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Evaluation of Indicators for Simulation's Prediction Quality of Material Demand in Matrix Production Systems

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Abstract

The resilient and relatively new production system "matrix production" challenges the design of the material supply. Through its dynamic behavior, the time, place and amount of material demand is uncertain. To support the supply planning process, it takes a method that predicts the material required in a given planning period. The usage of simulation can clarify the expected material demand in a given period. To evaluate the simulation's prediction quality and set a limit to the simulation experiments, an indicators or goodness-of-fit value is needed.
This article examines different statistical indicators with regard to their suitability for evaluating the prediction quality of a simulation and its multiple experiments. For this purpose, a use case is investigated to analyse how the indicators change over a number of experiments. The indicators are evaluated and discussed with respect to their suitability in further usage.

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Keywords: simulation; prediction; material supply; matrix production

1. Introduction

Changeable and resilient production systems are gaining importance in the producing industries. Companies configure flexible systems to encounter high variances, volatile market conditions, and the individualization of products [1–3]. One approach for an adaptable production system is the so-called matrix production [4]. The matrix production

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consists of flexibly linked process modules. Each module can operate a different set of processes and can be redundantly represented in the system [3, 5]. Through reconfiguration the system adapts to new or changing demands as well as to new products and variants. Reconfiguration happens on a mid-term basis. The benefits of the new system are the higher resource utilization and the ability to process a high number of variants in one production system. Whereas manufacturing and assembly benefit and operate more freely, the new system poses a challenge to the material supply chain [6]. Due to the redundant process modules and the flexible order control, the material demands at the process modules and stations are not clearly defined by the order program. In the real system, the large number of possible order flows can lead to an above-average high demand for individual materials at some stations, while other stations show no demand for these materials. The logistics and supply planner cannot overlook the dependencies, but the risk of incorrect materials is high.

To address this problem, simulation is used as a convenient tool to support the material supply planning. By using simulation, the execution of multiple experiments is common. Different experiments are loaded by a varying customer demand and therefore the system behaves differently. Normally, after a set amount of experiments, the simulation stops and an analysis of all experiments is done. The setting of a limit to the experiments is often done without a methodical approach. But, the amount of experiments is crucial to the analysis's significance. Therefore, this article outlines a method, predicting the material demand of each station in a matrix production using simulation and focus on how to evaluate the quality of the simulation experiments and how to set a valid limit to the amount of experiments needed. The use of simulation is new in this context. However, considering the quality of the forecast is a necessary enabler to use simulation in the industrial environment.

2. State of the Art

2.1. Matrix production

The concept of matrix production is a further development of the concept of flexible manufacturing systems. As mentioned, redundantly used process modules and flexible connections are the foundation of a matrix production system. A process module can be a single station or a line section. The linkage between stations can be e.g. a conveyor system or a transport unit, but between process modules it has to be a flexible transport unit. An order, representing a customer demand, utilizes the process modules required to complete the product. The decision for a specific route is made ad-hoc and in line with a chosen order control method. In differentiation and extension to the classical descriptions of flexible manufacturing systems [7, 8], matrix production does not only include automated machines that can be quickly converted, but the system design is freely configurable, manual stations/process modules are also considered, the order control has a high degree of flexibility and the batch size is up to batch size 1. This leads to a more complex system with a higher variant of processes and resources.

One main difference to classic production systems like line production is the mentioned flexible order control. The order control benefits of two usable degrees of freedom, which result due to the flexibly linked and redundant modules. [9]

The first degree of freedom is the operation-sequence-flexibility according to the product's priority graph.

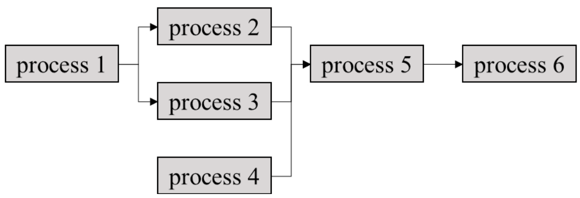

Fig. 1. Example of a priority graph.

Fig. 1 shows that, after the completion of process 1, it is possible to continue with process 2 or process 3. To do process 5, processes 2, 3 and 4 have to be completed. In matrix production, the process sequence can be set up flexibly in operations, so that two different process sequences arise for two orders with the same priority graph.

The second degree of freedom is the order-distribution-flexibility, when there are two or more process modules offering the required process. According the control rules, the process module gets chosen, which is beneficial in the specific moment. Fig. 2 illustrates both degrees of freedom.

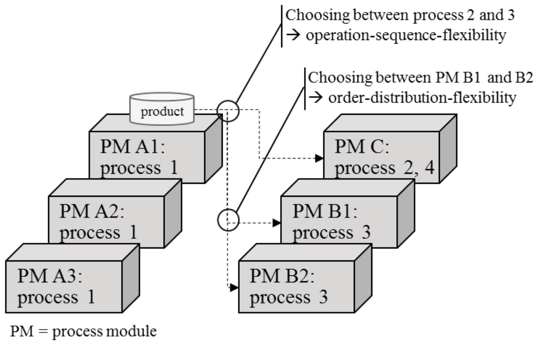

Fig. 2. Operation-sequence- and order-distribution-flexibility in a matrix production system. [1]

2.2. Challenges to material supply

The material supply is an enabler for manufacturing and assembly. Supplying the stations with material, it allows the conduction of processes. Therefore, it is important that material is available and the material demand of an order matches in terms of time, place, and quantity [10]. Further criteria are material quality and the costs of supply. In a matrix production, the matching of demand and supply in time, place, and quantity takes place under high uncertainty, as the orders switch their sequence and modules for further processing are chosen ad-hoc [6]. The criteria quality and cost are challenging as well, but they are not within the scope of this article.

Using the order-distribution- and operation-sequence-flexibility the sequence of all orders constantly changes. There is no fixed sequence. In addition, with intended ad-hoc control decisions a previous fixation of orders to process modules is not feasible. In conclusion, if there are redundant process modules, it is theoretically possible in a matrix production, that the control system leads all orders just to one of the redundant modules. This case induces an asymmetric material demand and risk of shortage.

On the other side, any supply of material requires a set period of time to allow for commissioning and transportation. There is a gap between ad-hoc definition of material demand in time, place, and quantity, and the required time of supply. Thus, the decision on quantity, place, and timing of supply must plan for multiple future scenarios. Due to the variety of processes and resources of a matrix production, batch size 1 and the freedom of control, this supply problem is new in its scope.

To overcome this problem, it is necessary to build a flexible supply system and align supply processes with system behavior. This is a task of mid-term supply planning.

2.3. Simulation

Simulation allows for a simplified reproduction of a real system [11]. It represents consecutive dynamic processes with a certain transition probability. Simulation provides new insights into complex systems [12, 13] and is therefore increasingly used in production planning and management [11, 14]. For production systems, material flow simulation is mainly used, which is part of discrete-event simulation.

Firstly, simulation is used to set up a model, and secondly, to run multiple experiments and analyze the results of the experiments. When investigating a complex system and dynamic processes with transition probability, multiple experiments are mandatory [12, 15]. Each experiment has different but valid input factors and may behave differently during the simulation experiment. The benefit of simulation is that it allows investigating multiple behavior options and thus supports the ongoing decision-making process [12, 13].

3. Use of simulation to predict medium-term material demand

The characteristics of a matrix production pose a challenge to the material supply system. The supply system has to adapt itself to be able to match changes in demand and keep supplying the operative process correctly. From a mid-term perspective, the design of the supply system needs to be able to meet these challenges.

Therefore, it is crucial to know the expected material demand of each process module. As mentioned, the exact material demand at order level cannot be defined a priori due to being defined in operations. Nevertheless, from a mid-term perspective, it is possible to derive a certain range of expected material demand when multiple orders are considered. This is where simulation comes in as a useful tool. Simulation is used in the field of production planning for different tasks, like line balancing, assessment of rules for order sequencing or definition of safety stocks (compare page 4 of [16]). To the task of derivation of material demand it is not widely used, as most production systems, like line production, are less complex and do not require a deeper and dynamic analysis in a simulation. The general approach of using simulation can be still used.

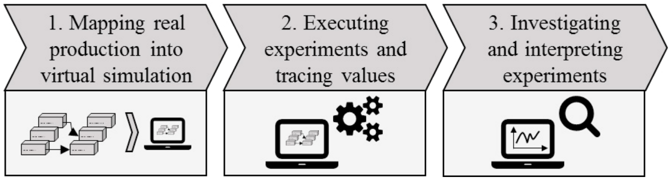

Fig. 3. Illustration of steps for predicting the material demand by using simulation.

Simulation as a prediction tool consists of three parts (Fig. 3) derived from [17]. In the first step, the real system is recreated in a simulation environment. It includes the translation of hardware, control methods, transition probabilities, and global demand forecast into simulation. The global demand forecast consists of an expected demand over a certain period that relates to the whole system. The second step is for executing the experiments. The observed variable denotes the material consumed in each process module. If an order selects a process module and executes the desired processes, it is assumed that material is available. As long as the experiment runs, the consumption constantly sums up. The conclusion of the experiment results in a list, indicating each process module and its material a consumption/demand. The third step investigates the results from all experiments. To this end, it is necessary to form the average over all experiments executed at the level of a process module and material combination. Then, the assessment of the average value points out if the value is valid as a representative in a mid-term perspective. If the value is valid, it is used for designing the supply system. If it is invalid, a further experiment is run and the assessment is repeated. The mentioned “value” can also be called “indicator”.

As mapping and executing a simulation are well-known steps, further research is needed for specific investigations into the matrix production, such as defining suitable indicator in the context of mid-term demand derivation. [18]

There are multiple ways to do an assessment. Stochastic investigations are preferable, as they are objective and can be run in an automated way. The objective of the assessment is to evaluate whether the experiments result in stable indicator. There are different stochastic indicators to evaluate the objective. A frequent approach is to review **confidence intervals** when analysing simulation experiments [19]. The review focuses on the spread and fault tolerance of all experiments. Another tool for investigating is the **coefficient of variation**. It sets the standard deviation relative to the mean. By nature, a proper way to investigate the stability of a value is to examine its change by time. Thus, possible indicators are the **change of the mean** as well as the **change of the coefficient** of variation.

Though these approaches are possible in theory, their implementation and interpretation require further investigation. The next chapter presents a case study to show, on the one hand, if the stochastic indicators are proper to use in the outlined supply perspective and, which indicators are favourable in practice.

4. Use case study and analysis

4.1. Description of use case study and analyzing style

The use case transferred to simulation is made up of two products (product A and product B). Product A has 30 different variants and product B has 25 variants. These products and their respective variants are manufactured in a matrix production system. Setting the process times in a stochastic range and giving each variant a range of expected order volume alters the order input and order processing. In conclusion, the parts of the system behave differently, depending on the randomly set order values (within the given range) during simulation. Parallel to each process operation, the simulation tracks the material consumed in a process. Each product consists of main components and of variant parts for different specifications and optional parts, which may or may not be used. In total there are 20 to 25 different parts in a product. The priority graph of each product consists of processes in a sequential and parallel structure.

The matrix production comprises redundant resources, including two redundant line sections, with four stations, for a sequence of standard processes. Other resources are connected in a flexible manner. Each resource can operate a given set of processes. Each process module has an input- and output buffer of three spaces, whereas between the stations of the line sections, there is a buffer of two spaces. The system is operated by an ad-hoc control logic, which decides the order to process module distribution by considering the shortest input puffer of each module and the order's priority graph. With this structure, the control logic covers the outlined degrees of freedom of the operation-sequence-flexibility and the order-distribution-flexibility.

The given simulation run is specified as to a simulated period of 20 days (one month) with a one-shift operation per day.

The simulation runs 100 times to gather data for the indicator analysis. This is a higher than usual amount of runs in the context of production simulation. The simulation behaves differently in each run within the given ranges of process times and derived orders of the variable set variant mix. The analysis investigates the above-named indicators, varying their accuracy and dimension of scope.

The confidence interval is examined to check if formula 1 is fulfilled. Therefore, in the middle of formula 1, one investigates the z-transformed values in dependence to the chosen confidence level. There are tables to derive the value of z. Further the standard deviation σ, the mean $\bar{x}$ and the actual simulation run n are part of the formula. The result needs to be less or equal a set limit, which defines an accepted and possible error F.

$$F \geq \frac{\sqrt{z_{\frac{\alpha}{2}}^2 \times \frac{\sigma^2}{n}}}{\bar{x}_n} \leq limit \tag{1}$$

In addition, the second indicator (coefficient of variation) needs to reach its set limit, defined by formula 2. The same applies to the change of mean and the change of coefficient of variation (formula 3 and 4). Formula 2 calculates the coefficient of variant c_v by investigating the standard deviation σ and the mean $\bar{x}$. The coefficient of variant has to be less or equal a set limit. In formula 3 and 4, one calculates the change of the mean/variation coefficient between the actual simulation run n and the last run $n-1$. In both cases, the change needs to be less or again a set limit.

$$c_v = \frac{\sigma}{\bar{x}} \leq limit \tag{2}$$

$$\bar{x}_{c,n} = \frac{\bar{x}_n - \bar{x}_{n-1}}{\bar{x}_{n-1}} \leq limit \tag{3}$$

$$c_{v,c,n} = \frac{c_{v,n} - c_{v,n-1}}{c_{v,n-1}} \leq limit \tag{4}$$

As the last two approaches are easy to calculate and interpret, the scope of dimension is added to set a second and stricter application of three serial runs. In this case, the limit needs to be fulfilled three times in a row. (Table 1)

Table 1. Investigated approaches of indicators and investigated specifications.

Indicator	Indicator specifications					
confidence intervals	Confidence level in [%]			Tolerated error in [%]		
	90	95	99	10	5	1
coefficient of variation	Limit in [%]					
	10		5		1	
change of mean	Limit in [%]			Scope in [runs]		
	10	5	1	1	3	
change of variation coefficient	Limit in [%]			Scope in [runs]		
	10	5	1	1	3	

In the analysis, these formulas and specifications are applied to any tracked material consumed, and summed up for each material and process module at each simulation run. If the limit of the narrowed investigation group, consisting of simulation run, process module, and material, is fulfilled or above fulfilment, the indicator is “fine” (≤ limit). Otherwise, it is “not fine” (> limit). This is investigated for each group.

4.2. General analysis and results

Table 2 visualizes a cross-section of the results. It shows the relative share of indicators and points out which of them fulfils the target values and which do not. It applies to all tracked sets of “process module-material” combinations. For example, the value “10 % <= limit” indicates that over all combinations in the investigated run there are 10 % ones fulfilling the set target and 90 % which do not fulfil the target limit. The values are illustrated for run 2, 3, 4, 5, 10, 15, 20, 30, 40, 50, 75 and 100. The logarithmic scale provides an overview of the behavior of the approaches. It takes into account that an additional run in the beginning affects the dynamics of the indicator more strongly than a later one.

The table outlines the following results: The coefficient of variation is not a suitable indicator to measure whether the result of the simulation (of all runs) is valid, since it does not clearly adapt to a limit by adding runs. Another simulation run does not seem to increase the prediction quality. This calls for further investigation.

By contrast, the other three indicators are valid indicators, because with additional simulating runs the amount of fulfilled target values increases and the amount of unfulfilled decreases.

In addition, setting stricter target values and defaults, such as a stricter confidence level or a larger number of runs, leads to a slower and later approximation to 100 % fulfilment. Similar to other cases, stricter default values require a larger set of data.

A differentiated consideration indicates that the use of the confidence interval fulfilment is the strictest indicator of the three remaining indicators. The change of the variation coefficient is less strict but stricter than the change of the mean value. The change of the mean value offers an overall fulfilment starting at about 30 runs, whereas the change of variation coefficient starts at about 40 runs. In the 100 investigated runs, there is no overall fulfilment by observing the confidence intervals.

A view across all indicators shows that the benefit of additional runs in the beginning is higher than later, if there are already many runs done. After approximately the fifth run, the change of all tracked values is significantly reduced.

Moreover, if, for example, the change of the mean value (over one run and 10 % limit) reaches 100 % fulfilment in run 30, the observation of the confidence interval indicates a fulfilment higher than 90 %. In run 10, it was a little less than 90 %. To reach 100 % fulfilment, the confidence interval requires more runs. Reaching a fulfilment of 100 % and closing a gap of less than 10 % requires more than 100 runs. This indicates an exponential amount of effort.

Table 2. Overview of the result, outlining the share of target value fulfilment and non-fulfilment.

Indicator	Indicator's specifications	control, if …	Run 2	Run 3	Run 4	Run 5	Run 10	Run 15	Run 20	Run 30	Run 40	Run 50	Run 75	Run 100
Confidence Interval	tolerated error: 10%	<= limit	40,5%	70,4%	78,9%	82,8%	87,3%	89,1%	91,3%	92,5%	94,5%	95,0%	98,3%	98,8%
	confidence level: 90%	> limit	59,5%	29,6%	21,1%	17,2%	12,7%	10,9%	8,7%	7,5%	5,5%	5,0%	1,7%	1,2%
	tolerated error: 10%	<= limit	22,9%	48,8%	68,4%	77,4%	85,1%	86,8%	89,3%	90,8%	93,0%	93,5%	97,5%	98,3%
	confidence level: 95%	> limit	77,1%	51,2%	31,6%	22,6%	14,9%	13,2%	10,7%	9,2%	7,0%	6,5%	2,5%	1,7%
	tolerated error: 10%	<= limit	6,5%	14,2%	34,3%	56,0%	80,3%	83,6%	85,1%	88,1%	89,8%	90,8%	92,0%	94,3%
	confidence level: 99%	> limit	93,5%	85,8%	65,7%	44,0%	19,7%	16,4%	14,9%	11,9%	10,2%	9,2%	8,0%	5,7%
	tolerated error: 5%	<= limit	22,9%	34,1%	48,0%	59,7%	77,4%	81,3%	82,8%	85,8%	87,3%	89,1%	90,0%	91,3%
	confidence level: 90%	> limit	77,1%	65,9%	52,0%	40,3%	22,6%	18,7%	17,2%	14,2%	12,7%	10,9%	10,0%	8,7%
	tolerated error: 5%	<= limit	13,2%	18,4%	28,6%	46,0%	72,6%	78,9%	81,3%	82,6%	85,1%	86,3%	89,3%	90,0%
	confidence level: 95%	> limit	86,8%	81,6%	71,4%	54,0%	27,4%	21,1%	18,7%	17,4%	14,9%	13,7%	10,7%	10,0%
	tolerated error: 5%	<= limit	3,7%	4,7%	8,7%	17,9%	53,5%	68,7%	76,1%	80,3%	81,6%	82,8%	85,8%	87,6%
	confidence level: 99%	> limit	96,3%	95,3%	91,3%	82,1%	46,5%	31,3%	23,9%	19,7%	18,4%	17,2%	14,2%	12,4%
	tolerated error: 1%	<= limit	6,5%	3,2%	1,2%	1,2%	1,7%	4,7%	8,7%	17,2%	25,9%	36,1%	53,7%	64,9%
	confidence level: 90%	> limit	93,5%	96,8%	98,8%	98,8%	98,3%	95,3%	91,3%	82,8%	74,1%	63,9%	46,3%	35,1%
	tolerated error: 1%	<= limit	3,7%	2,5%	1,0%	0,2%	0,7%	1,7%	3,5%	7,5%	16,2%	20,4%	37,3%	53,2%
	confidence level: 95%	> limit	96,3%	97,5%	99,0%	99,8%	99,3%	98,3%	96,5%	92,5%	83,8%	79,6%	62,7%	46,8%
	tolerated error: 1%	<= limit	2,5%	1,2%	0,0%	0,0%	0,0%	0,2%	0,5%	1,7%	4,2%	7,0%	17,4%	28,9%
	confidence level: 99%	> limit	97,5%	98,8%	100,0%	100,0%	100,0%	99,8%	99,5%	98,3%	95,8%	93,0%	82,6%	71,1%
Coefficient of variation	limit: 10%	<= limit	84,6%	83,1%	81,1%	82,3%	80,8%	80,6%	79,9%	80,6%	79,6%	79,4%	79,9%	79,9%
		> limit	15,4%	16,9%	18,9%	17,7%	19,2%	19,4%	20,1%	19,4%	20,4%	20,6%	20,1%	20,1%
	limit: 5%	<= limit	66,9%	59,0%	58,2%	57,0%	55,2%	55,5%	54,2%	49,3%	51,2%	51,5%	51,7%	53,2%
		> limit	33,1%	41,0%	41,8%	43,0%	44,8%	44,5%	45,8%	50,7%	48,8%	48,5%	48,3%	46,8%
	limit: 1%	<= limit	20,6%	5,5%	1,7%	1,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
		> limit	79,4%	94,5%	98,3%	99,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%
Change of the mean value	over one run: 10%	<= limit	89,6%	92,5%	96,3%	96,8%	99,3%	99,3%	99,3%	**100,0%**	**100,0%**	**100,0%**	**100,0%**	**100,0%**
		> limit	10,4%	7,5%	3,7%	3,2%	0,7%	0,7%	0,7%	0,0%	0,0%	0,0%	0,0%	0,0%
	over one run: 5%	<= limit	79,6%	87,8%	92,0%	91,3%	95,5%	98,0%	99,3%	99,0%	**100,0%**	**100,0%**	**100,0%**	**100,0%**
		> limit	20,4%	12,2%	8,0%	8,7%	4,5%	2,0%	0,7%	1,0%	0,0%	0,0%	0,0%	0,0%
	over one run: 1%	<= limit	26,4%	32,1%	49,8%	62,9%	80,3%	87,8%	91,8%	91,3%	94,8%	96,5%	98,8%	99,3%
		> limit	73,6%	67,9%	50,2%	37,1%	19,7%	12,2%	8,2%	8,7%	5,2%	3,5%	1,2%	0,7%
	over 3 runs: 10%	<= limit			85,8%	90,3%	96,5%	99,3%	99,3%	**100,0%**	**100,0%**	**100,0%**	**100,0%**	**100,0%**
		> limit			13,9%	9,7%	3,5%	0,7%	0,7%	0,0%	0,0%	0,0%	0,0%	0,0%
	over 3 runs: 5%	<= limit			74,6%	84,6%	90,8%	96,5%	99,0%	99,0%	99,8%	**100,0%**	**100,0%**	**100,0%**
		> limit			25,1%	15,4%	9,2%	3,5%	1,0%	1,0%	0,2%	0,0%	0,0%	0,0%
	over 3 runs: 1%	<= limit			6,5%	16,9%	61,4%	81,1%	83,8%	87,3%	93,0%	93,3%	97,5%	98,8%
		> limit			93,3%	83,1%	38,6%	18,9%	16,2%	12,7%	7,0%	6,7%	2,5%	1,2%
Change of the variation coefficient	over one run: 10%	<= limit		10,9%	25,6%	37,1%	78,9%	90,3%	95,8%	98,0%	99,5%	99,5%	**100,0%**	**100,0%**
		> limit		89,1%	74,4%	62,9%	21,1%	9,7%	4,2%	2,0%	0,5%	0,5%	0,0%	0,0%
	over one run: 5%	<= limit		5,0%	11,7%	13,7%	42,3%	81,6%	87,1%	88,6%	95,8%	95,8%	**100,0%**	**100,0%**
		> limit		95,0%	88,3%	86,3%	57,7%	18,4%	12,9%	11,4%	4,2%	4,2%	0,0%	0,0%
	over one run: 1%	<= limit		1,7%	2,2%	2,5%	7,2%	14,2%	19,7%	25,9%	42,3%	64,4%	92,0%	90,8%
		> limit		98,3%	97,8%	97,5%	92,8%	85,8%	80,3%	74,1%	57,7%	35,6%	8,0%	9,2%
	over 3 runs: 10%	<= limit				0,7%	52,5%	77,1%	86,6%	91,8%	98,8%	99,3%	**100,0%**	**100,0%**
		> limit				99,3%	47,5%	22,9%	13,4%	8,2%	1,2%	0,7%	0,0%	0,0%
	over 3 runs: 5%	<= limit				0,0%	6,5%	58,0%	68,2%	70,4%	88,6%	93,5%	99,8%	**100,0%**
		> limit				100,0%	93,5%	42,0%	31,8%	29,6%	11,4%	6,5%	0,2%	0,0%
	over 3 runs: 10%	<= limit				0,0%	0,0%	0,2%	0,2%	2,5%	6,5%	30,3%	74,1%	79,6%
		> limit				100,0%	100,0%	99,8%	99,8%	97,5%	93,5%	69,7%	25,9%	20,4%

4.3. Detailed analysis and additional insights

The general analysis outlines three valid indicators and demonstrates that stricter default and target values result in a higher number of required runs to meet the overall target fulfilment.

An ongoing analysis will take into account why the fourth indicator, the coefficient of variation, is not a valid approach. Furthermore, it will focus on why the dynamics of approximating the overall fulfilment decreases.

When investigating the two issues, it is useful to consider material consumption in a differentiated manner. Transferring the data sets to classes according to their mean consumption during the last runs highlights if there are any irregularities in consumption classes and target fulfilment.

Classes with a lower tracked consumption have a significantly lower fulfilment rate. Increasing the number of runs leads to a faster fulfilment share in classes with higher consumption rates than in lower ones. (Fig. 4 and Fig. 5)

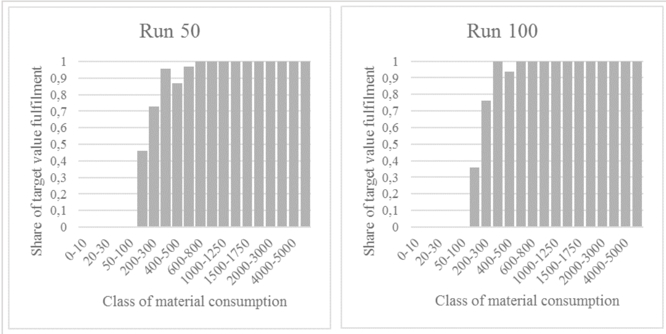

Fig. 4. Comparison of histograms of the indicator coefficient of variation at runs 50 and 100 with a set limit of 10 %.

As the use case and the tracing of material consumption in the simulated production system only allows for natural numbers, the spread around the mean is relatively higher for a set of smaller values than for a set of larger values. If the coefficient of variation sets the standard deviation in relation to the mean, the relation is bigger for smaller values than for bigger values. The limit would need adjustments regarding the natural height of a value. That explains why the use of the coefficient of variation is not a feasible indicator, as the adjustment is complex.

The issue of a relatively higher spread in lower consumption classes also applies to the change of the mean. However, by increasing the number of runs, lower classes fulfil the target value, too. To achieve this, the number of runs needs to increase exponentially. In conclusion, “process module-material” combinations with low consumption require a higher data set to appear stable.

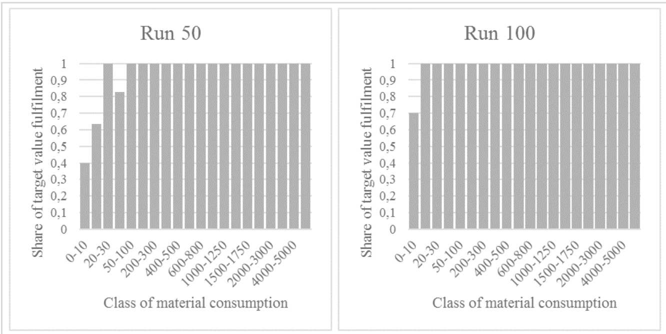

Fig. 5. Comparison of histograms of the indicator change of the mean at runs 50 and 100 with a set limit of 10 %.

5. Conclusion and outlook

Planning the material supply of a matrix production system is challenging. The new degrees of freedom that come with it result in uncertainty of quantity, place, and time of the material demand. To overcome and manage this problem, simulation seems a proper tool. It allows mapping the real production in a virtual environment and running experiments to derive certain behaviors with a view to the expected material demand at each process module.

Simulation experiments track the material consumed during the run. One experiment generates a single possible scenario. The sum of all scenarios generates a prediction of expected material demand.

To evaluate whether the prediction is valid, three indicators are possible: the confidence interval, the change of the mean, and the change of the coefficient.

The confidence interval achieves a high degree of stochastic certainty concerning the range of the expected material demand. Nevertheless, it is a huge effort regarding the number of runs to achieve a share of target value fulfilment of 100 %. The change of the mean and the change of the coefficient are less strict but also suitable approaches. If the results are part of a more extensive planning process, with employees from different levels and with stochastic expertise, the change of the mean offers an easy to understand transparent indicator. In practice, this indicator seems a valid approach.

The analysis also shows that the prediction quality of materials with lower consumption values in the simulation require more data than materials with higher consumption values. This leads to an exponential number of runs necessary for achieving overall target value fulfilment. The high number of runs requires an extensive effort though the benefits are small, as materials with low demand normally less affect, for example, the costs of a supply system. Further research is needed on how to address this issue.

The outlined use case refers to the production system complexity of a real system. But, the complexity of each production system differs. Therefore, it is interesting to consider further use cases to investigate the behavior and runs required of the three valid indicators.

Besides the investigated indicators, the prediction of material demand is just one step in planning material supply. How to use the predicted demand in the ongoing supply planning needs to be part of further research.

Last, simulation as a tool is successfully used in a further field of production planning and management. Also in this new field, it proves its benefits and suitability.

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