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POTENTIAL OF SIMULATION EFFORT REDUCTION BY INTELLIGENT SIMULATION BUDGET MANAGEMENT FOR MULTI-ITEM AND MULTI-STAGE PRODUCTION SYSTEMS

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ABSTRACT

Simulation is utilized to analyze multi-item and multi-stage production systems that are driven by material requirements planning (MRP). The range of possible parameter combinations and solutions increases as the model of the production system includes more components. In simulation experiments with a fixed number of replications per iteration, it might be unfeasible to test a large range of these MRP parameters. This paper discusses how to efficiently manage the simulation budget, to avoid wasting it in exploring non-promising solutions. Therefore, intelligent simulation budget management (SBM) is applied, where the results of the current iteration's replications are compared to the average results of the previous iterations. The current iteration is skipped if its average overall cost is outside the defined percentile boundaries. A simulation study using two multi-item and multi-stage MRP systems is performed to evaluate SBM potential. The results show that the SBM methodology leads to significantly reduced simulation efforts.

1 INTRODUCTION

Manufacturers make use of modeling and simulation techniques to analyze the performance of their production systems. Computer simulation are usually performed in the context of a computational budget (e.g., maximum allowed time). Hence, once this budget has been exhausted, key performance indicators (KPI) such as inventory cost or tardiness cost can be gathered and analyzed. The simulation budget usually refers to the maximum time available to execute the experiments or to the maximum number of replications that can be run. When stochastic factors are considered (e.g., random customer demands, random machine setup and processing times, etc.), their behavior is simulated, and replications with different random numbers are used to evaluate the results of the stochastic model. In many occasions, simply employing the available simulation budget without any criterion is an inefficient policy. This is due to the fact that optimizing the system design by means of simulation typically requires long execution times, specially when the number of parameters to set is relatively large Gao et al. (2019). Furthermore, a large number of simulation replications are often necessary to achieve an accurate estimate of a design decision, which is computationally very expensive Lee et al. (2010). Improving selection efficiency can be performed by assigning a different number of simulation replicates to each design, maximizing the probability of correctly selecting most of the best designs through statistical processes such as ranking and selection Gao et al. (2019). A promising approach of an intelligent simulation budget management (SBM) is evaluated in Seiringer et al. (2022). SBM is applied in the context of simulation heuristics, and it is used to stop an iteration –after a minimum number of replications– if the average cost of the current iteration is worse than a given threshold, which is based on previous iterations. This increases the potential to identify a better solution using a given budget, since this budget is employed in those areas of the solution space that seem more promising.

A hierarchical planning approach often used for the simulation of production systems is MRP. Due to its direct iterative application and its adaptability to different production system complexities, it is widely applied in industry Hopp and Spearman (2011). Also, ongoing research activities use this 50-year-old approach Xue and Offodile (2020), Mohr et al. (2018), Yadav and Jayswal (2018). As MRP is implemented in most of the available enterprise resource planning systems (ERP), our simulation study with MRP can contribute to provide insights on how to efficiently use the simulation budget. In this sense, this paper introduces some intelligent SBM concepts and offers an in-depth analysis of its performance. The study builds upon the previous results obtained in Seiringer et al. (2022), which use simheuristics to identify new best solutions. In our new approach, given parameter sets are simulated, and the best solution is stored for subsequent performance analysis. Also, different SBM settings are evaluated. In our simulation study, KPIs related to standard MRP, both with and without SMB, are compared. The simulation study will be based on enumerations, and includes all three MRP planning parameters, meaning safety stock, lot size, and planned lead time. The SBM performance analysis is done using the overall cost (inventory plus tardiness costs) of two simulated production systems with different levels of complexity. The main target of our investigations is to show how much simulation budget is required to find the best solution and, hence, how much simulation budget can be saved. The performed simulation study is used to answer the following research questions:

- *RQ1*: How much simulation budget (effort) can be saved when the SBM concept is applied, and what is the best SBM parameterization?
- *RQ2*: How is SBM efficiency influenced by the production system structure and the number of iterations?
- *RQ3*: What is the risk of overlooking the best solution when SBM concepts are applied?

Probably the main practical implication of our work is the reduction of the simulation time required for solving large-sized instances. As a result, the integration of simulation into information systems like ERPs will also be more efficient. In addition, as intelligent SBM will ignore bad solutions, complex production systems can be simulated within given time frames (night shift) or even online. The rest of the article is organized as follows: Section 2 describes related approaches for finding "good" solutions with a constrained simulation budget, also investigating the relations to production system simulation. In Section 3 the SBM concept is explained, and a simulation study is introduced in which this concept is applied. Section 4 provides the results of our simulation study as well as an in-depth discussion on them. Finally, Section 5 highlights the main contributions of this work and points out some future research lines.

2 RELATED WORK

Production planning has to be considered at all decision-making levels, i.e., strategic, tactical, and operational. Its objective is to have a balance between resource utilization, on-time deliveries, and reduced lead times Ankenman et al. (2011). As a tool, simulation has been widely used in this process because of its ability to evaluate different possible production plans and choose the one that works best Kibira et al. (2016) or to use simheurtics to evaluate minimum overall costs in an MRP planned production system

Seiringer et al. (2021). In addition, it is also used to find out whether a production plan developed by a mathematical programming model is actually executable, as well as if it is likely to provide an acceptable performance. Its ability to evaluate different scenarios has promoted the use of simulation in combination with mathematical programming models Ankenman et al. (2011). In this context, SBM concepts play an important role, specially when they maximize the probability of selecting the best simulated design in the ordinal optimization of the system Gao et al. (2019). This section presents an overview on the efficient use of the SBM, as well as a brief description on the production planning concepts.

2.1 Efficient Simulation-Based Parameter Optimization

Production systems are characterized by numerous interacting elements. This, in turn, causes numerous associated parameters to intervene in the processes. The combinatorial optimization problems arising from the production context are very complex. One of them is MRP, which plays an important role in the efficient management of the production planning related tasks, since it allows planning over different time horizons. In the literature, many of the MRP problems that have been studied are modeled with stochastic variables to represent the uncertainty associated with them in the real world. Some of these variables are demand, lead times, production yields, production capacity, etc. Guide Jr and Srivastava (2000), Dolgui and Prodhon (2007). Because of the stochastic nature of the objective function and constraints, simulation optimization processes are computationally more expensive He et al. (2010). Therefore, there must be a trade-off between the computational cost in searching for possible solutions in space and the most accurate results for the objective function with those promising solutions. The simulation budget is a variable within the simulation computational process that can also be optimized. Simulation budget management consists of checking the quality of the solution after each run (replication) within an iteration Seiringer et al. (2022). This means that, for each set of parameters, the total cost is compared to previous results and, if the solution is good enough, further runs (replications) of that iteration are made.

Different approaches have been proposed for SBM. For example, Chen et al. (2003) present an approach that allocates computational budgets in simulation trials to intelligently improve the efficiency of ordinal optimization, i.e., to maximize the probability of identifying the optimal ordinal solution. Lee et al. (2004) consider a real-life multi-objective classification and selection problem, which they solve by including the concept of Pareto optimality to determine all the designs of the problem –instead of just one–, and propose a sequential solution method to allocate the simulation replicas. Computational results show that the algorithm is efficient with respect to the total number of replicas needed to find the solution set. He et al. (2010) develop an allocation scheme that improves the updating of the sampling distribution and minimizes the expected mean squared error associated with the weighting function of the cross-entropy method. Chen et al. (2008) use optimal computational budget allocation to maximize the probability of correctly selecting all top-m designs. This methodology consists of an asymptotically optimal assignment and an easy-to-implement heuristic sequential assignment procedure. Their results show a relative efficiency that increases for larger problems, and improves the computational efficiency for optimization by simulation. An approach for surrogate-assisted optimization to optimize MRP planning parameters is described in Karder et al. (2020), where more efficient mathematical models replacing the real function.

Other approaches have been based on the incorporation of regression metamodels, such as the work developed by Brantley et al. (2013), who explore the potential to improve classification and selection efficiency by incorporating domain-wide simulation information into a regression metamodel. This method provides approximations of the optimal rules that determine the design locations for performing simulation runs, as well as the number of samples assigned to each design location. Xiao et al. (2017) also address the problem of selecting the best m and worst n designs from a total of k alternatives, based on their average performance values. To optimize the simulation budget efficiently, they make an asymptotically optimal allocation of simulation replicates among the k designs, in order to maximize the probability of correctly selecting the m best and n worst designs. Similarly, Gao et al. (2019) consider the same ranking and selection problem of selecting the optimal subset from a finite set of alternative designs. They assign a constraint on the total simulation budget to maximize the probability of correctly selecting the best designs. They incorporate information from the entire domain into the regression metamodels, and assume that the average performance of each design is approximately quadratic. They partition the solution space into adjacent partitions. Thus, they propose an approximately optimal simulation budget allocation rule in the presence of partitioned domains. Choi and Choi (2020) also, considers that it is important to identify both the best and the worst solutions in scenarios where the risk is high and more reliability is required. Accordingly, they propose a methodology capable of selecting both designs that can be very useful in systems such as the digital twin.

The efficiency of discrete event simulation is something that still needs to be optimized today. It has already been shown that solving the ranking and selection problem can intelligently allocate the simulation budget to maximize the probability of a correct selection of the best design. However, the integration of stochastic optimization algorithms with computer budget allocation rules has attracted the attention of several researchers in recent years Fu et al. (2021), Wang et al. (2021). This is because it has been shown that it is possible to find better solutions to stochastic optimization problems with fewer iterations. The SBM method evaluated in this paper contributes to this field as it includes simple statistical analysis of already available results, variance behavior of replications within an iteration, and problem specific knowledge on production planning optimization.

2.2 Production Planning

ERP is a key information system in manufacturing companies today because it allows them to plan and control production-related resources. Many of these commercial systems rely on the production planning method MRP to generate production orders Hopp and Spearman (2011). As stated by Rossi et al. (2017), MRP technique is widely employed by most manufacturing companies, even though field applications have found some weaknesses, including that it ignores production capacity constraints and variable lead-times. Nevertheless, the MRP approach is still useful, when planning the production of a dependent demand industry Heizer et al. (2020), and the main proof of its effectiveness is the high number of industrial firms that use it. MRP is based on a the simple iterative application of the four steps: netting, lot-sizing, backward scheduling and BOM explosion Hopp and Spearman (2011), which are implemented in the simulation framework used in this study. As input, the gross requirements for each MRP planning period of the planning horizon are selected. The gross requirements are the customers' orders for the associated due date. For components, the gross requirements are the quantity required from the previous BOM level multiplied by the quantity of the associated BOM level. In the first step, netting for each item and period, gross requirements are compared to the projected on-hand inventory; when the projected on-hand inventory is less than the safety stock in a planning period, the gross requirements cannot be covered. This calculated net requirement quantity provides the basis for the step of lot sizing. In the second step of lot sizing, the established lot sizing policy is applied to compute production lot sizes and batch aggregation is performed to reduce unnecessary machine setup time. During step three, backward scheduling is performed, i.e., based on the planned order end dates, the planned order releases are computed using the planned lead time. The last step, BOM explosion is done, to move through the BOM levels and calculate the gross requirements of subsequent items. Automated production systems must be efficient and flexible. Although many of today's planning systems have parameter customization options, it is still a trial-and-error procedure Zou et al. (2018). In addition to production planning, aspects of customer demand, shop floor control and processing play an important role for the developed simulation frameworks. Simulation has been a very useful tool when evaluating the results of optimizations in production planning. Several works have been developed to apply simulation techniques to find the efficient parameter values for production planning. For example, Lee et al. (2004) use simulation to evaluate the economic benefit of using ERP for production in the construction industry. Jeon and Kim (2016) presents a review of state-of-the-art applications of simulation techniques in production planning and control. They show the applicability of these techniques to modern manufacturing problems and provide a guideline for the selection of the right simulation technique. To simulate the production of MRP planned items, it is necessary to simulate machine processing, including the correct routing and release of materials. The combination of stochastic effects to be included in the simulation models and the large solution space when MRP planning parameters are optimized leads to high simulation efforts necessary. This motivates the development and evaluation of an intelligent SBM method for this application.

3 SIMULATION STUDY

This section describes the main components and settings of the applied simulation study, as well as how different enumerations are applied to evaluate the performance of SBM concepts. Before the evaluated production systems are described, we introduce the event-based simulation framework.

3.1 Production System Simulation

The developed framework to simulate a production system uses discrete event-based simulation. A database is used to provide the master data, like the BOM, as starting information for the simulation. This master data is queried before the simulation starts. Once it is finished, the results are loaded into a table. The result table holds the data of tardiness and inventory costs per simulation run (iteration), as well as the associated replications. Within a simulation run, the computed statistics are reset after the defined warm-up phase, when a steady state of the production system is assumed. The simulation experiment is based on enumerations of the parameter space. Consequently, parameter variations are used to run the different parameter sets with the given number of replications. Simulating one parameter set includes the following steps:

1. Simulation model setup: Select the first parameter set that has not been simulated yet.
2. Simulation model setup: Get simulation settings, demand information, and other master data, and set the main MRP parameters for each planned item (safety stock, lot size policy, and lead time).
3. Simulation run: Start periodic demand generation, which produces customers' orders based on the computed inter-arrival rate associated with the expected order amount and demand sum for a period.
4. Simulation run: After the demand generation the MRP planning starts with the introduced steps (netting, lot-sizing, backward scheduling and BOM explosion) and generates production orders.
5. Simulation run: For each production order, the availability of the required components is checked and, if available and planned start is less or equal to the actual simulation time, the production order is passed to the first machine of the routing.
6. Simulation run: After processing, which includes the setup and processing times, the associated quantities are added to the stock booking list.
7. Simulation results evaluation: After the simulation run, i.e. for each replication, the inventory and tardiness costs are stored in the database.

The described simulation steps are performed for each parameter combination, until all the predefined parameter sets within one problem instance are simulated. To avoid wasting the simulation budget in unpromising solutions, the concept of simulation budget management is described in the following section.

3.2 Proposed Simulation Budget Management Strategy

The idea of skipping replications to minimize simulation budget wasting is discussed in Seiringer et al. (2022). There, SBM was evaluated in the context of simheuristics to identify the minimum overall cost of a simulation experiment with a limited simulation budget. The pseudocode presented in Algorithm 1 is based on the idea in Seiringer et al. (2022), however, it is adopted to be able to investigate all parameter sets in a predefined solution space. The adopted SBM concept was integrated into a production planning simulation framework, and Algorithm 1 is applied online for each iteration during the simulation experiment. In detail, the SBM method from Algorithm 1 works as follows: The initialization part is called when the experiment is started to define parameters and initialize the overall replication counter. Note that without the SBM strategy, the overall number of replications needed is simply the number of iterations times the maximum number of replications per iteration. Before each iteration, the *currentReplicationCount* must be set to 0, as it is iteratively increased until the maximum number of replications per iteration (*maxReplicationsPerIteration*) is reached or the stop criterion applies. Also, the stop criterion and the percentile boundary are initialized before each iteration. When SBM is applied, the solution quality of an iteration is evaluated after each replication and written to the variable *averItertationOverallCosts*. In our case, this is started after three new replications. This number is chosen to ensure already some variance reduction before the iteration performance is compared to the percentile of all current iterations. Further replication for an iteration are stopped, when the average cost (*averItertationOverallCosts*) is higher compared to the computed percentile overall cost value of all currently known iterations. The computation of the k-th percentile is reduced after each replication. In Algorithm 1, the starting value is $ub = 0.4$ with a percentile step (*percentileStep*) of 0.0175. This leads to a minimum of 0.05 after 20 replications, which is also the set lower bound for the k-th percentile value. Note that this comparison is the core of the evaluated SBM method, i.e. more replications are allowed only if the current overall iteration costs *averItertationOverallCosts* are lower than a threshold from the whole currently known solution space. For $ub = 0.4$ this means that the *averItertationOverallCosts* have to be lower than the best 40% of currently known solutions. After evaluating the costs of one parameter set, i.e. one iteration, the *avgIterationOverallCosts* are added to the set of already known solutions *setOfAllSolutions* and the simulation of the next iteration is started. Since this algorithm is based on a set of already available iterations, it is started after 5 iterations, i.e. the 6th iteration is the first one which can have less than 20 replications. Overall, the SBM methods has four parameters that might influence the simulation budget reduction, which are: *ub*, *percentileStep*, minimum number of replications per iteration, and minimum number of iterations to start SBM. Preliminary analysis showed that *ub* and *percentileStep* have the highest influence, therefore, these two parameters are analyzed in the numerical study.

Algorithm 1 Simulation budget management

```
if Initialization then
    totalReplicationCount ← 0
    percentileStep ← 0.0175
end if
ub ← 0.4
stopCurrentIteration ← false
currentReplicationCount ← 1
while currentReplicationCount ≤ maxReplicationsPerIteration ∧
    stopCurrentIteration = false do
    totalReplicationCount ← totalReplicationCount + 1
    currentReplicationCount ← currentReplicationCount + 1
    if avgIterationOverallCosts > GetPercentilValue(setOfAllSolutions, ub) ∧
currentReplicationCount > 3 then
        stopCurrentIteration ← true
    end if
    setOfAllSolutions ← setOfAllSolutions + avgIterationOverallCosts
    ub ← ub − percentilStep
end while
replicationsPerIteration ← currentReplicationCount
```

3.3 Production Systems

To evaluate the proposed SBM concept, two different production systems are introduced in this section. Each production system is designed with a planned utilization of 90%, including 10% of the time required for machine setup. Therefore, the machine is seized 80% of the time for items processing. In order to introduce random elements into the production system, customer demand and machine setup times follow a log-normal probability distribution. As these two values should always be positive, the log-normal distribution is suitable. Note that the log-normal distribution is applied for demand and setup times in several production system simulation models (see Seiringer et al. (2022) and Seiringer et al. (2021)). It is efficient in providing positive random numbers without truncation (as would be needed in the normal distribution), it can simply be parameterized by mean and variance of the underlying normal distribution (for which the exponential function is applied), and provides random numbers near to real world behavior. The specific set of values for these probability distributions can be found in Table 1. For both evaluated production systems, customer demands are generated based on the inter-arrival times, which follow an exponential probability distribution. The inter-arrival time is computed based on the total period quantity divided by the expected order amount. For each arrived customer order, the customer required lead-time (CRL) and order amount are computed using a log-normal distribution. The specific values can be found at the description of the production systems. For end items 10 and 12, an average demand per day of 47 items is used, and for end items 11 and 13 an average demand of 70 is considered. For both production systems, the routing order is fixed. Table 2 shows an overview of the employed simulation parameters for both production systems to reach the 90% utilization.

Table 1: Stochastic parameters associated with production systems 1 and 2.

Parameter	items	μ_i	σ_i^2	CV_i
order amount	10 & 12	10	2	0.1414
order amount	11 & 13	15	6	0.1633
customer required lead time	10 & 12	6	9	0.5000
customer required lead time	11 & 13	6	10	0.5270
machine setup time in min	all	144	36	0.5000
average demand per day	item 10 & 12 = 47 units; item 11 & 13 = 70 units			

3.3.1 Production System 1 (PS1)

The first production system is illustrated in Figure 1. This simple production system consists of three BOM levels. The two finished products, item 10 and item 11 at low level code (LLC) 0 are produced on machine $M2$. The two components at LLC 1, item 20 and item 21 are produced on machine $M1$. At LLC 2, item 100 represents a raw material that is always available. Each upper LLC always requires one unit of the lower LLC.

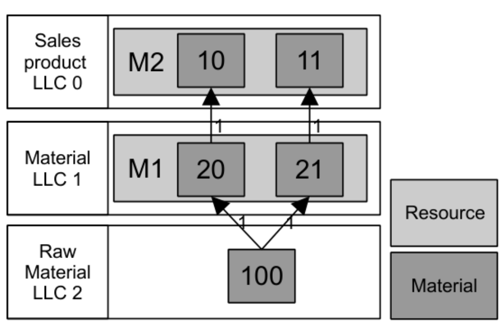

Figure 1: BOM of Production System 1.

Table 2: Deterministic Parameters for Production System 1 and 2.

	Item			
Parameter (PS1/PS2)	10/12	11/13	20/20	21/21
FOQ	170/170	253/253	170/212	253/212
SS	200/200	250/250	200/212	200/212
PL	2/4	2/4	2/4	2/4
Processing time in min	10.4/10.4	10.4/10.4	10.4/5.2	10.4/5.2
Holding costs per day	1/1	1/1	0.5/0.5	0.5/0.5
Tardiness costs per day	19/19	19/19		
FOQ = Fixed Order Quantity; SS = Safety stock; PL = Planned lead time				

3.3.2 Production System 2 (PS2)

The second and more complex production system, which is illustrated in Figure 2, consists of a three level BOM. On the top level, LLC 0, the finished items 10 to 13 are produced. Each item at LLC 0 and LLC 1 has to pass two machines. For example, the routing of item 20 is from $M201$ to $M202$, and for item 10 from $M101$ to $M102$. The same production flow exists for items 200, 21, 12, and 13. The raw materials 100 and 200 at LLC 2 are always available. The processing time of $M101$ and $M102$ are equal for items 10 and 11. For items 12 and 13 the processing on machines $M111$ and $M112$ are also the same. Likewise, for $M201$ and $M202$ the same processing time was used.

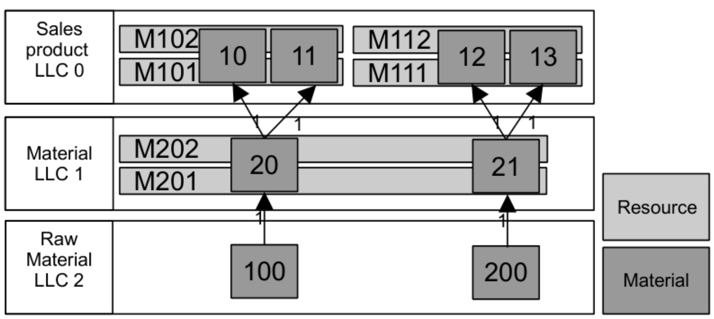

Figure 2: BOM of Production System 2.

3.4 Experiment Plan and Definition

For both production systems, the simulation runtime was set to 500 periods, including 100 periods as warm-up time. After the first 100 periods, the statistic elements are reset to compute results from a simulation system considered in steady state. During the simulation study, all three MRP parameters are changed per item to compute new overall costs. Based on Table 2, the parameters are selected whereby for safety stock 0 to 2, with 0.25 step, is chosen as multiplier for possible parameter values. For lot size and lead time values from 1 to 10, with step size 1, are chosen as multiplier and are applied during simulation. This leads in total to $9 \times 10 \times 10 = 900$ different parameter combinations per item, and all items have different planning parameters. This leads to a very large solution space for both production systems from which parameter combinations can be chosen, e.g. $900 \times 900 \times 900 \times 900$ possible parameter combinations for production system PS1. To test the performance of the SBM strategy, instances of 100, 500, and 1000 parameter combinations are defined. To evaluate the performance between the same number of parameter instances, they are randomly generated three times, i.e. 9 test instances are generated for both production systems. For each parameter instance, a different seed value was used in order to randomly select different parameter combinations. Applying different seed values guarantees the reproducibility of the generated parameter instances and associated simulation runs and results. The first production system with the four MRP planned items (10, 11, 20, 21) leads to 12 MRP parameters to be optimized and the second production system with 6 MRP planned items (10, 11, 12, 13, 20, 21) leads to 18 different MRP parameters per iteration. Four different lower bound (lb) and upper bound (ub) settings are tested to investigate SBM behavior with different levels of accepting solutions for additional replications. The applied lb and ub combinations are (S1) lb$= 0.05$, ub$= 0.4$; (S2) lb $= 0.1$, ub$= 0.5$; (S3) lb$= 0.02$, ub$= 0.8$; and (S4) lb$= 0.02$, ub$= 0.2$. The strictest combination is setting (S4), the loosest setting is (S3) and setting (S1) is the same as in Seiringer et al. (2022). Three instances per SBM setting are selected as they are able to show, if SBM application leads to the same minimum overall costs compared to consume the whole simulation budget.

4 SIMULATION RESULTS AND DISCUSSION

In this section, the results of the performed simulation study are presented and discussed. In total, for both production systems (PS1 and PS2) $576,000$ individual replications were run to compute results without SBM and $259,400$ replications are required to compute SBM based simulation results. For PS1, $122,871$ replications and for PS2, $136,529$ replications are performed with SBM. These numbers include simulation runs for both production systems, all three instances (100, 500 and 1000) and the four tested SBM parameterizations. This means an overall reduction of 55% of the required replications, when SBM is applied. More detailed results are presented in Table 3, where the budget reduction for PS1 and PS2 for all four SBM settings and all three instances are illustrated. The table data are illustrated in Figure 3 for a better traceability of the different result sets. The computed budget reduction represents the percentage of replications saved, when SBM is applied, in comparison to the setting where the maximum number of replications is consumed.

Table 3: Simulation Budget Reduction of Production System 1 and 2.

Production System 1: Budget Reduction (min repl=3)					
No of Instances	(S1) lb $= 0.05$ ub $= 0.4$	(S2) lb $= 0.1$ ub $= 0.5$	(S3) lb $= 0.02$ ub $= 0.8$	(S4) lb $= 0.02$ ub $= 0.2$	Average
100	63.37%	54.77%	51.75%	69.82%	59.93%
500	62.76%	57.94%	51.75%	73.17%	61.41%
1000	63.77%	57.50%	50.74%	73.74%	61.44%
Average	63.30%	56.74%	51.41%	72.24%	

Production System 2: Budget Reduction (min repl $= 3$)					
No of Instances	(S1) lb$= 0.05$ ub $= 0.4$	(S2) lb $= 0.1$ ub$= 0.5$	(S3) lb $= 0.02$ ub $= 0.8$	(S4) lb$= 0.02$ ub $= 0.2$	Average
100	55.45%	53.88%	47.27%	67.48%	56.02%
500	59.26%	52.41%	47.16%	71.17%	57.50%
1000	59.35%	52.25%	45.78%	73.25%	57.66%
Average	58.02%	52.85%	46.73%	70.64%	

min repl. = minimum replications, lb = lower bound, ub = upper bound

For both production systems, the lowest average budget reduction (PS1$= 51.41\%$, PS2$= 46.73\%$) can be reached with setting (S3), which represents the loosest application of SBM. In contrast, the highest average budget reduction can be reached with setting (S4) also for both production system with PS1$= 72.24\%$ and PS2$= 70.64\%$. Regarding *RQ1* the potential of effort reduction increases with the reduction of lb and ub, independent of the production system and number of simulated instances. The used value ranges of the upper bound is between 0.2 and 0.8, which is a larger region, compared to the lower bounds between 0.02 and 0.1. Consequently, it can be argued, that the influence of the upper bound on the budget reduction is higher compared to the lower bound. A remarkable observation is, that SBM always found the same minimum average overall costs as without SBM per iteration for both production systems, number of instances and used SBM settings. Concerning *RQ3*, this means that SBM can be applied without risk of losing the best solution in our study. A limitation here is, that further SBM parameterizations being able to save even more budget could be tested in further research to identify at which threshold value for ub and lb the SBM application does not always find the best solution. In *RQ2*, the production system structure and size of solution space is targeted. From the results in Table 3 the answer for *RQ2* is, that for the simpler production system (PS1) more simulation budget can be saved compared to the more complex production system (PS2).

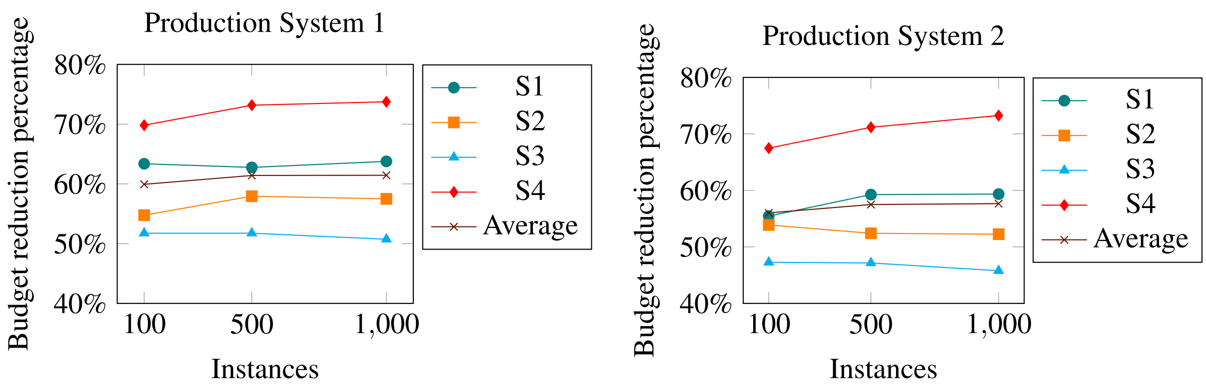

Figure 3: Budget reduction percentage in both production systems.

This finding is expressed by a higher average budget reduction over all three number of instances independent of the SBM setting, e.g.: PS1 S1 63.30% > PS2 S1 58.02%, ..., PS1 S4 72.24% > PS2 S4 70.64%. Regarding the number of instances, an interesting finding is, that for both production system structures, the average simulation budget reduction over the SBM setting per number of instances increases only marginally. For PS1 between 100 instances with 59.53% and 1000 instances with 61.44% number of instances, the budget reduction only increases by 1.51%. The same situation can be observed for PS2, there the budget reduction could only be increases by 1.64% from 100 instances with 56.02% to 57.66% for 1000 instances. This means with 900 iterations more, only a budget reduction increase of less than 2% for both production systems was reached. Additionally, the budget reduction between 500 and 1000 instances is also marginal. This is an interesting fact, which should be targeted in further research activities.

An additional issue addressed in *RQ1* is to identify the best SBM settings, to optimize the budget reduction. From the results in Table 3 it can be assumed that the lower the SBM range (lb and ub) the more simulation budget can be saved and that specifically ub should be high to reach a high simulation budget reduction. In our study, for S4 the lowest percentile bounds were applied and delivered the highest average budget reduction PS1 S4 = 72.24% and PS2 S4 = 70.64%, for both production systems. In summary, the results in Table 3 illustrate the existing potential for simulation budget reduction when applying the developed intelligent SBM method.

5 CONCLUSIONS AND FUTURE WORK

For production planning, the approach of material requirements planning (MRP) is a widely used concept in industry and also for ongoing research activities. Setting cost-efficient values for the MRP parameters safety stock, lot-size and lead time has direct consequences on the performance of the production system. The high number of possible MRP parameter combinations increases the complexity and time to identify cost-efficient values and is not manageable by hand. The application of production system simulation supports the evaluation of a large range of different MRP parameter settings. To avoid wasting of simulation budget for not promising MRP parameter combinations, this article evaluates the recently published concept of intelligent SBM. The developed SBM method stops to evaluate further replications for the current iteration, if its overall costs are above a percentile based threshold value of the already available solutions. In the undertaken simulation study, SBM was evaluated using two different production system structures of different complexities. For both production systems, four SBM parameterizations with different strictness of lower and upper bounds and three test instance sizes are tested. From the simulation results it can be concluded, that SBM works better for a simple production system structure and the stricter, the lower bound of the SBM percentile range is, the higher is the possible simulation budget reduction. It can be summarized that, with the application of SBM, about 70 % of the simulation budget can be saved. An interesting finding is also, that with an increasing test instance size, i.e. more parameter combinations to be tested, the potential of simulation budget reduction increases only marginally. This finding will be investigated in further research activities together with some more detailed studies on the SBM parameter influences on simulation budget reduction. In further research also the combination of SBM and simulation-based optimization will be addressed and more efficient simheuristics to optimize planning parameters will be developed.

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