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Optimization of Business Transactional Processes in a Digital Supply Chain

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Abstract

A new continuous time multistage scheduling Mixed-Integer Linear Programming (MILP) model is proposed to optimize the business transactional processes in supply chains. The novelty of this approach is in using techniques from the Process Systems Engineering (PSE) and Operations Research (OR) communities to address a side of supply chain optimization (information flow) that has not been targeted previously. This model accounts for the allocation of resources in processing orders at each of the stages of a business transactional process. The objective of the model is to improve customer experience, using on-time-delivery (OTD) as a surrogate metric for this target. An illustrative example, featuring a subset of the business transactional steps in the Order-to-Cash (OTC) process is presented, showing the potential of using mathematical programming to improve supply chain performance. The model enables identifying bottlenecks in the processes and determining where additional resources should be allocated. The model can also be used as a valuable tool to assist customer service representatives in establishing realistic promise-to-delivery dates for their clients.

Keywords: scheduling, MILP, supply chain, optimization, business transactions.

1. Introduction

Supply chains have been traditionally modelled and optimized by the Process Systems Engineering (PSE) (Grossmann, 2012) and Operations Research (OR) (Owen and Daskin, 1998) communities, with the focus being on the optimization of material flow within the supply chain network. Literature has shown the need to expand this vision to also include the financial flows in supply chain optimization. Jahangiri and Cecelja (2014) show how financial models of supply chain can be used to understand the effect of supplier penalty and manufacturer lead time on the company profit. Kees et al. (2019) show the benefits of integrating material and financial flows to improve both the availability of drugs in a hospital supply chain as well as the hospital economic performance. Yi and Reklaitis (2004) show the impact that an integrated material and cash flow model can have on the design of chemical plants. Guillen et al. (2006) show the economic benefits of integrating process operations and financial decisions when optimizing a chemical supply chain. However, there is another type of flow that has been overlooked by the optimization communities: information flow. Supply chains are commonly managed via Enterprise Resource Planning (ERP) systems, which log the data associated with business processes. Previous work in this regard has focussed on the simulation (Villarraga et al., 2017) and design (Niedermann and Schwarz, 2011) of business processes, rather than the optimization of its operations.

The purpose of this paper is to propose a mathematical programming model for optimizing the transactional processes in a supply chain. As an example, the model is applied to the Order-to-Cash (OTC) business process. The OTC process is one of the business processes present in virtually all companies, involving the transactions that occur between the time when an order is placed by a client, to the time when payment is received for the goods delivered. The objective is to minimize the occurrence of late product deliveries and thus reduce the time between when orders are placed, and payment is received for the delivered products. Additional benefits of the model include helping to inform production order due dates as well as promise-to-delivery dates for order fulfilment. The model presented in the paper is analogous to the sequential multistage models used by the PSE community for scheduling multistage batch plants (Mendez et al., 2006), but it differs in several important respects from the traditional multistage scheduling models. Although the model is a new model for modelling multistage processes, the novelty of this project is in using techniques from the PSE and OR communities to address an aspect of supply chain optimization that has been largely overlooked by the optimization communities.

2. Problem Statement

The OTC process is analogous in its structure to a flowshop problem. When a company receives a set of orders, $o \in O$, from its clients, there are a set of tasks, $l \in L$, that need to be performed by agents, $a \in A$, until products are delivered to the clients and payment of invoices is received. Each agent has a queue with positions $p \in P$ to which orders are assigned for processing. The system can be described as a directed graph of queues that map the trajectory of each order within the supply chain. The overall goal is to assign orders to agents and reorder the queue positions to maximize the number of orders delivered on time. Thus, the problem seeks to find an optimal order processing policy, as opposed to the traditional queue management policies of first-in-first-out (FIFO), last-in-first-out (LIFO), smallest-to-largest, or largest-to-smallest (Villarraga et al., 2017).

3. Mathematical Model

The mathematical model for the OTC process is based on the following assumptions,

1. Order release dates, due dates, and processing times are deterministic. In practice orders are placed dynamically, but in the base model, the system is assumed to be static.
2. There are no transition times for orders between steps or stages in the OTC process. Unlike chemical plants, which require waiting times for materials to be transferred between units, instantaneous transitions are possible since data (information) are available to all agents in the OTC process via the company's ERP system.
3. There are no transitions times between orders in an agent's queue. Unlike chemical processing units, which often require transition times for changeovers, business processing units (agents) can process orders back to back due to their non-material nature.

4. Each order can only be processed at most once at each stage. Inefficiencies in the OTC process may lead to orders being processed multiple times by an agent. However, this degree of complexity is not included in the base model.
5. Each order represents one batch of product. In industrial systems, orders can correspond to multiple sub-orders, and sub-orders can correspond to multiple batches, fractions of batches, or even entire production campaigns in some cases. The assumption of one batch per order is made for simplification purposes.
6. No resource constraints are considered aside from human personnel constraints.

The model described in this section uses continuous time via time slots (Mouret et al., 2011) to model the time events, and is analogous to the model presented by Pinto and Grossmann (1995) for scheduling multistage batch plants. Some differences with the latter model are:

- The model allows for the possibility of not all orders being processed on time. When this occurs in a real scenario, the promise-to-delivery dates would be adjusted by the customer service representatives.
- Order transfers between stages are instantaneous due to the use of ERP systems.
- Based on the agent type, processing times may or may not depend on the quantity ordered.
- Time matching of order stages and unit slots is not required. The assignment of units (agents) to stages is defined *a priori* by the structure of the OTC process steps.
- Instead of minimizing the earliness of an order's end time, the proposed formulation targets maximizing the on-time completion of orders.

3.1. Model Constraints

3.1.1. Time Bounds

There is a start time, $t^s_{o,p,a} \in \mathbb{R}^+$, and an end time, $t^f_{o,p,a} \in \mathbb{R}^+$, for each order assigned to a queue position. The start time occurs between the release date, T^r_o, and due date T^d_o of the order (**Eq. 1**). The binary variable $x_{o,p,a}$ denotes when an agent a has order o in queue position p. The time an order leaves a queue is the sum of the start time and the order processing duration and must occur before the due date of the order (**Eq. 2**). $\tau_{o,a}$ is the average processing time of agent a for order o and can depend on the material quantity requested as well as the material type.

3.1.2. Assignment Constraints

Eqs. 3-4 allow each order to be processed at most once at each stage and allow at most one order to occupy each queue position in the queue of each agent.

3.1.3. Precedence Constraints

Eq. 5 ensures that queue positions are used consecutively in each agent's queue. Agent precedence relations are given in **Eq. 6**. **Eq. 7** enforces that if there is an order present in a queue position, then its start time must be after the end time of the order in the queue position immediately ahead of it. T_{max} is the scheduling horizon. **Eq. 8** ensures that if an order is scheduled to be processed at a downstream stage, it can only be processed after the previous stage, has finished processing it.

$$x_{o,p,a} \cdot T_o^r \leq t_{o,p,a}^s \leq x_{o,p,a} \cdot T_o^d \qquad \forall o \in O, p \in P, a \in A \tag{1}$$

$$t_{o,p,a}^s + \tau_{o,a} \cdot x_{o,p,a} = t_{o,p,a}^f \leq x_{o,p,a} \cdot T_o^d \qquad \forall o \in O, p \in P, a \in A \tag{2}$$

$$\sum_{a \in A_l} \sum_{p \in P} x_{o,p,a} \leq 1 \qquad \forall o \in O, l \in L \tag{3}$$

$$\sum_{o \in O} x_{o,p,a} \leq 1 \qquad \forall p \in P, a \in A \tag{4}$$

$$\sum_{o \in O} x_{o,p_1,a} \geq \sum_{o \in O} x_{o,p_2,a} \qquad \forall p_1, p_2 \in P, p_1 + 1 = p_2 \quad \forall a \in A \tag{5}$$

$$\sum_{a \in A_{l_1}} \sum_{p \in P} x_{o,p,a} \geq \sum_{a \in A_{l_2}} \sum_{p \in P} x_{o,p,a} \qquad \forall l_1, l_2 \in L, l_1 + 1 = l_2 \quad \forall o \in O \tag{6}$$

$$\sum_{o \in O} t_{o,p_1,a}^f \leq \sum_{o \in O} t_{o,p_2,a}^s + T_{max} \cdot \left(1 - \sum_{o \in O} x_{o,p_2,a}\right) \qquad \forall p_1, p_2 \in P, p_1 + 1 = p_2 \quad \forall a \in A \tag{7}$$

$$\sum_{p \in P} \sum_{a \in A_{l_1}} t_{o,p,a}^f \leq \sum_{p \in P} \sum_{a \in A_{l_2}} t_{o,p,a}^s + T_o^d \cdot \left(1 - \sum_{p \in P} \sum_{a \in A_{l_2}} x_{o,p,a}\right) \qquad \forall l_1, l_2 \in L, l_1 + 1 = l_2 \quad \forall o \in O \tag{8}$$

3.2. Objective Function

The On-Time-Delivery (OTD, percentage of orders fulfilled before their due date) metric is a key performance indicator of the OTC process. Since the model is intended for dynamic implementation, the objective function to be maximized is the total number of business transactions (**Eq. 9**), which measures the sum of orders processed by all agents. This is the objective function of choice since it increases the chances of obtaining a high OTD throughout the optimization horizon. Customer segmentation dictates order priority, such that orders from high priority customers have a higher w_o.

$$OTD = \sum_{a \in A} \sum_{p \in P} \sum_{o \in O} w_o \cdot x_{o,p,a} \tag{9}$$

4. Illustrative Example

The MILP model was applied to a subset of the OTC process with three stages and four agents (see **Figure 1**). The order and system details are given in **Tables 1-2**. The illustrative example was run using JuMP 0.19.2 (Julia 1.2.0) with Gurobi 8.1.0 as the MIP solver using a PC with an Intel i7, 1.9 GHz, 64-bit processor, and 24 GB of RAM.

Solution time was 0.07 s to full optimality. To show the benefits of using the model over traditional scheduling, the model results were compared to those of a human scheduler using the priority-first approach (orders are scheduled based on customer priority). The results given in **Figure 2** show that for this case, the human scheduler only attains a 60% order fulfilment, whereas the model provides a schedule with 100% order fulfilment. Thus, the benefits of using the model to schedule the operations of the OTC process are evident in even small cases with five orders. Although a human scheduler could potentially come up with the same schedule as that of the optimizer after much trial and error, such a task becomes virtually impossible as the number of orders increases.

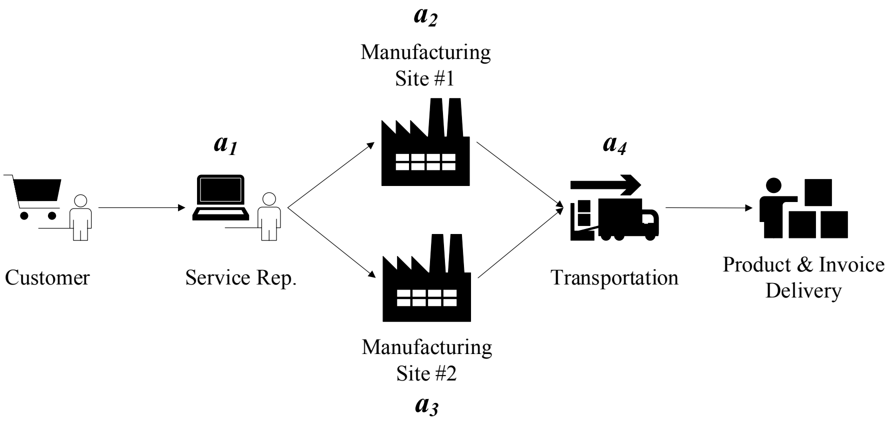

Figure 1. Simplified OTC process flow for illustrative example

Table 1. Order specifications in the illustrative example

Order	1	2	3	4	5
Day Released	0	1	2	2	7
Day Due	10	10	10	12	14
Priority	Medium	High	High	Low	Low

Table 2. OTC agent processing times

Agent	a_1	a_2	a_3	a_4
Processing Time (d)	1	3	3	2

5. Conclusions

A new sequential multi-stage process model is presented to optimize the queues of the agents involved in the OTC business process to improve on-time delivery. An illustrative example is given, which shows that the allocation of resources is key in orders fulfilment. The proposed model can be used to identify bottlenecks in the process and determine which stages need an increase in personnel or a decrease in processing times to improve system performance. Future work in this area includes integrating the business transactional model with manufacturing scheduling models to account for the details involved in the manufacturing and logistic stages of the supply chain. In terms of implementation, a rolling horizon approach can be used for dynamic optimization. Scaling to industrial sized problems, which also contain additional complexities such as rework, and variable processing times will also be addressed in the future.

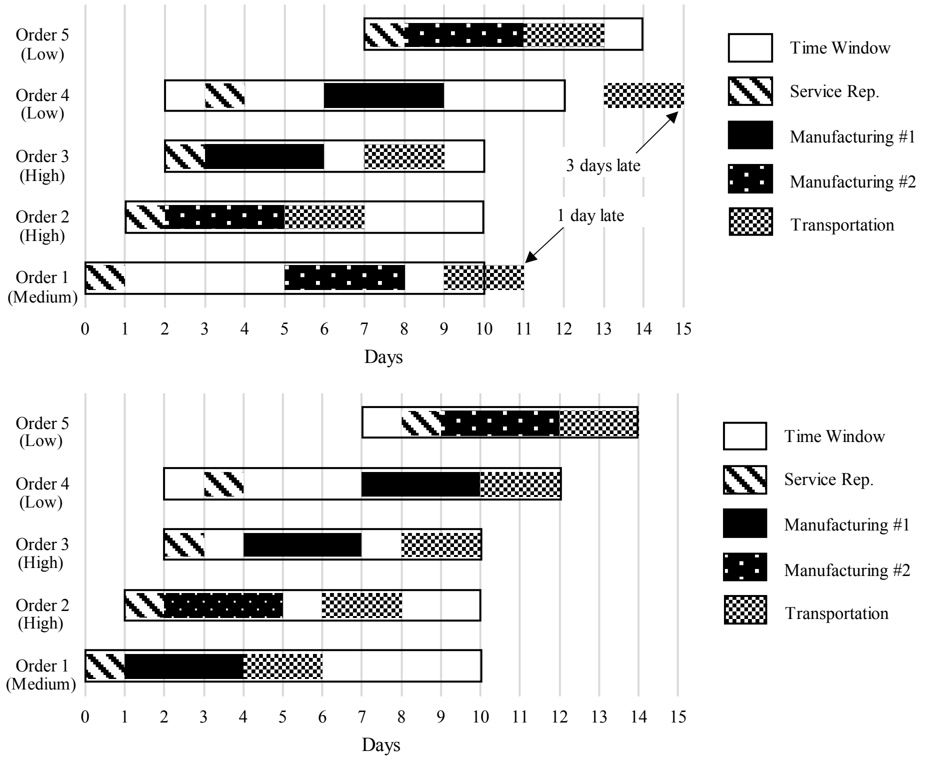

Figure 2. Priority-first human scheduler (top) and model optimized schedule (bottom)

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