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STRATEGY EVALUATION USING SYSTEM DYNAMICS AND MULTI-OBJECTIVE OPTIMIZATION FOR AN INTERNAL SUPPLY CHAIN

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ABSTRACT

System dynamics, which is an approach built on information feedbacks and delays in the model in order to understand the dynamical behavior of a system, has successfully been implemented for supply chain management problems for many years. However, research within in multi-objective optimization of supply chain problems modelled through system dynamics has been scares. Supply chain decision making is much more complex than treating it as a single objective optimization problem due to the fact that supply chains are subjected to the multiple performance measures when optimizing its process. This paper presents an industrial application study utilizing the simulation based optimization framework by combining system dynamics simulation and multi-objective optimization. The industrial study depicts a conceptual system dynamics model for internal logistics system with the aim to evaluate the effects of different material flow control strategies by minimizing total system work-on-process as wells as total delivery delay.

1   INTRODUCTION

In general, optimization modeling approaches using, e.g., mathematical programming, require equation-based models of the system under study. The models also require a comprehensive knowledge of optimization from the developers and most real-world problems are too complex to be formulated as manageable mathematical equations (Hong 2005). As a matter of fact, pure optimization models, when used on their own, are incapable of incorporating the dynamic behavior and complexities of systems or processes such as supply chains (Better et al. 2008). Hence, in a supply chain optimization problem, the supply chain needs to be depicted through simulation modeling, in order to capture its dynamic behavior, and to be combined with optimization methods to attain optimal solution sets. Such a combined use of the two approaches is called simulation-based optimization (SBO). SBO is the process of obtaining optimal system settings from sets of decision variables, i.e., input parameters, where the objective functions and performance of the system are evaluated through the output results of the simulation model over the system (Ólafsson and Kim 2002).

The simulation methodology used for the SBO framework in this paper is based on system dynamics, which is an approach built on information feedbacks and delays in the model, in order to understand the dynamical behavior a system Hedenstierna (2010) points out that system dynamics has been instrumental in understanding supply chain behavior which started with Forrester (1961), who proved the existence of the bullwhip effect and, in relation to this, the detrimental effect of promotions on supply chain performance. Hedenstierna (2010) also explains that due to the system dynamics' tendency to consider several different types of flow networks, there is often a need for multi-objective approaches. Actually, such an idea can be found in much earlier publications by researchers such as Gottschalk (1986) and Towill and Del Vecchio (1994). They discussed the use of multi-criteria utility functions. It is only

recently that the research community has initiated experimentation with multi-objective optimization in combination with system dynamics models, such as Duggan (2008), Aslam et al. (2011) and Dudas et al. (2011). A comprehensive literature survey, presented in Aslam et al. (2011) where the authors have investigated 42 journal papers which concern multi-objective optimization (MOO) for supply chain management (SCM) problems, shows that the majority of papers, or more exactly 53%, have used a mathematical approach e.g., linear programming, mixed integer programming, mixed integer linear programming, etc. By further investigating the authors showed that the most popular mathematical approach used to model supply chains was mixed integer non-linear programming, which accounts for 33% of the papers which is then followed by mixed integer linear programming, as the second most implemented mathematical approach at 21%, while the rest of the methods are fairly equally distributed. Simulation approaches on the other hand, e.g. discrete event, agent based or system dynamics simulation, only accounted for 24% of the implemented modeling techniques and where only one paper was found implementing system dynamics and multi-objective optimization for SCM problems. Hence, it seems that the exploration of using simulation-based optimization, especially within the context of multi-objective optimization, is far from adequate. Generally speaking, a multi-objective optimization procedure generates a solution set in the objective space in which some of the solutions are optimal trade-off solutions among the optimization objectives. These optimal solutions are generally known as Pareto-optimal solutions which together constitute the so-called Pareto front. Thus, the generation of multiple Pareto-optimal solutions through the multi-objective optimization procedure is better able to support a decision maker than a single-objective optimization, as the decision maker is provided with several optimal solutions to choose from when making a decision (Ng et al. 2012).

This paper presents an industrial application study based on the SBO framework by combining system dynamics simulation and MOO. The industrial study depicts a conceptual system dynamics model for internal logistics and production flow at an manufacturer in Sweden. In contrast studies, where the supply chain and its corresponding logistical system are examined from an external point of view, that is, as an inter-company supply chain in which the suppliers and customers are included, this application study is focused on the internal supply chain and logistics of a single manufacturing facility. From an academic perspective, the main purpose of this application study is to verify that the SD-based modeling, MOO is applicable to tackle real-world industrial supply-chain problems. From an industrial perspective, the study also demonstrates how the methodology can assist decision makers at the manufacturer in the development/improvement of a manufacturing facility in the future. In particular, one industrial goal is to investigate the effects of different material flow control strategies (e.g. push and pull) on the investigated system. With this industrial goal, a total of nine different modeling scenarios have been developed in collaboration with the company, for the purpose of investigating and evaluating various manufacturing strategies and concepts for the future manufacturing facility. The remaining part of this paper is organized as follows, in the next section an comparison between system dynamics and discrete event simulation, then the application study is presented including model description and simulation scenarios. The subsequent sections presents the MOO formulation is presented as well as the results and analysis, and finishing with the conclusions.

2 SYSTEM DYNAMICS AND DISCRETE EVENT SIMULATION

As mentioned the modeling method for supply chains proposed in this paper is based on system dynamics (SD), which is an approach built on information feedbacks and delays in the model, in order to understand the dynamical behavior of a system (Angerhofer and Angelides 2000). A SD model facilitates the representation, both graphically and mathematically, of the interactions governing the dynamic behavior of the studied system or process, as well as the analysis of the interactions and their emergent effects. Modeling with SD enables users to take a causal view of reality and implements quantitative means to investigate the behavior of the system and its response to various policies. According to Campuzano and Mula (2011), SD is a rigorous approach to qualitatively describe and explore supply chain processes,

information, strategies, and organizational limits. It also facilitates modeling, experimentation and the analysis of both qualitative and quantitative aspects of supply chain design and the management of the supply chain and its network, without requiring comprehensive information or precise data, because it emphasizes the dynamic performance of the investigated system through the combination of feedback loops. Sterman (2000) describes a supply chain as a system containing multiple autonomous entitles, which is characterized by a stock and flow structure for acquisition, storage, converting inputs into outputs, as well as the decision rules governing these flows. The existing flows in the supply chains, such as information, material, orders, money, etc., create important feedbacks among the members of the supply chain, thus making SD a well-suited approach for modeling and analyzing supply chains (Georgiadis et al. 2005).

Another frequently utilized modeling, experimentation, and analysis tool for decision support of logistics and supply chain problems is discrete-event simulation (DES). The two modeling methods, i.e., SD and DES, are quite different in their approaches. DES models a system as a network of queues and activities, and where the system state is changed at a discrete point of time, whereas SD models, as explained, are based on stocks and flows in which the system state is continuously changing (Brailsford and Hilton 2001). Tako and Robinson (2009) explain that in DES each entity, i.e., products, is individually represented where specific attributes are attached to these entities in order to follow and determine what happens to them during the simulation. On the other hand, in SD, entities are represented in a continuous quantity, like a fluid passing through a tank, making it impossible to follow individual entities. A comparison of various differences between SD and DES is presented in Table 1.

Table 1: Comparison between SD and DES, adopted from (Brito et al. 2011; Tako and Robinson 2010).

Aspects	DES	SD
Modeling perspective	Analytical, emphasis on detail complexity	Holistic, emphasis on dynamic complexity
Problem Scope	Operation/Tactical	Strategic
Randomness	Utilizes random variables through statistical distributions	Stochastic features are less often utilized, averages of variables are used instead
Building Blocks	Network of queues and activities	Series of stocks and flows
Resolution	Individual entities, attributes, decision and events	Homogenized entities, continuous policy pressure
State Change	At discrete point of time, model state is updated at an event-step	Continuous, model state is updated at very small time step
Data	Quantitative	Quantitative and Qualitative
Feedback effects	Models open loop structures, less interested in feedbacks	Models casual relationships and feedback effects
Model Results	Provides statistically valid estimates of system performance.	Provides a full picture, quantitatively and qualitatively of the system performance

Morecroft (2007) argues that the differences do not only lie within the technical characteristics of the two approaches, i.e., queues versus stocks, discrete versus continuous, stochastic versus deterministic, but also in their worldview. In accordance with this aspect, SD deals with a deterministic complexity and DES with a stochastic complexity. While the dynamic behavior in SD is based on the feedback structure in the model, in a DES model the dynamic behavior arises from the interactions between the random processes. According to Morecroft (2007), this suggests that the unfolded future in a SD model is partly and significantly predetermined, whereas in a DES model the unfolded future is partly and significantly a matter of chance. While a problem from a SD worldview is investigated by first identifying the feedback loops as well as the essential stocks, policies and information flows of the system and then redesigning these policies in order to change the feedback structures and improve system performance, in the DES

worldview the problem is addressed by first identifying connecting random processes, together with their underlying probabilities, queues, and activities, and then identifying more appropriate ways of handling the stochastic nature of the system, in order to improve system performance (Morecroft 2007). Morecroft (2007), together with several other researchers such as (Brailsford and Hilton 2001; Brito et al. 2011), point out that DES is more suitable for operational and tactical level problems, since DES is able to handle operational detail as well as stochastic processes which are suitable for portraying details within operations, such as a process of products moving through a set of interacting stochastic machines in a production line. In addition, as random processes release individual entities, such as a product into a successive machine, DES is able to represent the details of the movements and queues of these individual products in the production line. In other words, the attention to details is an essential characteristic of DES modeling. SD models, on the other hand, according to the above-mentioned authors, are more suitable for handling strategic level issues with their aggregated stock accumulation, flows, and coordinating network of feedback loops. Morecroft (2007) explains that in contrast to DES, a SD model would provide a distance view of the operations in a production line where, instead of portraying machines, conveyers, buffers etc., the SD model would portray inventory, workforce, pressure-driven policies for inventory management and control, as well as workforce hiring. Furthermore, due to the holistic view of the production line operations, a SD model is able to depict feedback loops that embrace the different functions and departments of the depicted system. However, despite the differences between the two approaches, Sweetser (1999) points out that the main objective of both simulation approaches is to understand the behaviors of a modeled system over time, as well as to compare the system's performance when subjected to various conditions. According to Morecroft (2007), the selection between these approaches depends on the scope of the problem, the scale and level of detail required, as well as the modeler's preference. For a comprehensive discussion regarding the differences and similarities between DES and SD, as well as their suitability regarding problem scope, i.e., strategic, tactical or operational, the reader is referred to Brailsford and Hilton (2001); Brito et al. (2011); Tako and Robinson (2010). As previously explained, SD is the modeling approach utilized in this work as the application study requires a more holistic perspective of the studied system in order to provide a complete picture, both qualitatively and quantitatively, of the system performance. Additionally, the computation time for an evaluation is significantly lower for a SD model then for a DES model of equivalent level of abstraction, making SD a more preferable choice from a SBO point of view.

3   INDUSTRIAL CASE STUDY: SYSTEM DESCRIPTION

The investigated system, depicted in Figure 1, contains two manufacturing areas, an interim inventory, a finished goods inventory (FGI), as well as a shipping area. The material or product flow of the system is initiated in the first manufacturing area, Manufacturing 1, and continues through the Interim Inventory to the second manufacturing area, Manufacturing 2, which in turn supplies the FGI with finished products before they are shipped off to customers. Manufacturing 1 consists of four production lines; Line 1, Line 2, Line 3 and Flex-line, where lines 1, 2, and 3 are product specific, that is to say that only a single product of the product family is processed on these lines, whereas the flex-line has the possibility to accommodate and process multiple products. Similarly, Line 1 and Line 2 in the second manufacturing area have a comparable allotment of production in which line 1 is product specific, i.e., only a single product is manufactured on this line, and line 2 processes multiple products. Each production line has its own internal production set-up and flow, therefore, the aim of the analysis is to investigate the effect of different manufacturing strategies at a primary level, by exploring the system from a holistic perspective. Hence, each internal production line configuration or set-up is only considered at an aggregated level where no consideration is taken for the internal technological processes. As is common in any production system modeling, the production lines are treated as a black box in which the unfinished product is accumulated until the defined delay time of the production process, i.e., line cycle time or lead time, has passed.

The two inventories, interim and FGI, function as stock keeping units from which material or products are depleted and sent downstream the material flow. The shipping area is not physically included in this case study, however, the required information flow for the current study concerning the shipment and consignments of products has been taken into account. The production lines in the manufacturing areas accommodate the processing of three different products and their subsequent variants. Figure8.2 shows the product flow of the three products manufactured in the system; the red arrows represent the production flow of Product A (PA), while the blue and green arrows represent the production flow of Product B (PB) and Product C (PC) respectively. As Figure 1 displays, the main flow of PA is through both lines 1 in respective manufacturing area, whereas the main production flow of PB runs through line 2 in both manufacturing areas. However, both line 1 and line 2 in manufacturing 1 are subjected to a production capacity constraint. Thus, when maximum capacity is reached in the discussed production lines, the surplus demand is then allocated to the flex-line, which is assumed to have unlimited production capacity. All other production lines, except the two discussed, i.e., line 1 and line 2 in manufacturing 1, are not subjected to any capacity constraints. The third product, PC, on the other hand, flows through line 1 respectively line 2 in the two manufacturing areas and, as Figure 1 shows, PB and PC are processed on the same production line in the second manufacturing area.
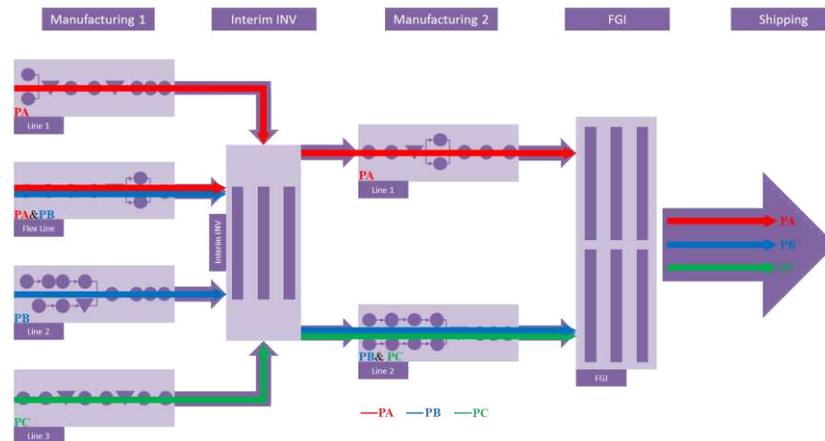

Figure 1: Product flow through the entire system under study.

3.1 The System Dynamic Model and Its Modules

The system dynamics model developed for the industrial application study portraying the above described manufacturing system has its origin in the stock management model for inventory and production control introduced by Sterman (2000), the model developed for this industrial application study only exploits the modeling principles of the stock management structure. The structure diagram, presented in Figure 2, shows the basic structure of the simulation model, developed for the case study, together with primary functions and decision policies. The aim of a structure diagram is to present the stock and flow structure together with the decision structure of the model, at a more abstract level than presenting individual equations for each stock or decision variable in the simulation model; thus providing an overview of the simulation model and highlighting the feedback structure presented in the model.

As Figure 2 illustrates through the highlighted rounded rectangles, the simulation model consists of eight governing functions and decision policies, namely, Production, Production Scheduling, Master Production Schedule, Replenishment & Dispatching, Demand Forecasting, Backlog, Order Fulfillment and Customer Order Rate. Where production scheduling, master production schedule and replenishment & dispatching are the main functions that highly differ from the stock management model introduced by

Sterman (2000). The blue feedback arrows represent the information feedback which applies to all modeling scenarios, whereas the three red arrows with dotted lines represent information feedback loops which may vary from scenario to scenario and where any combination of these information feedback signals might be considered. As in the case of the original stock management model, the production lines at respective manufacturing area are represented as a stock where the WIP levels at each production line are increased through Production Start Rate and depleted through Production Rate at respective production line. The master production schedule function generates a master production schedule from the information feedback received from the forecast and subsequently can provide the production scheduling and replenishment & dispatching modules with the demand information, depending on if the information feedback is included in the scenario. The master production schedule module also calculates how the demand should be distributed among the four production lines in the first manufacturing area.
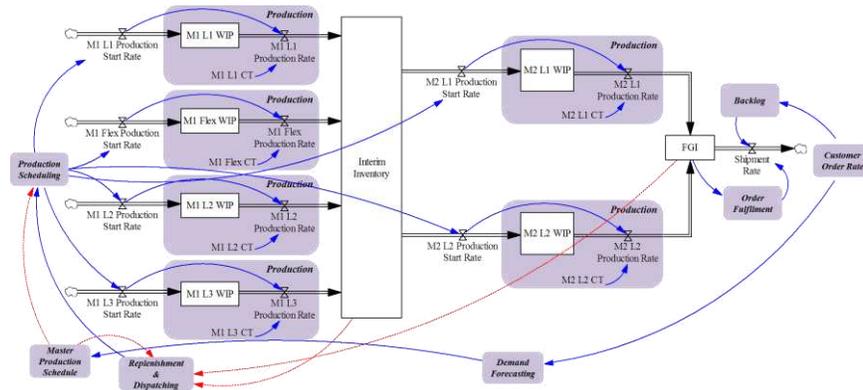

Figure 2: Structure Diagram of the investigated industrial system

The Production Scheduling module on the other hand deals with a more detail scheduling of the production lines in manufacturing areas one and two. The production scheduling can receive information feedback from the replenishment & dispatching module, depending on if the information feedback is included in the scenario, regarding the stock balance of the interim inventory and FGI for the three product types. The module can also receive information feedback from the master production schedule, depending on the scenario that is. Thus, from the information feedback of the two modules, production scheduling is able to detail steer the production rate of each production line, by adjusting the production start rate depending on the forecasted demand and the amount of stock available at the two inventories. Hence, while the master production schedule module determines where a product should be manufactured, i.e., in which production line, the production scheduling module decides the amount that should be manufactured at each production line through the production start rate. The replenishment & dispatching module on the other hand seeks to replenish the consumed products from the inventories, as well as dispatch the replenishment demand to the appropriate production line, based on a set of dispatching rules. Thus, when the replenishment demand is dispatched to the different production lines, the dispatching decision variable follows a heuristic which is based on production lines M1-L1 and M1-L2 being prioritized and needing to be utilized to their maximum capacity. So, if there is a reduction in the replenishment demand, e.g., for PA, the dispatching variable $DISP^\lambda$(is defined in section 5) will first dispatch a lower demand to M1-Flex to reduce the production of PA at M1-Flex. When the production rate of PA in flex line is down to zero, the dispatching variable $DISP^\lambda$ will then start to reduce the production of PA in M1-L1. Similarly, if the replenishment demand would suddenly increase, after forcing the production rate of PA in M1-Flex down to zero and reducing production in M1-L1 below its maximum capacity, dispatching heuristics will first increase the production rate of M1-L1 to its maximum capacity and then dispatch all the surplus replenishment demand to M1-Flex. Thus, M1-L1 is always

prioritized in order to ensure that it is highly utilized. M1-L2 and PB is subjected to the same exact heuristics. For a comprehensive overview of the different modules of the simulation model, including their equations and modeling structures please refer to Aslam (2013)

3.2 Simulation Scenarios

As mentioned earlier, one industrial goal of this study is to explore the effects of push and pull strategies on the investigated system, through MOO and post-optimality analysis. Therefore, several scenarios were created, shown in Table 1,with the aim of evaluating the effects of different production strategies, as well as investigating the effect of various points of origin of information feedback for the demand-pull signal and replenishment of the inventories. Scenarios 4-6, as well as scenario 8, were developed together with the manufacturing company according to their wish in testing different alternatives of flow control whereas 1-3, 7 and 9 were hypothetical (academic) scenarios extended from the other "industrial" scenarios to evaluate the effects of pure push and pull based control as well as if the replenishment of the inventories is eliminated.

Table 1: Summary of simulation scenarios.

	FGI feedback to FGI Replenishment	FGI Replenishment	Interim inventory Replenishment	Origin of Demand-Pull signal	Production scheduling in M1 based on	Production scheduling in M2 based on
Scenario 1	NO	NO	NO	NO	MPS & FGI Safety Stock Coverage	MPS
Scenario 2	YES	YES	NO	NO	MPS & FGI Replenishment (Repl.)	MPS
Scenario 3	YES	YES	NO	NO	MPS & FGI Repl.	MPS & FGI Repl.
Scenario 4	YES	YES	YES	NO	MPS & Interim inv. Repl.	MPS & FGI Repl.
Scenario 5	YES	YES	YES	M2 Production Start Rate	Demand-Pull & Interim inventory Repl.	MPS & FGI Repl.
Scenario 6	YES	YES	YES	M2 Production Rate	Demand-Pull & Interim inventory Repl.	MPS & FGI Repl.
Scenario 7	YES	YES	NO	FGI	Demand-Pull & FGI Repl.	MPS & FGI Repl.
Scenario 8	YES	YES	YES	FGI	Demand-Pull & Interim inventory Repl.	MPS & FGI Repl.
Scenario 9	YES	YES	YES	FGI	Demand-Pull & Interim inventory Repl.	FGI Replenishment

(Left margin: "Pure Push" at top and "Pure Pull" at bottom with downward arrow)

Before the simulation scenarios are introduced, it is necessary to provide a clear definition to distinguish between a push and a pull system, because several different definitions of these strategies can be found in the literature. This paper uses the definition presented by Hopp and Spearman (2011), who define a push system as a system *"...in which work is released without consideration of system status...(p.96)"* and a pull system as a system *"... in which work is released base*d on the status of the *system...(p.96)"*. The authors explain that a system which releases work solely according to a MPS based on a forecast or customer orders is considered a push system, because, according to the definition, it does not take the current status of the system into account. However, in many real-world factories, a sole push system is rarely found. For example, releasing work without considering the status of the system, such as inventory, could generate overcrowded inventories, since work will be released although the system is already completely full. Therefore, in many factories which use MPS, the system is a hybrid push/pull (Hopp and Spearman (2011) control, in the sense that some information feedback of the system status is used to control the work release rate into the system. This also means that the information feedback

mechanism is able to regulate the MPS, based on the current system status. Therefore, in this application study, various degrees of these hybrid push/pull combinations are investigated. For example, should the production in the first manufacturing area be solely based on the MPS, i.e., a pure push strategy? Or should consideration also be taken of the inventory levels and safety stock levels of the interim inventory or the FGI, or perhaps both? Another question, which is addressed by the scenarios, is from where should the demand-pull signal originate, i.e., from where should the production of manufacturing area one be pulled, since the demand signal can either originate from the interim inventory, manufacturing area two, or the FGI. Full-scale images of the simulation models developed in Vensim for the nine scenarios can be found in Aslam (2013). Table 1 presents a summary of the simulation scenarios, where the table shows whether the replenishment of the interim inventory or the FGI is implemented or not, it also defines the origins point of the demand-pull signal in the different scenarios as well as convening what information is used by the production scheduling module in the two manufacturing areas for the different simulation scenarios.

4   MOO FOR THE CASE STUDY

The aim of this case study is to evaluate different manufacturing strategies, through the scenarios presented in the previous section, applying multi-objective optimization. The optimization objectives for the case study are the same throughout the different scenarios. However, the amount of input parameters used for the optimization varies from scenario to scenario, depending on their strategy and use of the modules in the model, such as replenishment of the interim inventory which is only conducted for some scenarios. The optimization of the case study, and thus the scenarios, is based on two objectives, where the first is to minimize the total WIP of the investigated system, that is, the total of all unfinished products in manufacturing area one through manufacturing area two, excluding the FGI. The second optimization objective is to minimize the total delivery delay of all three products combined. Thus, the goal of the optimization is to investigate at what level of WIP in the system does one get delivery delay and does this vary depending on which scenario is used. The objective function for the optimization is denoted as, where $\varphi \in \{Interim\ Inventory, FGI\}$, $\rho \in \{TotPA, TotPB, PC\}$ and $\lambda \in \{M1 - L1, M1 - L2, M1 - Flex, M1 - L3, M2 - L1, M2 - L2\}$:

$$OF \begin{cases} Min\ OF^{f1}(TotSWIP) = Min\ \mu_{TotSWIP} \\ \\ Min\ OF^{f2}(TotDD) = Min\ \mu_{TotDD} \end{cases} \tag{1}$$

$$\text{where } \mu_{TotSWIP} = \sum_{t=0}^{T} \frac{\sum WIP^{\forall \lambda} + TotIINV}{T}, \mu_{TotDD} = \sum_{t=0}^{T} \frac{\sum DD^{\forall \rho}}{T} \tag{2},(3)$$

$$\text{where } I = SSC^{\varphi(\rho)}, IAT^{\varphi(\rho)}, TDD, TAOR \tag{4}$$

$$\text{and} \quad O = \mu_{TotSWIP}, \mu_{TotDD} \tag{5}$$

subjected to $ICS = 0.1 \leq SSC^{\varphi(\rho)} \leq 8,\ 1 \leq IAT^{\varphi(\rho)} \leq 8,\ 1 \leq TDD \leq 8,\ 1 \leq TAOR \leq 4$

and $OCS = OF^{f1} \leq 1500,\ OF^{f2} \leq 110$

OF = All optimization objectives, represent all objective functions used in the optimization. OF^{f1} = First objective function, represents the optimization function to minimize total system WIP. OF^{f2} = Second objective function, represents the optimization function to minimize total delivery delay $TotSWIP$ = Total system WIP, denotes the total amount of unfinished products in the system excluding the FGI. $TotDD$ = Total delivery delay, denotes the company's total delivery delay of a product regardless of product family. $TotIINV$ = Total Interim Inventory, denotes the total stock of the interim inventory regardless of product family. I = Input variables, indicate all the input variables utilized in the

optimization; O = Output variables, indicate all the output variables utilized in the optimization. ICS = Input Constraints, indicate the upper and lower bounds of the decision variables. OCS = Optimization Constraints, indicate the constraint put on the optimization restricting it to only consider solutions as feasible if they are within the constraint limits. $IAT^{\varphi(\rho)}$ = Inventory Adjustment Time of product ρ in inventory φ, denotes the time period over which the system tries to diminish the gap between the actual inventory level and the desired inventory level. $SSC^{\varphi(\rho)}$ = Safety Stock Coverage of product ρ in inventory φ, denotes the time period over which the system wants to maintain a safety stock. Provides a safeguard against unexpected variations in demand which might cause delivery delays or missed shipments. $TAOR$ = Time to Average Order Rate, denotes the time period over which the expected customer order rate is adjusted to the actual customer order rate TDD = Target Delivery Delay, represents the delivery delay goal of the company and is the delay period within which the company seeks to deliver the incoming orders. $DISP_t^\lambda$ = Dispatching of production to production line λ, in period t,, denotes how the production for the replenishment of the inventory and safety stock should be dispatched, i.e., which production line should increase or decrease their production start rates, in order to keep the inventory at a desired level . $\mu_{TotSWIP}$ = Mean total system WIP, denotes the mean value of the total system WIP. μ_{TotDD} = Mean total delivery delay, denotes the mean value of the total delivery delay. $\mu_{DD\rho}$ = Mean delivery delay of product ρ, denotes the mean delivery delay of product ρ. WIP_t^λ = The work in process of production line λ, in period t, denotes the work in process inventory of a production line.

5   RESULTS AND ANALYSIS

The optimization for each scenario was run for 60,000 evaluations, where the initial population of 100 solutions was generated through the uniform Latin hypercube approach whereas the utilized optimization algorithm is the widely-used NSGA-II (Deb et al. 2002). The results of the optimization runs are presented in Figure 3, which shows four scatter diagrams of the Pareto front generated from each scenario. The first plot presents the optimal solutions within the optimization constraints, i.e., $TotSWIP \le 1500$, $TotDD \le 110$, the second plot presents the optimal solutions where $OF^{f2} \le 24$, while the third and fourth plots present the optimal solutions where $TotDD \le 5$ and $TotDD \le 3$, respectively. By examining the Pareto solutions for the scenarios in Figure 3, one clearly sees that the scenarios with the demand-pull signal outperform, i.e., achieve significantly lower total delivery delay for the same total system WIP, the scenarios where the forecasted demand and the master production schedule are used. The only exception is the Pareto front of scenario 7, which despite implementing a demand-pull signal is outperformed by scenarios 3 and 4 for some regions of the optimization objectives. For instance, scenario 3 outperforms scenario 7 when $TotDD \le 4.3$, since scenario 3 is able to obtain lower total delivery delay for the same total system WIP and, in the same way, scenario 4 outperforms scenario 7 for $TotDD \le 26$. In Figure 3, one also observes that scenarios 1 and 3 are able to achieve significantly lower total delivery delay with equivalent values of total system WIP than scenario 2. However, for $TotDD \ge 27$, scenario 2 outperforms scenarios 1 and 3, since it is able to find solutions which have similar total delivery delay, but with a lower total system WIP. As we know, the aim of the study was to investigate at what level of WIP what delivery delay one would achieve and does this vary depending on which scenario is used. However, by examining the Pareto-optimal solutions in the first plot where they range between $TotSWIP \le 1500$, $TotDD \le 110$, it seems highly unlikely that the managers would be interested in solutions on the outskirts of the second objective, which no doubt have lower WIP values but a delivery delay of 100-110 hours, that is, a week of production time seems quite high. If instead it was evaluated that the company managers would want a maximum total delivery delay of 24 hours, the optimization results in the second plot of Figure 3 show that implementation of scenario 2 would not be recommendable, since only a few solutions are able to meet the proposed requirement. Similarly, if the company were to define a policy of having a maximum delivery delay of five hours, the third plot in Figure 3 reveals that there are no Pareto solutions, not only for scenario 2, but also for

scenario 1, demonstrating that these two scenarios with their strategies are not able to meet the requirement of a maximum delivery delay of five hours. If the company were to implement an even more aggressive policy and reduce their delivery delay commitment to two hours, for example, then the optimization results in the fourth plot in Figure 3 show that, scenarios 1 and 3, scenario 7 can also be ruled out, since only a few Pareto solutions would fulfill the delivery delay policy requirements proposed. Now, trying to answer the most obvious question of which scenario is best is, however, not that obvious and easy. Looking at the first plot in Figure 3, it would seem that scenario 9 outperforms all other scenarios, since scenario 9 is able to achieve a lower WIP for a similar delivery delay value for most of the Pareto solutions. However, a close look at the fourth plot in Figure 3 reveals that in a certain region, that is, $1.14 \leq TotDD \leq 1.75$, scenario 8 actually outperforms scenario 9.
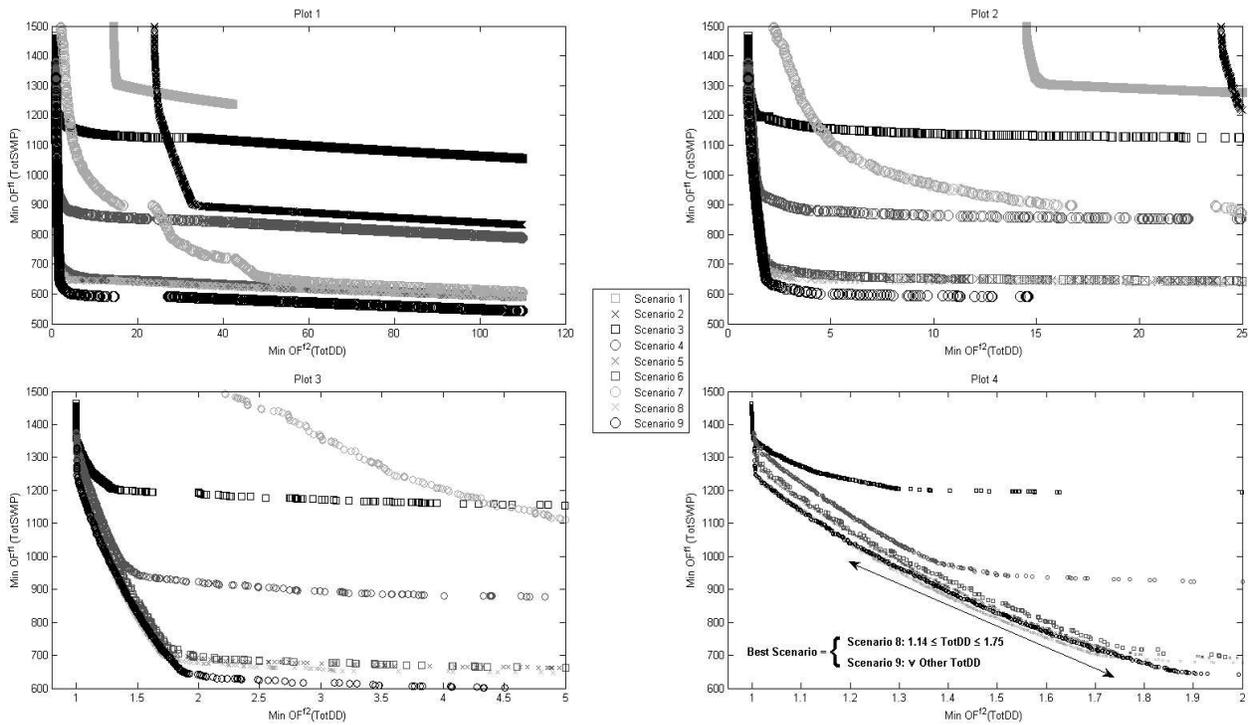

Figure 3: 2D scatter plot all scenarios.

At this stage, the shaded area in plots 1-3 in Figure 3 indicates the region in which the manufacturing company assumes their conceptual system will operate. Examining this estimated region, which has an approximate range of between [1200-1500] in total system WIP for a delivery delay of around five hours, within which the company assumes to be able to ship-off the arrived customer order, it can be seen that the conceptual system setup proposed by the manufacturing company actually outperforms scenarios 1 and 2. However, their conceptual system setup is outperformed by all the other optimization scenarios, since the optimization is able to find system setups which generate a lower $TotDD$ for a lower $TotSWIP$ than assumed by the manufacturing company.

6   CONCLUSION

This paper has presented an industrial application of SD-MOO, where the SD model depicted a conceptual internal logistics process at one of the industrial partners. The aim of the study was to model, evaluate, and analyze various manufacturing strategies, from a MOO perspective, and implement post-optimal analysis, in order to gain manufacturing and logistical insight from the optimization results. To

implement this, nine different scenarios were modeled, ranging from a pure push-manufacturing strategy to a pure demand pull-based approach. In addition, the scenarios in between implemented a varying degree of information sharing through feedback loops and push- and pull-based concepts. All the modeled scenarios were evaluated on the basis of two conflicting optimization objectives, minimize the total system WIP while minimizing the total delivery delay, in order to find the best Pareto-optimal trade-off solutions for the problem at hand. The MOO results show that scenario 9, which implements a pure demand-pull strategy, outperforms all other scenarios, by achieving lower total system WIP for similar total delivery delay for most of the Pareto optimal solutions. A further analysis revealed that the replenishment of the interim inventory plays a crucial role in the performance of the system, since the five best scenarios all implemented a replenishment of the interim inventory. Another discovery made by comparing and evaluating the scenarios was that for all scenarios, implementing a demand-pull strategy, with the replenishment of the interim inventory, increasingly improved the performance as the demand-pull signal moved downstream the internal supply chain, thus indicating that the demand-pull signal should originate from the FGI, i.e., when a product is shipped to a customer. Finally, this work has illustrated the possibility of performing MOO on simulation models based in SD and obtaining Pareto-optimal solution set from the SBO framework. This opens a new possibility of performing SD-MOO not just for supply chain problems, but also for problems from any domains, as long as the system in question can be modeled in SD and multiple conflicting objectives can be identified. Utilizing SD-MOO provides and additional opportunity quantitative analyze SD models that generally are utilized system behavior over time. However, one reflection that is important to consider the system behavior when quantitatively optimizing SD system models: An optimal solution might be great from a quantitative perspective, however when investigating it qualitatively, i.e. analyzing the system behavior, it might not be feasible.

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