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Data analytics-based decision support workflow for high-mix low-volume production systems

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In order to answer the ever-fluctuating demand of high-mix low-volume production environments, reconfiguring the production systems and improving their performance rely heavily on the application of advanced decision support tools. Estimating the expected values of the performance measures (KPIs) in the face of these decisions, however, is even more challenging in such an environment as the complex structure, behavior and input demand creates an enormously large variable domain restraining the analysis. The paper introduces a novel workflow for providing simulation-based decision support for improving KPIs of high-mix low-volume production systems by reducing the size of the input domain with the application of unsupervised machine learning techniques.

Decision making, Simulation, Data analytics

1. Introduction

Companies responding to fluctuating demand of a broad variety of products and accompanied services need special faculties of changeability, adaptiveness, and responsiveness to remain competitive. There is a common understanding that in so-called *high-mix and low-volume* (HMLV) production environments both the structure and the behaviour of the systems should be tailored to the changing conditions by finding trade-offs between a tangled and typically conflicting set of *key performance indicators* (KPIs) and *cost*. Floating above all the waves generated by external sources (market demand, suppliers) or internal causes (resource availability, inventory levels), HMLV companies have to show a consistently stable, high-level performance especially in terms of quality and service level [1][2].

On a daily basis, HMLV production can be managed by cross-functional, proactive workforce supported by appropriate pull mechanisms, order grouping and visualisation techniques [3]. *Production levelling* decouples market demand from production orders so that mix and volume loads the available resource base in a balanced way. This technique is widely, often implicitly, applied. *Clustering* of products by ABC/XYZ analysis or some machine learning method into families and defining patterns for their execution sequence on bottleneck resources can greatly stabilize service level [1]. When expected delivery times are short, the techniques of lot-splitting and limiting the load of order releases can be well applied [4]. A combined measure including organizational and technological aspects is suggested in [5] for increasing machine equipment effectiveness and throughput, specifically in HMLV production. Extension of resource capacities or availability (by proper maintenance), inclusion of buffers, increased levels of inventories and work-in-progress can also result in consistently high delivery performance, but rarely at affordable cost levels. However, the analysis of the interplay of all but the most important structural and behavioural factors is cumbersome, even for approximate, system dynamics [6] or logistics curve [7] models of a single work system. Hence, it remains still open how to warrant consistently high performance level towards customers in an HMLV environment.

Recently, in parallel with the proliferation of massive sensing, data processing and storage techniques characteristic to cyber-physical production systems [8], the broadly shared view evolved that (big) *data analytics* can provide the right response to the growing complexity of production management, by replacing or complementing some of its functions [9][10]. While admitting the success of advanced *machine learning* methods in identifying models and predicting the behaviour of complex production systems [11][12], it must be emphasised that just those algorithmic methods which are able to work over very large datasets are hardly capable of exploiting the available engineering background knowledge. Still, there is a common view that *simulation*, and in particular discrete event-based simulation (DES) provides the most efficient set of tools for analysing the complex impact of decisions which are related both to the *static structure* and *dynamic behaviour* of a production system [13][14]. Fine granularity of details, semantic clarity, transparency, conformance to real systems, rich assortment of available modelling and evaluation tools are all on the side of merits, while main shortcomings are limited generality, potentially haphazard, uncharacteristic future scenarios and extreme computational load. The latter issue can be alleviated by simulation metamodeling [15][16], but only at the cost of transparency. Hence, the goal of this work is to *combine the strengths of model and data-driven analytics* in a novel way, specifically in the service of improving the management of HMLV production systems.

2. Problem statement and solution approach

Point of departure of this study is that a company is already in command of some key enabling techniques of cyber-physical production [8]. First and foremost, it is able to build digital models of its physical and logistic processes, and is routinely using enterprise information and (semi-) automated production planning and control systems. It collects and maintains data related both to its external business environment as well as its internal operations on all the strategic, tactical and operational levels in a systematic and synchronized way. Much precious, often implicit and tacit production engineering and management knowledge provides the background of these systems, whereas one can assume with good reason that the immense amount of data accumulated in past records hides pieces of information which can be turned into knowledge for improving the performance of the overall system. The general questions are whether there are ways from the realm of models to that of the data, and *vice versa*; can the various potentials be exploited in conjunction. If so, how can such an improvement process be included into the decision-making process of a company? When it comes specifically to HMLV production, how can such a company fulfil its commitments towards its customers under changing circumstances by relying on its advanced cyber-physical faculties? The answer lies in a new way of using the models for analysing the impact of potential changes either in the structure or the behaviour of the system by experimenting with *generalized, compressed past records*. This makes projection from past to future admissible and the whole approach computationally tractable.

Accordingly, the proposed analysis and decision-support workflow has the following main stages:

1. *Scope setting*. Selection of the most relevant factors which have an essential impact on the operation of the HMLV production system. Market demand, system structure and capacity, planning and control logic, buffering and inventory policy, supplier performance, availability and reliability of machine and human resources, maintenance policy are such typical factors. Scope of analysis is also set by the determination of KPIs, primarily delivery performance, lead time, quality, resource utilization and cost efficiency. Note that when quality is non-negotiable, as it is predominant in the practice, the *conflict of delivery performance and cost* emerges as the core issue in managing HMLV production systems.
2. *Model building.* Developing a detailed DES model of the production system at hand, together with its external environment. The model should capture all the factors setting the scope, but its granularity can be even much finer.
3. *Rough-cut sensitivity and cost trade-off analysis*. Grouping the factors affecting the operation of the system along the dimensions of *internal vs. external* and *structural vs. behavioural*, reflecting source and type. After factorial experiment design [14] the execution of sweeping simulation runs and identifying and ordering those factors which mainly influence the selected KPIs. Visual management tools [17] can help to pinpoint them, or even their combinations. Finally, selecting those control factors which can be managed at a reasonable cost.
4. *Focused analysis with model and data-driven analytics.* Identification of the possible decision situations, understanding and building up a detailed decision workflow of the *as-is* situation, together with the information basis of the decisions (e.g., in what situations are specific sequencing rules used). *Generalizing* past data by means of machine learning techniques and running detailed predictive simulation runs with decision alternatives over these compressed datasets. Selecting the best choice, together with the context defined by the generalized situation.
5. *Verification and validation*. Performing experiments for the comparative analysis of the original and the improved decision-making processes, by using the digital models.
6. *Maintenance and update.* Under changing circumstances, repeating the workflow time and again. Beyond updating the digital models, changes instigated should be revised with a frequency which corresponds the actual decision horizon.

3. Industrial case study

A real-life case study, using the proposed workflow is introduced here, building on results achieved earlier by *scope setting and model building*. The use case was delivered by a HMLV company well advanced in digitalisation (winner of the Industry4.0 award of the Hungarian Factory of 2017 contest). Specifically, a combined system was selected for the case study, producing daily ca. 1700 products of 39 types (each of high complexity) belonging to four families. The facility could be taken as a factory within the factory (see Fig. 1).

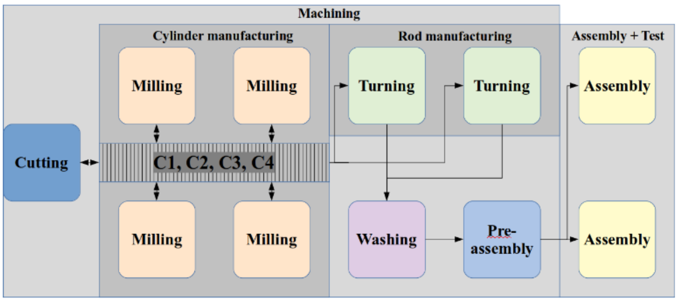

Fig. 1. Material flow in the sample production system

The machining area contains four CNC milling centres and two CNC turning machines and a conveyor line. The manufacturing process starts with the tube cutting, followed by the machining, while the piston rod manufacturing is performed in parallel with the machining of the tubes. The machinery area provides supply to the preassembly area, where semi-finished products required in multiple product families are assembled, after the washing operation. There are two assembly work cells for the final assembly and test of the finished products, in a one-piece-flow production with manual material transport. The conveyor belt has a length-dependent buffer capacity and each station has a specified buffer area of fixed size.

In the above setting, the direct industrial motivation is to consistently improve the delivery performance at reasonable cost. Hence, in response to the (external) requested delivery due date, a reliable *confirmed delivery due date* (CDD) should be determined for each customer order (CO), possibly close to the requested. Once the CDD is fixed, it can only be changed by serious degradation of the delivery performance. Thus, planning and control of the manufacturing system—and the way how to improve CDD conformance—is a critical issue.

Applying the proposed workflow (stage 1), the rough process model of the decision flow was built, a set of input mixes and related volumes were collected for a one-year period, as well as a couple of internal and external factors were identified influencing the CDD assigned to a certain customer order (see Fig. 2).

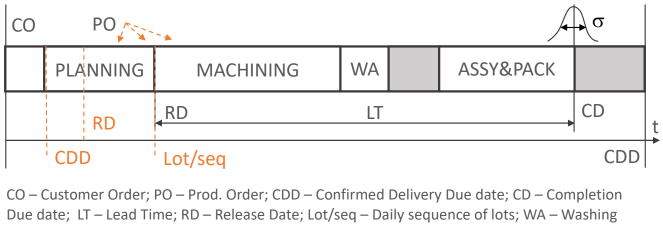

Fig. 2. Timeline of an order with main decisions (orange).

As main *external factors* the product item number, the volume/day are relevant, while *internal factors* are grouped as structural (buffer sizes, operator and machine and operator availability) and dynamic (lot-splitting and -sequencing) (for details, see [2]).

As highlighted in Fig. 2, during the planning process the customer orders (CO) are converted to production orders (PO) by assigning CDD and release date (RD) at the planning level. The *decision points* are marked with orange. At the RD a simple pattern of lot-splitting and -sequencing rules is combined at operational level, in order to form a viable daily sequence of POs for the coming time period (by default 2 shifts). LT defines the time required for a PO to be completed with all its required operations while started at RD and finished at CD. It is important to note that the primary goal of the analysis was to reduce the number of unmet CDDs, i.e. to keep CDD conformance. Hence, after setting up the relation between LT and the assigned CDD (CDD = β + LT(*lot, seq,*…)) the focus was on reducing LT variance for individual orders (see grey area between CDD and CD in Fig. 2), and the *makespan* for a complete daily demand as far as possible. Makespan is the indicator for measuring the completion time of a set of POs to be produced in an allocated time window (by default 2 shifts).

4. Data and model-driven analysis

4.1 Sensitivity analysis of service level and cost trade-off

Having the detailed simulation model of the above described production system in hand, a rough-cut sensitivity analysis was performed (factorial experiment design, with high and low values assigned to the factors, see [2]) in order to find the most relevant ones and to measure their effect on CDD conformance. As it turned out, the availability of human operators had limited effect on the makespan, while in some cases low availability of certain milling and turning machines significantly deteriorated the output. This was strongly related to the daily mix and so to the workload on these machines. From the simulation experiments, in particular sequencing and lot-sizing (dynamic), as well as buffer sizes (structural) emerged as the most significant influencing factors, at zero and reasonable cost, respectively. Therefore, subsequent analysis (stage 4) focused on them.

4.2 Dynamic changes—lot-sizing and sequencing

Following the workflow stages, an in-depth analysis of the selected dynamic factors is presented below. As lot-sizing and sequencing are carried out on a daily basis, for analysing their effects on the makespan a series of experiments were conducted on a dataset containing daily input mixes (i.e. daily inputs for sequencing and lot-sizing). This *baseline dataset* had to cover a representative time period, whereas, so as to keep the computational demand of simulation runs at bay, it had to be of limited size. Extending the work introduced in [2], the size of the baseline dataset was reduced by *unsupervised learning* (k-means clustering) [18]. All in all, the baseline dataset contained 235 daily input mixes from which a series of clusters were formed. The predefined numbers of clusters were 5, 10, 25, 50, 75 and 100, respectively. Each cluster is represented by its centroid, which is the closest (in terms of Euclidian distance) data point from the cluster to the geometric mean of the cluster. Thus, each centroid corresponds to an actual daily input mix. Fig. 3 presents a heatmap of the baseline dataset, where the columns stand for the products, and each row is a daily input mix. Additional columns on the left represent the six kinds of clusterings. Rows are sorted according to the 25-means clustering (C25, see left hand side of Fig. 3). Daily mix groups visually arise from the map; for instance, in C25 the first two clusters are dominated by a single product (P32), whereas the differences of the two clusters are due to demand for geometric variations of the same product type (P), and demand for products of another type (S).

So as to asses and compare the representative power of various clusterings, simulation experiments were run on the baseline dataset and the centroids by applying the combination of different sequencing and lot-sizing rules. Rules were suggested by planners of the factory and the literature [1][4]. The sequencing rules are composed of sub-rules, which are executed on the input mix in a fixed order (see also Table 1). First, *ordering* specifies how the daily input mix is sorted: *base* uses a predefined, heuristic pattern; *max* performs a descending sort according to volume; *oscillation* sorts descending and then appends every second item to the end of the sequence in ascending order. *Grouping* specifies if products with matching secondary attributes (like diameter, length) are to be grouped together after sorting. There are two *lot-splitting* techniques: *cycle* splits each item of the sequence according to a predefined lot-size and appends the rest to the end of the sequence and repeats this until no item is above the given lot-size. *Local* only splits the lots, but keeps their ordering. Table 1 shows the sub-rules and their domains, which can be combined to form 10 different sequencing rules altogether, which are later referred to by combining the values of the sub-rules (e.g. "max_False_cycle").

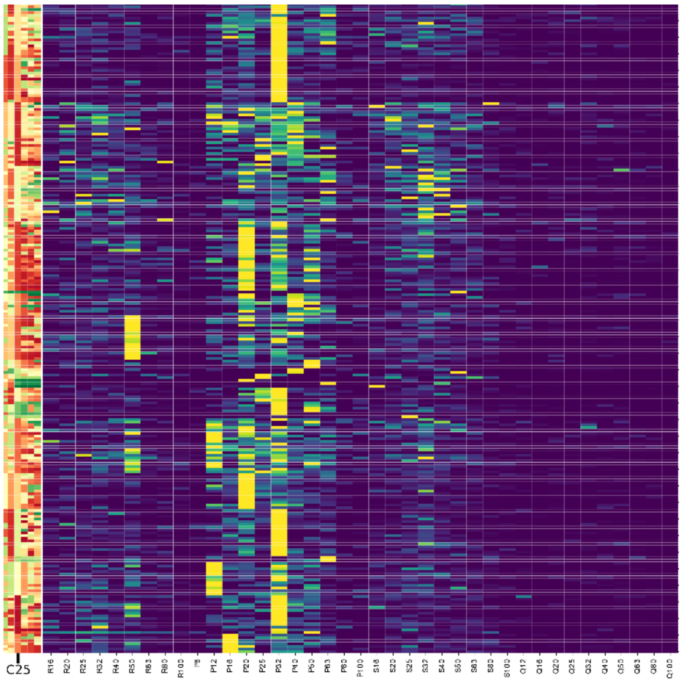

Fig. 3. Heatmap of six clusterings (with color-coded labels on the left) of the daily input mixes (brighter colors denote larger volumes).

Table 1 Sub-rules specifying the sequencing and lot-sizing rules and their domains.

Ordering	Domain: grouping	Domain: lot-splitting
base	{False}	{cycle, local}
max	{False, True}	{cycle, local}
oscillation (osc)	{False, True}	{cycle, local}

The simulation experiments were evaluated by comparing how the various sequencing and lot-sizing rules performed on each dataset. The performance metric for a given rule and dataset is the percentage of daily input mixes for which the application of the rule resulted in a makespan that remained below 105% of the best, minimal makespan for that specific input mix. A comparison of the different rules' performance for each dataset is illustrated in Fig. 4, while the MAE.S column of Table 2 shows the Mean Absolute Error (MAE) of rule performance on the various clusters compared to that on the baseline dataset.

Table 2 Numerical comparison between the performances of the different datasets.

Dataset ID	MAE.S	MS.S	MAE.B
C5	0.166	0.963	0.273
C10	0,149	0.958	0.180
C25	0,106	0.947	0,092
C50	0,057	0.946	0,091
C75	0,054	0.924	0,062
C100	0,036	0.922	0,015
base	0	1.000	0

Based on the graph and the numerical results it can be seen that the C25 dataset can properly represent the baseline dataset, thereby reducing its size by an order of magnitude. For the input mixes in each cluster the rule performing the best on the cluster centroid was assigned, which resulted in decreased makespans as it can be seen in Table 2. The MS.S column displays the makespan in percentage of that of the baseline dataset. The results show that the effects of dynamic changes and the evaluation of different sequencing and lot-sizing rules can be successfully carried out on representative, but smaller datasets created by unsupervised learning. It became also clear that it is worth adapting the sequencing and lot-sizing rules to the actual daily demand.

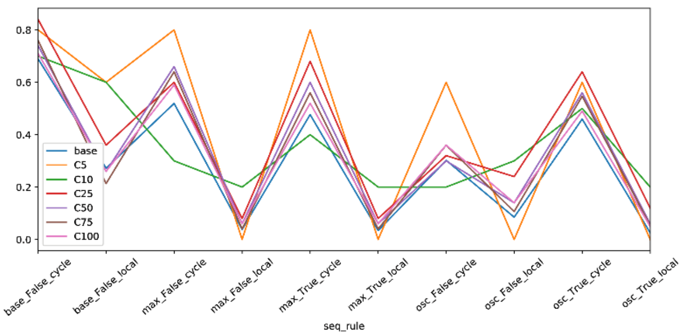

Fig. 4. Impact of clustering of daily demands to performance prediction.

4.3 Structural changes—buffer sizes

In contrast to lot-sizing and sequencing, the decisions resulting in structural changes do not happen on a daily basis. Making such changes requires substantial resources and thus, it is essential to evaluate their effects through reliable experiments beforehand. Similarly to the analysis of dynamic changes, the dataset used in the simulation experiments has to be concise and representative at the same time.

Using the results of the already available clustering, a series of experiments were conducted in order to do sensitivity analysis as for adjusting the sizes of different buffers. As it is shown in Fig. 1, the C1-C4 conveyors supplying the milling machines also act as buffers. The product routings for each product define which milling machine and therefore which conveyor to use. This means that changing the length of a conveyor is expected to have an input mix dependent effect on the makespan. In the experiments, for each dataset the length of each conveyor was increased (one at a time) and the resulting makespans for the different clusterings were compared just like the performance of the sequencing rules. Now the performance measure was the percentage of cases when changing a given buffer resulted in the best makespan. Column MAE.B of Table 2 shows the mean absolute error for the different clusterings, and one can see that the C25 dataset provides similar values for buffer size changes as for dynamic changes, thus making it a suitable choice for representing the input mixes.

4.4 Verification of decisions

In order to validate the effects of the structural and dynamical changes based on the insights gained from the C25 dataset, experiments were done on input mixes of the baseline dataset with the modified system structure and control. Hence, the size of the most sensitive buffer was increased and each daily input mix was classified according to the C25 clustering. Sequencing and lot-sizing was performed thus in a situation dependent way, by the application of the rule best performing on that specific cluster. The resulting daily makespans were then compared to the daily makespans of the original model which was driven by the baseline dataset. Table 3 gives descriptive statistics of the results, showing the percentage reduction of the makespan summarized by pushing time windows of 1, 5 and 10 days, respectively, over the whole horizon (which is 235 days long). It can be concluded that even though on a daily basis the impact of novel methods may vary (first column), on a longer horizon they definitely provide suitable base for improved decision-making in a HMLV production system. The expected makespan reduction of the imposed changes indeed paid off, thus founding their real-life implementation.

Table 3 Numerical performance comparison of the different datasets.

	Roll. Sum (1)	Roll. Sum (5)	Roll. Sum (10)
mean	0.966	0.967	0.950
std.	0.512	0.233	0.170
25%	0.832	0.868	0.886
50%	0.933	0.907	0.905
75%	1.001	0.942	0.930

5. Conclusions

Decision making in companies which have to fulfill ever-fluctuating demand in a HMLV production environment is an extremely challenging task: mistakes are barely tolerated since the negative effects almost immediately reach the customers, whereas the right and cost efficient answers have to be found in a complex web of interrelated options.

The paper suggested a novel workflow for decision support that combines model- and data-driven analysis, by making intensive use of advanced tools of industrial digitalization, discrete event simulation and unsupervised learning in particular. Main stages of the workflow follow a sequential refinement strategy, starting from strategic scope setting, followed by model building and rough-cut sensitivity analysis, and then by focused simulation experiments over compressed datasets. For this stage in particular, k-means clustering of a baseline dataset representing the daily demand mix of products spanning a relatively long horizon was suggested.

Guiding through a real-life industrial use case, the paper has shown that the workflow can discern both structural and behavioral factors—like buffer sizes, or lot-sizing and sequencing rules—whose adaptive changes can consistently improve overall system performance. Further progresses can be expected by using the simulation model as a digital twin, or applying data analytics to enhancing the integrity of collected datasets, as suggested in [19].

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References

[1] Bohnen F, Buhl M, Deuse J (2013) Systematic procedure for leveling of low volume and high mix production. *CIRP Journal of Manufacturing Science and Technology* 6(1):53-58.
[2] Gödri I, Kardos Cs, Pfeiffer A, Váncza J (2018) Scenario-based analysis of a high-mix low-volume production environment. *17th Int. Conf. on Modelling & Applied Simulation (MAS 2018)*, 17-19 Sept, 2018. pp. 173-179.
[3] Powell DJ (2018) Kanban for lean production in high mix, low volume environments. *IFAC-PapersOnLine*, 51(11):140-143.
[4] Thürer M, Fernandes N, Carmo-Silva S, Stevenson M (2018) Lot splitting under load-limiting order release in high-variety shops: An assessment by simulation. *Journal of Manufacturing Systems* 48:63-72.
[5] Becker JMJ, Borst J, van der Veen A (2015) Improving the overall equipment effectiveness in high-mix-low-volume manufacturing environments. *CIRP Annals* 64(1):419-422.
[6] ElMaraghy H, Deif AM (2014) Dynamic modelling of impact of lean policies on production levelling feasibility. *CIRP Annals* 63(1):389-392.
[7] Nyhuis P, von Cieminski G, Fischer A, Feldmann K (2005) Applying simulation and analytical models for logistic performance prediction. *CIRP Annals* 54(1):417-422.
[8] Monostori L, Kadar B, Bauernhansl T, Kondoh S, Kumara S, Reinhart G, Sauer O, Schuh G, Sihn W, Ueda K (2016) Cyber-physical systems in manufacturing. *CIRP Annals* 65(2):621–641.
[9] Colangelo E, Kröger T, Bauernhansl T (2018) Substitution and complementation of production management functions with data analytics. *Procedia CIRP* 72:191-196.
[10] Flath CM, Stein N (2018) Towards a data science toolbox for industrial analytics applications. *Computers in Industry* 94:16-25.
[11] Kozjek D, Vrabic R, Rihtarsic B, Butala P (2018). Big data analytics for operations management in engineer-to-order manufacturing. *Procedia CIRP* 72:209-214.
[12] Bang SH, Ak R, Narayanan A, Lee YT, Cho H (2019) A survey on knowledge transfer for manufacturing data analytics. *Computers in Industry* 104:116-130.
[13] Negahban A, Smith JS (2014) Simulation for manufacturing system design and operation: Literature review and analysis. *Journal of Manufacturing Systems* 33(2):241-261.
[14] Law A, Kelton D (2015) *Simulation Modeling and Analysis*. McGraw-Hill, 5th ed.
[15] Pierreval H (1992) Rule-based simulation metamodels. *European Journal of Operational Research*, 61(1-2):6-17.
[16] Li M, Yang F, Uzsoy R, Xu J (2016) A metamodel-based Monte Carlo simulation approach for responsive production planning of manufacturing systems. *Journal of Manufacturing Systems*, 38:114-133.
[17] Kurpjuweit S, Reinerth D, Schmidt CG, Wagner SM (2018) Implementing visual management for continuous improvement: barriers, success factors and best practices. *Int. J. of Production Research*, published on-line, p. 15.
[18] Hastie T, Tibshirani R, Friedman J (2008) *The Elements of Statistical Learning*. New York, NY, USA, Springer Series in Statistics. 2nd ed.
[19] Schuh G, Reuter C, Prote J-P, Brambring F, Ays J (2017) Increasing data integrity for improving decision making in production planning and control. *CIRP Annals* 66(1):425-428.