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SIMULATION BASED MANUFACTURING SYSTEM IMPROVEMENT FOCUSING ON CAPACITY AND MRP DECISIONS – A PRACTICAL CASE FROM MECHANICAL ENGINEERING

Andreas J. Peirleitner
Klaus Altendorfer

University of Applied Sciences Upper Austria
Wehrgrabengasse 1-3
A-4400 Steyr, AUSTRIA

Thomas Felberbauer

St. Pölten University of Applied Sciences
Matthias Corvinus-Straße 15
A-3100 St. Pölten, AUSTRIA

ABSTRACT

In this paper a practical case from an Austrian mechanical engineering company is presented. Simulation based manufacturing system improvement is applied to their component manufacturing plant. Based on the high number of items in the real case, a method for reduction of simulation model complexity applying item aggregation is developed in this paper. In the first improvement step, strategic capacity investment decisions are supported with the use of simulation. In the second step, a MRP planning parameter optimization is performed to improve service level and inventory. Additionally, the effect of capacity related decisions concerning setup time reduction and load-dependent outsourcing is evaluated. The results of this simulation study show that service level and inventory can be significantly improved by optimization of planning parameters and reduction of setup times. In addition, the study shows that load-dependent outsourcing is a viable alternative to capacity investment.

1 INTRODUCTION

Manufacturing companies strive to improve delivery performance towards the customer while minimizing internal costs. However, they are faced with high product complexity and variety as well as uncertainty in the production process or customer demand. The performance of an existing manufacturing system can be improved by different improvement measures. Concerning strategic decisions, investments in new machinery are possible. Tactically the optimization of production planning parameters can be fostered. On the operative level, process management tools, e.g. six sigma, value stream method, etc. are commonly applied to improve the production process. Also the use of flexible capacity due to outsourcing is often possible. To gain some insights on the effectiveness of these improvement measures in a real world setting, this paper presents the results of a simulation study for a sheet metal processing manufacturing system. This manufacturing system is embedded into the component manufacturing plant of an Austrian mechanical engineering company and produces plastics injection molding machines and automation equipment. The customers of the component manufacturing plant are the company-owned assembly plants. The relevant performance indicators for the analyzed component manufacturing plant are: the delivery performance of the component manufacturing plant towards the assembly plants (i.e. service level), Work in Process (WIP), Finished Goods Inventory (FGI), and shop floor utilization.

A specific driver of complexity within this simulation project is the high product variety in the manufacturing system. Approximately 40,000 different items are produced in the studied department. It is not possible to model this amount of different items due to simulation time as well as data acquisition effort. The development of an item aggregation method as well as the evaluation of the improvement measure effects constitute the main contribution of this paper. Based on the above stated general research topics and the company requirements for the analyses of specific improvement scenarios, the following research questions are studied:

1. How can the complex real world production structure be aggregated to get a simulation model which delivers valid insights for the real world situation? (Section 4)
2. What is the necessary capacity investment for the increased forecasted demand of the next business year? (Section 5.2)
3. What are appropriate planning parameter settings for the specific items in the manufacturing system? (Section 5.3)
4. How can a specific setup time reduction improve the key performance indicators of the production system? (Section 5.3.3)
5. How can load-dependent outsourcing improve the key performance measures? (Section 5.4)

The component manufacturing plant receives orders for items from the assembly plants. The items within the component manufacturing plant are produced in a job shop structure. Production planning is conducted according to Material Requirements Planning (MRP) and orders are dispatched according to their due date on the shop floor. Therefore, the planning parameters to be optimized are lot size, planned lead time and safety stock for each item. In Hopp and Spearman (2008) these MRP parameters are discussed. Note that without simplification this would lead to 120,000 optimization parameters. Even a quite narrow range for each parameter would combinatorically lead to an enormous search space. Due to the big search space and the complex and therefore slow simulation model (340 seconds per simulation run) also efficient metaheuristic search concepts cannot be applied for optimizing parameters individually. To enable a thorough discussion of the manufacturing system performance, the key performance indicators are not aggregated into a single (cost-) objective, but a bi-objective approach including inventory (WIP+FGI) and service level is applied.

Simulation is used within this project as analytical models can not cover the complex production structure, all stochastic influences and interdependencies. To answer the research questions, a simulation study is applied including different scenarios and a grid search optimization scheme. Because the company plans to increase sales in the next business year, in the first step a strategic investment decision has to be made for the future market scenario because internal capacity, i.e. overtime, cannot be expanded. In the second step, different improvement measures are investigated basis on this new capacity to improve the key performance indicators. Because several authors (Enns 2001; Jonsson and Mattsson 2006; Louly and Dolgui 2013) report that MRP planning parameters have a significant effect on manufacturing system performance, these parameters are optimized for all simulation scenarios. Basis for optimization are actual planning parameters from the ERP (Enterprise Resource Planning) system. Further improvement measures proposed by the company are the use of flexible capacity and a setup time reduction, whereby the latter is supported e.g. by results of Felberbauer, Altendorfer, Jodlbauer (2013).

After the literature review in the next section, a detailed description of the simulation model and the manufacturing system are presented. The handling of the huge amount of items is dealt with in section 4 where a method for reduction of simulation model complexity applying an item aggregation is presented. A detailed discussion of the different improvement measures concerning capacity and planning decisions is provided in the results section 5.

2 LITERATURE REVIEW

The appropriate setting of MRP parameters lots size, planned lead time and safety stock is extensively studied in literature. Whybark and Williams (1976) study the effects of safety stock and safety lead time under uncertainty with simulation for a MRP controlled system under different types of uncertainty. Buzacott and Shanthikumar (1994) also study the tradeoff between safety stock and. safety lead time. In their paper a single stage manufacturing system, controlled by MRP, and facing forecast errors and processing time variability, is studied. The effects of lot size and planned lead time is also studied by Enns (2001). Louly and Dolgui (2013) present a model to simultaneously decide lot size and planned lead time in a setting with constant customer demand and stochastic production lead times. In a similar study of Altendorfer (2015) the influence of lot size and planned lead time on service level and inventory for a single-stage manufacturing system is studied. A simultaneous safety stock and planned lead time optimization is provided by Altendorfer and Minner (2014). For more literature on the parametrization of MRP systems under uncertainty we refer to Dolgui and Prodhon (2007) and Mula et al. (2006). All of these papers identify a significant influence between MRP planning parameters and logistical performance of manufacturing systems but are limited by assuming a streamlined production system. For modeling real complex manufacturing systems facing multiple stochastic influences and using MRP for material planning, discrete event simulation is used by Altendorfer et al. (2016), and Gansterer et al. (2013), whereby the latter uses simulation-based optimization for MRP planning parameter optimization. For an overview of simheuristics see Juan et al. (2015).

3 MANUFACTURING SYSTEM AND SIMULATION MODEL DESCRIPTION

A generic and scalable simulation framework is used for this simulation project. The core concept is presented in Hübl et al. (2011) and Felberbauer et al. (2012). The manufacturing system is modeled in the simulation software AnyLogic and parameterized by a database which allows defining and evaluating different simulation scenarios without adaptions of the simulation model. For further applications of this framework see Felberbauer, Altendorfer, Gruber Daniel et al. (2013), Felberbauer and Altendorfer (2014), and Altendorfer et al. (2016).

In Figure 1 the material flow and information flow of the real world manufacturing system is illustrated. The mechanical engineering company is producing plastic injection molding machines. The component manufacturing plant is a supplier to the assembly plants. In the simulation study only the department of sheet metal processing within the component manufacturing plant is investigated. An order from the assembly plant is always a bundle of sheet metal components, called delivery batch, needed for assembly. The further processing within the assembly plants is not modeled, however, assembly process planning in the assembly plant influences the order due dates for the component manufacturing plant. This influence is included in the stochastic demand stream generated in the simulation model. 40 different types of plastic injection molding machines are assembled, each having a lot of different variants. For these 40 machine types, 398 clusters of delivery batches can be identified which include a set of common sheet metal items and some specific ones related to the respective machine variant. The number of single sheet metal items in the investigated manufacturing system is 40,000. Note that section 4 discusses how this high number of items and, therefore, planning parameters is handled in the simulation study.

The demand for the sheet metal items is known a long period in advance, because the plastic injection molding machines are produced MTO (make-to-order) and the customer required lead time for these machines is rather long. However, the component manufacturing plant is still facing information uncertainties in demand. On the one hand there are changes in the assembly sequences of the assembly plants which lead to due date changes for the sheet metal items. On the other hand there are orders with very short delivery dates which are usually orders for items with modified specifications or quality issues. This information uncertainty can either lead to increased inventory levels or late deliveries. All necessary information for demand uncertainty is derived from historical data.

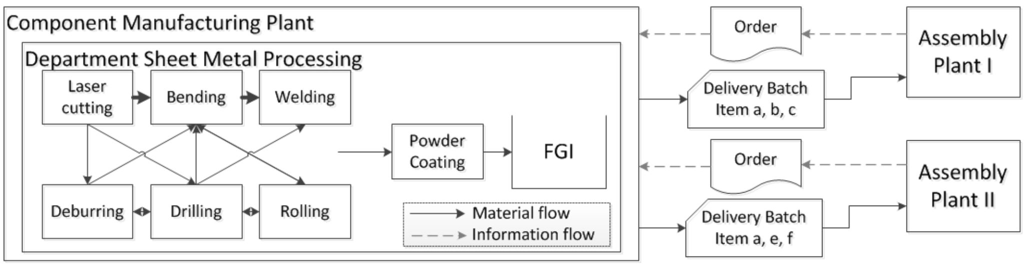

Figure 1: Material and information flow between assembly plants and component manufacturing plant.

In the simulation framework a hierarchical production planning approach according to the MRP II concept is implemented. For planning of material requirements, MRP is used and is calculated on a daily basis. Gross-requirements are calculated based on the due dates and delivery batch demands from the assembly plants. With the MRP-functionalities netting, lot sizing, backward scheduling and bill of material (BOM) explosion, planned order releases are calculated based on the MRP parameters lot size, planned lead time and safety stock including actual inventory levels and scheduled receipts. Based on available planning parameters from the ERP system, the lot sizing policy fixed order period (FOP) is used, meaning the net-requirements of the following x days are produced in one lot. In the actual ERP system parameterization, lot size FOP7 (i.e. the net requirement of one week are produced in one lot) is assigned to those items with high demand levels, lot size FOP14 (i.e. the net requirement of two weeks are produced in one lot) used for regular demand items and FOP28 is applied for items with low demand. Note that this clustering is not strictly applied in the current ERP system planning parameters. For each processing step, a planned lead time is stated in the ERP system and the planned lead time for one material is calculated as sum over all respective processing steps. If, for example, item i is produced on machine A and B with planned lead time of 1 day and 2 days respectively for these processing steps, the planned lead time for item i is 3 days. In the current ERP setting, a safety stock is only assigned to a few items. Planned order releases are converted to real production orders if all required sub materials are available at the planned release date. Note that raw materials are assumed to be always available.

Production orders are then produced in the job shop according to their routing information usually including several mechanical processing steps, a welding step and sometimes a powder coating step. The machine groups focused in the simulation study are laser cutting (4 machines), bending (8 machines) and welding (21 welding boxes with 17 welding employees). The most frequent routing is laser cutting, bending and welding in the same order. Additionally there are machines and other manual work stations like deburring, drilling, and rolling for the mechanical processing of the items, but as these are not the main resources in the job shop they are not incorporated in the detailed analysis. The main focus of the study lies on the machine groups bending and welding. The routing information of the items includes specific processing and setup times. For machine group welding a detailed modelling of hierarchical skill levels for workers is implemented. This means that employees with a higher skill level can additionally weld stainless steel, whereas employees with “normal” skill level cannot, and therefore are not that flexible. For all machines and employees a shift calendar is implemented based on their ERP system data.

After manufacturing of the items they are stored in the FGI until all items for one delivery batch are finished and the due date is reached. For performance evaluation, however, the service level of the simulated manufacturing system is calculated on item level. Therefore, the service level is the number of ready for shipment items at delivery date divided by the number of all delivered items. This specific type of service level measure is required from the company and, therefore, analogously applied in this study. Note that also data for a delivery batch based service level is available.

Stochastic distributions within the simulation framework are implemented for processing time and setup time based on expert input as well as for customer required lead time (including changes in due dates), and order amount (including changes in items needed) based on historical data.

4 REDUCTION OF SIMULATION MODEL COMPLEXITY APPLYING ITEM AGGREGATION

In this section a method for aggregation is presented to answer the research question, how the real world production structure can be simplified to get a simulation model which delivers valid insights for the real world situation. As mentioned above, 40,000 different items are produced in the investigated shop floor. If all items would be included into the simulation model, it would have been necessary to collect data for 40,000 routings with their respective processing steps and planning parameters. Especially, for items which are only occasionally produced the data quality suffers and also the simulation model would not be able to handle such a high amount of data. However, if the routing of all items would have been replaced only by a probabilistic routing and processing, a lot of relevant system interdependencies would be neglected. Therefore, a specific clustering scheme to identify the relevant items and a respective capacity load approximation to mimic the effect of items not modeled in detail has been developed.

For item clustering, the first step is to identify the probability of usage for each item in the respective delivery batches. The items have been linked to one of the 398 different delivery batch clusters and for each combination of delivery batch cluster and item the probability that an item was used is calculated. Whenever the usage probability is greater than 0.8, the item is modeled in detail with its respective routing information and planning parameters. Applying this analysis reduces the number of simulated items to 1,520, which are only 4% of the original 40,000 items. However, this number is still high enough to mimic the interrelations between items and delivery batches.

Because this reduction of item number would lead to a significant shop load reduction (the average shop load of the 1,520 items is approx. 34%), the remaining shop load for each machine has to be approximated with anonymous production orders that have the same stochastic behavior, meaning the same lot operation cycle times, as the simulated items. However, this stochastic behavior strongly depends on the planning parameter lot size when setup times occur which is the case in this study; see also Altendorfer (2015) for a discussion of the relationship between lot size, inventory and service level. The following approach is applied for each machine group to correctly implement this effect.

Firstly the overall workload of the respective machine group in the validated data set, i.e. historical data, is calculated as C_O and the workload induced by the 1,520 simulated items is calculated as C_A per year. Based on the lot size Q_i of simulated item i, equation (1) shows the average number of lots being produced per year w_i when the average item demand per year is x_i.

$$w_i = x_i / Q_i \tag{1}$$

Equation (2) identifies the average lot processing time P_i of item i with S_i being the average setup time and K_i being the single item processing time.

$$P_i = S_i + Q_i K_i \tag{2}$$

The average lot processing time $\overline{P}$ of the respective machine group is defined in equation (3). This $\overline{P}$ is the average size of the anonymous processing orders to mimic the not modeled items. For the validation model, the number of anonymous orders per year is then $R = (C_O - C_A)/\overline{P}$ which can simply be transformed into an input rate for these orders.

$$\overline{P} = \sum_i P_i w_i \Big/ \sum_i w_i \tag{3}$$

For each new lot sizing policy L, a simulation run can be conducted which identifies the new workload of the simulated items at the respective machine group C_A^L and a new $\overline{P}^L$ can be calculated based on equations (2) and (3). Using the information that the new lot sizing policy also changes the workload at the machine group leads to equation (4) which shows the number of anonymous orders to be produced per year R^L with lot sizing policy L.

$$R^L = \frac{\left(C_O - C_A\right)\dfrac{C_A^L}{C_A}}{\overline{P}^L} \tag{4}$$

If, for a simplifying example, the lot sizing policy for all items would be FOP7 in the validated model, and the new lot sizing policy to be tested is FOP14, this would lead to $C_A^{FOP14} < C_A^{(FOP7)}$ because overall setup efforts drops by approx. 50%. On the other hand, $\overline{P}^{FOP14}$ is nearly the double of $\overline{P}^{(FOP7)}$ (not exactly because the setup time does not change) which leads to the situation that with the new lot sizing policy FOP14, approximately only half of the anonymous orders with the doubled size are created.

5 RESULTS

In this section, the different research questions from the introduction are addressed. The performance measures observed are service level [%], utilization [%] of both main machine groups bending and welding as well as WIP [pcs], FGI [pcs] and inventory [pcs] (i.e. WIP plus FGI). For the simulation study a simulation time of 1460 days is used, whereby the first 365 days are the warm-up time, and 20 replications are made. Note that the run time for one simulation run is approx. 340 seconds.

5.1 Model Validation

The simulation study is based on a model validation, which is conducted with company experts. Therefore, the demand distribution of the last business year is applied and the performance measures created in the simulation study are compared to the real system performance. First results showed a deviation for FGI and utilization. In discussion with company experts and analysis of historical data it has been identified that for some items a safety stock is held for avoiding stock out situations, which is not registered in the ERP system planning parameters. Therefore additional safety stock was implemented for 21 items. The deviation in utilization for the machine groups bending and welding has been corrected by a slight increase of the machine availability based on company expert information. Table 1 shows the performance indicator comparison for real manufacturing system and simulation model for which the simulation model validity has been approved by company experts.

Table 1: Performance measures for the real system as well as the validated simulation model results.

	Real System	Validated model
Service Level [%]	95.8	96.5
Utilization bending [%]	92.0	92.1
Utilization welding [%]	86.5	86.5
Work in process [pcs]	3,955	4,263
Finished goods inventory [pcs]	21,119	21,134
Inventory (WIP + FGI) [pcs]	25,074	25,397

5.2 Capacity Investment for Forecasted Demand Increase

For the next business year, for which the simulation study is conducted, the most likely future demand scenario includes an increase in demand. Therefore, the first decision for the manufacturing system is to identify the necessary capacity investment, incorporating the stochastic customer and production environment. The company expects that the item demand will grow by approx. 10% in the next business year. Note that according to the company management, the investment should be limited to the minimum necessary extent, reaching a high machine utilization. Table 2 shows the performance measures for the validated model, i.e. is the simulation of the last business year, in comparison to two investment scenarios for the next business year. Note that this demand for the next business year is also the basis for all further investigations. Despite the additional investment in scenario 1 and 2, increasing demand by 10% leads to an increase in system load and significantly reduces service level in both investment scenarios. The utilization of bending increased by 4.3 percentage point with the additional investment of 1 machine (scenario 1 and 2). Investment scenario 1 leads to WIP increase of 227%. An explanation for that are temporary capacity bottlenecks at the machine group welding, induced by the stochastics in customer demand and in the production process. Therefore, in investment scenario 2, capacities for welding are further increased, which reduces utilization in comparison to scenario 1 and leads to an increase of the utilization of 3.2 percentage point compared to the validated model; but WIP still increases by 85%. While most of the performance measure changes are obvious with respect to the increased system load, it could be expected that FGI decreases as more items are late. However as described in section 3 batches are only delivered when all items are available. Therefore, items which are already finished are waiting for the late ones which is resulting in higher finished good inventory levels. After discussion with company experts, investment scenario 2 is applied for the investigation of further improvement measures discussed in the next sections.

Table 2: Performance measures for validated model and both investment scenarios.

KPI	Validated model	Investment scenario 1	Investment Scenario 2
Service Level [%]	96.5	87.9	92.4
Utilization bending [%]	92.0	96.4	96.4
Utilization welding [%]	86.5	94.5	89.7
Amount bending machines [pcs]	8	9	9
Amount welding employees [pcs]	17	18	19
Work in process [pcs]	4,263	13,943	7,871
Finished goods inventory [pcs]	21,134	50,736	26,629
Inventory (WIP + FGI) [pcs]	25,397	64,679	34,500

5.3 Manufacturing System Improvement Based on Capacity Investment Decision

After identification of the required capacity investment in section 5.2, different improvement measures are applied according to the company objectives of reaching high service level and low inventory. The performance indicators service level and inventory (WIP + FGI) are not transformed into a single objective function. A bi-objective approach is applied to enable a thorough discussion of the trade-off between these two conflicting objectives.

As introduced above, one improvement measure is a planning parameter optimization for MRP parameters lot size, planned lead time and safety stock. Optimizing these parameters for each item individually, is restricted due to runtime of simulation experiments. Therefore, a factor for each optimization parameter is introduced. These three parameter factors for lot size, planned lead time and safety stock are optimized applying a grid search, i.e. a full factorial simulation experiment, with 10 steps per parameter. These factors are multiplied with the initial ERP system planning parameters, i.e. a lot size factor 1 means that the initial setting is used, e.g. FOP7, and lot size factor 2 would then mean FOP14. Even though this limits the improvement potential of the solutions found, an advantage of this simplification is that this leads to consistent results. Furthermore, the results can be interpreted more easily and implemented in practice, as all items are modified in the same extent.

5.3.1 Parameter Optimization Based on Current ERP System Planning Parameters

The following analyses addresses the research question concerning appropriate planning parameter settings for specific items in the manufacturing system. The ERP system planning parameters provide the basis for this parameter optimization as explained in the paragraph above. However, some preliminary studies showed that the currently implemented, rather unstructured, safety stock policy is outperformed by a more structured one which has been implemented as follows. The safety stock level is varied as the multiple of the average lot size for the respective item. Figure 2 shows the results for the performed parameter optimization. On the X-Axis inventory, on the Y-axis the service level and on the secondary axis the optimized parameter setting for lot size and safety stock is presented. The service level curve shows the Pareto frontier of this bi-objective optimization. If only the capacity investment decision from section 5.2 is applied without any MRP parameter optimization, a service level of 92.39% at an inventory of 34,500 pcs is reached, which is indicated by the red dot in Figure 2. Looking at the service level curve already shows the significantly better manufacturing system performance with optimized parameter settings. At the same inventory of 34,500 pcs a 5% higher service level can be reached. Note that the optimized planned lead time, which is not visualized at the secondary axis but shown above the graph, increases with increasing inventory. A service level objective of about 95%, stated by the company and similar to the validated model, an inventory of approx. 30,000 pcs is reached. The optimized lot size factor is 1.3, the optimized planned lead time factor is 1 and no safety stock should be used for planning of items. A general finding in this study is that higher lot sizes, i.e. lot size factors >1, are appropriate for all relevant service level settings. This can be explained with the decreasing system load induced by the lower amount of setups. Furthermore, the results show that for the huge amount of products in this manufacturing system, a safety stock for all individual items seems to be rather inefficient with respect to inventory and service level. Only for service level objectives above 98%, safety stock is held.

Another interesting insight is the relationship between lot size and planned lead time. The results indicate that higher service level, which implies on the Pareto frontier a higher inventory, can either be reached with an increase in production lot size or in planned lead time. Looking specifically at an inventory of 34,000 pcs shows that the increase in optimized planned lead time (from factor 2 to factor 4) leads to a decrease in the optimized lot size which shows the interrelation between these two parameters. The results from Figure 2 also highlight the tradeoff between the company objectives of increasing service level and reducing inventory. For a high service level, high inventory levels have to be accepted and vice versa. The results provide some decision support for the company on this trade-off and show what parameter combination leads to the respective pair of objectives.

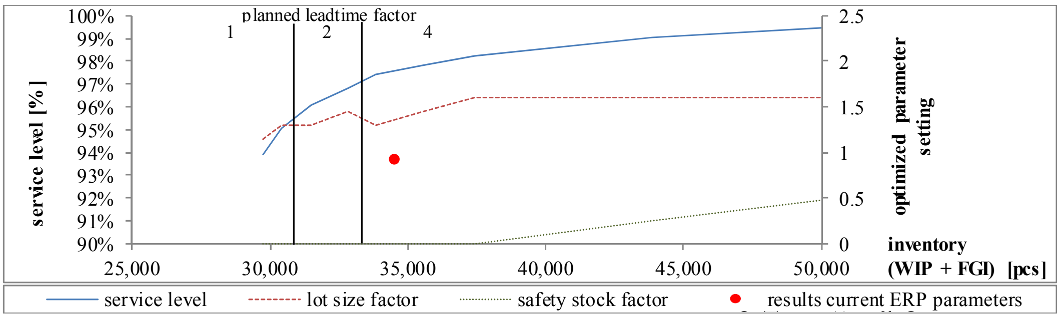

Figure 2: Parameter optimization results with optimized parameter settings.

5.3.2 Parameter Optimization Based on Improved Item Clustering

The parameter optimization above is performed based on ERP system planning parameters and specifically the predefined item clusters concerning the lot size have been used. In this section, a capacity consumption driven ABC analysis is introduced for improving the item clusters and optimizing the planning parameters. The capacity consumption for an item is calculated based on processing times at the main machine groups bending and welding. A-items with cumulated capacity consumption ≤60% are produced in FOP7, B-items witch cumulated capacity consumption >60% and ≤90% are produced in FOP14. The remaining C-items are assigned FOP28. A safety stock is only implemented for A-items, based on the average lot size. The planned lead time is still based on the ERP system planning parameters. The intuition behind this clustering is that with the appropriate choice of lot size and safety stock the production can be harmonized.

Results in Figure 3 show a further potential for improvement of service level. Specifically for low inventory values, a significantly positive effect on the service level can be observed with the lot size and safety stock policy according to ABC analysis. At an inventory of 29,700, for example, with the lot sizing and safety stock policy according to the ABC clustering the service level can be increased from 93.9% to 95.4%. However, this positive effect decreases with higher service level values and above an inventory level of 35,000 pcs or a service level of approx. 97.5% both item clustering strategies show similar results. A further interesting finding with respect to inventory is that the optimized lot size is lower and the planned lead time is higher in comparison to the current clustering settings. The main advantage of the lot sizing and safety stock policy according to ABC clustering is that this technique can as well be applied for all items not included in the simulation model. Furthermore, through the assignment of lot sizing and safety policies to the individual clusters, parameters are homogenous within the cluster.

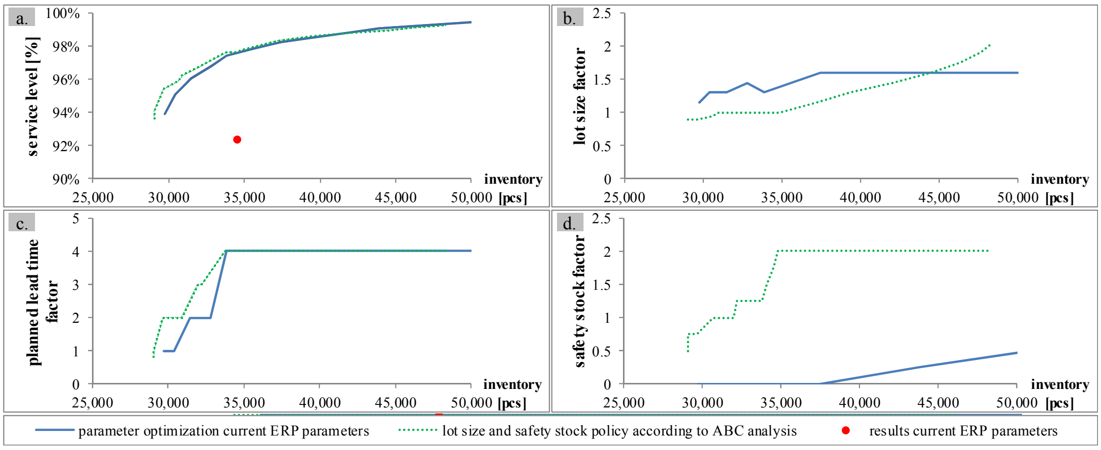

Figure 3: Comparison of optimization results with item clustering to results for current ERP settings.

5.3.3 Setup Time Reduction Effects

In this section, the improvement of key performance indicators with a specific setup time reduction is addressed. According to company experts, a setup time reduction of 30% for all items and machines can be reached through organizational projects. Therefore, a planning parameter optimization is conducted in this section for this improved manufacturing system. Figure 4 again shows the Pareto frontier for service level and inventory as well as the appropriate planning parameter settings.

An intuitive result is that the reduction of setup times does even for the ERP system planning parameters lead to a significantly higher service level at a lower inventory (see the yellow square in Figure 4). A further intuitive result is that with these lower setup times also lower lot sizes become

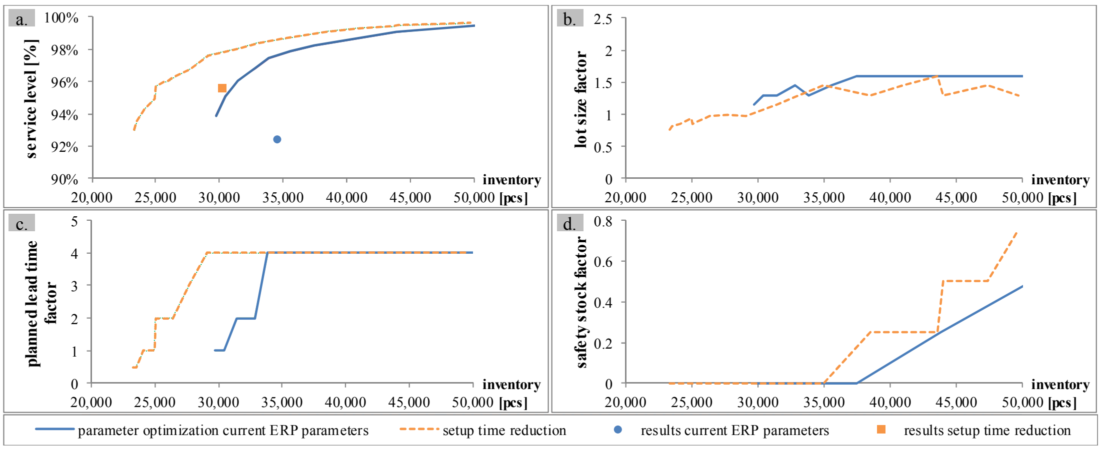

Figure 4: Comparison of optimization results for setup time reduction to results for current ERP settings.

appropriate and higher service levels can be reached without safety stock. This implies that due to the lower setup times, the shop load decreases, the production lead time reduces and more orders can be finished on time. Looking at the specific numbers shows that with an inventory of 25,000 pcs, which was the inventory in the last business year and cannot be reached without further measure in the forecasted business year (see Table 1 and Table 2), a service level of 96% is possible. An interesting finding is that optimized planned lead time with respect to service level is similar between the optimization with and without setup time reduction. This implies that even though lower lot sizes are possible, production orders still have to start significantly earlier than in the ERP system for reaching service levels above 94%. For the production company, these results provide a decision support to evaluate the trade-off between the positive effect of a setup time reduction on service level and inventory with the costs of the organizational projects to reach this reduction.

5.4 Manufacturing System Improvement Based on Load-dependent Outsourcing

In this section load-dependent outsourcing is discussed for the forecasted business year (with increased demand) but without additional capacity investment. Therefore, results in this section are an alternative to the capacity investment discussed in section 5.2. Based on the planning parameter optimization results above for 95% service level, the planning parameters are set to lot size factor 1.3, planned lead time factor 2 and no safety stock. The flexible capacity is modelled only for the main machine groups bending and welding. Based on company experts, there might be an external supplier which could be activated for these two production steps and which can provide flexible capacity. The operational handling of this outsourcing is organized as follows: items are outsourced whenever more than a predefined amount of capacity, called capacity load limit, accumulates in front of the machine group. This production capacity load limit is varied as a multiple of the planned lead time of the specific machine group. Processing of items at the external supplier takes 5 days and it is assumed that there is no limit on external capacity.

The results in Table 3 show the for the respective production capacity load limits service level (top left) and inventory (bottom left) reached as well as the percentage of capacity demand which is outsourced at machine group bending (top right) and welding (bottom right). With increasing production capacity load limit for one specific machine group, the percentage of outsourcing decreases for the specific machine group. This is an intuitive result because with an increasing production capacity load limit more production orders need to queue in front of a machine group for the outsourcing opportunity to

Table 3: Performance measures with load-dependent outsourcing.

		capacity load limit machine group welding													
		1		2		3		4		6		8		12	
capacity load limit machine group bending	1	95.9%	14.27%	95.9%	14.46%	95.8%	14.65%	95.5%	14.44%	94.8%	14.61%	93.1%	14.64%	90.2%	14.38%
		31,172	6.87%	31,194	6.46%	31,249	5.42%	31,649	4.99%	32,516	3.44%	35,523	2.36%	45,057	1.59%
	2	95.9%	8.85%	95.7%	8.79%	95.5%	8.81%	95.3%	8.91%	94.9%	8.86%	93.0%	9.02%	90.2%	8.87%
		31,132	7.19%	31,259	6.14%	31,473	5.06%	31,735	4.38%	32,250	3.34%	35,777	2.07%	45,265	1.56%
	3	95.3%	6.26%	95.1%	6.21%	94.9%	6.22%	94.6%	6.21%	93.9%	6.25%	92.4%	6.22%	89.8%	6.20%
		31,375	6.89%	31,531	6.70%	31,830	6.14%	32,134	4.78%	33,257	3.17%	36,805	2.07%	46,856	1.52%
	4	93.4%	5.63%	93.4%	5.64%	93.2%	5.62%	93.1%	5.66%	92.4%	5.66%	91.3%	5.64%	89.5%	5.62%
		33,005	7.17%	32,982	6.80%	33,253	6.03%	33,534	4.37%	35,424	2.80%	39,062	1.91%	49,293	1.51%
	6	90.8%	5.40%	90.8%	5.39%	90.7%	5.41%	90.7%	5.38%	90.5%	5.40%	90.2%	5.37%	89.3%	5.36%
		39,674	7.50%	39,658	6.01%	40,097	5.43%	40,536	4.53%	42,511	2.63%	46,393	1.92%	57,068	1.51%
	8	89.5%	5.37%	89.4%	5.35%	89.4%	5.41%	89.4%	5.37%	89.4%	5.35%	89.3%	5.35%	88.9%	5.37%
		45,685	6.24%	45,960	6.70%	46,278	5.89%	46,471	4.68%	48,185	2.45%	52,369	1.85%	63,104	1.47%
	12	88.2%	5.36%	88.2%	5.33%	88.2%	5.37%	88.2%	5.36%	88.2%	5.36%	88.3%	5.35%	88.3%	5.35%
		59,621	6.94%	59,344	6.78%	59,802	5.50%	60,277	4.14%	61,950	2.65%	65,851	1.87%	77,255	1.47%

service level	percentage outsourcing machine group bending
inventory (WIP + FGI)	percentage outsourcing machine group welding

be activated. With decreasing production capacity load limits, service level improves and inventory reduces which is linked to the reduced system load in these situations. However, service levels above 96% cannot be achieved, which is an interesting finding. A detailed analysis shows that for higher service levels again the planning parameters would have to be optimized as conducted in section 5.3.

The results in this section provide a deeper insight into the positive effects of flexible outsourcing capacity and enable the company to trade-off the additional costs for outsourced capacity with the benefits concerning investments, inventory and service level. Furthermore, the results can be applied to identify a good production capacity load factor for these two machine groups.

6 CONCLUSION

In this paper the sheet metal processing manufacturing system of an Austrian mechanical engineering company is improved focusing on capacity planning decisions. For handling the complex real world production structure, a method for item aggregation is presented. Based on a clustering scheme relevant items are identified and a respective load approximation for not in detail modeled items is applied. The study shows that with item aggregation valid insights for the real world situation can be delivered. In the first step of the simulation based manufacturing system improvement, strategic investment decisions for increased forecasted demand are supported. Based on the insights of the first step in the second step, different improvement measures are investigated to further improve the key performance indicators service level and inventory. The first studied improvement measure is a parameter optimization for the MRP planning parameters lot size, planned lead time and safety stock. It is shown that with the appropriate MRP setting, service level and inventory can be significantly improved. On the operational level a setup time reduction in combination with a parameter optimization showed an enormous improvement potential. Furthermore, also the improvement measure of load-dependent outsourcing showed a positive effect on performance indicators if external processing can be used based on the actual system load. It is found that load-dependent outsourcing is an alternative to capacity investment if higher customer demand is expected.

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AUTHOR BIOGRAPHIES

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

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

THOMAS FELBERBAUER works as a Professor in the field of Production planning and simulation at the St. Pölten University of Applied Sciences (Austria). His research interests are discrete event simulation and exact and heuristic solution methods. He received his PhD degree developing solution methods for stochastic project management. His email address is thomas.felberbauer@fhstp.ac.at.