a decision support system capable of maximizing the profit when implemented in a real-world application, re-optimized on a defined frequency. A shorter scheduling horizon could reduce the model complexity, thus improving the implementability of integrated planning and scheduling models.

Since one of the effects of matching the scheduling and planning horizons is balancing the trade-offs of both models in the objective function, when decreasing the scheduling horizon, the objective function needs to be scaled to maintain the balance in the trade-off. The scaling factor chosen is the ratio of the optimization horizons between scheduling, h, and planing, H (Eq. 1).

$$z_{IPSM} = Max \quad \frac{h}{H} z_{pl} + z_{sc} \tag{1}$$

In Eq. 1, z_{IPSM}, z_{pl}, z_{sc} represent the objective function for the integrated planning and scheduling model, for the planning model, and the scheduling model, respectively. h represents the optimization horizon for the scheduling, and H is the optimization horizon for the planning model.

An alternative approach to shortening the scheduling look-ahead horizon is to solve a relaxation of the model considering continuous variables in the last portion of the optimization horizon (Fig. 4), which yields a model closer to the full space optimization, but also with the benefits of complexity reduction. Since the effects of designing integrated models with shorter scheduling horizons is not evident, we evaluate the models using a simulation framework to determine if the decisions prescribed by each model allow to maximize the benefits for the system. The different scenarios and their performance are presented in Section 7.

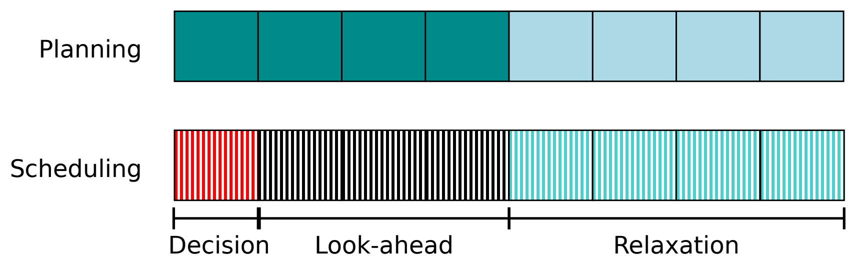


Figure 4. Integration of planning and scheduling with relaxation period

4.2 Communication through inventory policies

The second assumption commonly made in the literature is that the planner communicates with the scheduler through production and inventory targets. Since the planning decisions are optimized less frequently than the scheduling decisions, setting strict targets may lead to conflicting objectives for the scheduler who must adapt the production plan more frequently in response to a changing environment. An alternative observed in practice is the communication through inventory policies. When the planner sets the policy parameters, the scheduler can adjust the production plan while maintaining optimized inventory management decisions. A model with an (s,S) inventory policy (Vrat et al., 2016) (Fig. 5) and weekly review based on the proposed planning models by Brunaud et al. (2019) is considered in this paper.

Under the (s,S) policy the inventory is reviewed in specified intervals. If the inventory is found below level s an order for the difference between the base stock level S and the inventory level at the review period is placed. In the example from Fig. 5, the review periods are fixed. However, the timing and amount of replenishments and the policy parameters, are optimization variables. The proposed workflow is for the planner to optimize the mid-term plan together with the inventory policy, and then pass the (s,S) parameters to the scheduler to optimize the production plan to meet short-term deliveries, while managing the finished product inventories according to the prescribed policy. This communication alternative is also evaluated in Section 7 using simulation.

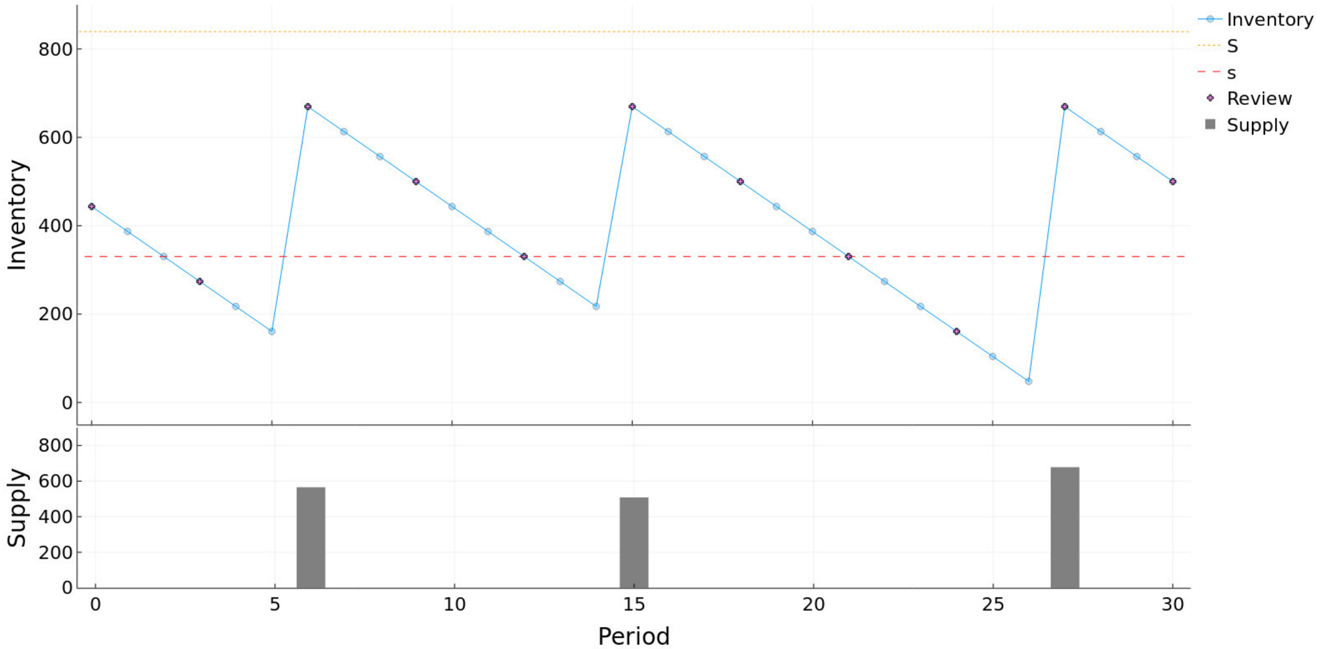


Figure 5. (s,S) inventory policy example with review of 3 periods, and lead time of 3 periods

5 Optimization models

As mentioned in the previous sections, the integrated planning and scheduling model is composed by a planning model and a scheduling model joined by linking constraints. In this section both models are described in detail.

5.1 Planning model

The planning model is a discrete time multiperiod model with weekly time resolution, with an optimization horizon of Θ time periods. Given a set of plants $i \in I$, that need to serve the demand for different products $p \in P$ of a set of customers $c \in C$, the goal is to allocate production to the different plants taking the demand forecast as input. The supply chain network for the model is shown in Fig. 6. The output of the model is the flows from plants to customers, and the inventory levels for products at each plant.

For each inventory in the system, an (s,S) inventory policy is also optimized. The review period is fixed to one week. A single pair of values for the (s,S) parameters is determined for the entire optimization

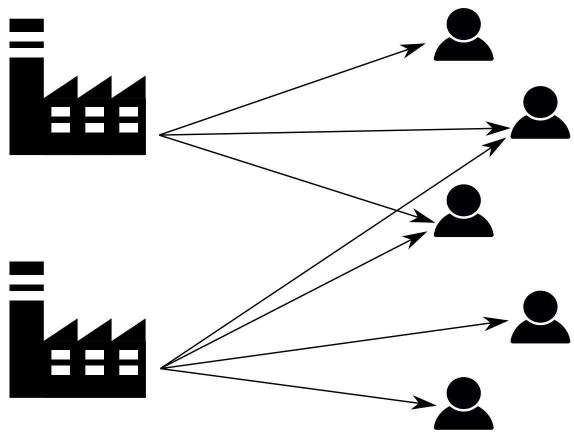


Figure 6. Supply chain planning network

horizon. The planning model is defined by Eqs. (2)–(10)

$$(PM): Max \quad \sum_{icp\tau} \eta_p f_{icp\tau} + \sum_{icp\tau} \gamma_{ip} r_{icp\tau} - \sum_{ip\tau} HC_p invp_{ip\tau} - \sum_{icp\tau} TC_{ic} f_{icp\tau} - \sum_{ip\tau} PC_{ip} x_{ip\tau} \tag{2}$$

$$s.t. \quad \sum_i f_{icp\tau} + \sum_i r_{icp\tau} = DF_{cp\tau} \qquad \forall c, p, \tau \tag{3}$$

$$invp_{ip\tau} = invp_{ip\tau-1} + x_{ip\tau} - \sum_c f_{icp\tau} \qquad \forall i, p, \tau \tag{4}$$

$$rt_{ip\tau} = \sum_c r_{icp\tau} \qquad \forall i, p, \tau \tag{5}$$

$$\epsilon - M u_{ip\tau} \le invp_{ip\tau-L} - s_{ip} \qquad \forall i, p, \tau, \tau > L \tag{6}$$

$$invp_{ip\tau-L} - s_{ip} \le M(1 - u_{ip\tau}) \qquad \forall i, p, \tau, \tau > L \tag{7}$$

$$invp_{ip\tau} + x_{ip\tau} - S_{ip} \le M(1 - u_{ip\tau}) \qquad \forall i, p, \tau \tag{8}$$

$$S_{ip} - invp_{ip\tau} - x_{ip\tau} \le M(1 - u_{ip\tau}) \qquad \forall i, p, \tau \tag{9}$$

$$f_{ipc\tau}, r_{icp\tau}, rt_{ip\tau}, invp_{ip\tau}, x_{ip\tau} s_{ip}, S_{ip} \ge 0, u_{ip\tau} \in \{0, 1\} \tag{10}$$

The main decision variable is the flow between plants, and customers. $f_{icp\tau}$ represents the amount of product p delivered to customer c from plant i in week τ, with its corresponding transportation cost TC_{ic}. It is assumed that all the products arriving to a customer are sold at a price η_p. Alternatively, the planner can choose to have part of the demand forecast ($DF_{cp\tau}$) supplied by a third party manufacturer or by a facility that is not explicitly considered in the system (not part of the set I). This is allocated in the plant-specific variable $r_{icp\tau}$, and cumulative in variable $rt_{ip\tau}$ (Eq. 5). Products allocated through this alternative generate income with price γ_{ip}, where $\gamma_{ip} < \eta_p$. This parameter depends on the plant i and the product p; it is assumed that there is an alternative source for each manufacturing facility charging different rates, usually negotiated through contracts. Demand allocation is controlled by Eq. 3.

The production amount is encoded by $x_{ip\tau}$, while the inventory is $invp_{ip\tau}$. These variables are determined with the inventory balance constraint from Eq. (4), The inventory level has an associated cost due to the inventory holding cost HC_p, while the unit production cost is PC_{ip}. Finally, the inventory policy is optimized with Eqs. (6)–(10). The trigger level s_{ip}, and base stock level S_{ip} use a binary variable $u_{ip\tau}$ to indicate when a replenishment is done. Eqs. (6) and (7) ensure a replenishment is triggered when the inventory level is less than s_{ip}. In these constraints ϵ is a small positive tolerance, L is the replenishment lead time, and M is a large positive quantity. The inventory policy constraints are a simplified version of the formulation proposed by Brunaud et al. (2019).

5.2 Scheduling model

The scheduling model is a discrete time Unit-Operation-Port-State-Superstructure (UOPSS) formulation (Zyngier and Kelly, 2012). The UOPSS formulation was chosen because of its flexibility and scalability (Brunaud and Grossmann, 2019). The model is based on units that can perform different tasks, connected with tanks or other units through ports (Fig. 7). The scheduling horizon is divided in T discrete time periods each with equal duration, usuarlly in the order of hours.

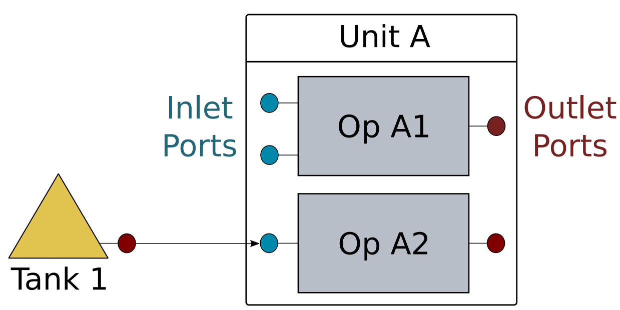


Figure 7. Basic elements of the UOPSS scheduling formulation

Compared to the base UOPSS formulation, a few extra considerations are required. First, a backlog variable is included to account for demand amounts that cannot be satisfied on time. Second, a demand redirection variable is considered to adjust the orders that are allocated to third party manufacturing by the planner. The variables of the model for a single manufacturing plant are the following:

su_{jkt} : a binary variable indicating if operation k starts in unit j at the beginning of period t
sd_{jkt} : a binary variable indicating if operation k is shutdown in unit j at the beginning of period t
sw_{jkt} : a binary variable indicating if operation k continues operation in unit j at period t.
y_{jkt} : a binary variable indicating if operation k is active in unit j in period t
b_{jkt} : the size of the batch processed in period t, executing operation k in unit j
$invs_{jpt}$: inventory of material p at tank j at the end of period t at the scheduling level
xo_{vt} : flow through outlet port v at period t
xi_{vt} : flow through inlet port v at period t
$x_{vv't}$: flow between port v and port v' at period t
d_{pt}: demand of product p satisfied at period t
bl_{pt}: backlog amount of product p at period t
rd_{pt}: redirected demand of product p at period t

All the variables are defined for each manufacturing plant. The subindex i for each plant at every variable has been omitted for simplicity. The constraints of the model are given by Eqs. (11)–(27).

$$\sum_{k\in K_j}\sum_{\theta=0}^{PT_{jk}} su_{jkt-\theta} \leq 1 \qquad \forall j,t \tag{11}$$

$$y_{jkt} = \sum_{\theta=0}^{PT_{jk}-1} su_{jkt-\theta} \qquad \forall j,k\in K_j,t \tag{12}$$

$$sw_{jkt} = \sum_{\theta=1}^{PT_{jk}-1} su_{jkt-\theta} \qquad \forall j,k\in K_j,t \tag{13}$$

$$sd_{jkt} = su_{jkt-PT_{jk}} \qquad \forall j,k\in K_j,t,t-PT_{jk}\geq 1 \tag{14}$$

$$y_{jkt} - y_{jkt-1} - su_{jkt} + sd_{jkt} = 0 \qquad \forall j,k\in K_j,t\geq 1 \tag{15}$$

$$y_{jkt} + y_{jkt-1} - su_{jkt} - sd_{jkt} - 2sw_{jkt} = 0 \qquad \forall j,k\in K_j,t\geq 1 \tag{16}$$

$$su_{jkt} + sw_{jkt} \leq 1 \qquad \forall j,k\in K_j,t \tag{17}$$

$$sd_{jkt} + sw_{jkt} \leq 1 \qquad \forall j,k\in K_j,t \tag{18}$$

$$b_{jkt} \leq b^U_{jk} su_{jkt} \qquad \forall j,k\in K_j,t \tag{19}$$

$$b_{jkt} \geq b^L_{jk} su_{jkt} \qquad \forall j,k\in K_j,t \tag{20}$$

$$xi_{vt} = \rho_{jkv} b_{j,k,t+1} + \mu_{jkv} su_{j,k,t+1} \qquad \forall j,k\in K_j, v\in IP_{jk}, t\leq T \tag{21}$$

$$xo_{vt} = \rho_{jkv} b_{j,k,t-PT_{jk}-1} + \mu_{jkv} su_{j,k,t-PT_{jk}-1} \qquad \forall j,k\in K_j, v\in OP_{jk}, t \tag{22}$$

$$invs_{jpt} = invs_{jpt-1} + xi_{vt} - xo_{v't} \qquad \forall j,p,t>1, v\in IP_{jp}, v'\in OP_{jp} \tag{23}$$

$$xi_{vt} = \sum_{v'\in\Omega_v} x_{v'vt} \qquad \forall v,t \tag{24}$$

$$xo_{vt} = \sum_{v'\in\Delta_{jkv}} x_{vv't} \qquad \forall v,t \tag{25}$$

$$\sum_{j\in J_p}\sum_{v\in OP_{jp}} xo_{vt} = d_{pt} \qquad \forall p,t \tag{26}$$

$$d_{pt} + bl_{pt} + rd_{pt} = D_{pt} \qquad \forall p,t \tag{27}$$

$$b_{jkt}, xi_{vt}, xo_{vt}, x_{vv't}, invs_{jpt}, d_{pt}, bl_{pt}, rd_{pt} \geq 0 \tag{28}$$

$$su_{jkt}, sw_{jkt}, y_{jkt}, sd_{jkt} \in \{1,0\} \tag{29}$$

Eqs. (11)–(18) are the logic constraints of the system, where PT_{jk} is the processing time for operation k in unit j in terms of number of time periods, and K_j is the set of operations that can be performed in unit j. Eqs (19) and (20) are the logistic constraints that link continuous variables with binary variables; the parameters b^L_{jk} and b^U_{jk} are lower and upper bounds for the batch size, respectively. Eqs (21)–(25) are the material and flow balances of the system; ρ_{jkv} is the variable proportion that flows through port v when a batch of size b is produced, while μ_{jkv} is the amount that flows through port v, independent of the batch size. ρ_{jkv} is the consumption or production factor for materials or resources that depend on the batch size, while μ_{jkv} is the factor for resources that are consumed or produced in fixed amounts. The set IP_{jk} represents the inlet ports of operation k at unit j, while OP_{jk} is the set of outlet ports. Ω_v are the origin ports for inlet port v, while Δ_{jkv} are the ports connected to the outlet port v for operation k in unit j. Eq. 27 is the demand satisfaction constraint for the system. The demand orders D_{pt} can either be satisfied (d_{pt}), redirected (rd_{pt}), or backlogged (bl_{pt}). It is assumed that each customer order is assigned to a single plant and the assignment is known in advance. As mentioned before, the amount that can be redirected is a decision made in conjunction with the planner, when the model is optimized without the input from the planner, the variable rd_{pt} is fixed to zero. The redirection decision is communicated as to the scheduler as an aggregated amount. The scheduler must use that information to decide which specific orders are selected for redirection. For a detailed description of each constraint, the reader is referred to Zyngier and Kelly (2009).

To link the planning and scheduling models through inventory policies, additional constraints to execute the policy are required in the scheduling model. Eqs. (30)–(35) enforce the inventory of finished product p is replenished when the level falls below s_p. These constraints are analogous to Eqs. (6)–(10) in the planning model.

$$\epsilon - M u_{pt} w_{jpt} \leq invs_{jpt} - s_p \qquad \forall p, pj \in J_p, t \tag{30}$$

$$invs_{jpt} - s_p \leq M(1 - u_{pt} w_{jpt}) \qquad \forall p, j \in J_p, t \tag{31}$$

$$\sum_{\theta=\max(t-L+1,1)}^{\theta=t} z_{p\theta\, jp\theta} \geq u_{pt} w_{jpt} \qquad \forall p, j \in J_p, t \tag{32}$$

$$\sum_{\theta=t}^{\theta=\min(t+L-1,T)} xi_{v\theta} + slp_{pt} - S_p + invs_{jpt} \leq M(1 - z_{pt}) \qquad \forall p, j \in J_p, t, v \in V_p \tag{33}$$

$$S_p - invs_{jpt} \sum_{\theta=t}^{\theta=min(t+L-1,T)} xi_{v\theta} - slp_{pt} \leq M(1 - z_{pt}) \qquad \forall p, j \in J_p, t, v \in V_p \tag{34}$$

$$S_p, s_p, slp_{pt} \geq 0, u_{pt} w_{jpt}, z_{pt\, jpt} \in \{1, 0\} \tag{35}$$

where ~~u_{pt}~~ w_{jpt} is a binary variable indicating when the inventory falls below the replenishment level, ~~z_{pt}~~ z_{jpt} is a binary variable indicating when production is triggered to replenish the inventory, L is the replenishment lead time in hours, J_p is the set containing the singleton index for the tank j that holds product p, and V_p is the inlet port for the same tank. The positive slack variable slp_{pt} is used to allow deviations in production, from the targets proposed by the planner. The set of constraints enforces that a replenishment is triggered the first time the inventory is found below level s_p.

The objective function is to maximize the profit from delivery of products, minus inventory costs and penalties for backlog, and not meeting the planning targets. The planning targets are given as soft constraints because a scheduler can always choose to ignore the target in practice, or may not be able to replenish the stock fully. The objective function for the scheduling model is given by Eq. (36). The complete scheduling model for plant i, SMP_i for communication through inventory policies is given by Eqs. (11)–(36).

$$\sum_p \sum_t (\eta_p d_{pt} - HC_p invs_{pt} - \beta bl_{pt} - \nu slp_{pt}) \tag{36}$$

When the communication between planners and schedulers is done by inventory and production targets, an additional term to penalize for the deviation of the inventory target is required. The objective function for this case is given by Eq. (37).

$$\sum_p \sum_t (\eta_p d_{pt} - HC_p invs_{pt} - \beta bl_{pt} - \xi slp_{pt} - \xi sli_{pt}) \tag{37}$$

The parameter β is the backlog penalty, while ξ is the penalty for not meeting the targets set by the planner. The positive slack variable sli_{ipt} accounts for deviations in the inventory targets. Its use is defined in the linking constraints in the next section. The scheduling model for communication through inventory and production targets for plant i, SMT_i is given by Eqs. (11)–(27) and (37).

5.3 Linking constraints

In a modular modeling approach, integrated models can be constructed by connecting different models through linking constraints. An integrated planning and scheduling model is constructed connecting model PM with one or more scheduling models, whether is SMT_i or SMP_i. The linking constraints involve variables of both connected models.

When the communication is done through targets, Eqs. (38)– (40) are the linking constraints.

$$invs_{ip\theta} + sli_{ip\theta} \geq invp_{ip\tau} \qquad \forall i, p, \tau, \theta \in \Theta_\tau \tag{38}$$

$$\sum_{\theta \in \Theta_\tau} \sum_{v \in V_p} (xi_{iv\theta} + slp_{ip\theta}) \geq x_{ipt} \qquad \forall i, p, \tau \tag{39}$$

$$\sum_{\theta \in \Theta_\tau} rd_{ip\theta} = rt_{ip\tau} \qquad \forall i, p, \tau \tag{40}$$

In each linking constraint, the left-hand side contains variables coming from the scheduling model, while the right-hand side has only variables from the planning model. In all the constraints the index t represents the time periods of the planning model (weeks). Eq. (38) enforces the satisfaction of the production target $invp_{ipt}$. If the target is not satisfied, the slack variable sli_{ipt} takes a positive value with the corresponding penalty in the objective function. Similarly, Eq. (39) enforces the satisfaction of the production target x_{ipt}. If unsatisfied, the corresponding slack variable slp_{ipt} takes a positive value. The leftmost term in the constraint is the material flow incoming to the storage tank for product p. The set Θ_τ represents the time periods of the scheduling model that correspond to a given planning period. For example, Θ_1 could be the set of hours of the first week, $\Theta_1 = \{1, 2, 3, \ldots, 168\}$. Eq. (40) helps to coordinate the orders that are being redirected to a third party manufacturing. When the communication is done through inventory policies the linking constraints are obtained from equating the values of s_{pt} and S_{pt} for the planning and the scheduling model in addition to Eq. (40).

6 Simulation framework

Enterprise wide-optimization models are developed to help managers, planners, and schedulers to select the best decision among many alternatives. The models are meant to be executed with a certain frequency (the decision horizon), updating the input parameters to obtain a new decision valid until the next time the model is executed. Since we propose models that are different than the previous work in the literature, a simulation framework is developed to evaluate the models, mimicking the conditions in which decision makers use the models.

6.1 Simulation agents

The simulation framework considers several agents that provide information or make decisions at different points in time. The decision agents and their interactions are described in Fig. 8

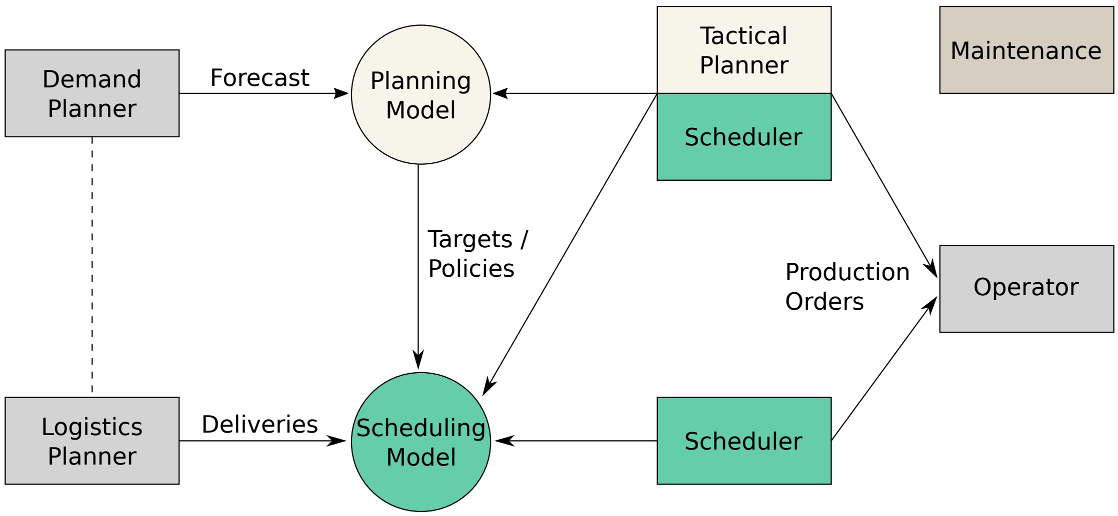


Figure 8. Simulation agents and their interactions

The agents included in the simulation framework and their actions are the following:

Demand Planner. Updates a mid-term demand forecast, which corresponds to the average weekly demand for each product at each customer site. The forecast takes into consideration the short term delivery orders received by the logistics planner.

Logistics Planner. Receives and allocates the delivery orders for the short term. The orders define the product, time, and amount for each product at each manufacturing plant. Keeps track of the status of each order including deliveries and backlogs.

Integrated Planner and Scheduler. The interaction between planner and scheduler is captured as a single agent that solves the integrated planning and scheduling model in intervals spaced by the planning decision horizon. In addition to the short term plan, the output includes production and inventory targets, or inventory policies. When the communication is done through targets, this agent makes decisions running an integrated model comprised by models PM, SMT_i and linking constraints from Eqs. (38)–(40). When the communication is done through inventory policies the integrated model is defined by aggregating models PM, SMP_i, the linking constraint from Eq.

(40), and the linking constraints defined from equating the variables s_p and S_p in models PM and SMP_i.

Scheduler. In intervals defined by the scheduling decision horizon, the scheduler agent defines the short term plan considering the new delivery orders and the guidelines from the planner. The scheduler agent operates only at times when the integrated agent process is not executed, i.e. the integrated agent replaces the role of the scheduler agent. The scheduler agent makes decisions running the model SMT_i for communication through targets or SMP_i for communication through inventory policies.

Operator. At every hour, this agent executes production, loading and unloading processing equipment, and also serving demand deliveries. It is assumed that partial deliveries are possible. If there is not enough material to serve an order, the available material is delivered and a new backlog order is created one week later for the difference.

Maintenance. Repairs equipment when required. The spacing between equipment failures is an exponential random variable, while the duration of a failure is assumed to have normal distribution.

6.2 Sources of uncertainty

In order to define a realistic simulation, several sources of uncertainty must be considered in the framework. The ones considered in the current application are the following:

Demand uncertainty. The forecast estimated by the demand planners is not perfect due to varying demand. The demand forecasted can be smaller or larger than the short term orders received.

Processing time. The short term plan is elaborated considering the average duration of the processing operations. However, operations can finish earlier or later. A delay term with a Poisson distribution is considered. The term can also be negative, indicating that an operation actually finishes earlier.

Delivery times. Although the logistics are planned with the best information available, it is often the case that pick ups arrive earlier or later than anticipated. This is also captured in the simulation framework.

6.3 Evaluation metrics

The objective of the simulation is to compare the "goodness" of the decision models. To accomplish this task, several metrics are defined and evaluated for each simulation run. The first and main metric is the profit, which includes sales from delivery of products substracting the inventory costs. Late and insufficient deliveries, as well as production in secondary plants or third party manufacturing hinder the profits.

The second metric considered is the backlog percent, defined as the number of backlogged deliveries over the total deliveries. The last metric reported is the average inventory. A good plan will result in very few backlogs with the least amount of inventory as possible. As is evident from our results, there is a trade-off between these two metrics so it is important to analyze both.

6.4 Simulation workflow example

To better understand the way the simulation works consider an example workflow for a planning model with a decision horizon of four weeks, integrated with a scheduling model with a decision horizon of one week. The actual definition of the models is presented in Section 5. A flowchart of the workflow is shown in Fig. 9.

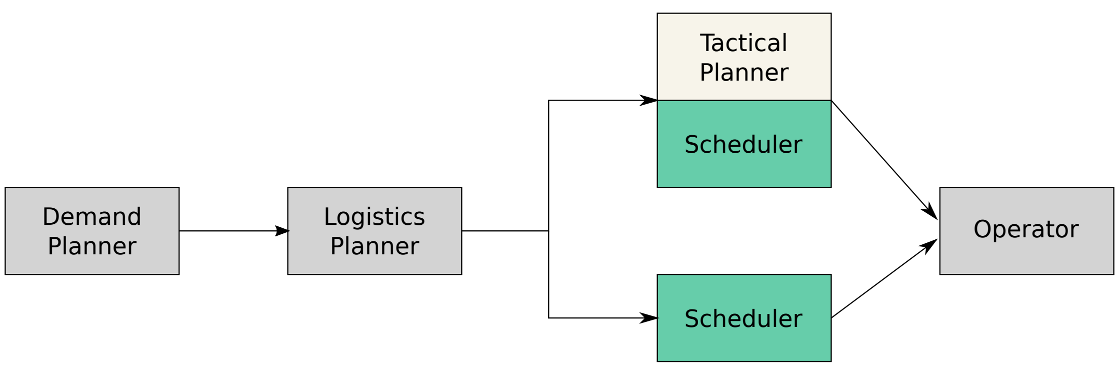


Figure 9. Simulation agents and their interactions

The simulation starts when the demand planner estimates the forecast for the mid-term, 8 weeks in the example case. Values that were previously estimated and lie within the forecasting horizon are updated. Next, the logistics planner collects the delivery orders for the next two weeks. If orders for a longer period are required, the values are extrapolated considering the same weekly distribution adjusting by the average demand in the forecast. For example, if there is an order for Thursday at 3 pm in week one, the order is extrapolated to week three considering an order for the same day and time, scaled by the ratio between the average demands of weeks one and three for the same product. Because of demand uncertainty, the total amount defined by the delivery orders for a given week does not necessarily match the forecasted demand.

With the information provided by demand and logistics planners, the production plan processes are triggered. Every four weeks the integrated planning and scheduling is performed, like the case of the beginning of the simulation. The next week, only the scheduling is performed fixing the variables that come from the planning model.

The short term plan in the form of a list of production orders that need to be executed is provided to the operator. The operator then checks every hour for events that require an action, such as loading equipment at the beginning of a task, unloading when a task is finished, and fulfilling delivery orders. When the unit where a task must be performed is not available, either because it is running another task or it is under maintenance, the task is postponed by one hour. At the next hour, the operator checks again if it is possible to start the task. Sales are accounted when a delivery task is completed, at full price when it is completed on time, and at a lower price otherwise due to late delivery penalties.

6.5 Computational implementation

The simulation framework is implemented in the Julia programming language (Bezanson et al., 2017), using JuMP (Dunning et al., 2017) to define the optimization models. The planning and scheduling models are defined separately and included into a single model graph using Plasmo (Jalving et al., 2017). The modular implementation allows to quickly modify parts of the model, such as the scheduling horizon or the linking constraints between the planning and scheduling models to easily generate the different scenarios for the study. In order to make the scenarios more comparable, they were run with the same number of repetitions using the same set of random seeds. In that way, they were exposed to the same demands and unplanned outages.

7 Case study

The effect of the scheduling look-ahead horizon and communication variables is evaluated through simulation. The case study considers a single planner integrated with a single manufacturing plant for the production of four products. The planning process is performed every 4 weeks, while the scheduling is done every week. The ~~look-ahead horizon for the planning is also 4 weeks, with a total optimization horizon of~~ planning optimization horizon is 8 weeks. The look-ahead horizon for the scheduling is 7 weeks in the base scenario. The time discretization for the planning is one week, while the scheduling horizon is divided into periods of 4 hours. The State-Task-Network diagram (Kondili et al., 1993) for the manufacturing plant is shown in Fig. 10. For each scenario, 20 simulation runs were executed, considering a simulated process time of 1 year.

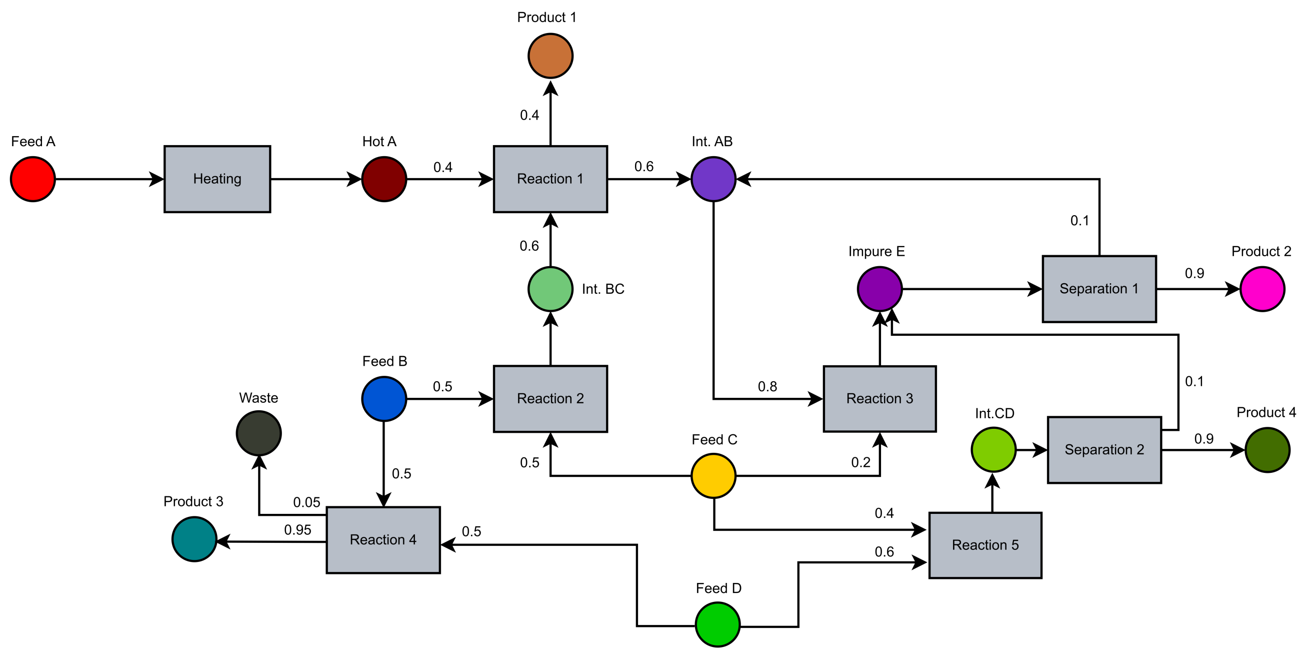


Figure 10. STN diagram for the manufacturing plant

7.1 The importance of communication

As stated before, the common practice in companies is for different decision makers to plan independently with few or no iterations. This is equivalent to not solving the IPSM to optimality. In this context, an iteration refers to the process in which the planner makes a decision and then communicates the outcome to the scheduler, who takes the planning decision as an input to the scheduler's own decision-making process. Then, the scheduler gives feedback to the planner, who proposes a new decision until both agree the integrated plan is the best for the entire system. This bargaining process can be mathematically represented with Benders decomposition (Benders, 1962; Brunaud and Grossmann, 2017), in which the planner solves the PM model, the scheduler solves the SMT_i (or SMP_i) model and provides dual information to generate a cut in the PM model. Fig. 11 is a schematic representation of this process.

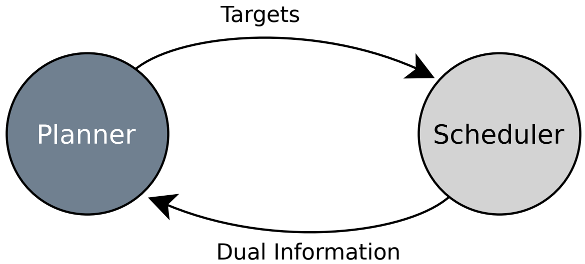
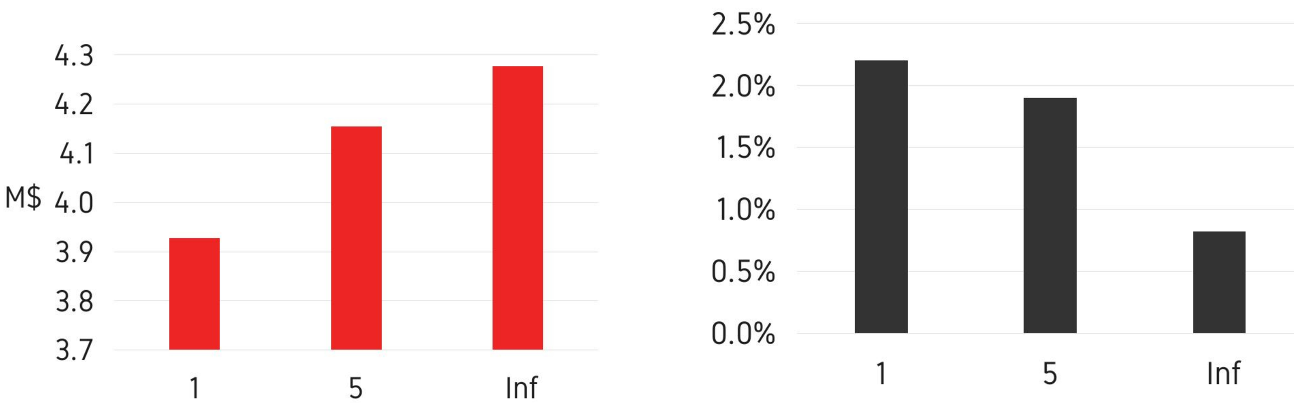


Figure 11. Representation of iterations between planner and scheduler

To illustrate the effect of iterations, and conversely, the benefits of integrated models, the process is simulated solving the IPSM with 1, 5 iterations, and to convergence within a 1% optimality gap. The last scenario is referred to as Inf, because there is no limit in the number of iterations allowed. The results for profit and backlog obtained are shown in Fig. 12.



(a) Profit

(b) Backlog

Figure 12. Summary of metrics for varying iterations between planner and scheduler

As expected, increasing the number of iterations increases the profit and decreases the backlog. The results help to validate the simulation and to stress the importance of fluent communication between planners and schedulers. To better understand the results, and conversely, the value of integrated decisions the results of the first week are analyzed in detail for the three scenarios considered. Table 1 shows a summary of the plan agreed by the planner and scheduler.

Because the number of iterations brings the solution closer the optimum for the integrated planning and scheduling model, it is expected that the profit increases. However, it is not possible to generalize these results. There could be cases in which the first iterations provide good solutions in few iterations, and if they are applied to a high variability scenario, mixed results could be obtained. In most cases

	1	5	Inf
Planning			
Demand	6128	6128	6128
Flow from $M1$	6128	6128	2402
3^{rd} Party	0	0	3726
Production Target	5363	7784	2369
Inventory Target	35	2457	767
Scheduling			
Net Demand	6311.3	6311	2586
Served	2209	2430	2586
Backlog	4103	3881	0

Table 1. First week plan summary for each scenario

with moderate variability, the results will hold, as the larger number of iterations represents more communication between planner and scheduler, leading to a stronger plan. In the scenario with 1 iteration, the planner instructs the scheduler of plant $M1$ to completely satisfy the demand of customer $C1$, while maintaining low inventory levels. Since there is no feedback in this scenario, the scheduler optimizes the best possible plan, and estimates that only $2,209$ kg can be supplied and a backlog of $4,103$ kg will be generated. It is important to note that the availability of a scheduling model enables an accurate estimation of the backlog amount.

At the other end, in the scenario where planner and scheduler iterate until convergence (scenario Inf), the planner is capable of correctly assessing the capacity of the scheduling, and redirect demand to a third party manufacturer in a timely manner. The scheduler agrees with the plan, and no backlog is anticipated. In the intermediate scenario with 5 iterations the planner increases the production target allowing to reduce the projected backlog.

After implementing the respective plans, the profits obtained after 1 week are \$19,259, \$54,422, and \$137,385, for scenarios 1, 5, and Inf, respectively. A summary of delivered amounts including completed deliveries, partial deliveries, and backlogs is shown in Fig. 13.

In the scenario Inf, the scheduler completes 100% of the orders committed, while in the other scenarios the excessive amount of deliveries committed leads to a large amount of partial deliveries and backlog, which lead to a smaller profit. The use of integrated models allows to correctly estimate production capacity to generate timely and efficient product allocations.

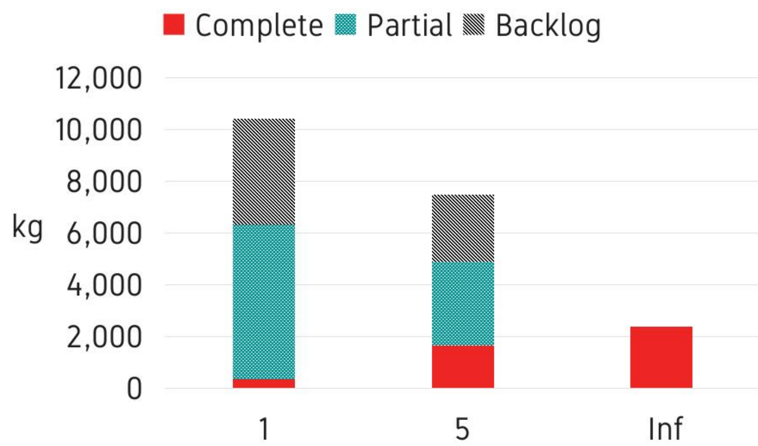


Figure 13. One week delivery summary

7.2 Effect of the scheduling look-ahead horizon

As explained in Section 4.1, different lengths of the scheduling look-ahead horizon are evaluated. The metrics collected are the profit, backlog, and average inventory level. Four scenarios are constructed integrating planning and scheduling through inventory and production targets. The scenarios considered are the following (Fig. 14):

Base Look-ahead horizon of 7 weeks. The planning and scheduling are solved in the same horizon of 8 weeks.

LA1 Look-ahead horizon of 1 week, with a total scheduling optimization horizon of 2 weeks. The planning objective function is scaled according to Eq. (1).

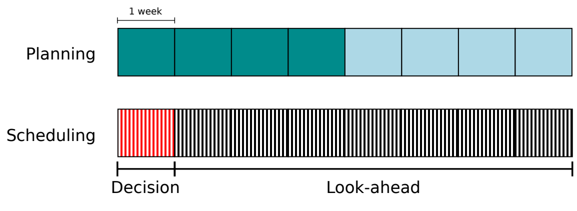
LA3 Look-ahead horizon of 3 weeks, with a scheduling optimization horizon of 4 weeks, matching the decision horizon of the planning model. The planning objective function is scaled according to Eq. (1).

LA3+R4 Same as LA3 but with additional 4 weeks of relaxation. For weeks 1-4 consider the scheduling model SMT, for weeks 5-8 the same model is considered but all the binary variables are relaxed to the $[0, 1]$ interval

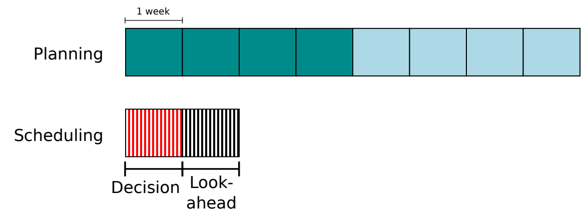
The average backlog and average inventory for 20 simulation runs is shown in Table 2.

The average profits and error bars for the 95% confidence interval for the mean are shown in Fig. 15.

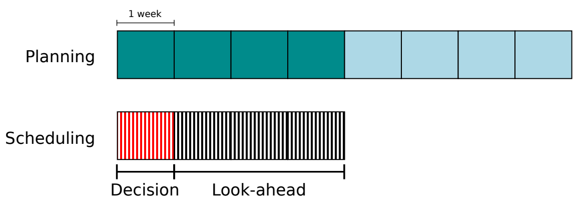
The results from Fig. 15 show that there is no significant difference in the means for models that have a look-ahead horizon of at least three weeks (scenarios Base, LA3, and LA3+R4). The results are



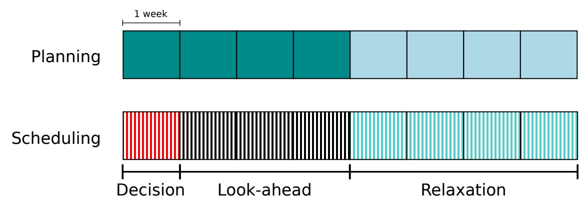
(a) Base



(b) LA1



(c) LA3



(d) LA3 + R4

Figure 14. Scenarios considered for the effect of the look-ahead horizon

Table 2. Average backlog and inventory of 20 simulation runs

	Avg. Backlog	Avg. Inventory
Base	1.19 %	457.11
LA1	9.89 %	381.87
LA3	3.98 %	466.43
LA3+R4	1.22 %	468.64

also related to the average backlog. The backlog for scenario L1 is significantly larger than for the other scenarios. The average backlog for scenario LA3 is also larger than the value for scenarios Base and LA3+R4. However, the profit is ~~not much worse~~similar. The average inventory is similar for the scenarios with the larger profit, at around 460 units, and lower for the scenario with the worst profit, LA1, at an average of 382 units. Because the planning model is optimized every four weeks, when the scheduling look-ahead horizon is at least three weeks, all the ~~variables that fixed for implementation~~ planning variables that are part of the frozen period (4 weeks) consider the effect of the scheduling in their optimization. This is not the case for the LA1 scenario. The planning decisions for weeks 3 and 4 are made without considering the effects on the scheduling, which does not allow to correctly anticipate the demand. This is reflected in the lower average inventory.

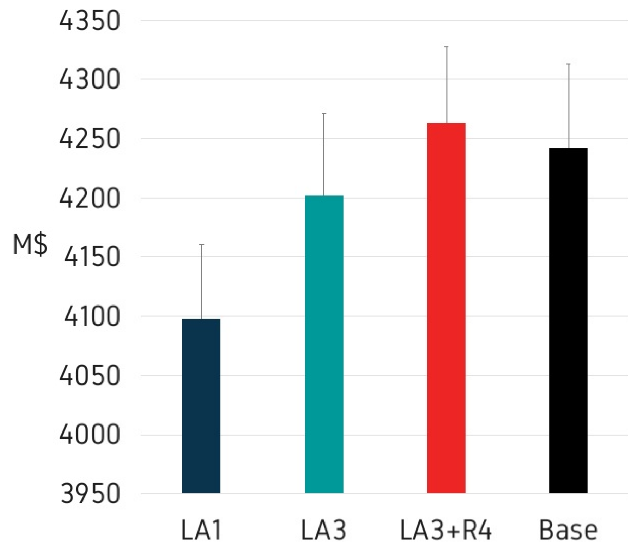


Figure 15. Average profit values for scheduling look-ahead horizon scenarios

7.3 Effect of communication variables

The second feature evaluated is the effect of the variables that the planner communicates to the scheduler. The traditional approach (Targets scenario) is to assume that the planner passes production and inventory targets to the scheduler. The alternative proposed is for the planner to communicate optimized inventory policy parameters (Policy scenario). In this case, the scheduler receives the values of s and S, which uses to manage the finished products inventories. The average values obtained for profit and backlog, with their respective standard deviations, σ, are shown in Table 3. For every run the optimization horizon for the scheduling is equal to the optimization horizon of the planner.

Table 3. Average profit and backlog of 20 simulation runs

	Avg. Backlog	$\sigma_{backlog}$	Avg. Profit	σ_{profit}
Target	1.21 %	0.37 %	4.26 M$	0.15 M$
Policy	1.30 %	0.44 %	4.30 M$	0.18 M$

Even though the average profit is somewhat larger for the Policy scenario, and the average backlog is lower for the Targets scenario, there is no significant difference between both scenarios in these metrics. The p-value of paired t-test is 0.20 for the profit, and 0.24 for the backlog. On the other hand, the average inventory is significantly lower for the Policy scenario (p-value 0.00058), as shown by the radial plot from Fig. 16, where the average inventory is reported for both scenarios at each simulation run.

The lower average inventory of the Policy scenario is explained by the increase of degrees of freedom

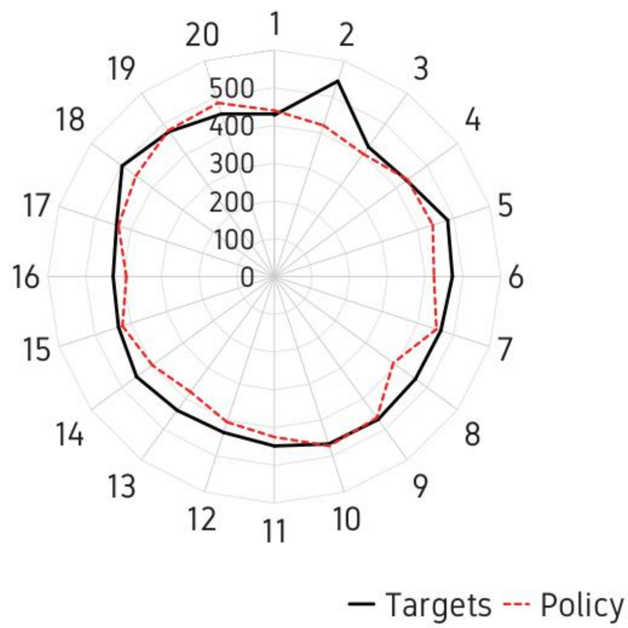


Figure 16. Average inventory in each simulation run

observed by the scheduler when the planner provides policy parameters instead of inventory targets. The scheduler can simultaneously determine the best plan to serve the short-term demand, while minimizing the inventory. It also allows the scheduler to adapt the plan better to changing conditions in the process. The policy provides a way to obtain better decisions without sacrificing the profit. The difference in inventory is not translated in a profit difference because the cost component of the inventory cost is too small compared to the revenue.

8 Conclusions

The problem of integrating planning and scheduling, one of the central challenges in Enterprise-wide Optimization (Grossmann, 2005), was addressed with novel modeling concepts. Alternatives for two of the most frequent assumptions in the integrated planning and scheduling literature were proposed and evaluated using simulation. The assumptions considered are that the planning and scheduling models need to be optimized in the same time horizon, and that the communication is done by passing production and inventory targets from the planner to the scheduler.

The paper also presents novel ideas in the construction of integrated planning and scheduling models. First, the use of modular modeling is demonstrated. This technique enables the seamless development of complex models, connecting different simpler models with linking constraints. The modular approach also helps to increase the understanding of the communication relationships in a complex system such as supply chain decision-making. Second, both planning and scheduling models that incorporate inventory policies were presented. They allow to simultaneously optimize inventory levels and policy parameters, which are useful to define simple guidelines for process operations.

The proposed simulation framework mimics the conditions in which the models are meant to be used as part of a decision support system. Agents to provide demand information, both mid-term and short-term are considered; together with planners and schedulers that run optimization models to make their decisions. The simulation framework and its use are a contribution themselves to motivate the evaluation of supply chain optimization models in realistic scenarios, beyond the typical evaluation of computational efficiency.

The comparison of models with reduced scheduling look-ahead horizon shows that it is possible to reduce the overall model size, while maintaining the same profit. This facilitates the implementation decision support systems including integrated models. The results show that as long as the scheduling optimization horizon matches the planning decision horizon the decision system will have a good performance. It is important to consider a high level of detail in decisions that are committed and remain unchanged for the rest of the operation. The good performance of the scenario LA3+R4 shows that having a rigorous model in both planning and scheduling levels does not necessarily translate into the best performance in practice.

In the second feature considered, the communication variables between planner and schedulers were evaluated. When the communication is done through through inventory policies the profits are similar to the profits obtained when the communication is done through production and inventory targets. However, the average inventory is significantly lower for the first case. This could also lead to improved profits in applications were the inventory costs are more important. The inventory is decreased because of the larger number of degrees of freedom that the scheduler has, compared to the communication through targets. Besides the quantitative benefits, this also brings benefits to the working relationship between planners and schedulers. As more decision options are available to schedulers, they feel more empowered to make better decisions in their area of responsibility. These benefits are also achievable maintaining the same levels of profit.

Because multilevel modeling systems are a representation of the decision-making organizational structures (Brunaud and Grossmann, 2017), the results obtained from the evaluation of optimization models can also influence the work processes and the organizational structures themselves. The novel modeling approaches for the integrated planning and scheduling presented from this paper are contributions to continue advancing towards the digitalization of manufacturing operations and the associated decision-making processes.

Acknowledgments

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