SCENARIO-BASED ANALYSIS IN HIGH-MIX LOW-VOLUME PRODUCTION ENVIRONMENT

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ABSTRACT

The challenge of high-mix low-volume production has reshaped manufacturing systems causing increased complexity in processes and growing sensitivity to the mix and temporal distribution of demand. Efficient evaluation and experimenting for decision support in such an environment is of key importance, however it is also extremely difficult as the complex interrelation between the affecting factors and the size of the input domain would require a large number of experiments to get reliable results. The paper introduces a method based on advanced data analysis for defining typical input scenarios, aiming to reduce the computational complexity of Discrete Event Simulation (DES) analysis. The presented approach was tested in a real-life combined (manufacturing and assembly) production line and the results showed that using scenarios for representing the typical input allowed reducing significantly the number of experiments required to execute sensitivity analysis of the structural (e.g. buffer size or workforce) and the operational (i.e. sequencing) parameters.

Keywords: Simulation, data analysis, robust planning, sensitivity analysis

1. INTRODUCTION

Today's manufacturing companies have to face increasing product variability and decreasing lot sizes at the same time. This results in a growing complexity both for all planning as well as execution levels of the production.

The challenge of high-mix low-volume production has reshaped manufacturing systems and having efficient evaluation techniques for decision support in such an environment is of key importance. However, it is also extremely difficult as the complex interrelation between the affecting factors and the size of the input domain would require a large number of experiments to get reliable results.

The DES approach, available for modelling productions systems' behaviour on a detailed level, has been applied for decades mainly for the evaluation and support of decisions in planning and control (Banks 1998; Law and Kelton 2015; O'Rielly and Lilegdon 1999). The simulation models that are used for making or evaluating these decisions (e.g., by projecting the values of different key performance indicators, KPIs in time) generally represent the flow of materials to and from processing machines and the operations of machines themselves (Rabelo et al. 2003).

In the paper research results of an in-depth investigation and improvement of the delivery performance of manufacturing plants with a special focus on high mix–low volume production are presented.

The suggested novel top-down process modelling methods are validated and verified by simulation experiments.

2. PROPOSED NOVEL DELIVERY PROCESS STABILIZATION METHOD

2.1. Factors affecting delivery performance related KPI-s

Competitiveness of manufacturing companies is defined in general by three Key Performance Indicators (KPIs):

- cost efficiency;
- quality of products and production processes;
- delivery performance.

If these KPIs are in line with the worldwide benchmark figures produced by manufacturing companies of similar type, then the profitability of the company should be on a level expected by the investors as well.

When assessing delivery performance, one should distinguish between two related KPIs: the fulfilment of the *requested delivery date* (RDD) and the *confirmed delivery date* (CDD). Our focus will be set on CDD which is depending on a number of factors such as raw material inventory level, total supply chain lead-time, manufacturing /machining capability, suppliers' capability, as well as quality of planning (this list is not exhaustive).

1. *Manufacturing/machining capability:* The availability of manufacturing and machining capacities clearly affect CDD. Here, a number of various factors have to be considered, such as the machines' age and condition, the efficiency of implemented total productive maintenance (TPM) policy, the flexibility, changeability and compatibility of resources, the skill and availability of maintenance personnel, the change-over time applied in high mix – low volume environment, the capability of moving a product from one machine center to another one in case of machine break-

down, and the utilization of the machines in general. Investments in new capacities, personnel or maintenance, or flexibility and changeability will definitely incur extra costs on the one hand, but have a positive impact on the delivery performance on the other hand.

2. *Raw material inventory level:* Material availability determines when the product order can be launched in production. The probability to have raw material always available in production can be increased with higher stock levels. However, inventories incur costs as well: typically, the cost of capital of raw material inventory is calculated with a given percentage level defined by each company internally (obviously, this figure is always higher than the actual banking interest rate).
3. *Suppliers' capability:* Performance of suppliers is a key influencing factor in the CDD of a plant. Supply channels are controlled by contracts referring to minimum order quantity (MOQ), required quality, item prices and transportation cost, tooling, as well as supplier's flexibility. While having a reduced supplier network may result in more efficient and frequent deliveries, lower transportation costs and overall prices, it makes, at the same time, the plant more dependable (and vulnerable) to supplier contingencies.
4. *Total supply chain lead-time:* The shorter the total supply chain lead-time, the better are the chances to deliver products at CDD. Production and supply planning have a key role in lead-time reduction. In an ideal case instead of the manufacturing processes, the real bottleneck is the lead-time of raw materials from suppliers. Note that lead-time reduction on the supplier side will not only improve CDD performance of the plant but, at the same time, reduce also the required (safety) stock level.
5. *Quality of planning:* While the requested delivery date (RDD) is an exogenous factor in managing production, the CDD is the result of planning. If the promise confirmation is given to the customer on the basis of careful and principled planning that takes into consideration future load, resource and material availability, and does it in a robust way, then the chances of keeping this promise are clearly better. On the cost side, however, advance planning requires precise and up-to-date status information, appropriate information and communication technologies (ICT), disciplined and orchestrated management of a number of planning functions, and sophisticated decision-making mechanism.

2.2. Delivery process stabilization method

The above (far from exhaustive) list of issues show that the CDD performance is determined by a number of *internal* and *external* factors. Some of the factors are cross-correlated, and efforts in improving delivery performance in any way may easily deteriorate other KPIs, most importantly, *cost*. With other words, CDD improvement is never for free, and a trade-off has to be fund when setting target levels of attainable KPIs. Since in our actual problem domain *product quality is not negotiable*, the key problem boils down to finding ways to improve CDD performance at an acceptable cost that warrants both customer satisfaction and profitability of production.

Hence, the method is articulated around the following – closely related – stages, formulating a top-down approach:

1. *Scope setting and characterization:* Classify situations in high mix–low volume production, delimit those cases where CDD performance can be warranted by traditional techniques of production managements (e.g., by inventory control, or capacity planning). Make an in-depth investigation of cases which are critical, determine the main factors – both internal and external – that affect CDD performance.
2. *Sensitivity analysis and selection of factors:* Make a sensitivity analysis for assessing the impact of the above factors on CDD performance. Select those factors for further investigation whose influence – both positive and negative – on CDD are the most significant.
3. *CDD improvement techniques:* By relying on the selected factors, define those techniques that are implementable in a given production environment and contribute to the improvement of CDD without deteriorating product quality (which is taken as a non-violable requirement).
4. *Delivery performance* – cost trade-off: Assess the cost impacts of the selected (most promising) delivery performance improvement policies and find a balanced trade-off between meeting these two main KPIs. Results expected in form of an implementable method for measuring cost implications of CDD improvement techniques, waging CDD performance against cost and finding an acceptable trade-off.

In the paper methods related to the second item (sensitivity analysis and selection of most influencing factors) are introduced via the analysis of large-scale real-life datasets generated from the archives of a high mix–low volume production facility by applying simulation and data analysis techniques.

3. SCENARIO-BASED EXPERIMENT DESIGN APPROACH

Handling all the influencing factors within one experimental scenario, as described in the previous section, it can be considered as a problem of intractable complexity in the simulation domain. Therefore, the factors have to be separated, moreover, the number of factors and the number of resulting scenarios have to be reduced. In the following section a novel method is proposed for supporting scenario definition for simulation studies having significantly less number of experiments with the same expected output quality.

Classical *Design of Experiment* (DoE) techniques enables reducing computational efforts by selecting and focusing on the factors affecting most significantly the output variable (KPI). A well-known method is *factorial experiment design*, when assigning a possible/usual low and high value to all factors defined. After identifying the most significant factors, a more comprehensive study by the combination of the remaining factors are required. Note that for categorical (qualitative) factors (e.g., dispatching rule for jobs entering the system) the number of possible values is limited. However, non-categorical (quantitative) factors may have "infinite" values to be assigned with. The categorization of these values may reduce the number of scenarios when designing the experiments and not to lose diversity of input degrading modelling accuracy.

The proposed approach introduced here focuses on identifying the similarity between several values of *Demand* (Figure 1), taken as the main categorized input factor.

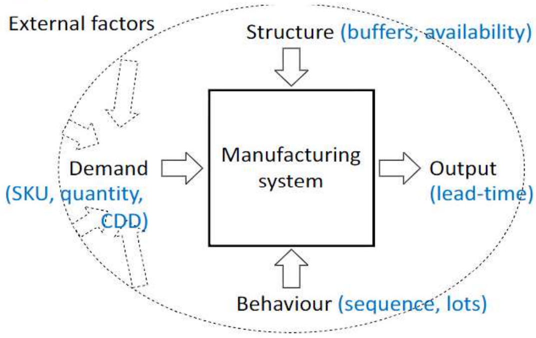

Fig. 1. Influencing factors of a manufacturing system on the production control level.

External factors are covered/modelled by the input factor *Demand* (Figure 1). *Demand* represents SKU (product code) of products, quantity to be produced and CDD, defined at the production planning level in form of a daily input-mix of products to be produced in the system. Product-related features are only considered in the simulation model.

5. *Structure*, internal: structural parameters, e.g., buffer sizes, availability of operators and machines.
6. *Behaviour*, internal: control parameters, e.g., selected routings, sequence of jobs, lot-sizing.
7. *Output*: lead-time and lead-time variance.

The purpose of the experiments is twofold:

a. Validate if the methods are applicable for the reduction of the number of scenarios needed for a comprehensive simulation analysis on system-sensitivity (reducing lead-time variance and so, improving CDD).
b. Categorization of the input factor *Demand* could result in assigning situation-related sequencing and lot-sizing rules to a finite number of demand patterns. This would support the planner in creating production schedules/sequences by applying a formalized method, considering the reduction of lead-time variance, as a primary target.

4. COMPUTATIONAL EXPERIMENTS

4.1. Case study

The production line under analysis is for making complex products, which includes both machining of raw materials and assembly of the final product. In general machinery and assembly areas and operations are separated in the production environment, as in machining usually the equipment is in the centre of decisions, while in assembly the focus of the process analysis is on the human workforce. This *combined* production line, therefore can be viewed as a factory within the factory, which also creates complex interrelated connections between the KPIs and the structural and operational parameters of the line.

Model building and abstraction is essential for any kind of analysis and decision support process. For sensitivity analysis in such a complex environment, where analytical solution is probably out of the scope, the application of declarative tools such as Discrete Event Simulation (DES) of material flow is widely accepted.

4.2. Description of the material flow

The machining area contains four CNC machine centres and two CNC turning machines and a conveyor line. The washing operation for machined parts is positioned between the machining and assembly area. There is a machine operator for each machine.

The process starts with the aluminium tube cutting, followed by the machining of the tubes – according to the production schedule. The piston rod manufacturing is done in parallel with the machining of the tubes. After these operations, the tubes and piston rods belonging to the same order are sent to be washed. After the washing operation these parts are put in a box. These boxes are in line, waiting for the final assembly operation.

Conveyor belts transport the cut material to four milling and two turning machines where the machined surfaces are finished. Each machine requires human operators for the change-overs and setups before the processes, served by a pool of machinery workers in the area, which also means that no dedicated workforce is assigned to any of the machines. Accordingly, the list of assigned tasks is defined by rules for each worker. The final step in the machinery is a washing station with manual material transport.

The machinery area provides supply to the preassembly area, where semi-finished products required in multiple product families are assembled. The final assembly and test of the finished products are performed in two assembly work cells, each one operated by one or two dedicated workers in a one-piece-flow production with manual material transport. Most equipment used in the assembly are designed especially for the products, however –in order to handle multiple product families and variants– there is a wide variety of applied fixtures and tools, which require manual change-over.

The conveyor belt has a length-dependent buffer-capacity and each station has a specified buffer area as a fixed-size number buffer.

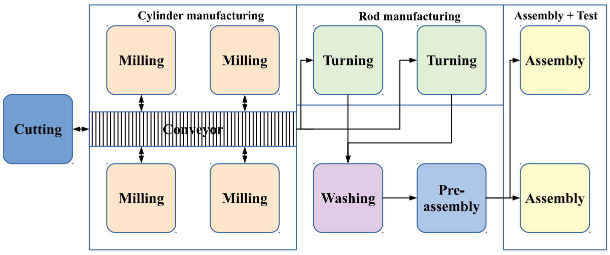

Fig. 2. Overview of the material flow in the production line.

4.3. Simulation modelling

The simulation model of the production line was created in the Plant Simulation DES software. The processes durations are modelled as product-dependent, stochastic cycle times, while the change-over times are given by a 4-dimensions matrix, characterized by the following product parameters: product family, diameter and stroke length. The sequence of the daily product mix is given as an input for the model.

The goal of the simulation experiments is *to analyse the sensitivity of the output* to the key structural parameters and to the input. These can be divided into two categories, namely structural and operational parameters. The operational parameters are the essential input product sequence of the model. The structural parameters define aspects of how the elements of the simulation model behave. The following were identified as structural parameters: size of buffers, machine availability and workers availability.

In order to execute the sensitivity analysis, the ultimate *outputs* of the simulation model are the completion date of the orders and the total throughput time for the daily production executed in 3 shifts.

4.4. Preliminary simulation experiments

Analysing the structural parameters is a typical application of DES tools and despite the possibly large domain of the variables such experiments can be handled efficiently. The domain of the structural parameters are summarized in Table 1.

	Min	Max	Values
Buffer size	0	∞	6
Human availability	60%	100%	4
Machine availability	85%	100%	11

Table 1. The domain of the structural simulation parameters.

The average runtime of an experiment is below 5 seconds, which means that –based on the defined values of the domain– the structural parameters can be evaluated in ~4000 seconds (assuming 3 experiments with each setting). This is well within the usual time requirement of complex simulation experiments; however, this assumes only one product sequence along every experiment. Unfortunately, the operational parameters have a significant impact on the analysed structural parameters and therefore they cannot be studied separately. Another consequence is that, due to the larger domain of the input sequence (a daily product mix can contain over 40 items) evaluating every combination is no longer feasible in the available time.

Fig. 3. shows the results of a preliminary simulation study, executed on experimentally defined scenarios, using baseline data as input. It can be stated that the same structural parameters resulted in completely different outcome showing it is important to include the effect of the product sequence (compared to *exp1* as baseline) into the sensitivity analysis (denoted as *exp19-exp21* in Fig. 3.).

A possible solution for handling this complexity is to aggregate the input domain into a set of input scenarios, which contain defined settings of both structural and operational parameters.

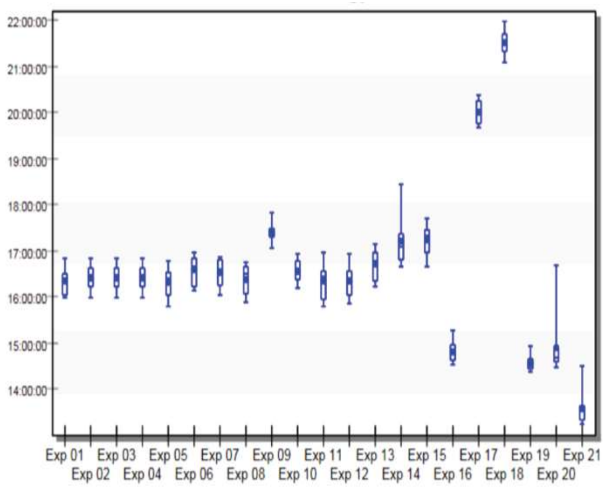

Fig. 3. Experiment settings (horizontal axis) exp16-21 deal with buffer sizes (structural parameters) and sequences of jobs, showing significant relevance on output (makespan, vertical axis, in hours).

4.5. Reducing the domain size of the input mix

The first step in handling the complexity is to reduce the domain size defined by the daily input mixes. A daily input mix is defined by the number of each product type planned to be in production on a given day. Thus, it can be formalized as a feature vector where each product type is described by its planned daily amount. Collecting data from a one-year time frame resulted in data for 243 workdays, where 39 different types of products were in production. It is an important assumption that this period is considered as representative for analyzing the behavior of the system and, therefore, it is set as the baseline of the analysis. The $p=39$ different products define the length of the feature vector, with $n=243$ observations.

The aim of the reduction here is to define a set of representative input mixes with a smaller cardinality than n, which can provide a similar behavior of the system. The system's behavior is evaluated by using the simulation model and comparing the following KPIs at each experiment:

- The average net lead-time (LT) of products.
- The total makespan (MS) required to finish the production of the input-mix.

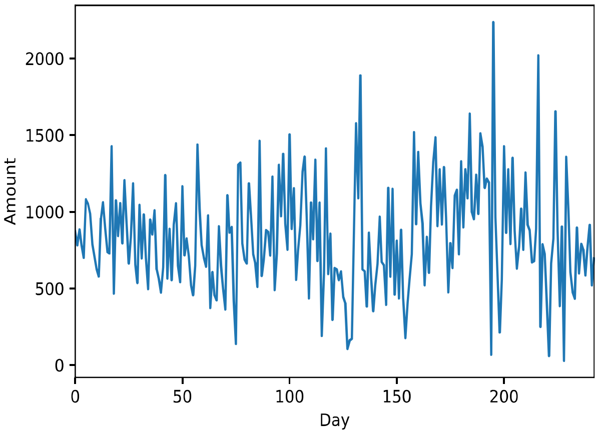

Fig. 4. Fluctuating daily workload

In order to create the reduced cardinality sets of input mixes the baseline data was analyzed using unsupervised learning, specifically clustering techniques. In this approach the only features or descriptors applied during the analysis were the above-mentioned daily workload of each product type. Therefore, the same feature vectors were used for measuring the dissimilarity between the daily input mixes. In order to eliminate the distortion caused by the fluctuation of the daily workload the baseline data is normalized at each day (Fig. 4 shows the fluctuation of the total daily workload).

On the normalized baseline data, the cluster analysis is performed by *hierarchical clustering* as –by using *dendrogram*– it provides an adequate visualization of the dissimilarity even with a considerable number of features without specifying the number of clusters beforehand. The *dendrogram* is created by applying the average or UPGMA algorithm. Fig. 5 shows the results of the hierarchical clustering. Note that–because of the normalization–the min (0) and max (1) values denote the largest and smallest workload calculated for each day, respectively.

Using the *maxclust* criteria the observations (i.e. the daily input mixes) are grouped into a set of clusters, with the following (decreasing) cardinality: 100, 50, 20, 10, 5.

This means that the original *n* observations were represented by 100, 50, 20, 10, 5 cluster centroids each of which is obtained by the geometric mean of the observations assigned to each cluster. An example result of the clustering, where the applied number of clusters is 10, is shown in Fig. 5.

Fig. 6. illustrates how the observations are assigned to clusters in each case. Note, that for lower number of clusters the majority of observations lie in one cluster. Compared this with Fig 5, it can be concluded that these major clusters represent days where a single product rules the majority of the daily workload, while days with more distributed workload form smaller clusters. The higher the number of clusters the more distributed they become over the daily observations.

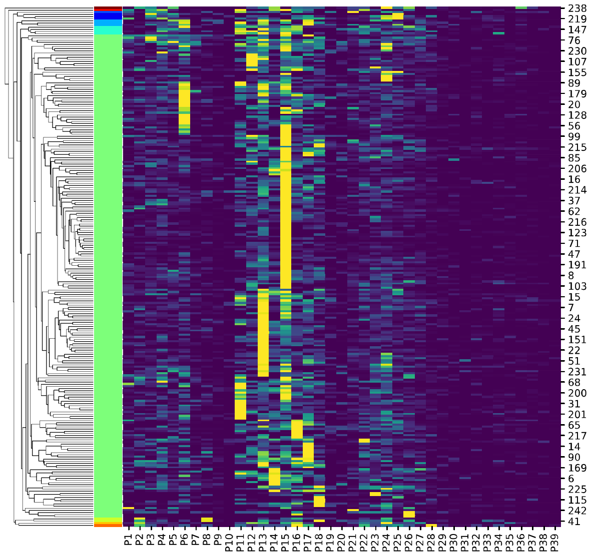

Fig. 5. Clustering the daily demands by quantity for SKU-s

4.6. Discussion of the simulation results

In order to evaluate the results of the clustering the centroids, which are using the normalized data, were multiplied by a constant representing the planned average daily workload, which is given by the company. The newly calculated daily input mixes then were evaluated by using the simulation model and compared to the baseline data. The simulation experiments are carried out with two settings. In the first run the daily workload of each product is handled as a single batch, while in the second run a simple lot splitting rule was applied, which forms lots with a maximal size of 49 (a value chosen as a best practice by the company).

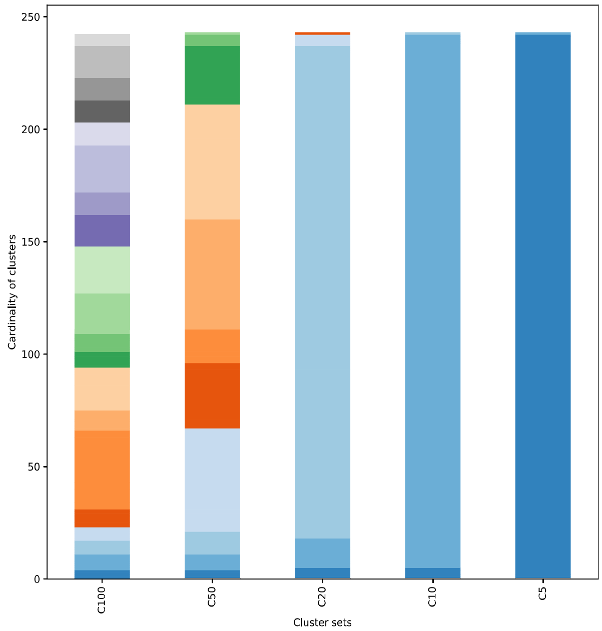

Fig. 6. The distribution of cluster labels for the 5 cluster sets

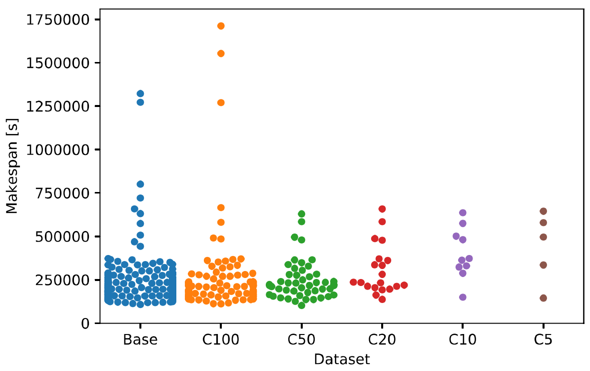

Fig. 7. Simulated makespan values for the baseline data and the five datasets created by clustering without lot-size control.

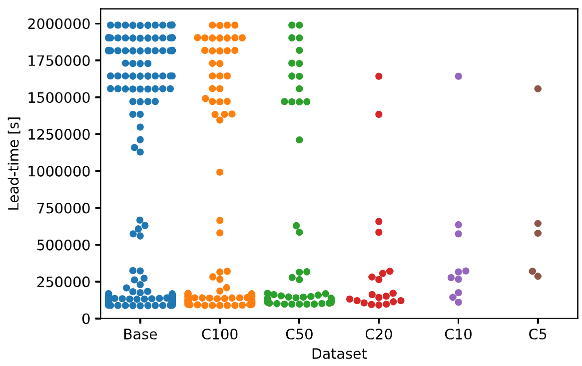

Fig. 9. Simulated average lead-time values for the baseline data and the five datasets created by clustering without lot-size control.

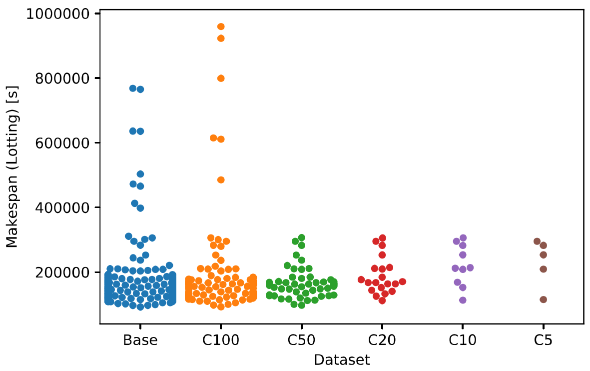

Fig. 8. Simulated makespan values for the baseline data and the five datasets created by clustering with lot-size control.

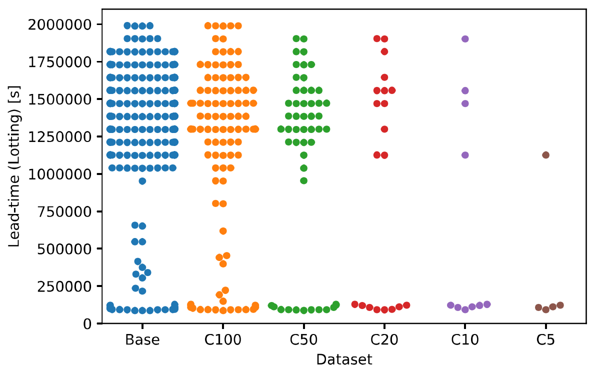

Fig. 10. Simulated average lead-time values for the baseline data and the five datasets created by clustering with lot-size control.

Fig. 7. shows the total makespan of daily input mixes without lot-size control, and Fig. 8. shows the total makespan with lot-size control. The figures display the results by using *swarmplots*, which are able to show cardinality of the clusters and the distribution of the values as well. Note, that the total makespan decreases when lot-size control is applied. This is probably due to the fact that large-sized lots can easily block resources for a long period of time, therefore causing low resource utilization. It can be concluded that even the low cardinality clusters represent the spread of the baseline makespan data well for the majority of the observations. However, it is also visible that the most extreme values do not appear in clusters where the domain size reduction is in the order of magnitude (C50, C20, C10, C5). This phenomenon is even stronger when lot size control is applied.

Fig. 9. shows the average lead-time for products in daily input mixes without lot-size control, and Fig. 10. shows the average lead-time with lot-size control. In these cases, the approach appears to perform better, as–without lot-size control–the spread hardly shrinks until dataset C50 and only dataset C5 shows significant shrink. When lot-size control is applied the results are even more consistent until dataset C5.

5. SUMMARY AND OUTLOOK

The paper introduced a method based on advanced data analysis for defining typical input scenarios, aiming to reduce the computational complexity of Discrete Event Simulation (DES) analysis.

The presented approach was tested in a real-life combined (manufacturing and assembly) production line of a high-mix low volume environment. The results showed that using scenarios for representing the typical input sets allowed significantly reducing the number of experiments required to execute sensitivity analysis of both the structural (e.g. buffer size or workforce) and the operational (i.e. sequencing) parameters of the line.

A method was introduced, as a possible solution for handling this complexity, in order to aggregate the input domain into a set of input scenarios, which contain defined settings of both structural and operational parameters. Thus, reduced cardinality sets were provided by clustering techniques on the input mixes of the baseline data, formulating a set of representative input mixes with a smaller cardinality.

In order to evaluate the results of the clustering, the newly calculated daily input mixes were evaluated by using the simulation model and compared to the baseline data.

It can be stated that by applying the proposed methods even the low cardinality clusters represent the spread of the baseline makespan and lead-time data well for the majority of the observations. However, it is also visible that the most extreme values do not appear in clusters where the domain size reduction is in the order of magnitude

As an outlook, the research work presented in the paper had two distinct goals. On the one hand, to validate, if the methods are applicable for the reduction of the number of scenarios needed for a comprehensive simulation analysis on system-sensitivity. On the other hand, categorization of the main input factor (*Demand*) could result in assigning situation-related sequencing and lot-sizing rules to a finite number of demand patterns. This would support the planner in creating production schedules/sequences by applying a formalized method, considering the reduction of lead-time variance, as a primary target.

The proposed solution is intended to be extended by more comprehensive analysis on applying and comparing different clustering methods, as well as introducing new dissimilarity measures for the clustering algorithms. Moreover, a set of new experiments on selecting other production related KPIs would be necessary, by applying the new data available from the clustering.

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