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# Scheduling of Material and Information Flows in the Manufacturing of Chemicals for the Order-to-Cash Process of a Digital Supply Chain

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## Abstract

A scheduling model is proposed to schedule order transactions and manufacturing operations in the order-to-cash process of a digital supply chain. The proposed model is compared to scheduling models that focus on either the order transactions or the manufacturing operations. The advantage of the integrated approach is found in the accuracy of the solutions attained, whereas the purely transactional model is found to be suboptimal, and the production scheduling model is found to be infeasible under certain circumstances. An illustrative example is presented where the integrated model is shown to increase both the system revenue (60% increase) and order-fulfilment (100% increase), compared to the transactional model. The production scheduling model is shown to be infeasible and overestimate the system revenue.

**Keywords**: Scheduling, Business Processes, Supply Chain.

## 1. Introduction

With the advent and widespread drive towards digitalization in the fourth industrial revolution, a clear opportunity has emerged for a more holistic approach to supply chain management. This endeavour requires reimagining supply networks as systems that unite physical, information, and financial flows, with multiple interactions across the enterprise where material, data, humans, and intelligent agents interact in a coordinated fashion (Büyüközkan and Göçer, 2018). Within the PSE community, Laínez and Puigjaner (2012) have called for an integrated approach to Supply Chain Management (SCM), with a shift from operations-based decision support systems to decision frameworks that integrate operational, financial, and environmental models.

In the last two decades, research has begun to respond to these trends and address this need for integration. One such study in this space is that of Guillen, et al. (2006), who present a planning/scheduling model for a chemical supply chain that integrates process operations and financial decisions. This work highlights the value obtained when financial and material flows are integrated in the scheduling decisions. However, their approach does not consider information flows in the supply chain, which is an area that has not received much attention. Information flows are captured in business processes, which model the transactions that occur on requests to the system involved. In supply chain, these requests can be external customer orders, such as in the order-to-cash process, or replenishment orders, such as in the procure-to-pay process. Scheduling events in business processes has been studied by the computer science and information systems communities (Xu, et al., 2010). The business process scheduling done in these works targets purely transactional business processes, such as banking processes that are executed in the cloud (Hoenisch, et al., 2016). However, when physical goods are involved, such as in material procurement or physical goods sales, the associated business processes become tightly coupled with the material flows in the system. Although scheduling business processes in this context has not received much attention, their close integration with physical flows is critical in chemical supply chains, where business processes like the order-to-cash process depend on the availability of inventory and the manufacturing of goods.

The scheduling of business process transactions in supply chain has been the focus of previous work by the authors. In their prior work, scheduling models have been applied to optimize the performance of the order-to-cash business process in a digital supply chain (Perez et al. 2020; 2021). However, the models have been applied primarily to the information flows in the supply chain and represent any physical processes as nodes in the transactional process network with a lumped processing time. The goal in this work is to extend what has been done previously by integrating a batch chemical manufacturing scheduling model with the order fulfilment supply chain model. The aim is to provide a more complete and accurate view of the supply chain by coupling material flows from chemical processing with the information flows from business processes. Thus, this work takes a step forward in the development of holistic decision support systems for digital supply chains.

## 2. Problem Statement

The order-to-cash business process manages the sequence of transactions that occur when a customer places an order. At each step, one or more agents is capable of performing certain transaction on an order. These agents can be human agents (e.g., planner, freight forwarder, customer service representative) or digital agents (for automated steps). Agents can be dedicated to a specific transaction, or they can be flexible such that they can perform transactions at different steps in the business process.

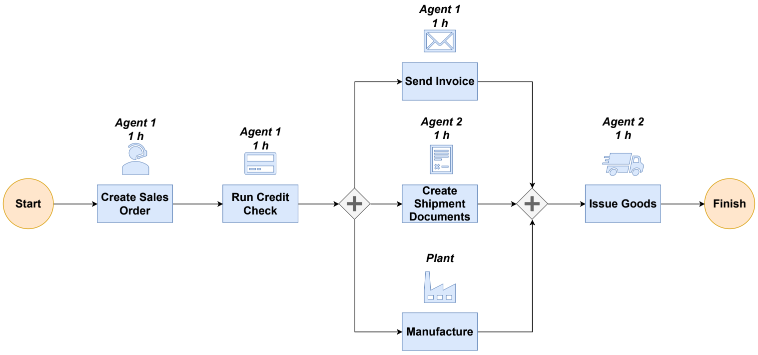
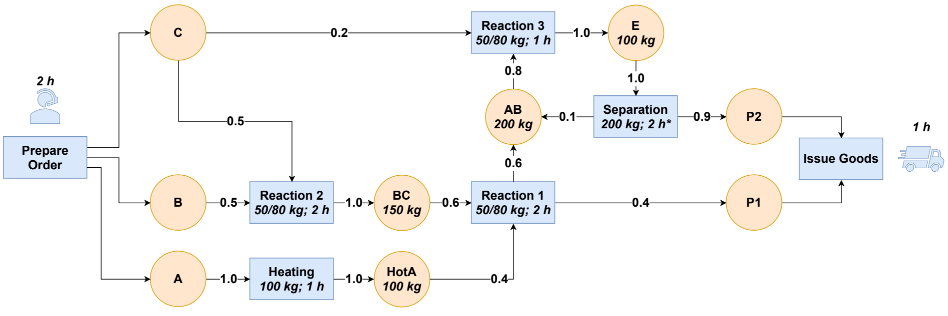


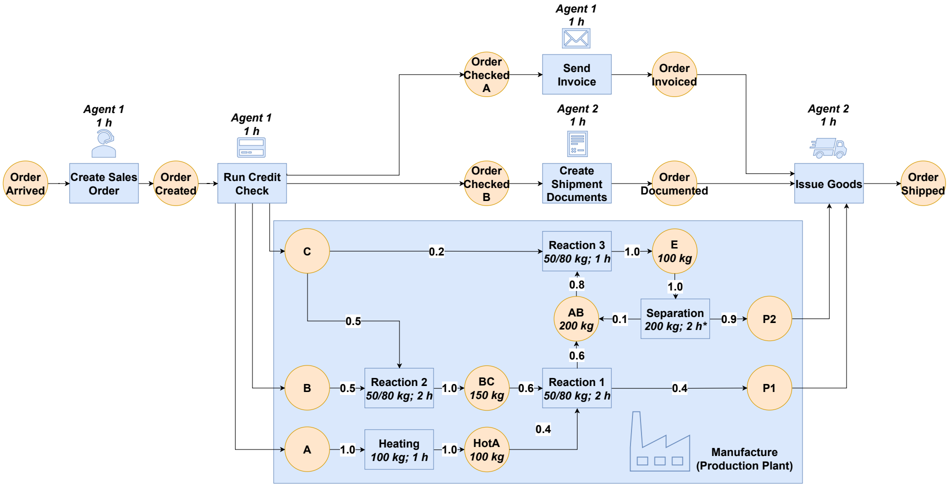
**Figure 1.** Illustrative order fulfilment process in a chemical supply chain

Consider the illustrative example in Figure 1, which shows a simplified customer order fulfilment process with five business transactions and one manufacturing step. The credit check step is a representation of many things that could hold or delay an order from being released to manufacturing. The invoice creation, shipment document creation, and manufacturing steps can be performed in parallel. Two agents are available to perform the five transactions on the orders as indicated in Figure 1. The manufacturing node can represent a batch chemical plant as the one in Kondili, et al. (1993), shown in Figure 2. The plant flowsheet involves a heating step, three reaction pathways, and a purification step to produce products P1 and P2 from raw materials A, B, and C. The main equipment in the batch plant includes a heating vessel with 100 kg capacity, two reactors with 50 and 80 kg capacities, and a distillation column (still) with 200 kg capacity. Intermediate storage tanks include a 100 kg tank for hot A, a 150 kg tank for BC, a 200 kg tank for AB, and a 100 kg tank for E. Raw material and final product storage are uncapacitated. Processing times are indicated next to each transaction in Figure 1 and each manufacturing step in Figure 2.



**P2 is produced after the first hour*
*AB residue is recovered after the second hour*

**Figure 2.** Flowsheet for batch chemical plant



**P2 is produced after the first hour*
*AB residue is recovered after the second hour*

**Figure 3.** State-Task Network representation for the integrated model

## 3. Mathematical Model

The process can be modelled as purely transactional, as shown in Figure 1, by viewing the manufacturing node as a transactional step with a fixed processing type for each product type (4 h for P1 and 6 h for P2). Alternatively, from a purely plant operations standpoint, the system can be modelled using the flowsheet in Figure 2, adding a 2 h delay after an order enters the system and a 1 h delay after a batch of product is produced to account for the first two and last order transactions, respectively. A third option, the proposed approach, is to model the system holistically, accounting for the order transactions and the detailed chemical plant model as shown in Figure 3. In this approach, the stochiometric amount of each raw material for each order quantity is made available when the credit check step is completed. Producing one unit of P1, requires one unit of A, 0.75 units of B, and 0.75 units of C. Produce one unit of P2, requires 0.59 units of A, 0.44 units of B, and 0.66 units of C. For each of the three modelling approaches, a State-Task Network (STN) model (Shah, et al., 1993) is used to schedule the system events.

The objective function of the optimization models is to maximize the revenue as indicated by the first term in Eq. (1). For the purely physical model (plant model) and the integrated model (transactions + plant model), a small $\epsilon$ penalty ($10^{-4}$) is assigned to the binary task triggering variables for the plant tasks (heating, reactions, and separation) to force the optimizer to favour fewer large batches over many small batches. The margin (revenue) for each order is modelled as a monotonically decreasing piecewise linear function. Eq. (2) gives the upper bound on the order margin ($z_o$), where $T_o^{fulfil}$ is the time that order $o$ is fulfilled, and $m_{i,o}$ and $b_{i,o}$ are the slope and intercept parameters for each linear function $i$. The discontinuity in the order margin function occurs at the order due date ($t_o^{due}$), where a penalty is assessed because of backordering ($m_{1,o} \cdot t_o^{due} + b_{1,o} \geq m_{2,o} \cdot t_o^{due} + b_{2,o}$). The fulfilment time, $T_o^{fulfil}$, is constrained by Eq. 3, where $D_{o,t}$ is a binary variable used to indicate that order $o$ was completed at time $t$ and leaves the State-Task Network (external consumption term in the state balance). Backordering is governed by the binary variable $B_o$ as shown in Eq. 4. Eq. 5 forces unfulfilled orders to have zero revenue. $F_o$ is a binary variable that indicates if an order was fulfilled within the scheduling horizon, as shown in Eq. 6. The disjunctions in Eq. (2) and Eq. (5) are reformulated using Big-M constraints.

$$\max \sum_o z_o - \sum_{k \in K^{plant}} \sum_{r \in R_k} \sum_t \epsilon \cdot W_{k,r,t} \tag{1}$$

$$\begin{bmatrix} \neg B_o \\ z_o \leq m_{1,o} \cdot T_o^{fulfil} + b_{1,o} \end{bmatrix} \vee \begin{bmatrix} B_o \\ z_o \leq m_{2,o} \cdot T_o^{fulfil} + b_{2,o} \end{bmatrix} \quad \forall o \tag{2}$$

$$D_{o,t} \cdot t \leq T_o^{fulfil} \quad \forall o, t \tag{3}$$

$$B_o = 1 - \sum_{t \leq t_o^{due}} D_{o,t} \quad \forall o \tag{4}$$

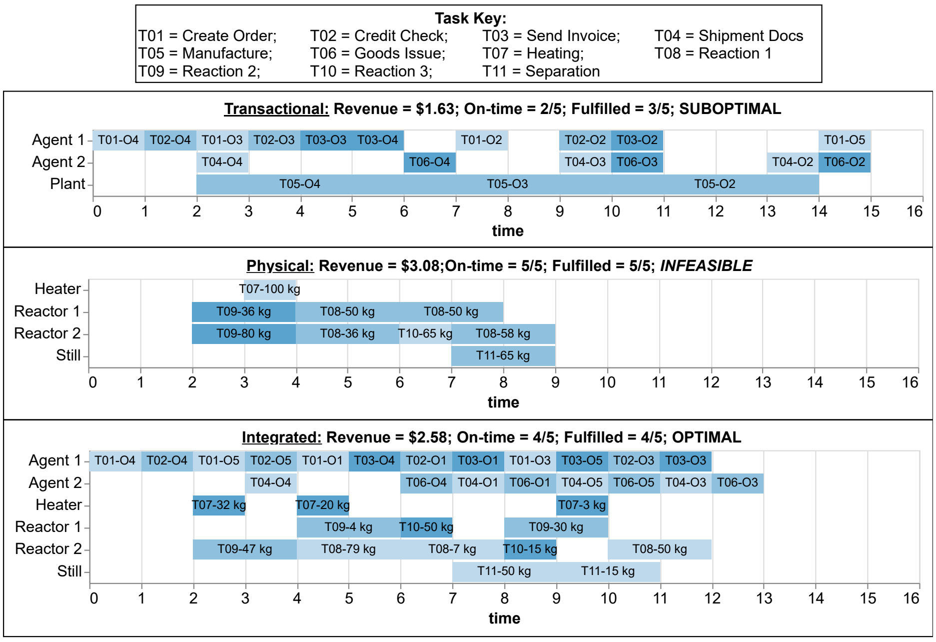
$$\begin{bmatrix} F_o \\ z_o \leq z_o^{UB} \end{bmatrix} \vee \begin{bmatrix} \neg F_o \\ z_o \leq 0 \end{bmatrix} \quad \forall o \tag{5}$$

$$F_o = \sum_t D_{o,t} \quad \forall o \tag{6}$$

## 4. Illustrative Example

In the illustrative example depicted in Figure 1, five orders are generated with random due dates and order margin parameters. Orders 2, 3, and 4 are for material P1, and orders 1 and 5 are for material P2. The demand of each material is also sampled randomly with a mean of 25 kg. A scheduling horizon of 15 h is used. The three modelling approaches (purely transactional with lumped plant processing times, purely physical plant model with upstream and downstream delays, and the integrated model) are implemented in JuMP 0.21 (Julia 1.6), using CPLEX 20.1 as the optimizer on a PC with an Intel i7, 1.9 GHz processor with 24 GB of RAM. CPLEX is allowed to access all 8 threads. The problem is relatively small (approximately 1,400 binary variables, 290 continuous variables, and 4,200 constraints for the integrated model), and solves within 1 s or less.

Figure 4 shows the results for each of the three scheduling approaches. The limitations of the purely transactional or purely physical models are seen in the results obtained. The purely transactional model ignores the integration of physical flows, making it suboptimal. Because intermediate AB, which is required to produce P2, is a by-product of P1 and P2, the time to produce P2 can be decreased when a batch of P1 has already been produced or is being processed alongside an order for P2. On the other hand, the purely physical model ignores the resource constraints on the transactional side, producing an infeasible schedule. The infeasibility arises from the fact that there are not enough agents to perform the first two steps on each order in the first 2 hours of the schedule. Thus, the production of intermediates for all orders cannot begin at t = 2 h. Furthermore, the model assumes that there are enough agents to issue goods once they are ready, which overestimates the system revenue as not all orders can be fulfilled immediately after the material is produced. In contrast, the integrated model finds the optimal schedule which fulfils 80% of the orders in the 15 h horizon, accounting for both agent availability and process integration at the plant.



## 5. Conclusions

An STN-based scheduling model is proposed to schedule orders in the order-to-cash process of a chemical supply chain. The information flows in the order-to-cash process are integrated with the physical flows of the manufacturing facility. An illustrative example is given, in which the model that integrates the transactional and the material flows is shown to attain a 60% improvement in terms of revenue over the model that lumps the material flows in a single manufacturing node. The integrated model also doubles the number of orders fulfilled in the scheduling horizon. The manufacturing-only model that lumps the initial order transactions and the goods issue step, is shown to yield infeasible schedules in a make-to-order system when the transactional steps are resource constrained. The infeasibility demonstrated in the illustrative example is indicative of actual circumstances encountered in industrial supply chains. The lack of rigorous coordination between manufacturing scheduling and order processing often leads to telephone calls and email exchanges between the scheduler and customer service representative to ultimately resolve conflicts between their respective domains. The proposed modelling approach is a first attempt to integrate the different flows involved in a digital supply chain. Future work will include adding financial flows (accounting ledger), and extending the material flows to those in a multi-echelon supply network.

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