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ON THE USE OF SIMHEURISTICS TO OPTIMIZE SAFETY-STOCK LEVELS IN MATERIAL REQUIREMENTS PLANNING WITH RANDOM DEMANDS

Barry B. Barrios
Angel A. Juan
Javier Panadero

Universitat Oberta de Catalunya – IN3
Euncet Business School
Av. Carl Friedrich Gauss 5
Castelldefels, 08860, SPAIN

Klaus Altendorfer
Andreas J. Peirleitner

School of Business and Management
University of Applied Sciences Upper Austria
Wehrgrabengasse 1-3
Steyr, 4400, AUSTRIA

Alejandro Estrada-Moreno

Dept. d'Enginyeria Informàtica i Matemàtiques
Universitat Rovira i Virgili
Av. Països Catalans 26
Tarragona, 43007, SPAIN

ABSTRACT

Material requirements planning (MRP) integrates the planning of production, scheduling, and inventory activities in a manufacturing process. Many approaches to MRP management focus either on the simulation of the system (without considering optimization aspects) or in its optimization (without considering stochastic aspects). This paper analyzes a MRP version in which the demand of final products in each period is a random variable. The goal is then to find the optimal safety-stock configuration of both the product and the parts, i.e.: the configuration that minimizes the expected total cost. This total cost is given by: *(i)* the inventory cost; and *(ii)* a penalty cost generated by the occurrence of stock outs. To solve this stochastic optimization problem, a spreadsheet simulation model is proposed and a heuristic procedure is employed over it. A numerical example illustrates the main concepts of the proposed approach as well as its potential.

1 INTRODUCTION

Material requirements planning (MRP) refers to a planning and push control system that minimizes the inventory levels while ensuring the material availability (Krajewski and Ritzman 2005). According to Orlicky (1975), an MRP system "consists of a set of logically related procedures, decision rules, and records designed to translate a master production schedule into time-phased net requirements". Hence, an MRP system allows for determining the number of parts, components, and materials required during the generation of each final product. Hence, MRP systems are traditionally employed by factories that make use of assembly operations during the production process.

A schematic representation of an MRP system is given in Figure 1. As described in Heizer et al. (2017), the starting point is a *master production schedule* (MPS), which defines the manufacturing of final products per period (e.g., a week). Then, a *bill of materials* (BOM) or *product structure file* identifies the

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specific parts required to produce each item (final product or higher-level part) as well as the required quantities of each part. The *inventory records file* contains data that has to be considered also, such as the number of units on hand and on order. From these sources, the MRP program expands the MPS into a detailed order scheduling plan for the entire production sequence. Following Jacobs et al. (2011), a typical MRP record contains gross requirements (total amount required for a particular item), scheduled receipts (orders that have already been released and that are scheduled to arrive as of the beginning of the period), projected available balance (amount of inventory that is expected as of the end of a period), net requirements (amount needed when the projected available balance plus the scheduled receipts in a period are insufficient to cover the gross requirement), planned order receipts (amount of an order that is required to meet a net requirement in the period), and planned order release (planned order receipt offset by the lead time). Some of the most frequent constraints in many MRP systems are the lot size (i.e., the number of items in each unit of order) and the minimum order size (i.e., the minimum number of items that need to be included in each new order).

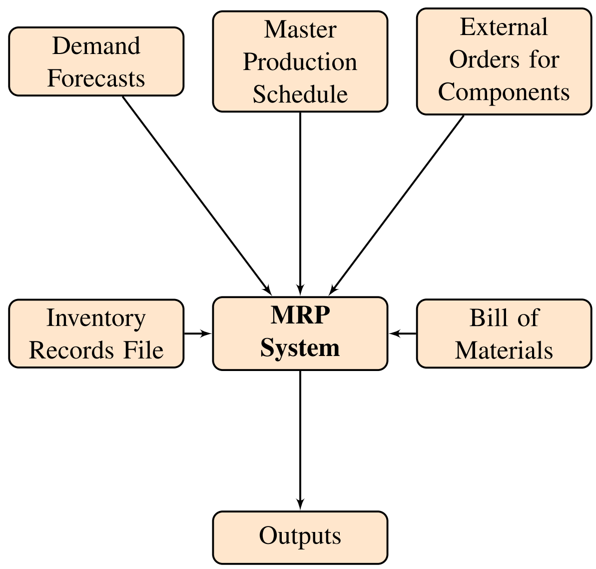

Figure 1: Sources of inputs in an MRP system.

One of the most common sources of uncertainty in MRP systems is due to the customers' demand for each final product, which affects the entire supply chain of parts requirements. Part of this demand might be known via orders already placed, but customers might also buy items as needed. Although forecast methods can be used to predict this pattern, in many cases the customers' demand per period is still a random variable. Thus, in order to consider these variations in customers' demands, it is common to run several MPS and check their respective feasibility in terms of available materials and / or completion times. This paper goes one step further by assuming a random behaviour of this demand and then developing a simulation-based heuristic methodology able to search in a vast space of feasible solutions to find the one that minimizes the expected total cost of the MRP system, where this cost is assumed to have two trade-off components: *(i)* the cost due to maintaining a safety stock to be used only in the case that actual net requirements exceed the planned ones; and *(ii)* the cost associated with stock-out events, which occur whenever the current level of safety stock are not sufficient to cover unexpectedly higher customers' demands.

The remaining of the paper is structured as follows: Section 2 provides a review of the existing literature on the use of simulation to deal with MRP systems; similarly, Section 3 briefly reviews existing work on simulation-optimization approaches and, in particular, those related to simheuristics, which refers to the combination of simulation with heuristics (Juan et al. 2018); Section 4 introduces a stochastic MRP example that we will use to illustrate our methodology and generate some numerical results; Section 5 provides additional details on the stochastic optimization problem we aim to solve; Section 6 describes the simulation-based heuristic that we use to solve the aforementioned problem; Section 7 analyzes the results of the numerical experiments carried out; finally, Section 8 summarizes the main findings of this work and points out directions for future research actions.

2 RELATED WORK ON SOLVING MATERIAL REPLENISHMENT PROBLEMS AND USING SIMULATION IN MRP SYSTEMS

Many inventory control policies use a deterministic reorder point for the items using analytical or queuing models. Inventory control models existed since the early 20th century, starting with one of the earliests one known as the economic order quantity (EOQ) (Roach 2005). These models extend to stochastic inventory models, including the so-called (r,Q) and (s,S) policies, in which demand and lead time uncertainties are represented by probability distributions. Additionally, to address demand uncertainty and prevent stock outs, the models incorporate safety stocks. Safety stock is extra inventory that is kept on hand to buffer against uncertainty. In an (r,Q) policy, when the inventory position reaches the reorder point, denoted by r, we place an order of size Q. In an (s,S) policy, we instead order up to a fixed level S. In this model, s is the safety stock level and S is the maximum replenishment level. The problem is formulated as a dynamic program and can solve the finite-horizon with non-zero fixed costs. The solution tell us exactly what to order up to in each period t for each starting inventory level x. The (s,S) policy is a periodic single-item inventory system, and it is an optimal policy for systems that meet the following assumptions: independent and identically distributed demand, ordering costs are linear plus a fixed setup costs. The (s,S) policy is known to be effective in a variety of inventory situations.

Demands are often volatile in practice, resulting in inaccurate forecasts true for products with short life cycles, large varieties, and long supply lead times – like the case of fashion goods. Events that are outside of the control of the company can also create demand uncertainty, i.e., an epidemic process, a trade war, etc. In this paper, we focus on a finite-horizon, single-product, and periodic-review inventory management problem utilizing MRP. We also consider uncertainty in customers' demands using probability distributions, where items are related to each other by successor or predecessor relations according to the BOM. A similar problem to the one discussed here is the *multi-item capacitated lot-sizing problem*. However, the multi-item capacitated lot-sizing poblem is deterministic in its traditinal form. A classical approach used to solve such problems is to decompose the problem, level by level, into single-level sub-problems. These sub-problems are then solved sequentially from end-products to raw materials. The production plans at each level define the demand at subsequent levels. Also MRP-type systems apply this approach, however, using a simple algorithm to identify the production orders. Most of the lot-sizing procedures are single-level which find optimal or near-optimal solutions for the single-item, deterministic, finite-horizon, dynamic demand, uncapacitated periodic review models. Wagner and Whitin (1958) proposed an algorithm based on a dynamic programming approach that gives the optimal solution to the single-level lot-sizing problem whereas the other lot-sizing procedures are all heuristics which do not ensure optimality. Afentakis et al. (1984) suggest dynamic programming and branch and bound for the problem of lot-sizing in multi-level periodic review, dynamic demand, multi-period inventory systems. Rao and McGinnis (1983) also address the problem of lot-sizing in multi-level periodic review by using a generalized network flow model, but getting solutions to large problems is difficult using their approach. It is for this reason why we need simple heuristic procedures to solve large size multi-level lot-sizing problems. Note that all of these approaches only address the lot-sizing part of the problem since deterministic demand is assumed. However, if demand is stochastic, safety stocks have to be included and optimized.

In the Winter Simulation Conference, there are a number of published papers on discrete event-simulation of supply chains and production systems. For example, Samvedi and Jain (2011) studied the impact of various inventory policies on a supply chain with intermittent supply disruptions. The study considers a 4-level single-product supply chain that includes a retailer, a wholesaler, a distributor, and a manufacturer. Wu et al.

(2013) built a simulation model to represent the dynamics of a dishwasher wire rack production system. A periodic review inventory policy was simulated. An adjusted (s,S) policy called (SS_i, P^*) was developed to deal with a conflict that arises when there are two products associated with one machine whose inventory levels both drop below s. In the adjusted (s,S) inventory policy, a trigger variable P^* is added into the classic (s,S) policy. An integer program was formulated to search for the optimal inventory policy, which minimizes the total inventory level at the work-in-progress buffer and storage areas through the use of a simulation model. Hübl et al. (2011) introduces a flexible discrete-event simulation model for analyzing production systems. The material flow is based on the information set in database for routing and BOM. This allows the analysis of the logistical performance of any structure applied in BOM and routing. Stochastic behavior for customer performance, processing times, setup times and purchasing lead time are included. The model combines three hierarchical levels whereby their interaction can be tested. All of these models apply simulation to simulate and/or optimize supply chain or production planning in stochastic environments which shows that this is a valuable field of research.

3 SIMULATION-OPTIMIZATION AND SIMHEURISTICS

Simulation is used to analyze complex systems under stochastic conditions (Faulin et al. 2008). Simulation-optimization approaches aim at hybridizing both optimization methods and simulation techniques in order to efficiently cope with: *(i)* optimization problems with stochastic components; and *(ii)* simulation models with optimization requirements (Figueira and Almada-Lobo 2014). A discussion on how random search can be incorporated in simulation-optimization approaches is provided in Andradóttir (2006), while reviews and tutorials on simulation-optimization can be found in Fu et al. (2005), Chau et al. (2014), and Jian and Henderson (2015). Among these simulation-optimization methods, Glover et al. (1996) and Glover et al. (1999) propose the combination of simulation with heuristics as a promising approach for solving stochastic optimization problems that are frequently encountered by decision makers in the aforementioned industrial sectors. Hence, this paper will focus on simheuristics, which can be seen as a specialized case of simulation-based optimization (April et al. 2003). As properly discussed in Ferone et al. (2019), simheuristic algorithms integrate simulation methods inside a heuristic / metaheuristic optimization framework to deal with stochastic optimization problems. Hybridization of simulation techniques with metaheuristics allows us to consider stochastic variables in the objective function of the optimization problem, as well as probabilistic constraints in its mathematical formulation (Fu 2002). Moreover, when dealing with stochastic optimization problems, performance statistics other than expected values must be taken into account: while in deterministic optimization one can focus on finding a solution that minimizes cost or maximizes profits, a stochastic version of the problem might require that we analyze other statistics such as its variance, different percentile values, etc. This section reviews some recent applications of simheuristic algorithms in the solving of stochastic optimization problems. We are mainly interested in recently published applications. In order to facilitate the reading, the reviewed papers have been classified by application area:

- *Vehicle and Arc Routing Problems:* Gonzalez-Martin et al. (2018) use a simheuristic for solving the arc routing problem with stochastic demands, while Fikar et al. (2016) proposes a DES-based heuristic to cope with a vehicle routing problem with synchronized pick-up and delivery actions. Different from the vehicle routing problem, in the arc routing problem the demands are located on the edges instead of on the nodes, and the graph is not necessarily complete, which implies that an edge might be traversed more than once by the same vehicle. Guimarans et al. (2018) introduce a simheuristic algorithm for the two-dimensional vehicle routing problem with stochastic travel times. Reyes-Rubiano et al. (2019) discuss the electric-vehicle routing problem with stochastic travel times and limited driving ranges, for which they propose a simheuristic algorithm.
- *Inventory Routing Problems:* Gruler et al. (2018), Gruler et al. (2020), and Raba et al. (2020) propose several simheuristic algorithms for solving inventory routing problems with stock-outs – some of these problems considering a multi-period horizon. The authors propose the combined use

of Monte Carlo simulation with a metaheuristic to minimize global inventory and routing cost when serving a set of retail centers that are subject to stochastic demands. The goal of minimizing the total expected cost is complemented with the idea of obtaining solutions with a low variability or risk. Similarly, Gruler et al. (2017a) and Gruler et al. (2017b) propose simulation-optimization approaches for efficient waste collection management in smart cities.

- *Scheduling Problems:* In the context of scheduling, Gonzalez-Neira et al. (2017) propose a simheuristic algorithm for solving a distributed-assembly flow-shop problem with stochastic processing times. The authors argue that only by combining simulation with metaheuristics it is possible to solve such realistic but complex optimization problems in reasonable computing times. Also in this context, Hatami et al. (2018) analyze the optimal setting of starting times in stochastic parallel flow-shop problems.
- *Facility Location Problems:* In Pagès-Bernaus et al. (2019), the authors apply a simheuristic approach to the design of a distribution network in an e-commerce environment. These authors test the performance of the simheuristic by comparing the results it generates against the ones obtained by a classical stochastic programming approach. As expected, the simheuristic can deal with large-size instances that cannot be solved by the stochastic programming approach in reasonable computing times. Also, Quintero-Araujo et al. (2019) propose a simheuristic algorithm for solving the capacitated location routing problem in the presence of stochastic customers' demands.
- *Manufacturing:* Rabe et al. (2020) propose the combination of a genetic algorithm with a discrete-event simulation model to optimize the work flow in a typical manufacturing process, and discuss how to speed up the hybridized approach so that the simulation component does not jeopardize the time invested in the optimization one.

This review shows that simheuristics have successfully been applied to solve different supply chain and production problems and are, therefore, a promising approach to also optimize the MRP safety stock levels.

4 MODELING A STOCHASTIC MRP SYSTEM

Figure 2 illustrates the bill of materials associated with the stochastic MRP we will consider in this paper. Despite being a simple BOM that only considers two levels, it allows us to illustrate how simulation-based heuristics can be useful in considering stochastic MRPs. Thus, level 0 contains a final product, A, which requires two parts located at level 1: to produce each unit of item A, 2 units of part B and 3 units of part C are required.

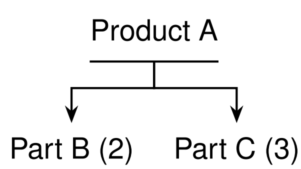

Figure 2: A 2-level BOM for our stochastic MRP example.

Figure 3 shows the MRP associated with the previously described BOM. It contains three main tables: one for item A (the product) and one for each of the parts. For an 8-period time horizon, the product table includes the typical MRP parameters (lead time, lot size, and minimum quantity per lot), decision variables (safety stock level in our case), and fields (expected item demand or gross requirements, planned on-hand inventory, planned net requirements, planned order receipts, and planned order releases). In this example, we are assuming that, i.e., in period 3 the expected demand is 8, while the planned on-hand inventory is 5. Taking into account that the safety stock value has to be maintained as 4 items, this means that the planned net requirements will be $8+4-5=7$, which leads to a planned order receipt of 8 (since the minimum quantity of items per lot is 4 and each lot size contains 2 items). Since the lead time is 1, that means that we need to set up a planned order release of 8 units in Period 2. The tables associated with items B and C follow a similar logic. Here, the main difference is that gross requirements at each period (e.g., 12 and 18 in Period 3, respectively) are defined by the corresponding planned order releases of product A (6 in Period 3) and the number of B and C items necessary to produce an item of product A (2 and 3, respectively).

	A	B	C	D	E	F	G	H	I	J	K
13							$100	<-- SSC item A			
14		Item A (product)		Lead time	1	Saf. Stock	4	Lot size	2	Min. Quant.	4
15			Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8
16		Expected item demand		5	10	8	7	6	9	10	5
17		Actual item demand		4	14	11	6	3	13	11	10
18		Planned on-hand inventory	10	10	5	5	5	4	4	5	5
19		Actual on-hand inventory	10	10	6	2	0	0	3	0	0
20		Planned net requirements		0	9	7	6	6	9	9	4
21		Actual net requirements		0	12	13	10	7	14	15	14
22		Planned order receipts		0	10	8	6	6	10	10	4
23		Planned order releases		10	8	6	6	10	10	4	0
24		Stock out?		0	0	0	0	0	0	1	1
25											
26							$72	<-- SSC item B			
27		Item B (part)		Lead time	2	Saf. Stock	12	Lot size	2	Min. Quant.	2
28			Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8
29		Gross requirements		20	16	12	12	20	20	8	0
30		Scheduled receipts		4	0	0	0	0	0	0	0
31		On hand inventory	20	20	12	12	12	12	12	12	12
32		Net requirements		8	16	12	12	20	20	8	0
33		Planned order receipts		8	16	12	12	20	20	8	0
34		Planned order releases		12	12	20	20	8	0	0	0
35											
36							$72	<-- SSC item C			
37		Item C (part)		Lead time	1	Saf. Stock	18	Lot size	1	Min. Quant.	0
38			Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8
39		Gross requirements		30	24	18	18	30	30	12	0
40		Scheduled receipts		10	0	0	0	0	0	0	0
41		On hand inventory	30	30	18	18	18	18	18	18	18
42		Net requirements		8	24	18	18	30	30	12	0
43		Planned order receipts		8	24	18	18	30	30	12	0
44		Planned order releases		24	18	18	30	30	12	0	0

Figure 3: Example of a stochastic MRP for product A with parts B and C.

As a novelty with respect to deterministic MRP approaches, our model considers stochastic demands for product A in each period. Hence, the actual gross requirement for this item might differ from the expected one. Simulation is applied to generate the random realizations for an expected demand stream and evaluate the respective costs. Note that in a larger experiment also the expected demand stream could be generated by simulation and an extension to rolling horizon planning is possible based on this basic implementation in the current paper. As a result, the actual on-hand inventory and net requirements might be different from the planned ones. Whenever items from planned order receipts plus items from the safety stock are insufficient to meet the actual net requirements, a costly stock out will occur. In Figure 3, this is what happens in Periods 7 and 8.

5 SETTING UP THE STOCHASTIC OPTIMIZATION PROBLEM

Using the previously described model, our goal is to find the configuration of safety stock levels for each item that minimizes the expected total cost for the manufacturer. This total cost is composed of: *(i)* the cost of holding items in safety stock –which is fixed given a configuration of safety stock levels; and *(ii)* the cost of suffering stock outs –which depends on the realization of the random demands. In our numerical experiments, we have made the following assumptions:

- The actual demand of product A in each period j, $j \in \{1,2,\ldots,8\}$, follows a *uniform* random variable between $\mu_j/2$ and $2\mu_j$, where μ_j refers to the expected demand of product A in period j (notice that our methodology can be employed in the same way regardless of the specific probability distribution that models these demands).
- The safety stock of each item $i \in \{A,B,C\}$, ss_i, is a non-negative integer variable no larger than 20, i.e., $ss_i \in \{0,1,\ldots,20\}$.
- The following unitary safety-stock costs: \$25 per unit of item A, \$6 per unit of item B, and \$4 per unit of item C. For the configuration shown in Figure 3, with $ss = (4,12,18)$, the resulting safety stock cost is $4 \cdot 25 + 12 \cdot 6 + 18 \cdot 4 = \$244$.
- A cost of \$250 for each stock-out occurrence, which in the case of Figure 3 means a stock-out cost of \$500. Hence, the total cost for one run of the simulation adds up to \$744.

6 SIMULATION AND HEURISTIC PROCEDURE

Once the spreadsheet model and the MRP inputs have been set –thus defining a particular instance of the problem–, different safety-stock vectors $ss = (ss_A, ss_B, ss_C)$ can be tested. Each of these vectors represent a possible solution to the stochastic optimization problem. For each proposed solution, a simulation can be run to test its associated expected cost, as well as other risk-related statistics (e.g., variance, quartiles, etc.). This simulation is based on the generation of multiple demand vectors, each vector containing a randomly generated demand for each period. In our experiments, we have employed 200 randomly generated vectors, and these are used to test each proposed solution in order to benefit from well-known variance reduction techniques, e.g., the common random numbers one (Glasserman and Yao 1992). Since our model only considers 3 items and we have limited the safety stock capacity to 20 units per item, the number of possible solutions is limited to $21^3 = 9,261$. Notice, however, that this number can grow very fast as we consider MRP scenarios with higher numbers of items and stock capacities. For such scenarios, the use of a metaheuristic algorithm is necessary in oder to efficiently explore the associated solution space. In particular, simheuristic algorithms (Rabe et al. 2020) seem to be a convenient methodological alternative for solving large-scale stochastic optimization MRPs. In our experiments, we have employed a simple heuristic that filters out all solutions that offer a higher safety-stock cost without reducing the stock-out cost. Thus, for instance, due to the fact that the safety-stock cost per unit of item A (\$25) is higher than the safety-stock cost of 2 items of B and 3 items of c (\$24), the solution $(0,2,3)$ will be cheaper than the solution $(1,0,0)$, etc. –notice that both solutions will have the same expected cost of stock-out. Similarly, solutions such as $(4,13,18)$ and $(4,12,19)$ can be discarded without the need for running any simulation, since they will be 'dominated' by solution $(4,12,18)$, which offers the same expected stock-out cost and a lower safety-stock cost. These simulation and heuristic procedures have been implemented in a VBA application which interacts with the spreadsheet model (Figure 4). Using a standard PC, $i5$ CPU at 2.27GHz with 8GB RAM, the total computational time invested in running our experiments and obtain the results was about 30 minutes.

7 ANALYSIS OF RESULTS

After running the simulation-based heuristic to efficiently explore the solution space, multiple solutions were generated by the heuristic and then tested in the simulation environment. Figure 5 shows a multiple box-plot with the results obtained for some of these configurations. The solution on the left, $(0,0,0)$ represents a configuration with no safety stock, while the solution on the right $(20,12,18)$ represents a configuration with the maximum level of 'effective' safety stock (notice that a solution such as $(20,20,20)$ will lead to the same effective safety stock since 3 units of part C are required to generate each unit of product A). For the instance considered above, the best-found solution is the configuration $(1,12,18)$, which gives an expected total cost of \$486.50. Also, its interquartile range is located at a low level, with 75% of the observations below the average of other solutions and without any observation above $\$1,500$. On the contrary, the configuration $(0,0,0)$ shows a high variability, with observations that range from \$0 to $\$1,750$.

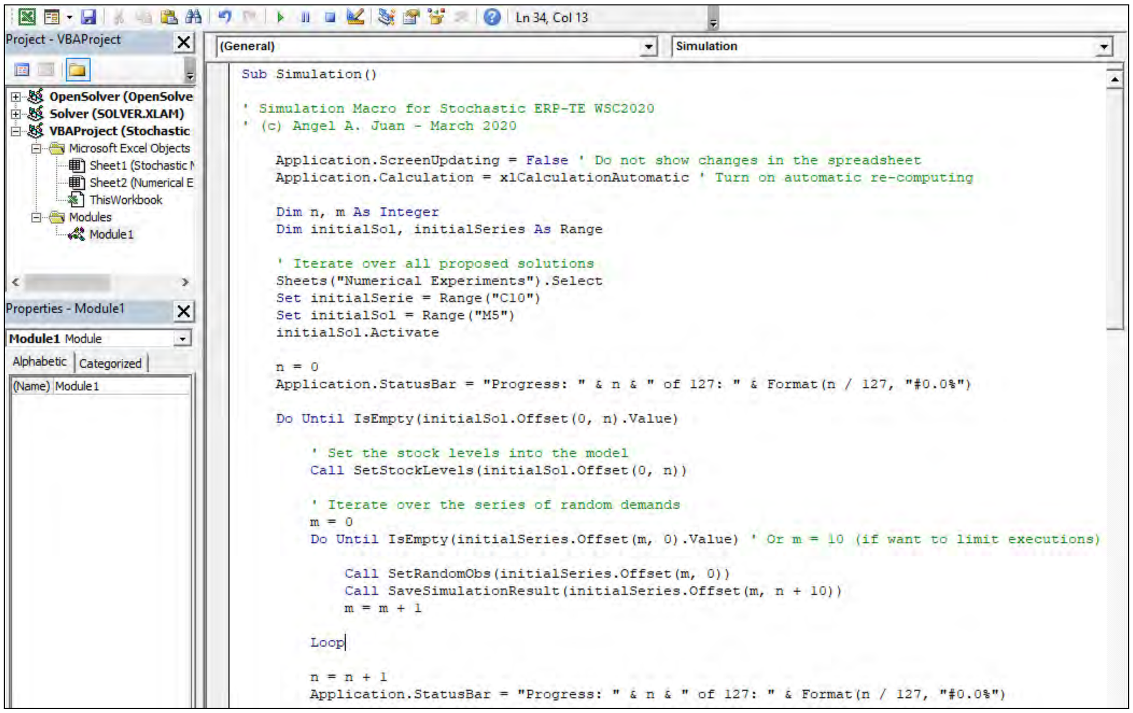

Figure 4: Part of the VBA code developed to run the simulation experiments.

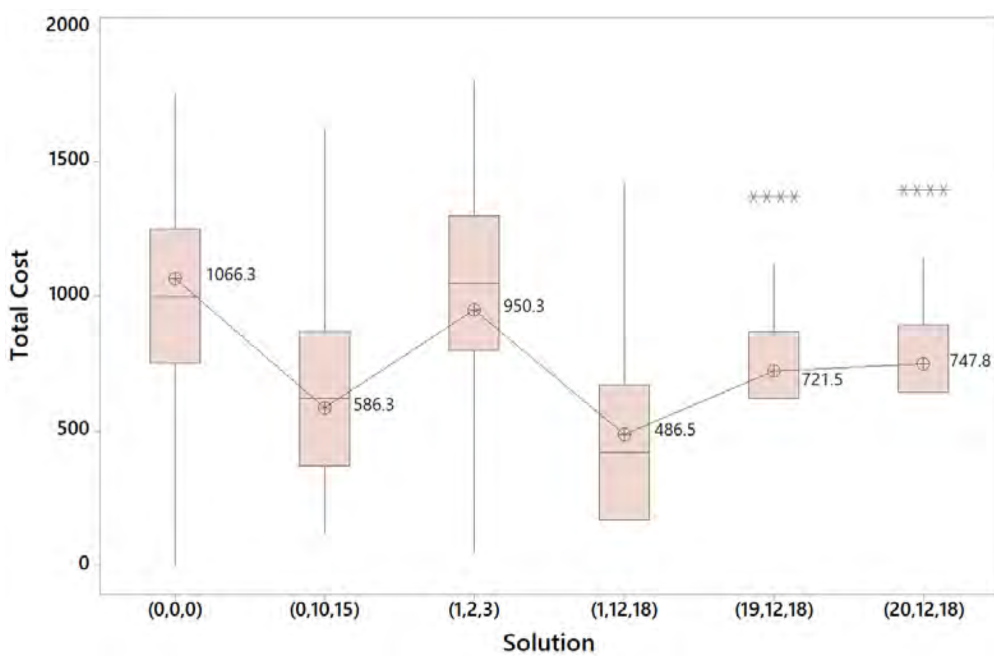

Figure 5: Boxplot of total cost realizations for different solutions.

Figure 6 shows the results of a Fisher's LSD test (Williams and Abdi 2010), which compares the differences between each pair of solutions in Figure 5. Notice that, at a 95% confidence level, the difference between the mean of any other solution and that of the best-found configuration $(1, 12, 18)$ is significantly different from 0, i.e., the best-found configuration is significantly better (in terms of expected total cost) than any of the other configurations considered. Similarly, the test shows that the no-safety-stock configuration, $(0, 0, 0)$, leads to a significantly higher expected total cost than the rest of the considered solutions.

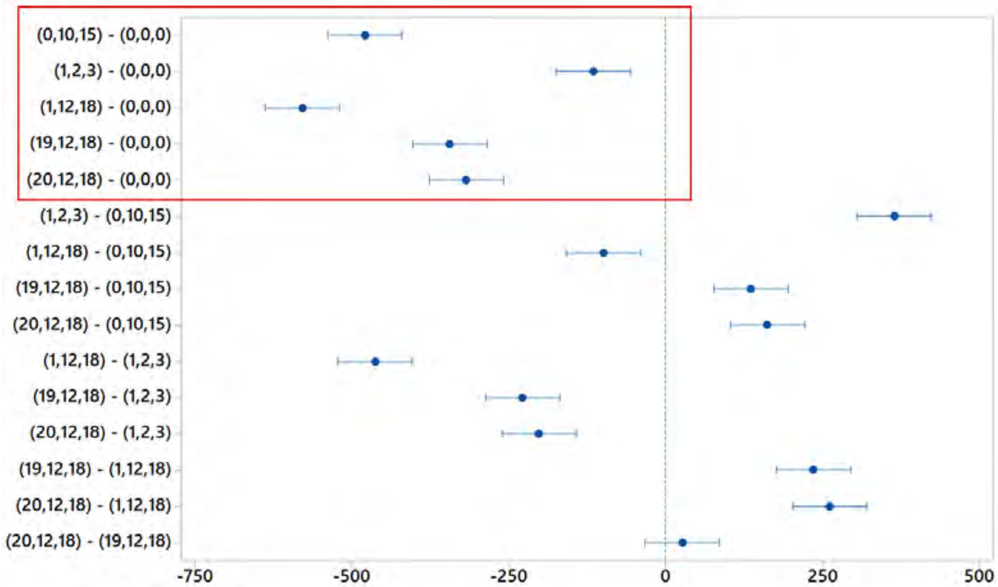

Figure 6: Fisher's LSD test for comparison of means (95% confidence level).

8 CONCLUSIONS AND FUTURE WORK

The material requirements planning (MRP) is one of the most critical processes in many manufacturing industries, since it directly affects the production outcomes and performance. While the deterministic version of the MRP has been widely analyzed in the literature, the stochastic version of the MRP has received less attention despite representing a more realistic scenario –e.g., one in which customers' demands for final products are random variables instead of deterministic values. This paper discusses a 2-layer stochastic MRP example composed of one final product and two component parts. The customers' demands for the final product are assumed to be stochastic, and the goal is to find the optimal safety-stock levels of each item that minimize the expected total cost for the manufacturer.

In order to deal with this stochastic optimization problem, a simulation-based heuristic is proposed and tested. The heuristic filters out promising solutions (safety-stock configurations) and tests them in a simulation environment to estimate their average cost and variability. The heuristic and simulation procedures are implemented as an Excel / VBA model and tested in a particular instance of the problem. The analysis of the results show that our combined heuristic-simulation approach is able to provide balanced configurations that outperform other 'extreme' solutions such as using no safety stock or employing the maximum levels of safety stock possible. Also, since the solution space scale fast as the problem size grows, the use of a simulation-based heuristic is more effective than just employing simulation alone.

As future work, we plan to: *(i)* develop a full simheuristic algorithm –including a complete metaheuristic framework– able to efficiently deal with large-sized MRP systems, e.g., those with more items, levels, and safety-stock capacities; *(ii)* test our simheuristic in an extended benchmark set with multiple instances;

(iii) analyze the sensitivity of the results to variations in the probability distributions that model customers' demands; and *(iv)* consider the effect of correlations among customers' demands from different periods.

ACKNOWLEDGMENTS

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AUTHOR BIOGRAPHIES

BARRY B. BARRIOS holds a B.Sc. in Physics from the Massachusetts Institute of Technology and a M.Sc. in Industrial and Systems Engineering from Virginia Tech. His main research lines are related to Discrete-Event Simulation for Enterprise Scale Systems. His e-mail address is barriosb@vt.edu.

ANGEL A. JUAN is a Full Professor of Operations Research & Industrial Engineering in the Computer Science Dept. at the Universitat Oberta de Catalunya (Barcelona, Spain). He is also the Director of the ICSO research group at the Internet Interdisciplinary Institute and Lecturer at the Euncet Business School. Dr. Juan holds a Ph.D. in Industrial Engineering and an M.Sc. in Mathematics. He completed a predoctoral internship at Harvard University and postdoctoral internships at Massachusetts Institute of Technology and Georgia Institute of Technology. His main research interests include applications of simheuristics and learnheuristics in computational logistics and finance. He has published about 100 articles in JCR-indexed journals and more than 225

papers indexed in Scopus. His website address is http://ajuanp.wordpress.com and his email address is ajuanp@uoc.edu.

KLAUS ALTENDORFER is Professor in the field of Operations Management at the University of Applied Sciences Upper Austria. He received his PhD degree in Logistics and Operations Management and has research experience in simulation of production systems, stochastic inventory models and production planning and control. His e-mail address is klaus.altendorfer@fh-steyr.at.

ANDREAS J. PEIRLEITNER is Research Associate in the field of Operations Management at the University of Applied Sciences Upper Austria. His research interests are discrete event simulation, hierarchical production planning, information uncertainty and supply chain optimization. His email address is andreas.peirleitner@fh-steyr.at.

ALEJANDRO ESTRADA-MORENO is a Lecturer in Departament d'Enginyeria Informàtica i Matemàtiques at Universitat Rovira i Virgili. He holds a Ph.D. in Computer Science and Mathematics. His main research interests are focused on Graph Theory, Analytics, and Operations Research. He has published more than 20 articles in JCR-indexed journals. His web site address is https://sites.google.com/view/alejandro-estrada-moreno and his email address is alejandro.estrada@urv.cat.

JAVIER PANADERO is an Assistant Professor of Simulation and High Performance Computing in the Computer Science, Multimedia and Telecommunication Department at the Universitat Oberta de Catalunya (Barcelona, Spain). He is also a Lecturer at the Euncet Bussines School, and a member of the ICSO@IN3 research group. He holds a Ph.D. and a M.S. in Computer Science. His major research areas are: high performance computing, modeling and analysis of parallel applications, and simheuristics. He has co-authored more than 30 articles published in journals and conference proceedings. His website address is http://www.javierpanadero.com and his email address is jpanaderom@uoc.edu.