SIMULATION-BASED GA OPTIMIZATION FOR PRODUCTION PLANNING

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Abstract Effective production planning requires models that are capable of accounting for the complexity and uncertainty intrinsic to manufacturing systems. While the identification of a globally optimal plan is desirable, a more important requirement is the ability of a model to produce production plans that are sufficiently realistic to be implemented in practice and are robust to perturbations in the system. Here, we present a simulation-based optimization approach that employs discrete event simulation and a genetic algorithm as a methodology to support decision making in the area of production planning. The model aims to minimize the sum of expected backorders and inventory costs, while incorporating system constraints and the uncertainty that derives from variations of manufacturing lead times, occurrence of work centre failures and repair service times. Preliminary results for a real-world problem indicate that the model is capable of producing feasible production plans that correctly account for the uncertainty intrinsic to the underlying manufacturing system.

Keywords: Discrete event simulation, Genetic algorithms, Production planning, Stochastic variables, Uncertainty.

1. Introduction

Production planning, which specifies how resources should be allocated to production activities [16], forms an integral part of medium-term planning within manufacturing processes. Given the increasing pressures faced by manufacturers, the development and deployment of effective models that support production planning is essential.

Ideally, an optimal production plan should be able to achieve customer satisfaction [18] along with profit maximization, while considering uncertainty in the system [14, 16]. Therefore, an appropriate methodology needs to perform optimization while accounting for the effects that uncertain parameters may have on the implementation of a production plan. This should then lead to an optimized solution that is robust towards various source of uncertainty in the manufacturing system. The lack of an instrument that is fully able to meet this requirement is one of the main reasons why, currently, decisions in production planning are often made in a subjective manner (based on the experience and "sixth sense" of a few people) or guided by inappropriate (simplistic) methodologies.

Optimization and simulation models have been previously deployed to solve the production planning problem, albeit independently. Optimization models are able to generate optimal or near-optimal solutions, but the real applicability of these solutions is often limited. This is because of the oversimplifying assumptions made by many optimization models and their inability to fully incorporate uncertainty [9, 17]. Furthermore, when trying to incorporate the high level of complexity and the stochastic [13] and dynamic nature of manufacturing systems [3] into optimization models, standard approaches become computationally intractable. On the other hand, simulation approaches are capable of capturing the uncertainty of the system [16] and of accurately reproducing its behaviour [11]. Therefore, simulation often provides a better representation of a real production system, since the variability introduced through exogenous and endogenous factors can be explicitly considered and the impact of these factors can be assessed [2]. However, in contrast to optimization approaches, the results obtained from simulation models are fundamentally descriptive: while a clear picture of the system is obtained, the results do not provide explicit guidance towards improved solutions.

In an attempt to combine the respective advantages of simulation and optimization techniques, simulation-based optimization has been suggested as a means of handling problems where the high level of complexity precludes a complete analytic formulation and the ultimate goal is the identification of a robust, near-optimal solution [10]. More specifically, the combined application of discrete event simulation (DES) and genetic algorithms (GAs) has been successfully applied to address several problems related to manufacturing systems. For instance, Azzaro-Pantel et al. [3] were able to improve the efficiency of a multi-purpose, multi-objective plant with limited storage by accurately modelling the dynamic behaviour of the production system through DES and solving the scheduling problem using a GA. Al-Aomar [1] combined DES and a GA to determine robust design parameters. The author integrated Taguchis's robustness measures of signal-to-noise ratio and the quality loss function into a GA in order to enhance the selection scheme. Ding et al. [8] employed DES to capture the uncertainty involved in the supplier selection process and used a GA to optimize the supplier portfolio. Cheng and Yan [5] applied an integration of DES and a messy GA to determine the near optimal combination of resources in order to enhance the performance of construction operations. This approach enabled the authors to cope with the complexity and large dimensionality of the problem and to obtain adequate solutions. Wu et al. [21] integrated DES with a GA to determine the order point for different product types of a cross-docking center in order to minimize total cost. Through this approach the solution space was efficiently reduced and more simulation effort was allocated to promising areas via smart computing budget allocation. Korytkowski et al. [12] proposed an evolutionary simulation-based heuristics, where DES and a GA were deployed to find near optimal solutions for dispatching rules allocation. The sequence of orders determined through this approach improved the performance of a complex multi-stage, multi-product manufacturing system.

Here, we describe a simulation-based optimization approach for production planning. The long-term aim of our work is to derive an effective modeling approach that is capable of determining feasibe and robust monthly production plans. Here, we formulate production planning as an optimization problem that requires the minimization of the expected sum of backorders and inventory costs, subject to a set of constraints of the manufacturing system (e.g. resource constraints) and uncertainties deriving from variations of manufacturing lead times, occurrence of work centre failures and repair service times. Our choice of methodology is motivated by the proven success of simulation-based optimization in related problems (see [1, 3, 5, 8, 12, 21] and above), and we develop a model based on the combination of DES and a meta-heuristic optimizer (specifically, a GA). Finally, we describe preliminary results on a real-world production planning problem.

2. Simulation-based Optimization Model

The production planning problem considered here is based on the real manufacturing system of a large company that specializes in the production of cleaning products, edible shortenings, fats, and oils. This study focuses exclusively on its activities related to the manufacturing of cleaning products.

Discrete Event Simulation (DES) is a good option to model the dynamic behaviour of this production system [3], as it allows for the incorporation of stochastic events and the variations of processes that occur in complex systems [19]. Specifically, the use of DES enables us to capture the uncertainty intrinsic to production planning that cannot be represented by deterministic models [16].

The application of simulation-based optimization implies the absence of an analytical problem formulation, i.e. the functional relationships between dependent and independent variables are not known explicitly [20]. Consequently, a suitable optimization approach needs to be able to perform optimization based exclusively on function values obtained via simulation, a so called "black-box approach". Considering the complexity and large dimensionality of the solution space, a suitable search strategy should be able to find near-optimal solutions in a large and complex solution space and be capable of escaping local optima. Finally, the optimization method needs to be robust with respect to noise, since the optimization procedure relies on stochastic responses generated by the simulation model [10]. Meta-heuristics present suitable candidates for this setting, and, in this study, a GA was selected as the optimizer. This choice was motivated by previous research indicating the robust performance of GAs under noisy conditions [4, 15], and, specifically, in the context of DES optimization [13].

The DES model of the production system was developed in SimEvents® (The MathWorks, Inc., 2013). This was integrated with MATLAB® R2013a (The MathWorks, Inc., 2013), and MATLAB's standard GA implementation was employed as the optimizer. Details of the simulation model and optimizer are described in the following sections.

2.1 Simulation Model

The DES model represents the production of 31 products k within 7 work centres l. A work centre corresponds to the set of resources (e.g., machines, people, etc.) needed to manufacture certain products. Given that some products can be manufactured in several work centres a total of 41 processes j are considered in the DES model. A process j includes all series of events involved in the initialization of orders of a product k, its manufacture in a specific work centre l and its storage in an specific sink s (with $s = 1, 2, \dots, 41$). Here orders are measured in number of lots. The simulation time t of each simulation replication is 24 days, which corresponds to the number of working days in a month.

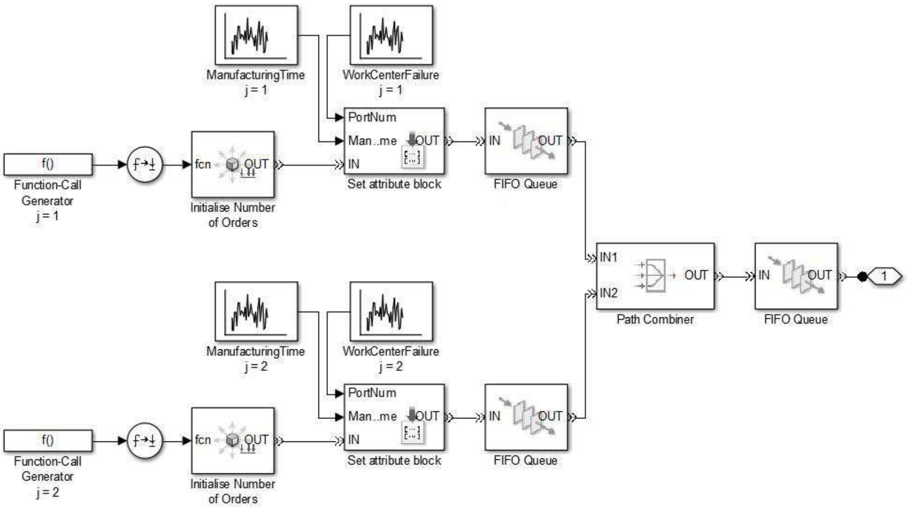

Figure 1. Order processing subsystem for work centre l.

The model component designed for the generation of orders for a single work centre l is illustrated in Figure 1. The production plan to be simulated is determined by the decision variables x_j (used as inputs for the function-call generator blocks), specified by the GA, and then the number of production orders for each process j are initialized (by event-based entity generator blocks). Given that some products k are required as raw materials during the manufacturing process of other products k, a higher priority is assigned to the initialization of orders for those sub-products in order to assure the static logic of the model.

Attributes are assigned to the different product lots (via attribute blocks). Specifications about the entity sink s (with $s = 1, 2, \ldots, 41$) where final products will be stored are assigned via an attribute called $OutputPort_j$. Furthermore, the time required to manufacture a specific production lot ($ManufacturingTime_j$) and the occurrence of a failure in a work centre while processing a production lot ($WorkCentreFailure_j$) are additional attributes assigned to each lot of product. Two different event-based random number generators are employed to set the last two attributes mentioned. Both event-based random number generators produce a signal sampled randomly from the probability distribution functions (PDFs) assigned to them. A synthetic data set was employed to estimate PDFs for each stochastic variable included in the current study, as data collection for these aspects of the system is currently incomplete.

Once the attributes have been assigned to the production orders, those orders are transferred to a queue following a first-in first-out (FIFO) discipline. Subsequently, those queues of production orders that have to be processed by the same work centre are merged (by a path combiner block) into a single FIFO queue.

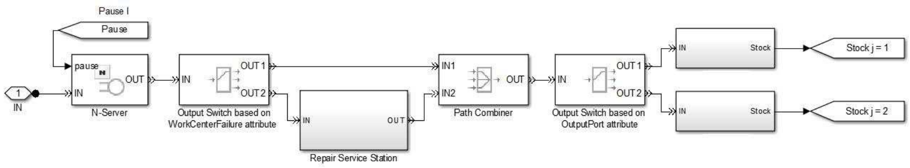

Figure 2. Production subsystem for work centre l.

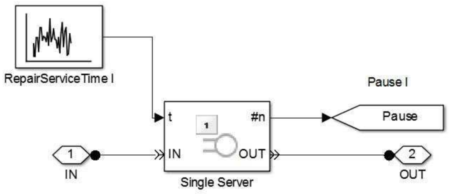

Figure 3. Repair service centre of work centre l.

The model components of a production subsystem and repair service centre are illustrated in Figure 2 and Figure 3, respectively. Each order is manufactured as soon as the corresponding work centre (represented by an N-server block) becomes available. In case of failure, the activity of that work centre is blocked by the control signal $Pause_l$. This signal is generated from the corresponding repair service centre and it outputs the number of entities present in that repair centre. Therefore, a signal with value greater than zero indicates that the work centre l is being repaired and stops its activity until that signal becomes zero (no entities present in the repair service centre).

In case that no failure occurs ($WorkCentreFailure_j = 1$), the production batch is transferred to the corresponding sink s (determined by $OutputPort_j$). Whereas if a failure occurs ($WorkCentreFailure_j = 2$), that product batch is transferred to a repair service centre prior to its storage. The delay caused by the work centre failure is sampled from the corresponding PDF assigned to $RepairServiceTime_l$. One important assumption made is that after a production batch has left the repair service centre no re-manufacture is required, since the manufacturing process has been already completed (passed through the N-server block). This is an effective way to model system failure without having conflicting events.

The stock of product k manufactured in work centre l, denoted by $Stock_{kl}$, is collected at the end of every replication and it is measured in number of lots. Based on $Stock_{kl}$, the total stock of product k ($Stock_k$) is calculated at the end of every replication as follows:

$$Stock_k = \sum_{l=1}^{7} Stock_{kl} \tag{1}$$

consequently, for products manufactured by a single work centre this formula reduces to:

$$Stock_k = Stock_{k1} \tag{2}$$

2.2 Optimization Model

The decision variables, denoted by x_j, are the number of lots to be produced in process j. A black box optimization approach is applied in which the decision variables specified by the GA provide the input to the DES model and the responses $Stock_k$ from the DES model are employed to compute the value of the fitness function. A total of 41 decision variables x_j, which are constrained to be positive integers, are considered in the model. Given the stochastic nature of the DES outputs, fitness is evaluated across n independent simulation trials (with $n = 10$). Specifically, the fitness value f is estimated for each individual x as follows:

$$f(x) = \bar{c} = \frac{1}{n}\sum_{m=1}^{n} c_m \tag{3}$$

For each replication m, the response ($Stock_k$) of the DES model is used to calculate c_m as follows:

$$c_m = \sum_{k=1}^{31} InventoryCost_k + BackorderCost_k. \tag{4}$$

Inventory and Backorder Costs are defined as:

$$InventoryCost_k = \begin{cases} (Stock_k - D_k) \times Cost_k & \text{if } Stock_k > D_k \\ 0 & \text{if } Stock_k \leq D_k \end{cases}$$

and

$$BackorderCost_k = \begin{cases} (D_k - Stock_k) \times Price_k & \text{if } Stock_k < D_k \\ 0 & \text{if } Stock_k \geq D_k \end{cases}$$

where, D_k indicates the demand for product k. Unsold amounts of product k are penalized proportionally to the corresponding standard cost per lot ($Cost_k$), whereas backorders receive a fine equal to the product price, which is the income lost ($Price_k$) for not selling that specific amount of product. Given a lack of information on real inventory costs and total cost derived from backorders per product (cost of customer dissatisfaction, cost of non-future purchases, cost of customers switching to other brands, etc.), standard costs and product prices are currently employed to penalize inventory and backorders, respectively. These two assumptions are not valid in reality for several reasons. First, excess of inventory can be sold in future periods and inventory costs are not equal to standard costs. Second, considering product price as the total loss caused by product backorders is inaccurate and unrealistic.

Additional constraints are imposed given that some products k are required as raw materials during the manufacturing process of other products k. Therefore, the requirement of sub-products is represented through linear constraints as follows:

$$\sum_{j=1}^{41} a_{ij} \times x_j \leq b_i \qquad (i = 1, 2, \ldots, 4) \tag{5}$$

where b_i denotes the quantity available of sub-product i and a_{ij} is the amount required of sub-product i to produce one lot in process j.

The default MATLAB implementation for solving integer and mixed integer problems using a GA is applied in the current study. A detailed description of the (MI-LXPM) GA and its truncation procedure (which ensures compliance with integer constraints after crossover and mutation) can be found in [7]. The inbuilt constraint-handling approach is the parameter free penalty function approach proposed by Deb [6].

3. Preliminary Results

The model enables an accurate incorporation of uncertainty derived from variations of manufacturing lead times, occurrence of work centre failures and repair service times. The time required to run 15 iterations of the GA is 12.15 hours. For this reason, very limited results are reported in the present study, and we mostly focus on the validity of the model designed. More extensive benchmarking of the approach (including longer optimization runs and statistics across multiple trials) is currently in progress.

As shown in Figure 4, when run for 15 iterations, the GA successfully reduces the expected sum of backorders and inventory costs. The best production plan after 15 iterations is presented in Table 1. For reference, the amount of demand to be covered, the consolidated number of lots per product to be manufactured and the actual number of lots produced is shown in Table 2. The allocation for work centre 204 provides a suitable illustration of the results obtained. For the majority of products (except for product B), work centre 204 displays a more reliable performance than work centre 203. For this reason, the suggested production plan (see Table 1) allocates a greater number of orders to work centre 204. This solution is in accordance with our expectations and illustrates that the reliability of work centres is correctly accounted for in the production plan generated.

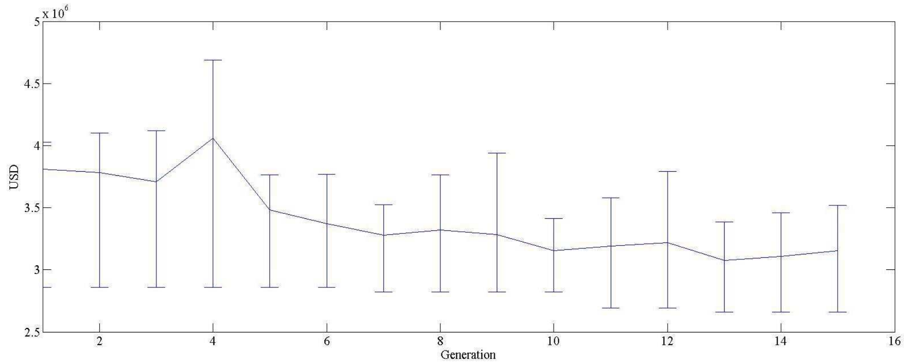

Figure 4. Best, mean and worst fitness value of the population at each iteration.

4. Future Research

There are a number of ways in which this research will be extended in future work. Regarding the simulation component of the work, data collection (from the company) needs to be completed. The data obtained will be used to estimate PDFs of all stochastic variables, so that the use of synthetic data can be avoided.

Regarding the optimizer, future work will include an investigation of parameter settings, the sensitivity to noise and, potentially, the comparison to alternative meta-heuristic optimization approaches. Moreover, the number (n) of simulation trials employed to evaluate fitness will be further analysed in order to balance quality of estimations and computational cost. Furthermore, a multi-objective formulation of the problem will be explored in order to account for the robustness of solutions in a more explicit manner. Specifically, the maximization of the signal-to-noise ratio may be used as an additional objective to directly account for the variability in the fitness values obtained [1].

Table 1. Number of product lots to be manufactured in a specific work centre.

Product	*Work centre*	*Prod. plan*[b]
A	204	14
B	203	7
B	204	6
C	203	10
D	203	6
E	203	10
F	203	8
G	203	7
G	204	14
H	203	3
H	204	11
I	203	3
I	204	8
J	203	14
K	203	6
L	203	12
L	204	13
M	203	7
M	204	19
N	204	14
O	203	5
O	204	10
P	203	4
P	204	4
Q	203	12
R	202	5
R	203	3
R	204	7
S	202	7
T	203	9
U	203	12
V	203	13
W	203	2
X	202	9
Y[b]	101	3
Z[b]	204	10
AA	204	6
AB[b]	205	8
AC[b]	205	16
AD	208	7
AE	301	9

[a]best production plan generated by the model after 15 iterations with $n = 10$.
[b]Sub-products.

Table 2. Demand, consolidated production plan per product and actual production achieved.

		Production [a]	
Product	*Demand* [a]	*Planned*	*Actual* [b]
A	10	14	7.3
B	9	13	6.1
C	12	10	4
D	10	6	2.4
E	15	10	4
F	13	8	3.2
G	12	21	10.1
H	11	14	7
I	9	11	5.5
J	8	14	5.6
K	15	6	2.4
L	12	25	11.6
M	13	26	12.6
N	12	14	7.3
O	13	15	7.3
P	9	8	3.9
Q	11	12	4.8
R	10	15	10
S	9	7	7
T	15	9	3.6
U	15	12	4.8
V	12	13	5.2
W	9	2	0.8
X	9	9	9
Y[c]	0	3	3
Z[c]	0	10	5.3
AA	10	6	3.3
AB[c]	0	8	8
AC[c]	0	16	16
AD	10	7	7
AE	10	9	9

[a] measured in number of lots.
[b] average value of 10 independent replications.
[c] Sub-products.

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