Simulation-Based Optimization for the Integrated Control of Production and Logistics: A Performance Comparison

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Abstract: Manufacturing systems' efficiency depends on the proper assignment of orders to resources. Due to existing interdependencies, the integrated consideration of production, inventory and delivery processes can improve the overall manufacturing performance. However, the integration can result in high complexity and stochasticity. Thus, the three areas are rarely addressed together. Thereof, this paper proposes an integrated simulation-based optimization method to cope with uncertainty and complexity. The proposed approach was compared to a benchmark approach and the obtained results show that the first is able to handle the complexity and stochasticity of real-world manufacturing systems, surpassing the performance of the latter.

Keywords: Supply Chain Planning and Control, Simulation-based Optimization, Integrated Planning, Simulation, Optimization, Simulated Annealing

1. INTRODUCTION

Supply chains embrace multiple material and information processes, linking the supply, production and distribution of products or services, crossing organizations' boundaries, adding value for customers and other stakeholders (Frazzon, 2009). Over the years, the vision of a company working not isolated but jointly with other companies has prevailed (Chae et al., 2014). Thus, increasingly complex supply chain structures within dynamic environments require responsiveness and productivity, in which existing system resources are employed as efficiently as possible (Ehm et al., 2015; Frazzon, Albrecht, et al., 2018). As a natural evolution, derived from an increasingly competitive environment, companies must interact, plan and act beyond their internal processes (Khan et al., 2014). However, software systems are commonly divided into modules for the planning of basic schedule (Enterprise Resource Planning Systems) and the control of processes on the operational level (Machine Execution Systems). The scheduling and control of production processes has a significant influence on the performance of manufacturing systems.

After determining a set of production orders based on demand forecasts or customer orders, the scheduling and sequencing of job processing with several machines have to be conducted optimizing performance indicators (Schuh et al., 2017). There are two different methods to define a suitable job sequence, either generating a production schedule in advance or using dispatching rules to continuously determining the priorities of jobs waiting to be processed by the resources. Computing a whole new schedule can be very time-

consuming. Moreover, schedules can become unreliable if they are not robust enough and the production processes are subject to stochastic effects, such as fluctuating processing times (Frazzon et al., 2018a).

In addition, while finished goods inventories and work-in-process are considered by assigning due-dates for production planning, raw material inventory control is generally not considered explicitly in production planning and control. Despite the fact that, traditionally, inventory planning is considered as an individual task separated from production scheduling and control, there are approaches to integrate both tasks (Kumar et al. 2016). However, these approaches focus on long-term planning decisions and do not allow for a reaction to dynamic changes in real-time.

Moreover, on the operational decision level, recent studies show that the integration of production and transport in supply chains provides potential to decrease costs, to enhance the on-time delivery of customer orders and consequently to improve supply chain competitiveness (Ehm et al., 2015).

Industry 4.0 and its wide range of concepts and technologies (Lasi et al., 2014) can contribute to the materialization of both productivity and responsiveness. In an ideal digital factory environment, computers, sensors and software, can collect data and compute the materials required for the manufacturing processes. This new industrial phase is characterized by the use of Internet of Things (IoT) data. It has led to a growth in the quantity of acquired data along the production processes through the communication of different equipments of a manufacturing system. In this environment with a high volume of data, more accessible technologies from

digital factories could be further developed order to achieve the goal of intelligent and self-learning manufacturing (Lee et al. 2014).

However, connecting many organizations, equipment generating data, operations and clients leads to a scenario of high uncertainty from different sources (Peidro et al., 2009). According to (Peidro et al., 2009), uncertainty arises from three sources in a supply chain: demand, process/manufacturing and supply. In this sense, uncertainty in supply chain modelling for planning and decision support imposes challenges, and it has to be considered in planning and control issues, in order to obtain robust policies and plans. In addition, the availability of real-time data regarding several areas of the systems enables real-time optimization, creating a convergence to the most operational level task, i.e., the production controlling strategies.

To cope with such behaviour, simulation-based optimization is an approach that holds capabilities to deal efficiently with a large scenario taking into account the dynamics of the systems, leading to nearly optimal solutions in a feasible time (Liotta et al., 2016). Simulation-based methods can be used to both develop and to evaluate complex systems. Aspects such as physical configuration or operating rules of a system can be considered. Its applications have grown in several areas, assisting managers in the decision-making process and allowing a better understanding of processes in complex systems (Sakurada and Miyake, 2009). These assumptions are expressed in mathematical, logical and symbolic relations between the entities or objects of interest of the system. In this way, potential system changes can first be simulated in order to predict their impact on system performance. Moreover, simulation also allows a decision-maker to evaluate various control policies (Pirard et al., 2011). Numerous replications of the simulations can be performed in order to evaluate the robustness of the implemented design. Unfortunately, the simulation does not guarantee an optimum design. However, the presented disadvantage can be balanced with the integration of other tools, such as mathematical modelling.

The combination of simulation and mathematical programming models in an iterative scheme aims to evaluate the effects of decisions on the performance of a manufacturing system. Thus, such works are focused on the integration of different modelling methodologies in order to combine the advantages offered by each of them for solving complex problems. Analytical models look for solutions evaluating optimal values of decision variables. However, the provided solutions are generally limited in their fields of application because of predetermined restrictive assumptions. Simulation models, in turn, are better able to capture the real behaviour of the system but are not adequate to solve optimization problems. The integration of analytical and simulation models, also called hybrid models, leads to representing a promising option for better results (Lin and Chen, 2015). Thus, hybrid models seek to combine the advantages and avoid the disadvantages of both tools (Peidro et al., 2009).

Liotta et al. (2016) state that simulation-based optimization is a strategy for dealing with uncertainty in the supply chain. Frazzon et al. (2018) propose a simulation-based optimization approach to deal with complex systems, which consists of an adaptive simulation-based optimization. In the conceptual model of the method proposed by the authors, real-time data feeds the simulation-based optimization, which generates scenarios performs local optimization strategies and provides feedback to enhance the simulation. Simulation can represent better dynamic environments that have stochastic behaviour, while optimization strategies can generate solutions with low computational costs. Kück et al. (2017) developed a data-driven and adaptive simulation-based optimization approach to determine suitable dispatching rules for production control in an application from semiconductor manufacturing. This method was extended by a data-exchange framework to achieve the capability of reacting on dynamic changes in real-time. In Frazzon et al. (2018b) an evaluation within a scenario of a Brazilian manufacturer of mechanical components for the automotive industry showed better operational performance compared to the procedure previously applied by the company as well as in comparison to static dispatching rules. However, the literature about simulation-based optimization lacks experiments in addressing material inventory planning and control, production planning and control and transportation planning and control, all integrated in one model. The model aims to be easier to develop and to deliver better fitting parameters for real scenarios.

This work proposes the application of a data-driven simulation-based optimization approach to cope with integrated production and logistics control in uncertain scenarios, i.e. scenarios with stochastic behaviour and dynamic events, addressing material inventory, production and transportation. The proposed approach is intended to be use by companies aiming to synchronize the production with the delivery and the raw material inventory, being able to generate satisfying solution under uncertainty. The approach is tested using a use case and its performance is compared to a literature benchmark. The paper is organized as follows: Section 2 presents the problem to be addressed, the benchmark approach and the proposed simulation-based optimization. Section 3 highlights and discusses the main results. Finally, the conclusion section summarizes the paper objectives, findings and results.

2. SIMULATION-BASED OPTIMIZATION FOR MATERIAL INVENTORY, PRODUCTION AND DELIVERY CONTROL

This section proposes and evaluates the performance of a simulation-based optimization approach for integrated material inventory, production and transport planning and control in a simple supply chain scenario. At first, the supply chain scenario is described. Subsequently, the benchmark approach and the simulation-based optimization approach are described and their performance evaluated.

2.1 Scenario Description

The simulation-based optimization for integrated material inventory, production and transportation planning and control approach is tested in the supply chain represented in Fig. 1, in which one supplier provides a single material to an original equipment manufacturer that processes the material and turns into a product to be delivered to five customers. The present supply chain structure aims to represent a frequent observed yet simple design among supply chains, comprising the three partners.
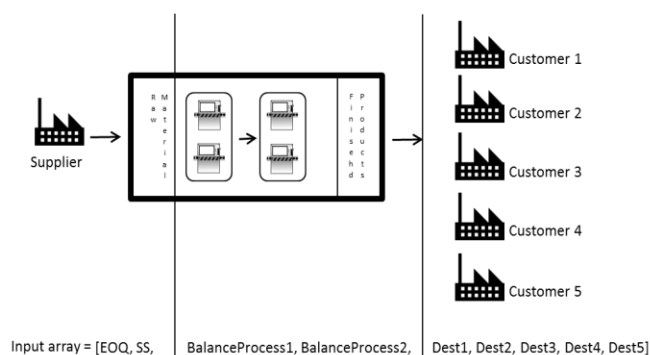

Fig. 1. Test case scenario

The production facility analyzes its material inventory every day. If it is below the safety stock (SS), it orders a fixed amount given as the economic order quantity (EOQ). Both safety stock and EOQ are decision variables.

The supplier tries to produce the ordered amount and delivers on the next day. No backlogging is allowed. The supplier production is considered as a single machine with a capacity for one product per time. In the production facility each job consists of two processes before being delivered. For each of these processes, two parallel machines are available, and the distribution of jobs between these machines is a decision variable for each process. This balance is defined as the percentage of products being allocated to the first parallel machine. The second machine produces the remaining products. Each one of the four machines has a single processing time determined by triangular distributions. The minimum and maximum processing times are: for machine 1 from process 1 = [10, 15], for machine 2 from process 1 = [5, 30], for machine 1 from process 2 = [10, 25], for machine 2 from process 2 = [15, 19].

The delivery takes place every day, right after receiving the daily demand from five customers. One truck is available to do the delivery. The truck is loaded every day at the middle of the day and loads at maximum, if available, the sum of the daily demands. At each stop, the truck delivers the largest amount possible, as the price of the products is the same for every customer. Once the truck is empty, it returns to the production factory. The unserved demands are lost since no backlogging is allowed. The daily demand for each client is determined by a singular triangular distribution, varying from 0 to 30, 15, 15, 60 and 30 for Customer 1, Customer 2, Customer 3, Customer 4 and Customer 5 respectively. The route to be travelled every

day by the truck is the last decision variable. Each customer has a geographical position and all travel links have different lengths. For each travel link travelled, the travel time is determined by the length of the link divided by a stochastic speed, also determined by a triangular distribution with minimum equals to 10 and maximum equals to 20. In the present work, the use of triangular distribution was chosen in order to obtain a high variability in the stochastic variable by only determining the range of possible values.

Thus, the objective consists of determining the safety stock, the economic order quantity, the products distribution between machines in each process (in percentage) and the delivery route to be applied every day. The solution was represented as an array of nine positions, as shown in the bottom of Fig. 1, where: the first two values represent the supplier, giving the EOQ and the SS as integers. The third (BalanceProcess1) and fourth position (BalanceProcess2) show the percentage of products allocated to the first of the parallel machines each. Finally the last five positions (Dest1, Dest2, Dest3, Dest4 and Dest5) are the sequence of customers to be served. Such a test case already provides several sources of uncertainty. The stochastic behaviour occurs due to the supplier production time, the processing time in each one of the four individual machines from the production facility, where each has its own probability distribution and therefore capacity, the travel time for each link travelled by the truck, and the demand of each one of the clients.

The performance of a control strategy is measured by the profit made by the production facility in ten days. The revenue is composed only by the sum of the products' prices that are successfully delivered to the clients. Each unit successfully delivered represents \$200 of revenue. The expenses are the sum of the following costs: The ordering costs are composed by a fixed ordering cost plus the individual cost of each product ordered. Inventory holding cost in the production facility are calculated every day. The production costs, which are different for each machine, are calculated by the amount of products processed in machine m times the cost of processing one product in machine m. For the delivery the utilized route cost are summed up, that are proportional to the realized travel times.

2.2 Benchmark Approach

The benchmark approach is used to evaluate the simulation-based optimization approach performance. Its control approaches were selected to mimic classical and empirical approaches commonly utilized on the daily routine of production and logistics control. On the material inventory control, the Economic Order Quantity (EOQ), calculated with the expression (1), and Minimum Safety Stock (SS), calculated with the expression (2), were adopted. Where **D** stands for average demand, **S** for the order placement cost, **H** for the inventory holding cost per unit, σ_d is the standard deviation of the demand, **l** is the lead time for delivery, and **z** is the inverse distribution function of a standard normal distribution, here assumed as 3 for the desired service level (99,87%).

$$EOQ = \sqrt{\frac{2 \cdot D \cdot S}{H}} \qquad (1)$$

$$SS = z \cdot \sigma_d \cdot \sqrt{l} \qquad (2)$$

On the production, the optimization algorithm Jaya is implemented. The algorithm optimizes an objective function $f(x)$ (i.e., minimizing the total cost of the production) through a series of interactions that changes the values of x at each interaction according to the equation (3), where x is the quantity of products to be produced in each machine at each echelon (Venkata Rao, 2016). For transportation control the Clarke and Wright saving algorithm was implemented (Clarke and Wright, 1964). The heuristic starts from a solution in which each of the n customers is visited in a separate tour. The cost of this solution is equal to twice the sum of the travel costs between the depot and all customers. For each customer pair, the algorithm then determines the saving that would result from connecting these customers directly. The algorithm then creates a savings list by sorting these $n(n-1)/2$ savings in decreasing order (Sörensen et al., 2019). The simulation was implemented in AnyLogic software and the optimization algorithms were implemented using Java programming.

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\left(X_{j,best,i} - |X_{j.k.i}|\right)$$
$$- r_{2,j,i}\left(X_{j,worst,i} - |X_{j.k.i}|\right) \qquad (3)$$

2.3 Simulation-based Optimization Approach

The simulation-based optimization (SBO) approach is presented in Fig. 2. At each iteration a solution is generated by a control algorithm. Then, this solution is tested in the simulation model, which replaces the objective function and describes in a better way reality since it incorporates the stochastic and dynamic behaviour observed in reality.
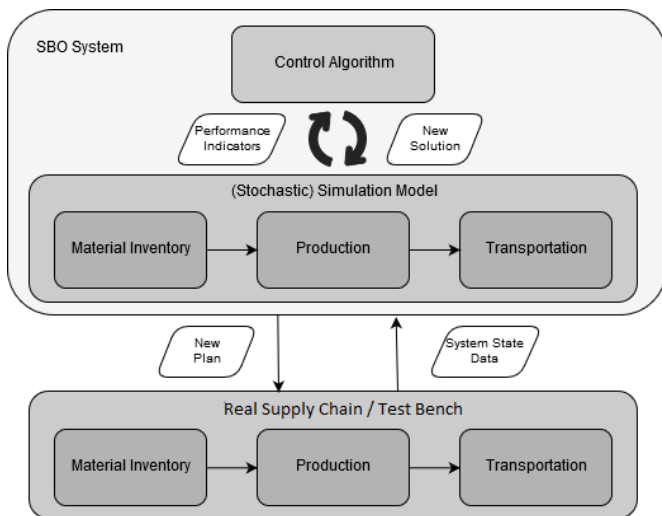

Fig. 2. Simulation-based Optimization for Material Inventory

To cope with faster convergence, some constraints were added in the control algorithm. For the economic order quantity, the generated value should be positive and close to the expected capacity of the supplier. The safety stock should also be positive and not much bigger than the maximum daily processing capacity of the production facility. The machines job distribution may vary between zero and one. The route destinations are mapping the five customers, so the values are between 1 and 5, but for each customer can only be assigned once. Each generated solution is tested through a simulation that represents ten days of the supply chain operations.

The control algorithm is based in the simulated annealing metaheuristic (SA) and implemented in Matlab. Küçükoğlu and Öztürk (2014) define SA as a stochastic method for solving combinatorial problems inspired by the metallurgy annealing process. SA resembles a process where a metal is heated to a high temperature and then cooled by a defined rate. The algorithm used in this work reads a first feasible solution specified by the user and evaluates it, entering a loop. At each iteration, it generates a new solution and compares it with the main solution. If the new solution is better than the main solution, the new solution is assigned as the new main solution; if it is not, the algorithm computes a probability as proposed by Küçükoğlu and Öztürk (2015), allowing it to escape from local optimums (Ropke and Pisinger, 2006). After each iteration, the temperature of the system is reduced by a defined rate. As the temperature reduces, the probability of the system accepting a "bad solution" as the main solution reduces too. The process continues until the temperature gets close to zero.

A new solution is generated by changing one of the nine parameters (safety stock, economic order quantity, the two distributions between machines in each process, and the sequence of clients to serve represented by five parameters) of the main solution to a random value within a defined range (to assure the solutions feasibility).

The evaluation of each solution is performed by running a simulation model within AnyLogic. The Matlab algorithm writes the variables' values of the current solution in a spreadsheet file and calls the AnyLogic model. An instance of AnyLogic is opened and runs the model with the values from the spreadsheet file. At the end of the run, the program exports the results (the profit found in the simulation) to a text file and tells Matlab that the simulation has finished. Matlab then reads the exported value and assigns it as the objective functions value for the current solutions parameters.

3. RESULTS AND DISCUSSION

Both approaches were run in a 10-days scenario to evaluate the profit obtained during this period and were executed ten times to evaluate the behaviour under stochasticity. Since the performance of the control strategy is measured by the profit, Fig. 3 shows the results regarding the Average Performance Comparison in financial units. The Benchmark Approach resulted in an average profit below the SBO approach, as presented in Fig. 3, the profit was 35% higher for the SBO approach.

Through this analysis, it can be verified that the benchmark approach obtained considerably lower profit. This may have occurred because its costs are generally higher due to the bigger number of orders defined by the selected method.
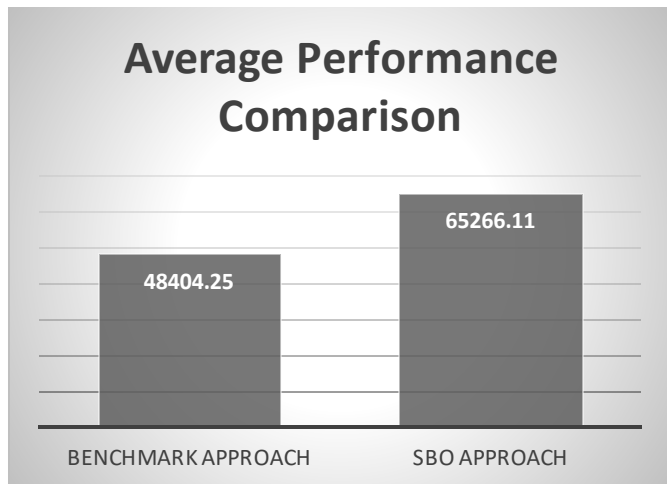

Fig. 3. Average Performance Comparison between approaches

In summary, the SBO approach provided satisfying results compared to the benchmark approach. The proposed approach kept bigger orders, seizing the low inventory holding cost and making savings in the number of orders. The approach also enabled the control algorithm to anticipate the opportunity of lower inventory costs and avoid the high order placement costs. Moreover, it was possible to select a more efficient delivery route for the demand uncertainty scenario. Therefore, the SBO approach showed a better ability to make good use of the scenario characteristics while responding to the uncertainties.
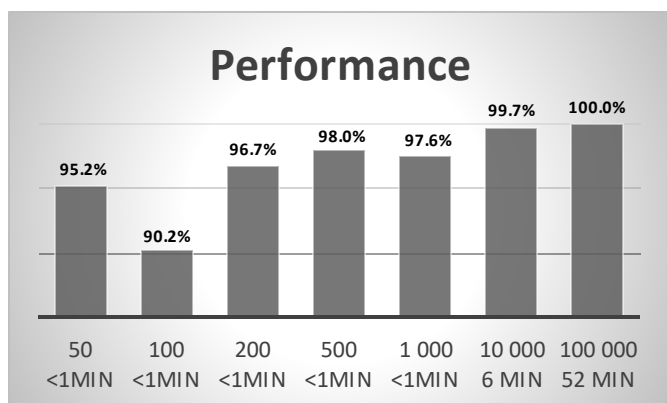

Fig. 4. Experiment performance compared to the best solution generated

Moreover, further experiments presented a fast convergence to a satisfying result. Fig. 4 presents the percentage of the best solution found by the experiment. Each bar represents an experiment, where the upper number in the label represents the number of iterations, and the lower number, the execution time. As presented, the simulation-based optimization was able to achieve more than 95% of the best solutions found with less than 1 minute running, for the test case applied, with the exception of the experiment with 100 iterations, which can be considered an outlier. Such cases may occur due to the random generation of solutions.

However, some further studies are recommended for a more in-depth evaluation of the approach. The first opportunity is to explore different qualities of the initial solution to evaluate the convergence when the initial solution is far from a good solution. Second, a study with parameters variations can clarify more aspects, such as sensitivity analysis. In addition, other approaches can be selected as benchmark approaches to evaluate the performance of the SBO compared to state-of-the-art approaches. Finally, the approach can be implemented in an adaptive way, to respond to dynamic events, such as a machine breakdown.

4. CONCLUSION

Supply chain structures are becoming more complex and dynamic. Such a transformation requires decision support tools, which are able to consider these characteristics. While Industry 4.0 concepts bring technologies that enable real-time data availability, decision support tools must be designed to consider this transparent dynamic behaviour better.

The present work reported a simulation-based optimization approach to simultaneously deal with material inventory, production and transportation processes control. Indeed, the concern of considering uncertainty and the dynamic behaviour of the supply chains has led to the proposal of hybrid approaches as simulation-based optimization by several authors. The presented approach obtained satisfying results significantly better than the benchmark approach.

However, it is desirable to extend the application of this approach to more complex scenarios in order to evaluate its behaviour. As future research, the development of improved heuristics should provide faster convergence. In addition, the performance of one simulation-based optimization relies on the accuracy of the implemented models, such as the simulation model and control algorithms, especially when dealing with uncertainty modelling. Thus, a test case in a real scenario is necessary to evaluate the complexity of obtaining such accuracy.

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