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Comparing Different Simulation-based Optimisation Approaches for Simultaneous Optimisation of Production Planning Parameters

Vergleich verschiedener simulationsbasierter Optimierungsmethoden für die simultane Optimierung der Produktionsplanungsparameter

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Abstract: This paper investigates optimal MRP-parameter settings i.e. optimal lot size, planned lead time and safety stock for a production system with multi items, multi stages and stochastic production system parameters. The production system faces uncertainty in demand, setup times, processing times, and machine failures. For the optimisation of the MRP parameters a simulation-based optimisation approach is used, connecting a generic simulation model to a framework for heuristics and evolutionary algorithms. The objective is to minimise tardiness and inventory cost. The performance of a genetic and an evolutionary algorithm are compared to a grid search procedure. The observations deliver further insights into the optimal MRP parameter setting, the traceability of the optimal parameters and their practical applicability.

1 Introduction

The target of manufacturing companies is to deliver on time according to the customer requirements, but also to consider internal costs. To enable a good performance of manufacturing systems, the parameterisation of production planning methods has therefore to include the internal as well as the external perspective. For a manufacturing system applying a material-requirements-planning (MRP) approach, the aim of this article is to find near-optimal MRP parameters values for safety stock, planned lead time and lot size. The internal performance is measured as inventory costs for work-in-process (WIP) and finished-goods-inventory (FGI) while the external performance is measured as backorder costs. A multi stage, multi item, stochastic production planning problem is investigated using a simulation-based optimisation approach. The production system faces uncertainties like stochastic demand, set-up times, processing times and machines failures. The performance of the two metaheuristics genetic algorithm (GA) and evolution strategy (ES) are compared to a grid search procedure. Furthermore, the optimal parameter values found with the metaheuristics are discussed for their practical applicability. The results of the grid search, using some available problem knowledge, are compared to the metaheuristics with respect to the overall costs and the practical applicability of the derived parameter values.

Both tested metaheuristics show a good performance with respect to solution quality, about 20% lower costs than the grid search, and converge in an acceptable amount of time. However, none of the metaheuristics finds a good solution within the grid search iteration number. Furthermore, the metaheuristics results show that they have disadvantages in practical applicability and traceability of the optimal planning parameters found.

2 Literature Review

According to Slack et al. (2004), MRP is a preferable method for production planning in systems with complex production system structures where extensive computations are needed to create an appropriate production schedule. Therefore, MRP is a core element of most recent ERP systems, and its position against other planning methods has strengthened since the 1990's (Jonsson and Mattsson 2006). The calculation of this algorithm is based on four steps: *Netting* (determine net requirements by subtracting on-hand inventory and scheduled receipts from the gross requirements), *Lot sizing* (combine the netted demand to appropriate lot sizes), *Backward scheduling* (calculating the planned start dates), *BOM explosion* (use start time, lot size and BOM to generate gross requirements for all required components) and *Iterate* (repeat step 1 to 4 until all components at all low level codes are processed). The MRPII concept (manufacturing resource planning) combines MRP with a hierarchical production planning concept, which is based on three planning levels: *Long-term planning* (strategy), *intermediate planning* (tactical) and *short-term control* (operational). The functions of MRPII are forecasting and aggregated production planning for long-term, MPS (master production scheduling) and MRP for the intermediate planning level and dispatching for short-term control. For a more detailed description of MRPII see Hopp and Spearman (2008).

The optimal setting of MRP planning parameters (i.e. lot size, safety stock and planned lead time) is a critical issue due to their influence on the performance of a production system. This influence is for example investigated in a recent work of Gansterer et al. (2014). Researchers are dealing with the problem of MRP parameter optimisation applying two kinds of methodologies. Firstly analytical models are used to do the parameter optimisation for streamlined production systems and secondly simulation-based optimisation, using metaheuristics, is applied to identify optimal parameter settings for more complex production systems. Many researchers (e.g. Yano 1987; Karmarkar 1987; Weng 1996 or Axsäter 2010) focus on an analytical solution for either one or two of the MRP parameters, while only few articles deal with the complexity of simultaneously optimising all three MRP parameters. However, the generalisation of the results derived from the analytical models to practical application is limited due to the streamlined settings in these models. Most of them have assumptions like single stage production systems, single material, or other production system parameters being assumed to be deterministic. This leads to the need of further ways to find a good parameter-setting for MRP systems. Another way to find (near)-optimal MRP parameters in high complex stochastic production systems is simulation-based optimisation (e.g. Fu 2002). Molinder (1997), for example, has shown how to combine simulation and a metaheuristic to iteratively optimise the three kinds of MRP parameters. He proposed simultaneous optimisation of all three MRP parameters as a way to further decrease total costs, but did not show appropriate results. Gansterer et al. (2014) partially resolved this lack of exploration by the use of a combined simulation-optimisation approach using different kinds of metaheuristics. A disadvantage of simulation-based optimisation with metaheuristics is that the solution found might not be the global optimum of the defined problem.

3 Model Description

For the simulation study, a generic scalable simulation model (SimGen) designed for production planning problems was used. This simulation model is parameterised by a database, which makes it possible to define and run different simulation scenarios without any adaption of the simulation model itself. The simulation model was programmed in AnyLogic 6.9, which is a multi-method simulation software. More details of SimGen are outlined in Felberbauer et al. (2012) or Felberbauer and Altendorfer (2014).

For the simulation-based optimisation, SimGen is connected to HeuristicLab, which is a graphical user interface (GUI) based framework for heuristic and evolutionary algorithms (Elyasaf and Sipper 2014). A so-called *External Evaluation Problem* facilitates the connection between AnyLogic 6.9 and HeuristicLab. The chosen algorithm in HeuristicLab (GA and ES) creates a set of solutions (i.e. MRP planning parameters) and separately sends them to the simulation model. The simulation model then evaluates solutions qualities and forwards it to HeuristicLab. After the evaluation, the algorithm creates an improved set of solutions and the cycle starts again. HeuristicLab stops the optimisation after a predefined number of runs.

3.1 Search Procedure: Grid Search

For the grid search procedure, which is an enumeration of the predefined restricted solution space, the connection to HeuristicLab is not used, but a parameter variation experiment is defined within the simulation software. The grid search was carried out to find appropriate results as a base for the comparison to the metaheuristics. One decision variable per MRP-parameter, i.e. lot size, planned lead time and safety stock, is introduced. These decision variables adapt the initial value for each material, e.g. for lot size, by the same factor. Assume that the optimal factor for lot size is 0.5, then the optimal value for material 10, with initial lot size 110 pcs., is 55 pcs., whereas the optimal lot size for material 2, with initial lot size 330 pcs. is 165 pcs.. The decision variables are varied between a minimum and maximum with a fixed step size. The minimum lot size factor was determined in some manual simulation runs, where overall utilisation was checked to be lower than 100%. The minimum for the planned lead time and safety stock factor is on its natural minimum, which is zero. The maximum is determined as the fourfold of the initial value. The grid search is limited due to the fact that the ratio between optimal parameters is predetermined. Therefore, the optimal parameter of one material cannot change without modifying all other material parameter values. Nevertheless, the latter explained limitation gives the possibility to enumerate in reasonable time through the whole solution space.

3.2 Search Procedure: Evolutionary Algorithms

For the evolutionary algorithms, all relevant MRP parameters are optimised for each single material, which lead to a number of 40 optimisation parameters. The parameterisation of the metaheuristics itself has been conducted in pre-tests.

Two algorithms, namely *evolution strategy* (ES) and *genetic algorithm* (GA) are tested for their performance. For both algorithms, the initial population was generated by a uniform random number generator. GA was run with a population size of 100, 1 elite, tournament selection with group size=2, blend-alpha-beta-crossover (alpha=0.75; beta=0.25) and a fixed-normal-all positions-manipulator with sigma=1. ES was parameterised with a population size of 20, 100 children, 2 parents per child, non-elitist population, self-adaptive-normal-all-positions-mutator and a uniform-all-positions-arithmetic-crossover with alpha=0.33.

Additionally, an adapted version of the ES starting with an initial population where all individuals are equal to the initial setting is tested. This *memetic evolution strategy* (mES), therefore uses problem specific knowledge, and applies ES as a local improvement search.

4 Production System

The modelled production system follows a flow shop structure which is inspired by a production company operating in the automotive sector. The flow shop consists of three machines (M1-M3) which correspond to turning, milling and grinding.

Figure 1 shows the bill of materials (BOM), the low level code (LLC), the work schedule and its associated machines. Each arrow represents one piece of material, which is part of another. The raw materials in LLC 3 are purchased parts which are assumed to be always available and no MRP parameters are optimised for these materials. All sales products and materials on LLC 1 and LLC 2 are MRP-planned.

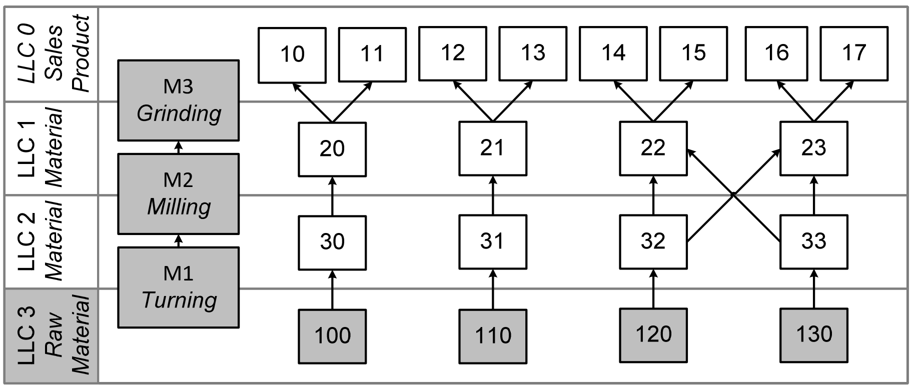

Figure 1: *Bill of Materials*

Items 10 to 17 are produced on machine M3 (grinding), items 20 to 23 are produced on machine M2 (milling) and items 30 to 33 are produced on machine M1 (turning). The mean setup time per order is for all machines about fifty times the mean processing time for a single item. Both parameters are randomly distributed. The specified values are equal for materials on the same LLC.

All even- and odd-numbered sales products have the same demand and mean amount of orders, which leads to the fact that at least two materials on all LLCs are similar (see Tab. 1). The demand per month for even-numbered sales products is 1,000 pcs. per month and the mean order amount is 10 pcs. (≈100 orders per month), for odd-numbered sales products this is 3,000 pcs. per month with a mean order amount of 15 pcs.. The demand per month is a fixed value with zero variance for all materials. The amount of orders is randomly distributed with a coefficient of variation (COV) of 0.25. Mean customer required lead time (CRLT) is 5 days for all orders and randomly distributed with a COV of 0.25.

Several random effects are implemented in the simulation model. Stochastic machine breakdowns and repair-times reduce the machine availability in this study to 95%.

4.1 Initial Lot Sizes

The initial values for lot sizes of all materials were calculated based on a planned utilisation factor of 80% for processing time and 85% with the consideration of machine breakdowns. 100% utilisation minus 85% planned utilisation results in a maximum of 15% time for setups. The number of possible setups per month is calculated by 15% (available time factor for setups) * 24 hours * 30 days / 1.5 hours (mean time per setup) = 72 setups. It has been assumed that every finished good needs the same number of setups per month resulting in 9 possible setups per month and material. Based on this information and the machine availability it was possible to calculate the initial lot size for all sales products, which is mean demand per month divided by 9. Table 1 outlines the appropriate initial lot sizes.

The initial lot sizes on lower stages of LLC were defined as the maximum lot size of the upstream materials.

4.2 Initial Planned Lead Times

Initial values for the planned lead times of the materials were set according to the necessary production lead time. The necessary production lead time was evaluated in a preliminary simulation study using 40 replications, no safety stocks and the initial values for the materials' lot sizes (see Section 4.1).

4.3 Initial Safety Stock

Initial safety stock was set to zero for all materials. For the following experiments safety stock is measured as a multiple of mean daily demand instead of pieces, which leads to improved comparability between materials. Furthermore, safety stock was only allowed for finished products, which leads to a reduced search space and is in line with the findings of Heisig (2002) and Whybark and Williams (1976).

4.4 Results for Initial Setting

The following Table 1 presents the initially determined production planning parameters for the considered system. The materials were grouped into 5 clusters by similar demand patterns and LLC. These clusters are used to compare the consistency of production planning parameters after the optimisation. A simulation run using the initial parameter setting of Table 1, leads to mean overall costs of 2,911.

Table 1: *Initial Parameter Setting*

Cluster	Materials	Demand per Month	Lot Size	Planned Lead Time
1	{10,12,14,16}	1,000	111	3
2	{11,13,15,17}	3,000	333	3
3	{20,21,22,23}	4,000	333	2
4	{30,31}	4,000	333	1
5	{32,33}	8,000	333	1

5 Numerical Study

The objective function value for all experiments is the mean overall cost, which is the sum of inventory and tardiness costs. To avoid situations with low costs due to excessively delaying customer orders, all customer orders that cannot be satisfied at the end of the simulation time are penalised with their tardiness. The ratio of the inventory cost rate to the tardiness cost rate is chosen to be 1:19 (see also Axsäter 2000 for details on this ratio). The holding costs are 1 for all sales products and 0.5 per day and piece for all other materials. In the experiments we simulated five whole years with the above described demand structure, whereby the first year is the warm up time of the simulation model and therefore excluded from the analysis. Each run is replicated 40 times to account for stochastic variance.

Each algorithm was run for 9,000 solution evaluations, which led to a total of 3.5 days computational time on a commercially available personal computer.

6 Results

In this section, on the one hand, the solution quality of the tested metaheuristics to optimise MRP parameters is evaluated. On the other hand, a measure for MRP parameter consistency is introduced to investigate their traceability and practical applicability.

Solution quality - Convergence of the presented solution methods

Figure 2 shows the solution value of the initial parameter setting and the performance of the four different solution procedures with respect to number of evaluated solutions. Please note that 2,500 evaluations are approximately 1 day parallel evaluation time. Therefore, the x-axis can easily be converted from evaluated solutions to computation time.

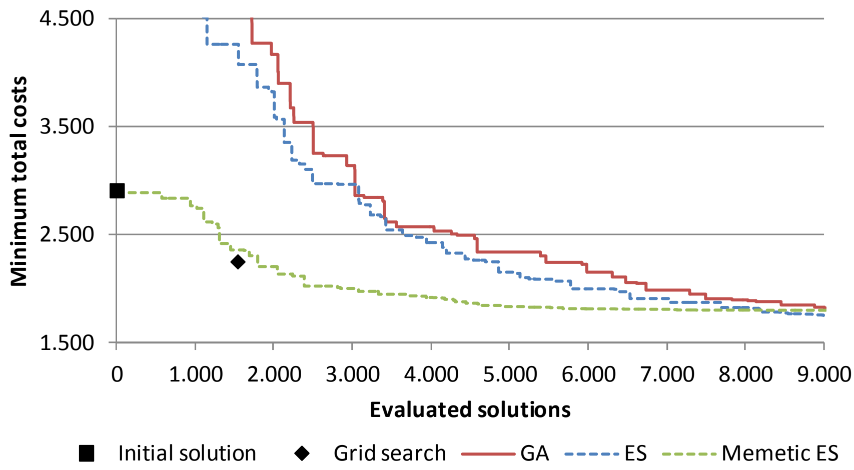

Figure 2: *Comparison of Solution Quality*

The solution value of the initial setting is 2,911. The best solution value derived from the grid search procedure is 2,252 using approximately 1,440 solution evaluations or 0.55 days computation time. The optimal parameter setting of the grid search procedure was 0.75*initial lot size, 0.50*initial planned lead time and 1.75*mean daily demand for safety stock.

Solution quality - Cost improvement with metaheuristics

The following Table 2 shows the best solution values of all solution procedures. All metaheuristic optimisation procedures found on average a 21% cost improvement in comparison to the grid search. However, the number of evaluations (computation time) needed is six times higher for the metaheuristics.

Table 2: *Comparison of Algorithm Qualities*

	Best Quality	*better than* Initial Setting	Grid Search	*% better than* Initial Setting	Grid Search
Initial Setting	2,911				
Grid Search	2,252	659		23%	
GA	1,820	1,091	432	37%	19%
ES	1,739	1,171	512	40%	23%
mES	1,783	1,128	469	39%	21%

Note that none of the metaheuristics found a better solution than the grid search within the same amount of evaluations. We assume that reasons for the higher number of evaluations needed are that the applied metaheuristics do not use a predefined step-size and exploit the potential through single material parameter optimisation. ES delivered the best solution value with 1,739 mean overall costs, which is a reduction of 40% compared to the initial setting and a reduction of 23% to the best grid search solution quality. A further interesting result concerning the metaheuristics is that the mES, which includes a problem specific start population, on the one hand provides a better solution value convergence, but leads on the other hand to slightly higher costs than the general ES.

Optimal MRP parameters - Consistency and traceability

Table 3 presents some details on the best MRP parameter values from the evaluated solution procedures. It shows the lot sizes for material 10, 12, 14 and 16 (Cluster 1 in Table 1) which have the same demand and production pattern and should therefore have similar planning parameters. From an analytical point of view, it is rather clear that the optimal solution for materials with equal parameters should be nearly the same for all of them. In the last row of Table 3, the coefficient of variance (COV) between the optimal parameter values for each solution procedure are calculated. The COV serves as measure for consistency between produced materials' parameter values. As production planning personnel will not apply MRP parameter settings which cannot be argued, this is a further argument why this COV value has to be low, to ensure the practical applicability of metaheuristic solution results.

Table 3: *Comparison of Optimal Lot Sizes*

Material	Initial Solution	Grid Search	GA	ES	mES
10	111	83	148	143	126
12			114	128	145
14			121	142	100
16			117	100	114
COV	*0,0%*	*0,0%*	*12,4%*	*15,6%*	*15,7%*
mean	*111*	*83*	*125*	*128*	*121*

From the grid search definition above, it is clear that this procedure leads to COV=0 and therefore a perfect consistent and traceable solution. All three metaheuristics tested in this study lead to a high COV, i.e. inconsistent MRP parameters for materials with equal demand and production patterns. An obvious reason for this observation is the optimisation of single materials' parameters instead of one parameter for all materials. This result points out a major shortcoming in the application of metaheuristic MRP parameter optimisation which is yet not discussed in literature but might be the key limitation for its practical applicability.

To improve solution consistency and traceability of results, a *mean parameter solution* is created within the material clusters for the related parameters (see last row *mean value* of Table 3 for the applied lot size of one cluster). This *mean parameter solution*, which is consistent and applicable, leads to a cost increase of about 10% for GA and ES. As this is still a cost advantage of 13% in comparison to the grid search algorithm, this might be a promising field of further research. Note that for the best mES solution this *mean parameter solution* leads to a too high utilisation, and therefore a set of the best solutions has to be tested. For real size problems, the material clusters are not ex-ante to be identified which means that a consistent and traceable solution heuristic should probably have a pre-processing step to identify these clusters.

Optimal MRP parameters - Lot size of components

Table 4 presents the best parameter setting for lot sizes, planned lead times and safety stocks, of the ES algorithm. We observed *very small lot sizes* compared to their related finished goods for all components. A closer inspection of this observation shows that the large FOQ-lot sizes of finished goods override the small setting of subordinated materials. Based on this finding, a re-evaluation of the best parameter settings with absolute lot sizes for all components of 1 is performed showing a further cost reduction of 1% for GA and ES. However, the costs for the best mES solution doubled, which again shows that a set of the best solutions needs to be tested. This shows that the optimal lot size for components is 1 in a production system, where setup times of superior materials are greater or equal than the setup times of the subordinate materials. For such a setting we conjecture that the MRP calculation scheme, overruling a large part of the components lot sizing policy, reduces the solution space for MRP parameter optimisation.

Table 4: *Best Parameter Setting - ES*

Cluster	*1*				*2*				*3*				*4*		*5*	
Material	10	12	14	16	11	13	15	17	20	21	22	23	30	31	32	33
Lot Size	143	128	142	100	233	241	176	194	13	22	1	7	8	2	1	1
Planned Lead Time	1	1	1	1	1	0	2	0	0	1	0	1	1	0	0	0
Safety Stock	61	46	53	41	178	221	147	228								

7 Conclusion

In this study the performance and applicability of metaheuristics for simulation-based MRP parameter optimisation is investigated. To identify the applicability of the optimised MRP parameters a measure for consistency and traceability is developed. The results of the study show that a simple grid search leads to perfectly consistent results but to rather high costs in comparison to the metaheuristics. On the contrary, the metaheuristics lead to a good cost performance, even though we still expect a remarkable solution gap to the optimal solution, but rather inconsistent solutions. A first attempt to increase consistency of optimal MRP parameters from metaheuristics shows a moderate cost increase. In this attempt, the mean value of parameters for predefined material clusters with similar demand and production patterns is applied. The results of this study show that further research is needed to develop problem specific search heuristics, probably divided into clustering and optimisation, to improve the performance and applicability of simulation-based MRP parameter optimisation.

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