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APPLYING SIMHEURISTICS FOR SAFETY STOCK AND PLANNED LEAD TIME OPTIMIZATION IN A ROLLING HORIZON MRP SYSTEM UNDER UNCERTAINTY

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ABSTRACT

Material requirements planning (MRP) is one of the main production planning approaches implemented in enterprise resource planning systems, and one that is broadly applied in practice. Since customers' demands evolve over time, the MRP method is usually applied in a rolling horizon planning, in which a safety stock and a planned lead time is usually employed to reduce the negative effects of uncertainty components in the production system or in the customers' demands. Considering uncertainty conditions in a rolling horizon planning leads to additional difficulties in determining the optimal planning parameters. In this paper, a multi-stage and multi-item production system is simulated by considering random customers' demands and other sources of uncertainty. With the goal of minimizing the sum of inventory and backorder costs, a simheuristic algorithm is proposed and tested.

1 INTRODUCTION

Material requirements planning (MRP) is applied in production planning for calculating production orders and procurement orders for finished, semi-finished, and raw materials based on the master production schedule. It is implemented in the production planning modules of most of the common enterprise resource planning (ERP) systems, and broadly applied in practice Hopp and Spearman (2011). MRP solves the medium term planning problem by computing the production and procurement orders using a simple algorithm that was developed decades ago Orlicky (1975). The planning algorithm consists of the four planning steps: netting, lot-sizing, backward scheduling, and bill-of-materials (BOM) explosion. The planning parameters applied in this algorithm are: the lot-sizing policy, the planned lead time, and the safety stock. Each of these parameters is defined for each material in the production system. The MRP approach is able to handle very complex production system and BOM structures, which is one of the reasons for its broad applicability. However, a lot of planning parameters are needed to conduct the MRP execution. In addition, MRP is an algorithmic approach to handle the production planning problem, i.e. no optimization is conducted within the planning run, which is applied in a rolling horizon manner to real production systems that face different uncertainties. Examples of such uncertainties in production systems are stochastic processing times, machine failures, constrained worker availability, or raw material shortages. Uncertainties in customers' demands include fluctuations in their values, required lead times, changes in requested orders, or cancellations. By optimizing the MRP parameter setting, the negative effects of these uncertainties can be

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reduced. For example, including safety times into the planned lead time reduces the effect of production lead-time uncertainties Buzacott and Shanthikumar (1994), while the safety stock kept in MRP diminishes the effect of customers' demands uncertainties. Hence, setting the MRP parameters to optimal levels under uncertainty conditions is still a viable field of research Dolgui and Prodhon (2007), Altendorfer (2019). Accordingly, this paper discusses new simulation-optimization methods that allow us to optimize the MRP parameters safety stock and planned lead time in a multi-stage and multi-item production system with stochastic customers' order amounts, customer required lead times, and machine setup times. Other sources of uncertainty mentioned above are explicitly ignored in this paper and left for further research. For a relatively simple production system, a discrete-event simulation model is developed in AnyLogic to conduct the rolling horizon MRP approach and mimic a shop floor exposed to the stated uncertainties. To the best of our knowledge, there is a lack of research work developing simulation-optimization methods to optimize MRP systems under uncertainty conditions. Hence, the main contribution of this paper lies in the development of a novel simheuristic algorithm Chica et al. (2020), which integrates the previous simulation model with a constructive heuristic to optimize the safety stock and planned lead time for each material.

The remaining of the paper is structured as follows: Section 2 provides an overview of related work on MRP systems and simheuristics. Section 3 offers a detailed description of the MRP system under study. Section 4 describes our simheuristic approach, while Section 5 performs a series of computational experiments to illustrate its potential. Results of these experiments are discussed in Section 6. Finally, Section 7 highlights the main contributions of this work.

2 RELATED WORK

MRP parameter optimization can be treated in analytical models, which simplify the production systems by employing a set of assumptions, which often neglect main sources of uncertainty or production system complexity. However, since these models usually lead to proven optimal solutions, they provide significant insights into the behavior of optimal solutions, i.e., optimal planning parameters. A second option to optimize the MRP parameters is to simulate a typically complex production system structure and apply either solution space enumeration or simulation-based optimization methods. For complex production systems with lot of MRP parameters, the solution space enumeration is not applicable due to simulation budget restrictions, i.e. it is not possible to simulate all parameter combinations in a reasonable amount of time. The literature in this section firstly treats some analytical models to optimize the MRP parameters safety stock and planned lead time. Then, it also shows how simulation is applied for this task. Note that the simheuristic developed in this paper can be defined as a special case of simulation-based optimization. From an analytical point of view, the MRP safety stock is included in the base-stock decision of inventory models, i.e., the base stock includes a safety stock. Specifically, the stream on literature, which includes advance demand information, mimics a production system similar to the one we model in this paper. Here also a work-ahead window is implemented that is similar to the planned lead time in MRP. Relevant capacitated inventory models can be found, for example, in Buzacott and Shanthikumar (1994), Sox et al. (1997), Axsäter (2010), Altendorfer and Minner (2014), and Altendorfer (2019). All of these papers assume that information on customers' demand is available in advance, and replenishment is not based on actual material withdrawal but on projected demand. Then, base-stock levels or safety stock levels are optimized. This modeling of demands is similar to the MRP netting step, and they find that better advance demand information leads to lower safety stocks requirements. These models also apply assumptions on the production system uncertainty, where mainly the production lead-time is modeled to be stochastic. For more literature on the MRP parameter optimization under uncertainty we refer to Dolgui and Prodhon (2007), Mula et al. (2006), and Altendorfer (2019).

Simulation has already rather early been applied to study MRP effects, e.g., Whybark and Williams (1976) discuss the relationship between safety stock and safety lead time in a simulation study. Also Van Kampen et al. (2010) address this trade-off by means of production system simulation. Enns (2001) applied simulation to study the effects of lot size and planned lead time in an MRP stochastic production system. In Altendorfer et al. (2016), the effect of customers' demands uncertainty on the performance of the production system is studied by simulating a multi-item and multi-stage MRP production system. Also Fildes and Kingsman (2011) apply simulation to investigate the effect of customer demand uncertainty in an MRP production system. Jodlbauer and Huber (2008) apply simulation-based optimization to set parameters of different production planning methods, including MRP. Gansterer et al. (2014) apply different heuristics to simulation-based optimization of MRP parameters in a stochastic production environment. Felberbauer et al. (2012) employ simulation to model MRP and kanban systems, discussing their interaction. A generic simulation framework to model MRP production systems under different types of uncertainty is presented in Hübl et al. (2011). Likewise, Karder et al. (2018) and Karder et al. (2019) propose genetic algorithms and surrogate models for simulation-based optimization of an MRP system, where a stochastic production system was modeled and simulated.

The approach of this paper is based on simheuristics, which is a hybrid methodology that combines operational optimization based on metaheuristics and simulation as an iterative process Rabe et al. (2020). Problem information feeds back into the system by filtering the solution space and converging towards increasingly optimal solutions Ferone et al. (2019). One of the advantages of this methodology is its ability to integrate stochastic variables when formulating the problem mathematically, either in the objective function or in the constraints April et al. (2003). Chica et al. (2020) provide a literature review on the applications of simheuristic algorithms in different industrial optimization problems. Both literature reviews highlight simheuristics ability to solve real-life optimization problems in uncertain scenarios. The main applications of simheuristics are in vehicle routing problems Fikar et al. (2016), Guimarans et al. (2018), inventory routing problems Gruler et al. (2018), Gruler et al. (2020), waste collection problems Gruler et al. (2017), scheduling problems Hatami et al. (2018), facility location problems Pagès-Bernaus et al. (2019), Quintero-Araujo et al. (2019), finance Panadero et al. (2018), manufacturing Rabe et al. (2020), and Internet computing Cabrera et al. (2014). This wide range of successful applications of simheuristics in different scenarios demonstrates its effectiveness in solving different logistics and manufacturing problems under uncertainty scenarios currently faced by real-life decision-makers, as is the case of the stochastic MRP considered in this paper.

3 MODELING A STOCHASTIC MRP SYSTEM

The MRP system under study has been modeled in the AnyLogic simulation software Borshchev (2013). Our model implements a mutli-stage and multi-item production system. The simulation model can handle stochastic demands as well as random processing times, and provides a standard MRP logic to treat customers' orders. The role of the simheuristic is to set safety stock and planned lead time parameters in order to minimize the overall cost, which is the sum of inventory and backorder costs. For the simulation experiments, a simple production structure is used, as illustrated in Figure 1. Despite being a simple BOM that considers only three levels, our example allows us to demonstrate how simheuristics can be meaningfully integrated into an MRP system. Two final products, products 10 and 11, at low-level-code (LLC) 0 are produced on machine $M2$. The two semi-finished products, materials 20 and 21, are produced on machine $M1$. For one unit of final product 10, we need 1 semi-finished product 20. Likewise, we need 1 piece of semi-finished product 21 for final product 11. The raw material 100, which is a purchased product, is needed for the semi-finished products 20 and 21. This raw material is assumed to be always available.

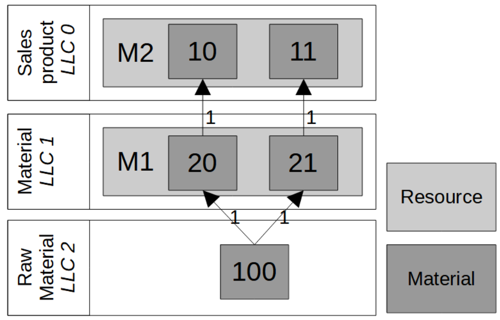

Figure 1: A 3-level BOM for our stochastic MRP example.

In Figure 2, the statechart of the AnyLogic model with the master production schedule (MPS) and standard MRP steps is illustrated. The simulation starts at the entry point *Start_PPS*, and conducts an initialization step to compute gross requirements, to delete finished production orders, and to count current inventory. The MPS component provides the independent demands, and is the starting point for the MRP procedure, which goes through the LCCs and search for the next material. For the complete planning horizon of a simulation iteration, safety stock and net requirements are computed by subtracting the on-hand inventory and any scheduled receipt from the gross requirements provided by the MPS. The next step is lot-sizing, where a fixed order quantity (FOQ) is used as lot sizing policy. The subsequent steps are backward scheduling – based on the constant planned lead time of the items – and BOM explosion – to calculate gross requirements for materials on lower LLC levels iterating over the complete BOM hierarchy.

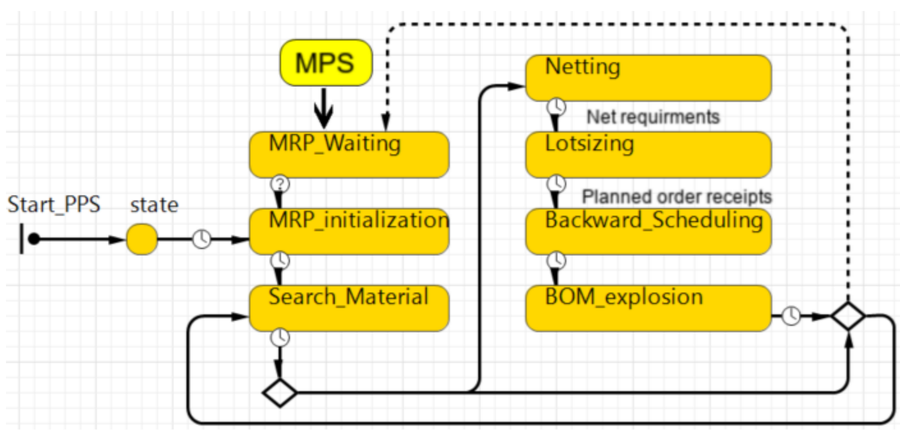

Figure 2: MRP simulation framework in AnyLogic.

The simulation run time is set to 1080 periods (days), while the number of replications is set to 20. Based on the described BOM structure, simulation experiments are performed. To limit the solution and parameter space, the values illustrated in Table 1 are used – notice that, when considering a more realistic setting, the values must be set with the input of production managers. Also, FOQ is employed as lot-sizing policy and customers order stochastic amounts with a stochastic customer required lead time. The investigated production system is available 24 hours a day and 30 days per month, which results in an available capacity of 720 hours per month. Possible holidays are not considered. The system is designed for a calculated planned capacity utilization of 95%, with the system assuming a 10% set-up percentage. As a result, 85% of the time is available for processing materials. The expected value of the processing time per production step is deterministic and is the same for all machines and materials. After each production lot, a stochastic setup operation occurs, i.e. the setup time is stochastic. For final products, the inventory cost is 1 cost units (CU) per piece and day. For semi-finished products, the inventory costs are 0.5 CU per piece and day. The tardiness cost for final products is 19 CU per piece and day. To observe the influence of different uncertainty levels in the order amounts, the scenarios low, medium and high are simulated; employed values are illustrated in Table 2. For all stochastic values, a log-normal distribution is applied and the respective values are set during the simulation iterations. As stochastic in a production system is investigated a log-normal distribution is suitable. Also due it's probability of only taking positive real values.

Table 1: Values of the simulation parameters employed.

Material	FOQ	Safety stock	Plan. Lead time	Processing time in h	Holding costs per day	Tardiness costs per day	Avg. daily demand
10	406	100	2	0.17328	1	19	47
11	610	150	2	0.17328	1	19	70
20	1016	250	2	0.17328	0.5		47
21	1016	250	2	0.17328	0.5		47

Table 2: Values of the stochastic scenarios parameters employed.

Scenario	Parameter	item	μ	σ^2	CV
low	order amount	10	10	2	0.1414
low	order amount	11	15	6	0.1633
low	customer required lead time	10	6	9	0.5000
low	customer required lead time	11	6	10	0.5270
low	setup time	all	12	36	0.5000
medium	order amount	10	10	8	0.2828
medium	order amount	11	15	24	0.3266
medium	customer required lead time	10	6	9	0.5000
medium	customer required lead time	11	6	10	0.5270
medium	setup time	all	12	36	0.5000
high	order amount	10	10	32	0.5657
high	order amount	11	15	96	0.6532
high	customer required lead time	10	6	9	0.5000
high	customer required lead time	11	6	10	0.5270
high	setup time	all	12	36	0.5000

4 DIFFERENT VARIANTS OF OUR SIMHEURISTIC APPROACH

The AnyLogic simulation model described above makes use of a vector of planning parameters which influence the performance of the MRP system being considered. Accordingly, these parameters need to be set in order to optimize the MRP performance for a production system facing different sources of uncertainty. Hence, the challenge is how to complete an efficient fine-tuning process of these parameters. The first step is to define, for each parameter, the associated range of possible values. This interval of real or integer numbers should be set with the help of the manager of the specific MRP system being considered. Next, we describe an initial approach that allows us to generate good values for the vector of parameters:

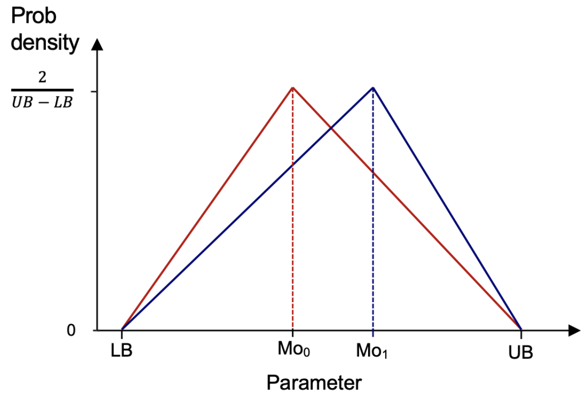

Figure 3: Triangular distribution with constant lower (LB) and upper bounds (UB).

1. For each parameter, a triangular probability distribution is considered, with the lower and upper bounds given by the associated range of possible values and the mode given by the midpoint of the range.
2. Considering these interval midpoints as values for each parameter, the AnyLogic model is used to execute a number of simulation runs, which allows us to obtain an estimate of the associated average cost. The current configuration is set as the initial best-found solution.
3. A random value is generated for each parameter utilizing the associated triangular distribution. In the case of integer parameters, the randomly generated value is rounded.
4. Employing the randomly generated values for each parameter, the AnyLogic model is used to execute a new simulation. This generates an estimate of the average cost associated with the new configuration of the parametric vector.
5. If the average cost of the new configuration is lower than the previous one, the best-found solution and the mode of each triangular distribution associated with the vector parameters are updated.
6. Steps 3 to 5 are repeated until the stopping criterion is met – i.e until the allowed number of iterations is reached.
7. The best-found configuration of parameters and its associated average cost are returned.

The previous algorithm describes a basic version of our algorithm (basic heuristic), which keeps the bounds of the triangular distribution constant and update only the mode as illustrated in Figure 3.

Rabe et al. (2020) suggest that a 2-stage and more computational-efficient variant could be employed instead, where: *(i)* in a first stage, we execute simulations with a reduced number of runs, which allows us to obtain only a rough estimate of the average cost but might prevent the simulation component to jeopardize the total computing time of the algorithm; *(ii)* keep a pool of best-found solutions – e.g., the top 5 or top 10; and *(iii)* run a more intensive simulation on each of the best-found solutions in the pool to increase the accuracy of the associated average costs. Applying this idea, two extensions of the basic version are developed. The first extended version (Ext1) consists of an initialization phase, i.e. applying the basic heuristic, and a range reduction phase where the range of the triangular distribution is reduced. The specific implementation makes it possible to reach a search space outside the original bounds, as shown in Figure 4. After an initialization phase based on the basic heuristic, this first extension Ext1 performs as follows:

1. For each parameter, a symmetric triangular probability distribution is considered, with the mode given by the results of the initialization phase applying the original heuristic.

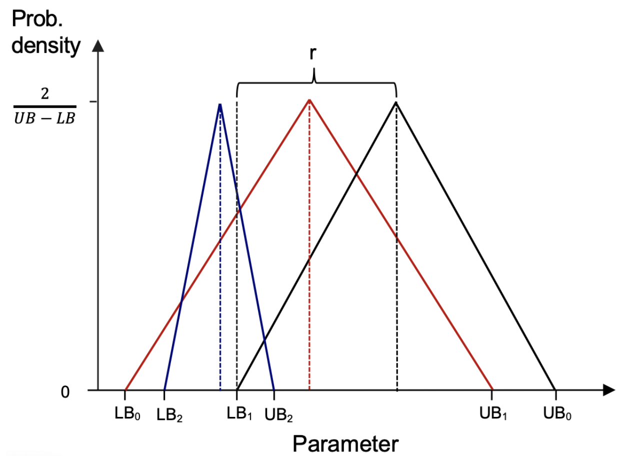

Figure 4: Symmetric triangular distributions.

2. Considering these mode values for each parameter, the AnyLogic model is used to execute a number of simulation runs in order to obtain an estimate of the associated average cost. The current configuration is set as the initial best-found solution.
3. The solution range is defined as: r_0 = mode − upper bound for each parameter.
4. A random value is generated for each parameter utilizing the associated triangular distribution. In the case of integer parameters, the randomly generated value is rounded.
5. Employing the randomly generated values for each parameter, the AnyLogic model is used to execute a new simulation. This generates an estimate of the average cost associated with the new configuration of the parametric vector.
6. If the average cost of the new configuration is lower than the previous one, the best-found solution is updated, and a new mode for each parameter is defined.
7. The new bounds for each parameter are computed as follows: $r_i = (1-\alpha) * r_{i-1}$, where, i is the simulation iteration number and α is the range reduction level.
8. Steps 4 to 7 are repeated until the allowed number of iterations is reached.
9. The best-found configuration of parameters and its associated average cost are returned.

Yet, in order to generate better solutions, a second extension (Ext2) of the heuristic is also proposed. This Ext2, which also includes an initialization phase according to the original heuristic, applies the parameter values of a pool of best solutions for the lower and upper bounds of the triangular distribution. In this extension only the values in the range of the current best solution bounds are possible, as shown in Figure 5. This second extension (Ext2) performs as follows:

1. For each parameter, a triangular probability distribution is considered with the bounds given by the associated interval of possible values and the mode given by the interval midpoint.
2. Considering these interval midpoints as values for each parameter, the AnyLogic model is used to execute a number of simulation runs in order to obtain an estimate of the associated average cost. The current configuration is set as the initial best-found solution.
3. A random value is generated for each parameter utilizing the associated triangular distribution. In the case of integer parameters, the randomly generated value is rounded.
4. Employing the randomly generated values for each parameter, the AnyLogic model is used to execute a new simulation. This generates an estimate of the average cost associated with the new configuration of the parametric vector.

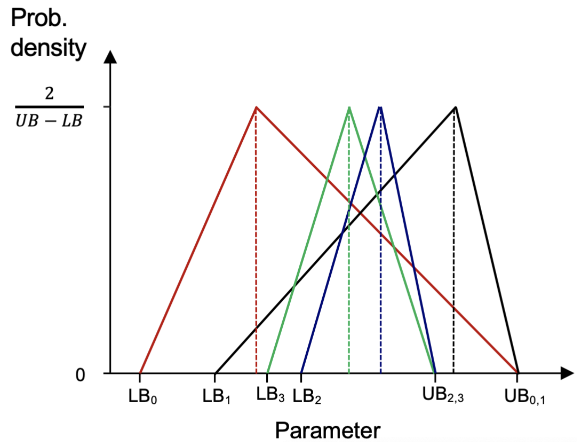

Figure 5: Triangular distributions with the lower and upper bounds in the range of the best solutions.

5. If the average cost of the new configuration is lower than the previous one, the best-found solution and the mode of each triangular distribution associated with the parameters in the vector is updated. The solution is saved for further use.
6. Steps 3 to 5 are repeated for X iterations. X identifies the initial search population.
7. The best Y results of all currently simulated iterations are taken, and new lower bounds, upper bounds, and mode are specified for each parameter as follows:
   a. Lower bound = minimum of all parameters for the Y best solutions.
   b. Upper bound = maximum of all parameters for the Y best solutions.
   c. Mode = (lower bound + upper bound)/2.
8. Steps 3, 4, and 7 to 9 are repeated until the allowed number of iterations is reached.
9. The best-found configuration of parameters and its associated average cost are returned.

5 COMPUTATIONAL EXPERIMENTS

The main target of the simheuristic algorithm is to find those parameter combinations providing the lowest average overall cost with the available simulation budget. The MRP parameters safety stock and planned lead time are optimized for each item, i.e. 8 planning parameters are optimized. The target of the simulation experiments is to observe the behavior of the simheuristic using 500 iterations and 20 replications. With 20 replications, some stochastic is introduced into each iteration. The limit of 500 iterations was set after several simulation experiments with 1000 iterations, showing no significant improvement by the developed heuristics after 500 iterations. In total, fourteen different simulation experiments were defined and applied on each given stochastic scenario. Reasonable starting parameters for safety stock of all materials are: $min = 0$, $max = 4$, and $mod = 2$, whereby the applied safety stock in MRP is this parameter value multiplied with initial safety stock from Table 1. Regarding the planned lead times for all materials, the starting parameters are: $min = 1$, $max = 5$, and $mod = 3$. The basic experiment was conducted with the basic heuristic and a random experiment was conducted using stochastic MRP planning parameters drawn from a uniform distribution. Applying the uniform distribution should demonstrate the simulation output with complete randomness within the defined bounds. Six experiments with extension Ext1 and extension Ext2 were also carried out. The six experiments for extension Ext1 are based on the parameters variations using no initialization and 100 iterations with α values of 0.05, 0.1, and 0.025. For extension Ext2, 100 and 200 iterations were utilized during the initialization

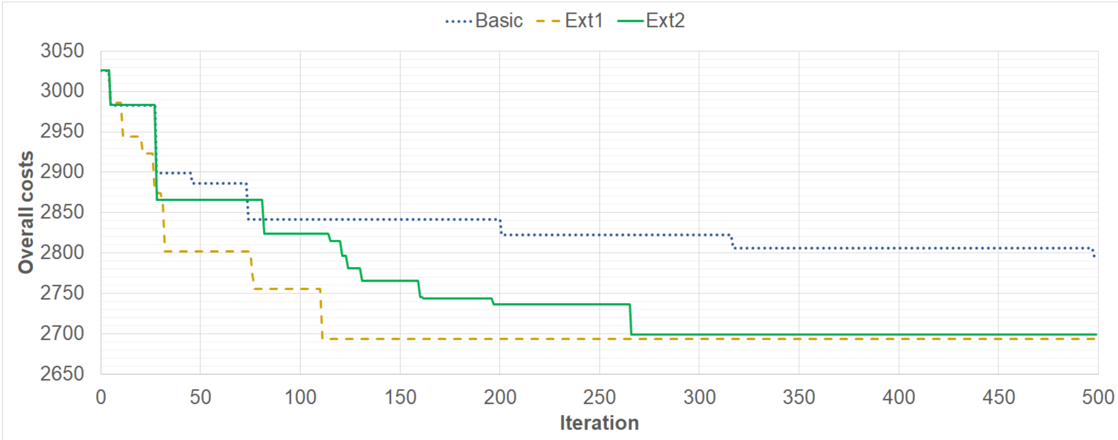

Figure 6: Plot of Minium overall costs per iteration #.

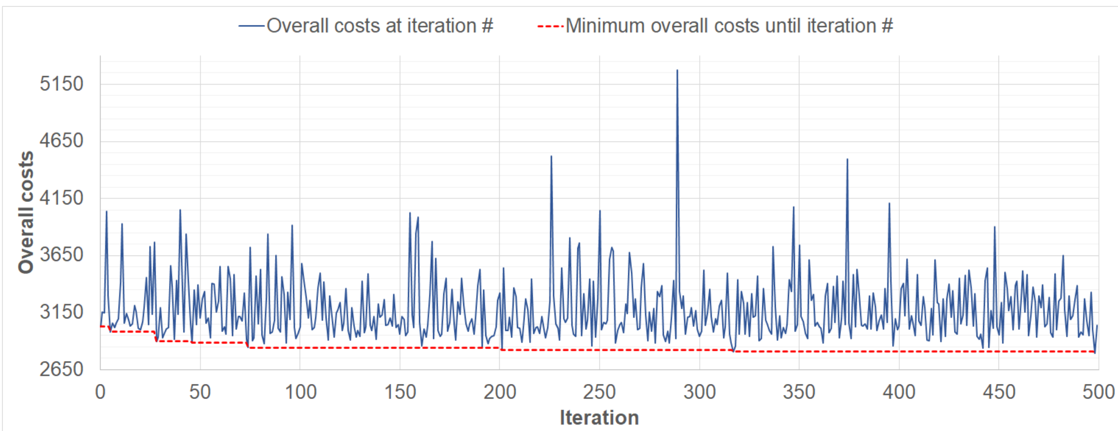

Figure 7: Overall costs - Basic - Basic/min/medium.

phase, with a changing pool of best found solutions of 3, 7, and 25. This preliminary study was conducted to identify good parameters for extension Ext1 and extension Ext2.

6 ANALYSIS OF RESULTS

We performed 42 different simulation experiments in total, 14 for each stochastic setting (low, medium, and high), with 20 replications per simulation iteration. In Table 3 the minimum overall costs (sum of inventory and backorder cost) are illustrated. These results represent the minimum and average costs for each simheuristic variant and stochastic scenario. Both heuristic extensions – Ext1 and Ext2, which change the upper and lower bounds of the scenario parameters – perform better than the basic heuristic and also much better than the Random variant with static upper and lower bounds. An analysis of variance (ANOVA) test shows that, in the case of the minimum values, there are no statistically significant differences among the different variants ($p-value = 0.134$). However, for the average values, statistically significant differences can be found ($p-value = 0.000$), with variants Basic and Random offering a poorer performance than Ext1 and Ext2. Average values are calculated as mean of all iterations cost performance.

A comparison of the minimum overall costs per iteration for Basic, Ext1, and Ext2 in the medium stochastic scenario is given in Figure 6. A graphical illustration of the overall costs per iteration for the Basic and Ext2 variants – in the medium stochastic scenario – is represented in

Table 3: Results comparison of stochastic settings.

	Basic	Basic	Ext1	Ext1	Ext2	Ext2	Random	Random
Stochastic scenario	Min	Avg	Min	Avg	Min	Avg	Min	Avg
low	2794	3146	2720	2857	2717	2870	2825	3406
medium	2795	3179	2694	2865	2699	2936	2789	3435
high	2860	3309	2761	2957	2852	3036	2938	3576

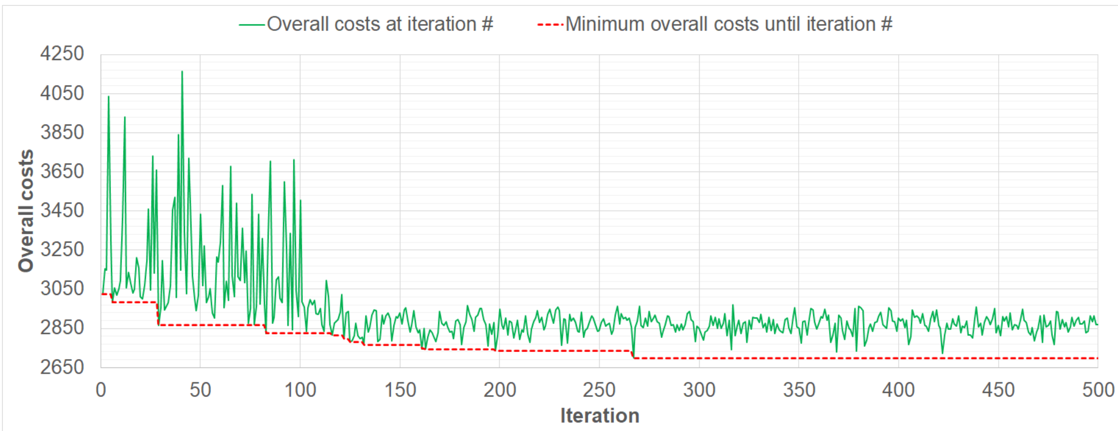

Figure 8: Overall costs - Ext2 (Range red. by top 7 results) - Ext2/min/medium.

Figure 7 and Figure 8. Notice the sharp decreasing trend achieved in Ext2, which shows the convergence of the algorithm as the number of iterations increases.

7 CONCLUSIONS AND FUTURE WORK

This paper analyzes a rolling horizon MRP system with random orders, required lead times, and machine setup times. In this context, the goal is to optimize the MRP planning parameters safety stock and planned lead time per item so that total costs are minimized. A simulation model implementing the MRP planning and the stochastic production system behavior is applied to evaluate the planning parameter performance. In order to deal with this challenging problem, a simple but fast simheuristic algorithm is proposed and implemented in AnyLogic. Actually, different versions of the algorithm are considered and compared in a set of numerical experiments. These experiments also consider different levels of variability.

Our results show that the proposed approach is quite promising, specially in a research area where there is a lack of similar studies considering MRP systems under uncertainty conditions. Limitations of the current study are related to the simple production system structure modeled, the focus on safety stock and planned lead time ignoring the planning parameter lot size and the simheuristic design. Therefore, future work should investigate more complex production systems including the lot size optimization. Furthermore, we plan to extend the heuristic component of the algorithm into a full metaheuristic, with the idea to enhance the results even further.

ACKNOWLEDGMENTS

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