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Technical paper

A method for considering aleatory and epistemic uncertainties as well as product variance in discrete event simulation of production systems

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ABSTRACT

When modelling a production system during its planning phase, aleatory uncertainties of production processes, epistemic uncertainties resulting from insufficient knowledge as well as variations in the production processes resulting from product variances must be considered. These different uncertainties and variances are interrelated, e.g. the influence of product variants on production processes may itself be subject to epistemic uncertainty. This paper presents a generic method to model aleatory and epistemic uncertainties in discrete event simulations of production systems as well as product variances in an integrated manner. We use functional relations between product parameters and production model parameters to efficiently account for product variances. We use possibility-probability transformation and second-order Monte Carlo simulation to account for epistemic uncertainty. For easy transferability to industrial practice, a step-by-step procedure is described that can be implemented in commercially available simulation tools. A use case from precast concrete production is presented to show the benefit of such an approach compared to a state-of-the-art benchmark.

1. Introduction

In production and logistics, simulation is used in about 80 % of cases in the planning phase (e.g. factory planning), in about 10 % of cases in the realization phase (e.g. inventory management, digital twin) and in the remaining fraction in the operation phase [1]. Thus, it represents an important tool for the planning of production systems. According to Jeon and Kim [2], discrete event simulation (DES) is one of the most widely used simulation methods in production planning. The review of Negahban and Smith [3] shows that there is also a vast interest in this topic in literature. DES is suitable for conducting experiments on a production system in a virtual environment. Many parameters of production system models, such as cycle times and machine failures, are subject to natural, non-reducible uncertainties. These aleatory uncertainties are quantified in the DES using probability distributions [4]. When modelling production systems that are already in operation, historical data can be used to infer probability distributions. However, when DES is used in planning, historical data are not available and the probability distributions often have to be estimated by experts [1]. An expert's estimate may be based on generally available information but may also include knowledge that is not explicitly available or cannot even be explicitly stated. Expert estimates are themselves subject to uncertainty due to insufficient knowledge. This epistemic uncertainty is not considered in current modelling practice. Therefore, there is a need for a systematic method to consider epistemic uncertainty when modelling production systems in the planning phase.

In addition to uncertainties, many companies face the challenge of individualized products in the context of mass customization [5]. This affects production through the need to produce a high number of variants. Complex products, for example in the automotive industry, are produced in up to 10^{21} variants [6]. In the construction industry, the number of variants is even higher because buildings, which are usually one-offs [7]. In this context of mass customization, it is not possible to individually describe each possible variant and its impact on the parameters of the production system model. Therefore, it is necessary to relate parameters of the product to parameters of the production model (hereafter referred to as product parameters and production parameters).

Aleatory and epistemic uncertainties as well as product variance also have interdependencies. Not only may estimates of aleatory

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uncertainties be subject to aleatory uncertainties and depend on product parameters, but the relation between product and production parameters may itself be subject to epistemic uncertainties. As will be shown in the following section, there is no approach in the scientific literature that considers aleatory and epistemic uncertainties as well as relations between product and production parameters when using DES in the planning phase of a production system. Therefore, these aspects cannot be fully considered at present. This results in incomplete information when making decisions about production systems.

Therefore, the original contribution of this work to the state of the art is as follows. For the first time, a method for DES in the planning phase of a production system is described that

- allows the consideration of aleatory and epistemic uncertainties as well as relations between product and production parameters,
- allows the consideration of interdependencies between these uncertainties
- and can be implemented with state-of-the-art software used for DES of production systems.

Thus, the method is beneficial for all industrial use cases

- where DES is used in the planning phase of a production system,
- where both aleatory and epistemic uncertainties need to be considered, and
- where the variance of the product is too large to explicitly model every possible variant.

Planning always precedes the operation of a production system. Aleatory uncertainties are present in most production processes because they are physically determined. Epistemic uncertainties are always present when there is insufficient knowledge about the production system that will eventually be realized. This is usually the case when the production system is not identical or is at least very similar to an existing production system. Therefore, many practical applications can be expected for the presented method.

The presented method uses analytical relations between product and process parameters to efficiently account for product variation. Aleatory uncertainties are represented by probability distributions whose parameters may themselves be subject to epistemic uncertainties. The method uses fuzzy numbers to account for epistemic uncertainty in its parameters, which are derived from expert estimations. Insights from possibility theory are used to transform them into probability distributions and second-order Monte Carlo simulation is used to obtain crisp realizations that can be used in commercially available DES tools. To illustrate and validate the developed method, it is applied to a use case from precast concrete production.

In Section 2 of the paper, we first give an overview of the extent to which the uncertainty and variability described above can already be considered in DES according to the state of the art. In Section 3, we describe a step-by-step method to consider aleatory and epistemic uncertainties as well as varying product parameters when modelling production systems during the planning phase. To demonstrate and illustrate our approach, we describe its application in an industrial use case in Section 4. In Section 5 we discuss and benchmark the results of this use case. Finally, we conclude with a summary and discussion in Section 6 and an outlook for further research in Section 7.

2. Literature review

First, we present selected papers from the state of the art that consider product variance in DES. We then briefly discuss aleatory uncertainties in production systems by using probability distributions. Since this is a standard approach when using DES of production systems, we cannot give a complete overview, but will present selected papers. Afterwards, we give a comprehensive overview of the related literature on the consideration of epistemic uncertainty in DES.

2.1. Product variants in DES of production systems

The following approaches model the influence of product variance on production parameters, such as cycle time, by modelling separate production parameter specifications for each product variant. Gong et al. [8] use DES to analyze the efficiency of producing certain variants of the product with certain production processes in the early development phase of a new product. They present a use case from the aerospace industry with 4 variants, whose associated production parameters are individually modelled. Zandieh and Motallebi [9] use DES to determine the optimal customer order decoupling point and the optimal production planning policy. They present a use case from the dairy industry, where there are individual probability distributions for cycle times that are individually modelled for each of the 26 product variants considered. Eriksson and Hendberg [10] analyze the potential and challenges of using DES in the context of Industry 4.0. They perform a DES based on a sample company, considering 2 product variants with individually modelled routings.

Overall, current approaches for considering product variance in DES of production systems involve an individual modelling effort for each variant and are therefore not suitable for a mass customization context.

2.2. Aleatory uncertainties in DES of production systems

There is a large amount of literature on the application of DES to an existing production system under aleatory uncertainty. Use cases can be finding strategies for the adjustment of work force [11,12], scheduling [13] or responding to machine breakdowns [14]. In the aforementioned papers, aleatory uncertainty is considered by using probability distributions to model uncertain parameters such as demand, cycle times or times between machine breakdowns. The probability distributions are defined based on real data from the operation of the existing production system. There is no epistemic uncertainty because the real system is fully observable. In addition, Schumacher and Buchholz [15] present an approach for modelling a production system that does not yet exist and suggest using historical data from other production systems or expert estimates to model aleatory uncertainty. However, modelling the epistemic uncertainty that may be present in expert estimates is also beyond the scope of their work. Another possibility of using DES in production planning is comparing different production concepts. Tiacci [16] uses DES for comparing straight with U-shaped production lines. Further applications of DES in manufacturing can be found in [17].

Overall, there are many existing approaches in the literature to model aleatory uncertainty without considering epistemic uncertainty. Approaches that do take epistemic uncertainty into account, and are therefore highly relevant to the application of DES in production system planning, are presented below.

2.3. Epistemic uncertainties in DES of production systems

2.3.1. Combining Fuzzy Inference Systems (FIS) and DES (FIS+DES)

In general, two principles can be distinguished for the consideration of epistemic uncertainties in DES: On the one hand, inferring crisp values for model parameters from a fuzzy inference system by defuzzification, as described in this section. On the other hand, defining model parameters as fuzzy variables, as discussed in the section on fuzzy discrete event simulation [18]. Fuzzy inference systems use rules to derive the fuzzy output from the fuzzy input and use defuzzifiers to transform the fuzzy output into a crisp output [19]. The fuzzy input and output can be, for example, values of parameters described in natural language, such as 'high' or 'low'. Membership functions, which specify the extent to which a given crisp value is associated with a given fuzzy value, are the basis for converting fuzzy values into crisp values (see [20] for an overview of defuzzification methods). The crisp values can be used as input for a DES. Thus, the combination of FIS and DES allows to account for epistemic uncertainties in the input data to a DES. The following papers deal with the combination of FIS and DES.

Shaheen *et al.* [21] describe a methodology for integrating fuzzy expert systems and discrete event simulation, which can be seen as a framework for FIS+DES. They describe the process of creating a rule-based expert system that can handle fuzzy variables and connecting such a system to a DES. They apply their methodology to simulate a tunneling process using tunneling machines. Ghaleb *et al.* [22] describe a use case in cement bag production, where a fuzzy inference system is used to determine parameters such as work and handling times for use in discrete event simulation. Kasie and Bright [23] develop a decision support system based on case-based reasoning to assign fixtures to parts. The cases are described by fuzzy variables, and the solutions obtained are simulated by discrete event simulation. Thus, epistemic uncertainty is considered when assigning fixtures to parts but not in the simulation of the process. Gerami Seresht and Fayek [24] use fuzzy set theory together with system dynamics and DES to determine the duration of earth moving operations in the construction industry. External variables are described as fuzzy variables in so far as they involve uncertainty. The variables are linked to other variables by a system dynamics model that is updated in real time during the construction process. The system dynamics model is used to determine parameters that are used for a DES of the construction process.

Overall, existing FIS + DES approaches do not take into account either aleatory uncertainties or product variance.

2.3.2. Fuzzy Discrete Event Simulation (FDES)

A fuzzy discrete event simulation is a DES whose delay times and timestamps are fuzzy numbers [25]. Therefore, updating the simulation clock is based on fuzzy arithmetic. A major challenge of FDES is the ranking of events. Since event times are fuzzy numbers, it is not trivial to decide which event in the event schedule will be executed next. There are several approaches to ranking in FDES (see [26] for a comprehensive review). FDES is widely used in the construction industry to support project planning (see [18] for a comprehensive review). The fact that FDES requires its own simulation mechanism is a disadvantage for its application in the production context, where well-established simulation tools exist, in particular Plant Simulation and AnyLogic, which are not able to represent such a simulation mechanism. Approaches of FDES in production such as Perrone *et al.* [27], Grieco *et al.* [28] and Hamidi *et al.* [29] use self-developed tools. By using FDES, epistemic uncertainty is taken into account in these approaches, but aleatory uncertainty is not. Grieco *et al.* [28] developed a hybrid approach where stochastic simulations are performed in parallel with a fuzzy discrete event simulation to gain insights from the comparison. However, the two simulation approaches are not integrated. Azadeh *et al.* [30] consider epistemic uncertainty arising from the fact that small data samples collected in production may not be representative of the probability distribution of their source. A probability function is estimated based on the samples and transformed into a fuzzy number by interpreting its confidence intervals as α cuts. For selected α-cuts, crisp numbers are determined by averaging the interval boundaries of the α-cut and are used as expected values for stochastic variables of the simulation. This approach accounts for both epistemic and aleatory uncertainty. However, by making the fuzzy numbers crisp by averaging the confidence intervals of the α-cuts, the span of the intervals, and thus the degree of epistemic uncertainty does not affect the results of the discrete event simulation. Product variants are also outside the scope of the approach. Furthermore, the approach requires historical data, which is usually not available in the planning phase of a production system. Finally, Sadeghi [25] developed an approach to make FDES usable on classical DES machines. An FDES is run in parallel with a classical DES. The fuzzy ranking problem in the FDES is solved by converting fuzzy numbers into crisp numbers. These crisp numbers are also used to determine the event time in the classical DES, so that the order of event execution in the FDES and the classical DES is identical. However, this approach requires a model for FDES to be created in addition to a model for classical DES, which cannot be done with commercial tools for DES in production planning. Product variance is not examined.

Overall, the problem with using FDES for production system planning is that there is currently no commercially available software for production system DES that supports fuzzy event scheduling, and aleatory and epistemic uncertainties are not considered in an integrated manner.

2.3.3. Interval Based Simulation (IBS)

Two different approaches to Interval-Based Simulation (IBS) can be found in the literature. Batarseh and Wang [31] use p-boxes to describe the epistemic and aleatory uncertainty of model parameters. A p-box represents the range of possible probability distributions for a given variable [32]. Each realization of a random variable is mapped to an interval based on the p-box. In the approach of Batarseh and Wang [31], the event scheduler of the developed DES assigns time intervals to events and computes further events by interval arithmetic. As this approach of IBS requires a special simulation mechanism, it has not yet been given access to commercial tools for production system simulation. In addition, it can exclusively be usefully applied when the parameters of the probability distributions can only be estimated as intervals, and thus epistemic uncertainties can only be partially considered.

Another approach to IBS in the context of DES is presented by Wang *et al.* [33]. They define model parameters subject to uncertainty as intervals and run the simulation for different values from these intervals. They use the simulation results from each run to train a supervised learning model to map different values of the input parameters to the simulation output. This IBS approach can be used in commercial production system simulation tools. However, aleatory uncertainties are not considered in the existing approach. Furthermore, it can only consider epistemic uncertainties that are given as intervals. Other information about the epistemic uncertainty, such as values that are more or less likely than others, cannot be considered.

2.3.4. Second-order Monte Carlo Simulation (SOMCS)

Second-order Monte Carlo Simulation (SOMCS) is a method to account for epistemic and aleatory uncertainty in simulations (see [34]). The parameters of the model are divided into those, subject to epistemic uncertainty and those subject to aleatory uncertainty. The simulation is run in two loops, an outer and an inner loop. For each simulation run, the outer loop determines the values of the parameters subject to epistemic uncertainty based on a probability distribution. Several times during each simulation run, the inner loop determines the values of the parameters subject to aleatory uncertainty. Parameters that define probability distributions for the inner loop (e.g. μ and σ for a normal distribution) may themselves be subject to epistemic uncertainty. The applications of SOMCS in literature are manifold, e.g. in the field of probabilistic risk analysis [35]. However, there are only very few papers in the fields of health care [36] and defense [37] that use SOMCS in combination with DES. And to the best of our knowledge, there are no such approaches in the context of production systems and are therefore applicable for the problem addressed in this paper. We will show later how SOMCS can be used to account for aleatory and epistemic uncertainties for DES of production systems.

Table 1
Comparison of existing approaches for the consideration of uncertainty and product variance in DES.

Approach		Consideration of product variants	Consideration of variable product parameters	Consideration of aleatory uncertain-ties	Consideration of epistemic uncertain-ties	Application in industrial production	Applicable in commercially available DES tools for industrial production
Aleatory uncertainties in DES	13, 15,14, 11, 12	○	○	●	○	●	●
Product variance in DES	8, 9, 10	●	○	●	○	●	●
FIS+DES	21	○	○	○	●	○	●
	22	○	○	○	●	●	●
	23	○	○	○	◐	●	●
	24	○	○	○	●	○	●
FDES	27	○	○	○	●	●	○
	28	○	○	◐	◐	●	○
	30	○	○	●	◐	●	●
	25	○	○	●	●	○	○
	29	○	○	○	●	●	●
IBS	31	○	○	●	◐	○	○
	33	○	○	○	●	○	●

○ = not considered
◐ = partially considered
● = fully considered

2.4. *Comparison of existing approaches*

Table 1 provides an overview of the extent to which existing approaches can fully account for aleatory and epistemic uncertainties as well as variable product parameters.

The literature review shows that there is currently no approach to consider both aleatory and epistemic uncertainties as well as variable product parameters in DES in the context of production system planning. Furthermore, there are no approaches that consider functional relations between product parameters and production system parameters. This means that it is not yet possible to consider a large number of product variants defined by their parameter values without having to model each variant separately. Therefore, the general problem of using DES in the planning phase of production systems is that uncertainty and variance cannot be considered adequately. Therefore, a method for the integrated consideration of aleatory and epistemic uncertainties as well as variable product parameters in the DES of production systems is presented in the following.

3. Method

The method described below allows the consideration of aleatory and epistemic uncertainties as well as variable product parameters in a DES of a production system. It therefore allows for a more accurate modelling of uncertainty and variance and it can be applied to general production systems. It is described step by step so that it can be reproduced by practitioners. Each step is illustrated with a practical example in Section 4. It is assumed that the structure and elements of the DES model already exist. Steps 1–5 describe how the uncertainties and dependencies related to the production parameters are determined and modelled. Fig. 1 gives an overview of the procedure. Steps 1–5 are the prerequisites for the following steps 6–9, which describe how to collect

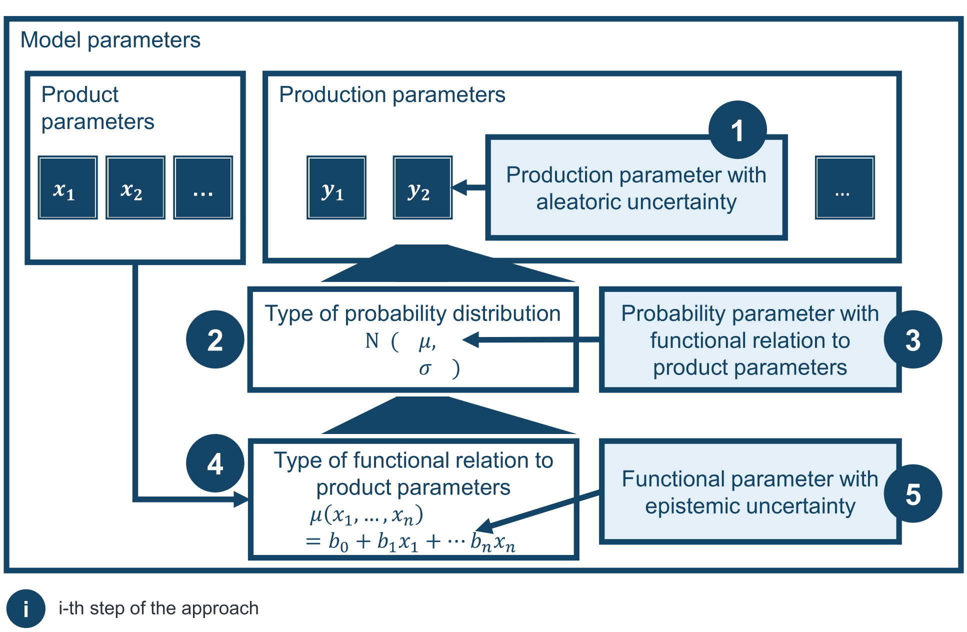

Fig. 1. Identification of uncertain parameters: Steps 1–5.

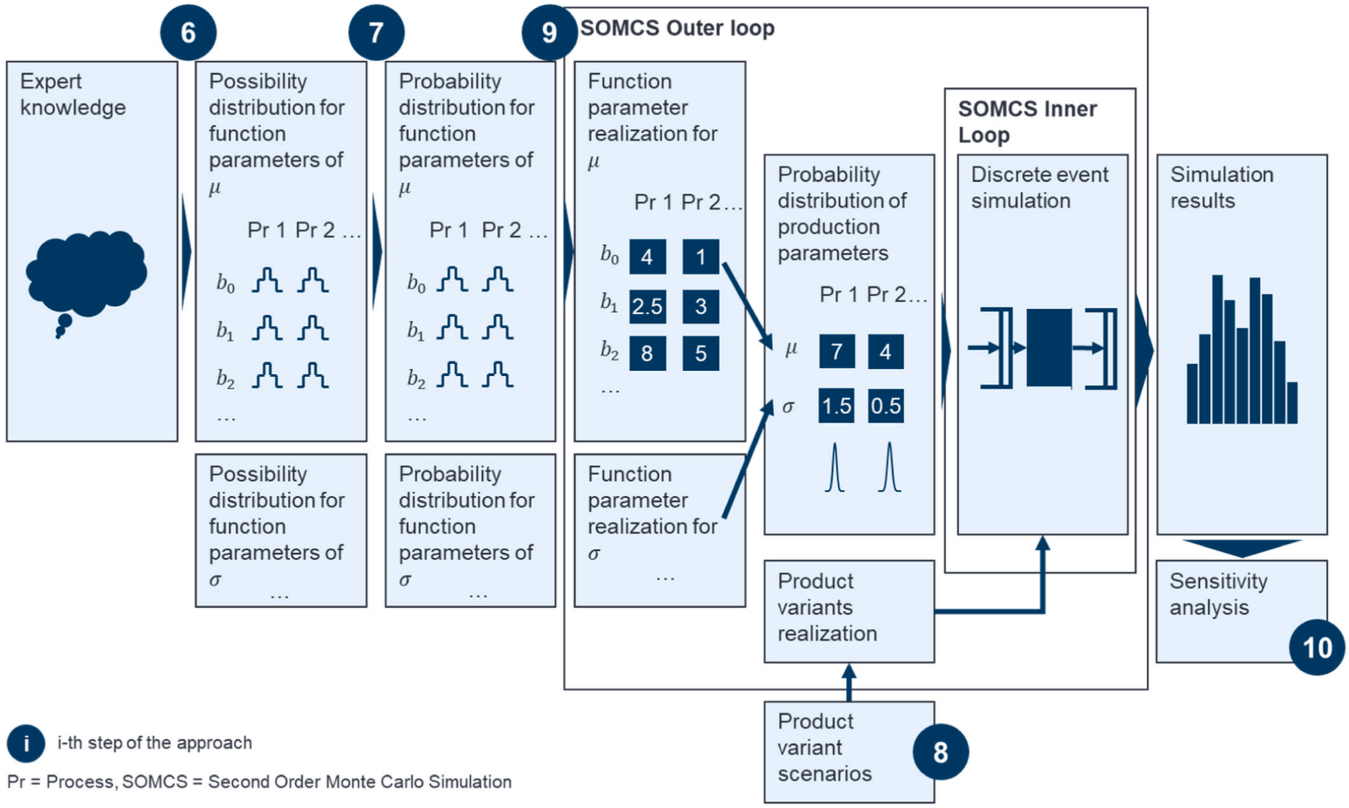

Fig. 2. Data acquisition and simulation: Steps 6–9.

data and perform a simulation considering the previously determined uncertainties. Fig. 2 summarizes the procedure and assigns the corresponding steps. Finally, a sensitivity analysis is performed in step 10.

3.1. Step 1: Determine production parameters that are subject to aleatory uncertainties

Our approach goes beyond modelling aleatory uncertainties, but should be able to cover them. The determination of production parameters subject to aleatory uncertainties together with their associated probability distribution types (see next section) is the basis for modelling aleatory uncertainties. It is common practice in simulation projects in the production environment [38], so we refer to the existing literature. In particular, these parameters can be arrival times, cycle times, or downtimes.

3.2. Step 2: Determine the distribution type for the associated probability distributions

Determining probability distribution types for production parameters is a common procedure when building models for discrete event simulation [38]. One way to do this is to draw on experience with comparable production systems. For more information on selecting probability distributions for DES in production, the reader is referred to Law [38]. The parameters of the probability distributions, hereafter called probability parameters, result from the selected probability distributions. For example, for a normal distribution, these are the expected value μ and the standard deviation σ. A normal distribution is used as an example in the following, but the method is applicable to all types of probability distributions as long as they can be specified by certain parameters.

3.3. Step 3: Determine production parameters as well as probability parameters that depend on product parameters

This step, as well as the next one, is necessary to be able to account for the product parameter variations introduced at the beginning. On the one hand, production parameters can depend directly on product parameters, e.g., a tool to be selected depends directly on the length of the product variant. On the other hand, they can depend indirectly on the product parameters by being subject to aleatory uncertainties. The associated probability parameters may themselves depend on the product parameters. For example, the expected value μ of the duration of a casting process may depend on the length of the product variant. The relations between product parameters and production or probability parameters have not yet been in the literature.

3.4. Step 4: Determine the functional relation between production parameters and probability parameters with the product parameters

The functional relation between product and production parameters or product and probability parameters can, on the one hand, be determined based on knowledge. This is the case, for example, when a physical model exists that describes the relation. On the other hand, the functional relation can be data-based, e.g. based on comparable production systems. In this case, regression can be used to determine the functional relation. The parameters of the function (function parameters) result from the selected function type. For example, if there is a linear relation $\mu(x) = b_0 + b_1x_1 + \ldots + b_nx_n$ between the expected value μ of a cycle time (probability parameter) and the product parameters x_i, the function parameters $b_0, \ldots, b_n$ must be determined. We use linear relations as an example because they are also present in our use case. However, the approach is not restricted to linear relations. Any kind of relation can be used as long as it can be specified by certain parameters.

3.5. Step 5: Determine production parameters, probability parameters, and function parameters that are subject to epistemic uncertainties

To consider epistemic uncertainty along with aleatory uncertainty and product variance in a production system model, parameters that are subject to epistemic uncertainty must be defined. In DES models of production systems, there may be production parameters that are not subject to aleatory uncertainty and do not depend on product parameters, and therefore can be directly specified, such as the cycle time of a particular fully automated station. If these parameters are determined based on expert estimates, they are subject to epistemic uncertainty. As a result of step 2, there may be probability parameters that are based on expert estimates and therefore also subject to epistemic uncertainty, such as an expected value μ of the cycle time of a particular manual station. Finally, as a result of step 4, there may be functional parameters that are based on expert estimates and therefore also subject to epistemic uncertainty. For example, the coefficient of the product parameter length in the functional relation between the product parameters and the expected cycle time of a particular processing station. Note that parameters of the model can be related in a cascading manner, as seen in Fig. 1. For example, production parameters may be subject to aleatory uncertainties and therefore represented by probability distributions. The associated probability parameters may themselves depend on product parameters with function parameters that must be estimated by experts and are therefore subject to epistemic uncertainty. The determination of parameters directly subject to epistemic uncertainty is considered in the literature on FDES, IBS, and SOMCS. Here, however, the scope is extended to probability parameters and function parameters.

3.6. Step 6: Determine possibility distributions of those parameters that are subject to epistemic uncertainties

To account for epistemic uncertainty in a simulation, it must be quantified. To do this, we use possibility distributions from quantitative possibility theory. Quantitative possibility theory combines the concepts of fuzzy set theory and probability theory. In contrast to probability theory, possibility theory uses two mutually dual set functions, the possibility measure Π and the necessity measure N [39]. Similar to the probability measure P, they assign values between 0 and 1 to event sets. N can be seen as the lower bound and Π as the upper bound of the true cumulative probability distribution. π describes the possibility distribution (fuzzy number) and always refers to an elementary event; Π and N are used to measure the possibility and necessity of entire sets of events.

Possibility distributions can be the result of numbers estimated by experts. Especially in the case of function parameters, such estimates are difficult because in some cases the individual function parameters have no relevant technical meaning. For example, in the case of the relation between product and production parameters described in step 4, b_0 represents the fraction of the expected value of a cycle time that is independent of the product variant and is thus a purely theoretical quantity. Therefore, the expert cannot rely on his knowledge to make an estimate. This would result in incorrect parameters if the expert would make an estimate anyway. In this case, an estimation based on reference variants is recommended. A reference variant is a selected variant with specific product parameter values for which an expert gives an estimate with a high degree of confidence. For example, this could be a product variant that is similar to a variant frequently produced on another production system. For this variant, the parameter to be determined can be estimated. If there are estimates for several reference variants, a system of equations can be set up from which the function parameters can be calculated. In the linear case shown above, it is also possible to estimate the first partial derivatives instead. These represent the change in expected value when a product parameter changes by one unit. It holds that

$$\mu_{res}(x_1, \ldots, x_n) = \mu(x_{ref}) + b_1(x_1 - x_{1,ref}) + \cdots + b_n(x_n - x_{n,ref}) \tag{1}$$

where μ_{res} is the resulting expected value, $\mu(x_{ref})$ is the expected value for the reference variant, x_i is the expression of the i-th product parameter, $x_{i,ref}$ is the expression of the i-th product parameter in the reference product, and b_i is the coefficient of the i-th product parameter – respectively the first derivate of the linear function. By estimating $\mu(x_{ref})$ as well as $b_1, \ldots, b_n$ the functional relation between the product and probability parameters is fully described. The associated questions for the expert estimation are "What would be a typical cycle time for the reference variants?" and "How does the cycle time typically change if product parameter i is changed by one unit relative to the reference variant?". In principle, a further development of the Taylor series is possible by taking higher-order derivatives into account. However, this is only an option if the expert is capable of estimating coefficients for the higher derivatives. The estimated parameters are subject to epistemic uncertainties which can be represented by possibility functions in the form of fuzzy numbers. Pedrycz and Gomide [40] list suitable estimation methods. In the vertical method, the modeler provides the expert confidence levels λ_i, to which he assigns confidence intervals A_i. These then form the alpha cuts of the fuzzy number [40]. An alpha cut $\widetilde{A}_\alpha$ of a fuzzy set $\widetilde{A}$ contains all elements that have a membership degree of at least $\alpha \epsilon [0,1]$: $\widetilde{A}_\alpha = \{x \in X : \mu_{\widetilde{A}}(x) \geq \alpha\}$ [41]. An alpha cut results when the membership function of the fuzzy number is cut with level α as a closed real number interval (crisp set). Thus, the vertical method exploits the representation theorem, which states that a fuzzy set can be represented by the set of its alpha cuts [42].

Confidence intervals contain the actual value according to the expert's opinion at the given confidence level. The higher the desired confidence level, the larger the interval. Assuming that these intervals are symmetric around the value with the highest confidence (e), they can be described by radii r_i. The procedure of data acquisition is illustrated in Fig. 3 with the example of three confidence levels $\lambda_1 = 0.5$, $\lambda_2 = 0.95$ and $\lambda_3 = 1$. The corresponding questions are "For which interval are you 50 % (95 %, 100 %) confident that the true value is included?".

3.7. Step 7: Transform Possibility Distributions

The possibility distributions defined above cannot be used directly as input to a DES model. However, they can be transformed into probability distributions so that for each simulation run crisp parameters are determined from them as input to the simulation model (see step 9). This step covers the possibility-probability transformation. The link to probability theory is established by consistency principles, of which there are several formulated in the literature. Only the general consistency principle is agreed upon. It states that events which are probable to a certain degree must be possible to at least the same degree [42]. Using P as the probability measure and Π as the possibility measure, we can conclude that

$$P \leq \Pi \tag{2}$$

A possibility-probability transformation is often necessary for systems where both epistemic (fuzzy numbers) and aleatory uncertainties (probability distributions) are used [42]. Only transformations from Π to P are considered here, since commercial simulation tools in the production context are purely probabilistic. There is no consensus in the

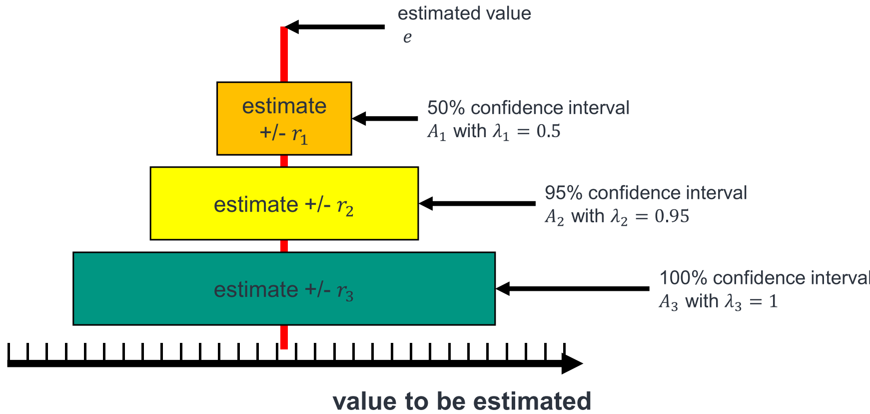

Fig. 3. Estimating possibility distributions by confidence intervals.

literature on a universally applicable transformation method, as different consistency principles are formulated [43]. In general, however, most transformation methods try to obtain the general consistency principle from Eq. 1. The most basic transformation is based on the principle of indifference according to Laplace's principle of insufficient reason. This states that everything that is equally possible should also be equally probable [44].

To transform possibility distributions into probability distributions, the method described by Dubois *et al.* [44] can be used. According to Laplace's principle of insufficient reason, the transformation method developed by Dubois et. al [44] assumes an equally distributed probability density for all elements x from the set A with the same degree of possibility $\pi(x)$. The indifference principle is then applied twice to the possibility distribution: Assign a uniform distribution $U(0,1]$ to the alpha-cut levels, draw a random α from it, and consider $A_\alpha = [a_\alpha^u, a_\alpha^o]$. Assume that the resulting alpha cut $A_\alpha = [a_\alpha^u, a_\alpha^o]$ has a uniform distribution $U([a_\alpha^u, a_\alpha^o])$ and draw a random value from it. If the possibility distribution can be described over a finite number n of alpha cuts A_{α_1}, $A_{\alpha_2}, \ldots, A_{\alpha_n}$ with possibilities $\pi_i := \Pi(A_{\alpha_i})$ in descending sorted order $\pi_1 = 1 > \pi_2 > \ldots > \pi_n > \pi_{n+1} := 0$ then a consistent probability distribution can be calculated as follows:

$$p(x) = \sum_{i=1}^{n} \frac{\pi_i - \pi_{i+1}}{|A_i|} \mu_{A_{\alpha_i}}(x), \quad \forall x. \tag{3}$$

Where $p(x)$ is the probability of event x, $|A_i|$ is the length of the i-th alpha cut, and $\mu_{A_{\alpha_i}}$ is the membership or indicator function of the i-th alpha cut. This transformation method satisfies the general consistency principle. The given confidence levels λ_i from Step 6 form a lower bound on the probability and can therefore be thought of as the necessity measure N of possibility theory: $\lambda_i = N(A_i)$. The confidence levels are thus calculated as $\lambda_i = 1 - \pi_{i+1}$ [45]. Equivalently transformed, we get $\pi_i = 1 - \lambda_{i-1}$, where $\pi_i := \Pi(A_i)$ and $\lambda_0 = 0$. Thus, for the example above with $\lambda_1 = 0.5$, $\lambda_2 = 0.95$ and $\lambda_3 = 1$ we get the possibilities $\pi_1 = 1$, $\pi_2 = 0.5$ and $\pi_3 = 0.05$ from which p can be calculated. Due to the finite number of alpha cuts, the requirements for the transformation method from Dubois *et al.* are satisfied.

3.8. Step 8: Define product variant scenarios

By establishing a functional relation between product and production parameters or product and probability parameters, the production of any product variant can be simulated without manual modification of the simulation model. This makes it possible to perform economic scenario analyses where the scenarios differ in the characteristics of the demanded variants as well as their share in the product mix. Such scenario analyses are relevant, for example, in the planning of a production system to dimension the capacities of the system or to deliberately plan its ability to change. A scenario can be set up by defining the product parameters to be considered and assigning probabilities to them. For example, it can be decided that product variants with lengths of 0.5 m, 1 m and 2 m should be considered and that the corresponding probabilities should be 30 %, 40 % and 30 % respectively. This can be contrasted with another scenario where, for example, a different probability distribution is chosen. This step is a special case of scenario analysis, as it is e.g. described by Hauser and Weck [46] where product parameters are considered in the scenarios. Furthermore, the defined relations between product and production parameters do not only allow to model discrete product variances but also continuous probability distributions over product parameter values. E.g. it can be assumed that some product parameters are equally distributed over a certain range. Lastly, discrete scenarios and continuous product variance can be combined as illustrated in section 4.4.

3.9. Step 9: Perform simulation runs using second-order Monte Carlo simulation

Using the probability distributions from step 7 crisp values for parameters subject to epistemic uncertainty can be determined for each simulation run (outer loop). Note that the parameters determined in this way can themselves be probability parameters. I.e. the probability distributions within the model are specified in the outer loop. Within a DES run (inner loop), multiple samples can be taken from these probability distributions. I.e., the outer loop considers the epistemic uncertainty, while the inner loop considers the aleatory uncertainty. This procedure corresponds to the concept of a second-order Monte Carlo simulation as described by Batarseh and Wang [31]. In addition, the outer loop must also account for the uncertainty arising from the product scenarios. That is, in each simulation run, possible specifications of the production system and the product mix are randomly chosen to represent epistemic uncertainties and varying product parameter probabilities, respectively. The second-order Monte Carlo simulation is shown schematically in Fig. 2.

3.10. Step 10: Perform sensitivity analysis

Like simulation models of production systems in general, the model built in steps 1–9 is based on assumptions. These are the distribution types described in section 3.2, the expert estimates as described in section 3.6, and the demand as described in section 3.8. The epistemic uncertainty in the expert estimates are accounted for by the second-order Monte Carlo simulation as described in section 3.9. The uncertainty about future demand is accounted for by a scenario analysis as described in section 3.8. As described in section 3.2, there are established methods for choosing distribution types. However, in some cases uncertainty about appropriate distribution types remain. This can be addressed by performing a sensitivity analysis. In this case, steps 2–9 are performed once per relevant distribution type. The influence of the distribution type can be determined by comparing the results of different distribution types visually or via statistical measures, as illustrated in Section 5. If the types for several probability distributions within the model shall be varied independently of each other at once, a design of experiment, potentially in combination with a supervised learning approach may be used to model the influence of the distribution types. However, this is not within the scope of the present paper.

Another question that may be relevant for the user of the method is how much epistemic uncertainty and varying product parameters influence the results. This as well can be answered by using sensitivity analysis. Additional simulation runs are performed where the respective effect is disabled. The effect of epistemic uncertainty can be disabled by replacing the possibility distribution introduced in section 3.6 by only the estimated value. The effect of varying product parameters can be disabled by only using discrete representative product variants in the simulation run. The influence of epistemic uncertainty as well as varying product parameters can be determined as described above by comparing the results visually or via statistical measures, as illustrated in Section 5.

4. Use Case

Within the research project SPP 2187 modular construction methods for more precise, more efficient and faster construction are investigated [7]. The basic idea is to replace on-site fabrication with stationary prefabrication of transportable concrete modules that are assembled on site. The modules are produced in a flow manufacturing process, whereby the properties of the modules are controlled by heat treatment [47,48] in addition to individual assembly [49]. To evaluate the potential of this approach, suitable production systems will be simulated. In order to evaluate their potential output under different boundary conditions, scenarios about the design and product mix of potential products have to be considered. The production system considered in this use case does not yet implement the production control shown in Frey and Lanza [50], but is intended to serve as a benchmark later on. This production control system should be able to reactively adjust the heat treatment duration of the modules to influence their properties in such a way that they are suitable for compensating deviations of previously produced modules in the individual assembly.

4.1. Product

The modules under consideration have a Y-shaped form with three arms of equal length and will be referred to as Y-modules in the following. The construction of structures using Y-modules is done by connecting the ends of their arms, resulting in a honeycomb structure (see Fig. 4). These honeycomb structures are made of heat-treated high-performance concrete with high load-bearing capacity [51], allowing dimensionally stable [52] and slender components with high material savings [53]. The Y-module has the five product parameters $x_1, \ldots, x_5$ shown in Fig. 5.

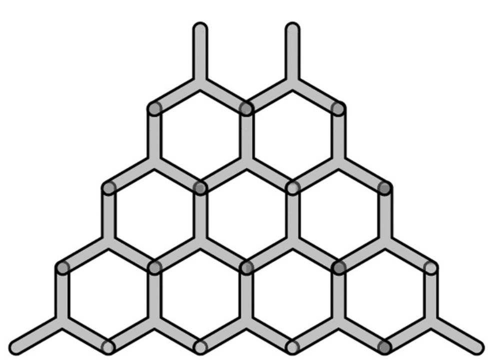

Fig. 4. Load bearing structure consisting of 14 Y-modules.

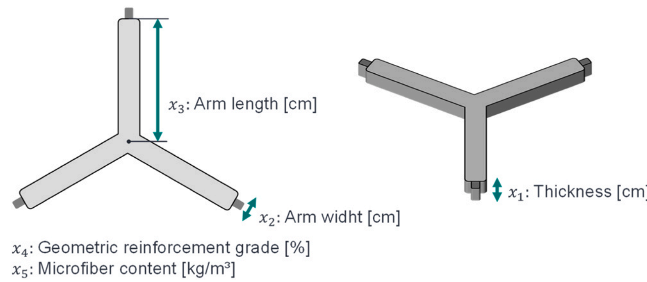

Fig. 5. Product parameters of Y-modules.

4.2. Production system

The Y-modules are manufactured in a highly automated pallet circulation system in 7 sub-processes (see Fig. 6). In process step 1, the formwork of the Y-module is prepared and in process step 2 the steel reinforcement is placed in the formwork. After these two preparatory process steps, the concrete is poured into the formwork and vibrated in process step 3. The concrete is then smoothed in process step 4. This is followed by heat treatment in process step 5. In process step 6, the Y-module is stripped. In process step 7, quality assurance takes place, where the achieved product parameter values are checked. The capacity of station 5 is 30, i.e. 30 modules can be processed simultaneously. For all other stations, the capacity is 1, i.e. only one Y-module can be processed there at a time. It is assumed that Y-shaped modules are produced with a lot size of 10. A production of 1000 modules is simulated.

4.3. Data acquisition

Currently, there are no production systems for Y-shaped modules. Therefore, the simulation model is based on expert estimates. The estimations were performed by a sales manager of a company that provides equipment for the production of precast concrete products. The expert noted that there is some uncertainty in estimating the model parameters because the Y-modules are new products.

4.4. Application of the developed method

Step 1: Determine production parameters that are subject to aleatory uncertainties. The cycle times of each production step are subject to aleatory uncertainties, although these are small due to the high degree of automation. Since it is assumed that preventive maintenance is performed in a plant of this type, random equipment failures are neglected.

Step 2: Determine the distribution type for the associated probability distributions. Since no other information was available and the cycle times were assumed to be the sum of the durations of independent physical processes, a normal distribution with μ and standard deviation σ is assumed according to the central limit theorem of statistics. Since a highly automated production system is assumed, the standard deviation of the cycle times was estimated by the expert to be "very low". Therefore, the standard deviation was assumed to be 1 % of the expected value for all cycle times without further modelling.

Step 3: Determine production parameters as well as probability parameters that depend on product parameters. The expected values μ_i of the cycle times per station i depend in each case on the product parameter values of the modules to be manufactured. For example, there is a physical relation between the cycle time of concreting and the volume of the module and therefore its dimensions.

**Step 4: Determine the functional relation between production parameters and probability parameters with the product

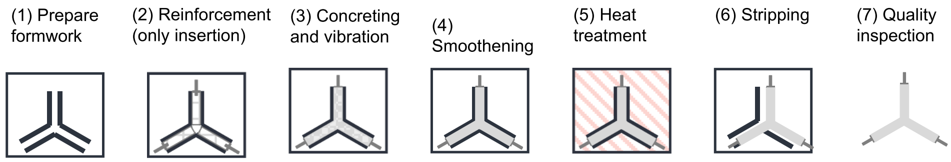

Fig. 6. Process sequence of the Y-module production.

Table 2
Expert Estimations. For the definition of r_1, r_2 and r_3 refer to Fig. 3.

		Process	Prepare formwork	Reinforce-ment	Concreting	Smoothening	Stripping	Quality inspection
Reference product variant [min]	Expected cycle time	estimated value	3	3	3	3	3	3
		r_1	0.5	0.5	0.5	0.5	0.5	0.5
		r_2	1	1	1	1	1	1
		r_3	2	2	2	2	2	2
First derivative of expected cycle time function [min/unit]	Thickness	estimated value	0	0	0.1	0	0	0
		r_1	0	0	0.2	0	0	0
		r_2	0	0	0.3	0	0	0
		r_3	0	0	0.4	0	0	0
	Arm width	estimated value	0	0	0.1	0.01	0	0
		r_1	0	0	0.2	0.02	0	0
		r_2	0	0	0.3	0.03	0	0
		r_3	0	0	0.4	0.04	0	0
	Arm length	estimated value	2	0	1	0.1	0	0
		r_1	1	0	1.2	0.2	0	0
		r_2	2	0	1.4	0.3	0	0
		r_3	3	0	1.6	0.4	0	0
	Geometric reinforcement grade	estimated value	0	0	0	0	0	0
		r_1	0	0	0	0	0	0
		r_2	0	0	0	0	0	0
		r_3	0	0	0	0	0	0
	Microfiber content	estimated value	0	0	0	0	0	0
		r_1	0	0	0	0	0	0
		r_2	0	0	0	0	0	0
		r_3	0	0	0	0	0	0

parameters. Based on physical considerations, we assume that the expected cycle times for formwork cleaning, reinforcement, concreting and smoothing depend linearly on the product parameters x_1, x_2 und x_3. If i is one of these processes, we get

$$\mu_i(x) = b_{i0} + b_{i1}x_{i1} + b_{i2}x_{i2} + b_{i3}x_{i3}. \tag{4}$$

Step 5: Determine production parameters, probability parameters, and function parameters that are subject to epistemic uncertainties.

Here, the coefficients b_{ij} of the linear functions set up in step 4 are selected.

Step 6: Determine possibility distributions of those parameters that are subject to epistemic uncertainties. As described above, possibility distributions are determined for the expected values $\mu_{ref,i}$ and the coefficients $b_{i,1}, \ldots, b_{i,n}$. Confidence levels of 50 %, 95 % and 100 % are chosen. Table 2 shows the table used for collecting the data with the expert's estimations.

Table 3
Specifications of the representative variants for the clusters low, medium and high.

	Low	Medium	High
x_1: Thickness [cm]	5	10	20
x_2: Arm width [cm]	10	20	40
x_3: Arm length [m]	0.5	1	2
x_4: Geometric reinforcement grade [%]	1	3	5
x_5: Microfiber content [kg/m^3]	100	150	200

Step 7: Transform Possibility Distributions. The developed possibility distributions are transformed into probability distributions as described above. Such a transformation is exemplarily shown for the

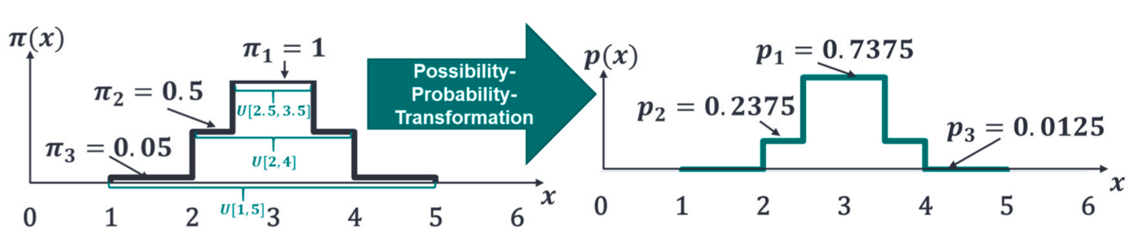

Fig. 7. Exemplary possibility probability transformation.

Table 4
Probabilities of occurrence of variants from the clusters low, medium and high in the three scenarios.

	Scenario 1	Scenario 2	Scenario 3
Probability of cluster low	10 %	30 %	70 %
Probability of cluster medium	20 %	40 %	20 %
Probability of cluster high	70 %	30 %	10 %

mean cycle time in Fig. 7.

Step 8: Define product variant scenarios. As mentioned above, the Y-shaped modules can vary in the parameters thickness, arm width, arm length, geometric reinforcement grade and microfiber content. Each assignment of values to these parameters defines a variant. The actual demand scenarios for the Y-shaped modules are not yet known. To demonstrate our approach, we make the following assumptions about the scenarios. As it is common in the industry, we assume that not all variants are equally likely. We assume that there are three clusters of variants called low, medium and high, each of which has a representative variant with the specifications shown in Table 3.

The variants in a cluster are assumed to be equally distributed around the representative variant with deviations of up to 25 % in each parameter. For example, for the variants in the "medium" cluster, the thickness can be between 7.5 and 12.5 cm. We simulate three different scenarios called 1, 2 and 3. They differ in the probability with which variants from certain clusters occur, as can be seen in Table 4. For example, in scenario 1 a variant from cluster "low" occurs with a probability of 10 % and has parameter values with probabilities equally distributed within a range of 25 % around the value of the representative variant for the cluster. Note modelling an infinite number of variants based on representative variants is only possible because we are modelling functional relations between product and production parameters.

Step 9: Perform simulation runs using second-order Monte Carlo Simulation.

The designed model is implemented in AnyLogic, a state-of-the-art software for DES, which is often used for material flow simulations in manufacturing companies. The input parameters are the distribution types as described in section 3.2, the expert estimates as described in section 3.6, and the product parameter scenarios as described in section 3.8. As described above, in the outer loop the expected values and thus also the standard deviations of the cycle times as well as the realization of the product mix are determined based on the transformed probability distributions. In the inner loop, a simulation run with 1000 modules to be produced in 100 lots was simulated. For each scenario, the outer loop was run 10000 times, i.e. 10000 simulation runs were performed. The total throughput time of all lots was determined.

Step 10: Perform sensitivity analysis. In our use case we perform sensitivity analyses for the distribution types, the influence of epistemic uncertainty and the influence of varying product parameters. As described in Section 3.10, we perform multiple iterations of steps 1–9 using different distribution types for the cycle times of the processes. In addition to the normal distribution that we have initially chosen, we consider log-normal distributions, which are commonly used in modelling cycle times, and uniform distributions, which are chosen when no information about the distribution type is available. All distributions are parameterized by their standard deviation and expected values.

We also repeat our experiments removing the effect of epistemic uncertainty as described in Section 3.10 and we repeat our experiments removing the effect of varying product parameters, i.e. using only three representative variants. We compare the results visually and using a two-sample Kolmogorov-Smirnov (KS) test. For the KS test, we compare the results of the 10000 runs using the actual model with the results of the 10000 runs using the adjusted model. Each of the two sets of samples is transformed into a cumulative distribution function representing the distribution of samples from the corresponding model. This results in two cumulative distribution functions for each comparison. The KS statistic indicates the greatest difference between the two cumulative distribution functions. The p-value indicates how likely it is that both sets of samples were generated by the same probability distribution. In other words, if the p-value is high, the difference between the models being compared becomes less statistically significant. This allows us to determine the influence of the above aspects on the results of the simulation.

5. Simulation results and benchmark

The benchmark for our approach is a state-of-the-art model using the same input parameters. It takes into account aleatory uncertainties in cycle times with a relative standard deviation of 1 %, as does our actual model. It does not use functional relations between product parameters and production model parameters, but only accepts predefined variants - the representative variants described above. The representative variants have predefined expected cycle times per station, calculated as described above, based on their product characteristics. Epistemic uncertainty is not considered. Fig. 8, Fig. 9 and Fig. 10 show the results for the three scenarios. Comparing the results of our approach for all three scenarios shows that the lowest total throughput time that occurs is about 69 h for all three scenarios. This is due to the fixed time that the modules spend in the oven. If other stations have lower cycle times than the oven, the oven becomes the bottleneck and determines the total throughput time. As a result, the cycle times for our approach appear to be truncated on the left. As the module parameter values tend to decrease from Scenario 1 to Scenario 3, the maximum total throughput time decreases from Scenario 1 to Scenario 3, resulting in lower ranges of results. For all three scenarios, the average total throughput time of our approach is slightly higher than the average total throughput time of the benchmark. This is because our approach incorporates more uncertainty than the benchmark and therefore has more variation in cycle times. This makes it more likely that there will be at least one station with a very high cycle time that will become the bottleneck and therefore define the total throughput time.

A comparison of our approach with the benchmark shows that the benchmark does not take into account the uncertainty that actually exists in the case under consideration. Its frequency distribution is much narrower than that of our approach for all three scenarios. The p-value of 0 when comparing the benchmark with our approach supports the claim that the results are significantly different. The reason for the difference between the results of our approach and the benchmark for the use case can be identified by looking at the results of the sensitivity analyses. When the effect of the continuous product variance is removed for scenario 1, it is difficult to see from the histograms alone that the samples are significantly different, as indicated by the p-value of 0.15. However, due to the large number of samples in each sample set, even small deviations indicate significant differences. I.e. considering the continuous product variance leads to significantly different results. The same applies to scenarios 2 and 3, where this effect is even more pronounced. When the effect of epistemic uncertainty is switched off for scenario 1, the frequency distribution changes significantly. Not only are the results significantly different from those of our approach with a p-value of around 0, but the difference is even greater than for the continuous product variance, as the KS statistic of 0.78 shows. Qualitatively equivalent insights can be gained for scenarios 2 and 3. It is therefore comprehensive that the benchmark performs worse in accounting for the uncertainty that exists in the case under consideration. This also affects the average total throughput time. For all three scenarios, the average total throughput time of our approach is higher than the average total throughput time of the benchmark. This is because our approach incorporates more uncertainty than the benchmark and therefore has more variation in cycle times. This makes it more likely that there will be at least one station with a very high cycle time that

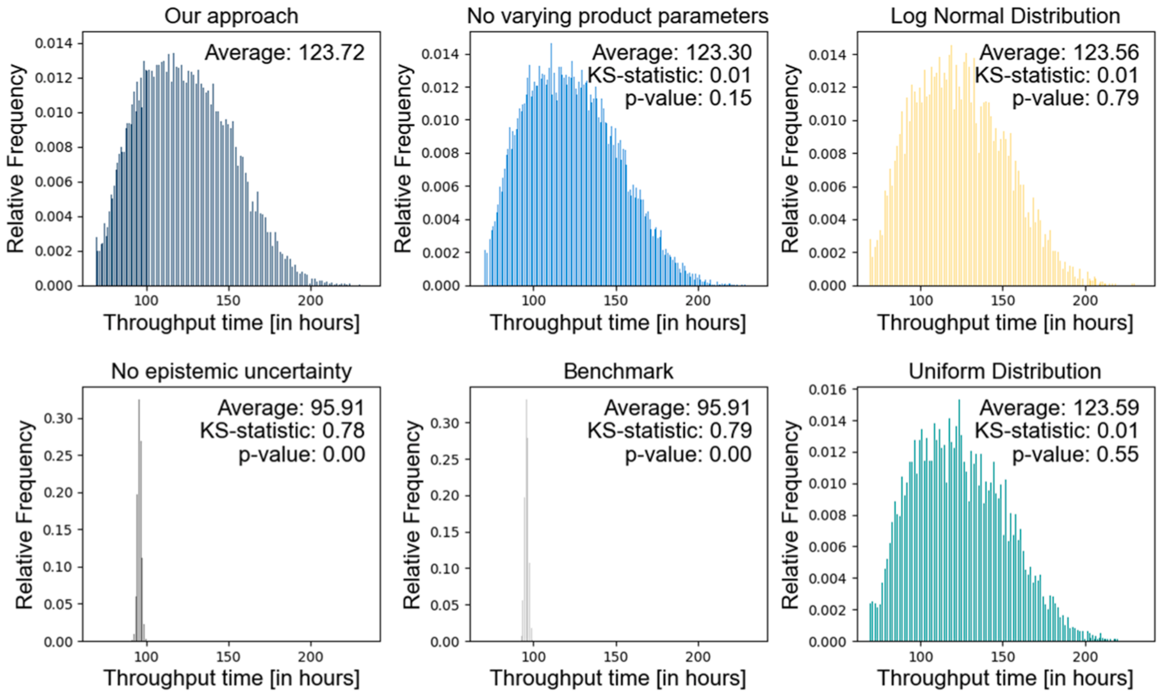

Fig. 8. Results for scenario 1 including our approach, the benchmark and the results of the sensitivity analyses.

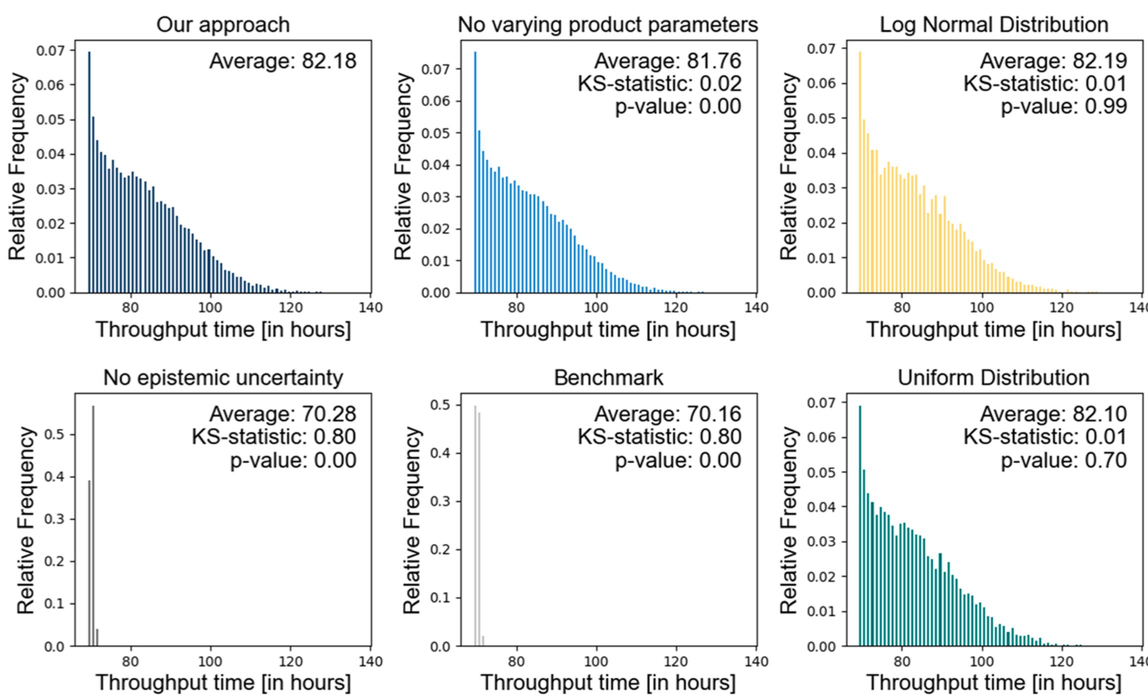

Fig. 9. Results for scenario 2 including our approach, the benchmark and the results of the sensitivity analyses.

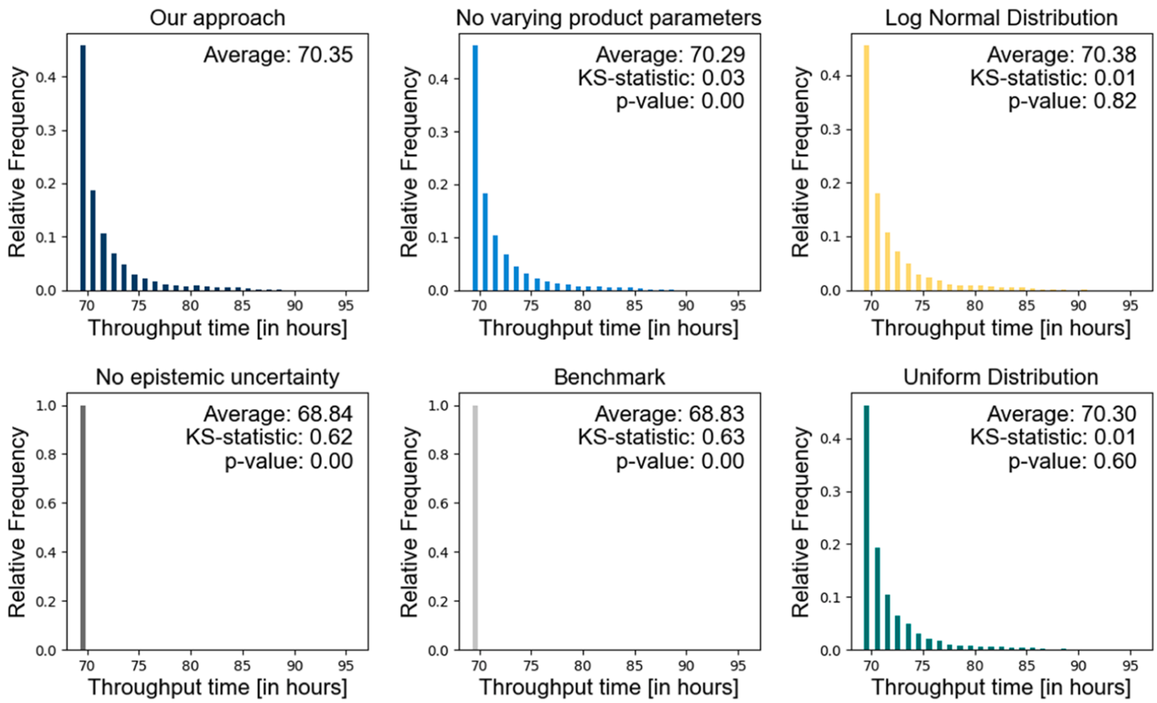

Fig. 10. Results for scenario 3 including our approach, the benchmark and the results of the sensitivity analyses.

becomes the bottleneck and therefore defines the total throughput time.

Looking at the results of the sensitivity analyses for the distribution types, we see that the distribution type is of secondary importance for our model. For Scenario 1, the results differ when using log-normal or uniform distributions for the cycle times. However, with a p-value of 0.79 and 0.55 respectively, the influence of the distribution type is less than the influence of epistemic uncertainty or continuous product variance. Nevertheless, the distribution type has a statistically significant impact on the results. Having more information about the distribution type would therefore improve the accuracy of the results. The same applies to scenarios 2 and 3.

The results of the simulation can be used for production planning. Questions such as "How likely is it that the lead time will be less than 90 h assuming scenario 1?" or "What lead time can we assume with more than 90 % confidence?" can be answered by looking at the quantiles of the lead time. The information thus goes beyond that of an average cycle time. As our approach considers more information from the input data than the benchmark, its results are more accurate. As we can see in all three scenarios, this makes a real difference to the result. If the benchmark results were used to plan a production system, certain variations in total cycle time would not be considered, which could result in a flawed plan. As described above, there are currently no other approaches that take these issues into account. Therefore, this approach increases the accuracy of planning production systems using DES.

6. Summary and discussion

We have developed a method to account for aleatory and epistemic uncertainties as well as functional relations between product parameters and the production model. The approach considers these aspects in an integrated manner: Functional relations to product parameters are considered when modelling aleatory uncertainties, and epistemic uncertainties are considered when modelling both aleatory uncertainties and functional relations. As the use case shows, the approach can be implemented in a widely used state-of-the-art software for material flow simulation in the manufacturing industry. It leads to simulation results that incorporate uncertainty and product variance more accurately. As we can see from the use case, those results can differ significantly from a state-of-the-art discrete event simulation of the same production system. Overall the method thus fulfills the requirements defined in Section 1. The application to the use cases showed that our approach can improve the quality of information used for production system planning. However, a challenge of the presented approach is that it is based on a SOMCS and therefore involves a high computational effort, which can lead to long computation times for more complex simulation models.

7. Outlook

The problem of long computation times could be addressed by further developing this method to be applicable within FDES. As there is no related approach in the literature, further research would be required, as well as further development of commercially available tools for discrete event simulation of production systems.

In the context of Industrie 4.0 digital twins which can be based on DES gain importance [54]. Further research is needed to make the method applicable to these use cases. For digital twins, epistemic uncertainties can be gradually resolved by including real data using approaches such as Bayesian inference.

Furthermore, the described method could be particularly relevant for remanufacturing. In particular, automated disassembly processes are new processes for many companies, and their modelling is subject to epistemic uncertainty. This must be adequately represented in the model. As automatic disassembly introduces new uncertainties, such as the uncertainty of component states, further research would be required to improve the proposed method.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relations that could have appeared to influence the work reported in this paper.

Data availability

Data sets generated during the current study are available from the corresponding author on reasonable request.

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