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Research Article

A Meta-Model Architecture and Elimination Method for Uncertainty Modeling

Haoran Shi, Shijun Liu, and Li Pan

School of Software, Shandong University, Jinan, China

Correspondence should be addressed to Shijun Liu; lsj@sdu.edu.cn

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Uncertainty exists widely in various fields, especially in industrial manufacturing. From traditional manufacturing to intelligent manufacturing, uncertainty always exists in the manufacturing process. With the integration of rapidly developing intelligent technology, the complexity of manufacturing scenarios is increasing, and the postdecision method cannot fully meet the needs of the high reliability of the process. It is necessary to research the pre-elimination of uncertainty to ensure the reliability of process execution. Here, we analyze the sources and characteristics of uncertainty in manufacturing scenarios and propose a meta-model architecture and uncertainty quantification (UQ) framework for uncertainty modeling. On the one hand, our approach involves the creation of a meta-model structure that incorporates various strategies for uncertainty elimination (UE). On the other hand, we develop a comprehensive UQ framework that utilizes quantified metrics and outcomes to bolster the UE process. Finally, a deterministic model is constructed to guide and drive the process execution, which can achieve the purpose of controlling the uncertainty in advance and ensuring the reliability of the process. In addition, two typical manufacturing process scenarios are modeled, and quantitative experiments are conducted on a simulated production line and open-source data sets, respectively, to illustrate the idea and feasibility of the proposed approach. The proposed UE approach, which innovatively combines the domain modeling from the software engineering field and the probability-based UQ method, can be used as a general tool to guide the reliable execution of the process.

1. Introduction

Uncertainty refers to the inability to accurately identify the further outcome and state of an event or phenomenon that has occurred under certain circumstances [1]. In the actual manufacturing production, many factors, such as equipment states, material properties, environmental changes, and manufacturing tolerances, will lead to uncertainty in the process execution, and the process defects caused by uncertainty will bring high labor costs and time costs to the manufacturer, in some cases, even some small changes can affect the regular operation of the subsequent equipment [2, 3]. Therefore, uncertainty in manufacturing scenarios has attracted widespread attention, and it is necessary to evaluate and eliminate uncertainty before process execution [4].

The manufacturing scenario has high complexity, manifested in two aspects as follows:

(1) The whole manufacturing chain covers a variety of production devices and processes, making it difficult to accumulate, utilize, and reuse industrial knowledge [5].
(2) The manufacturing scenario is characterized by typical uncertainty, manifested by the diversity of scenario realization, incomplete external requirements, and internal random events.

The latter is the specific manifestation of uncertainty in manufacturing scenarios, and the latter is often affected by the former; that is, uncertainty is more difficult to quantify and handle due to complex domain knowledge [6, 7]. This paper combines these two aspects of complexity to analyze how uncertainty can be handled.

In industry, the way to deal with uncertainty is usually divided into precontrol and postdecision [8]. Nowadays, with the development of Industry 4.0, traditional industrial production

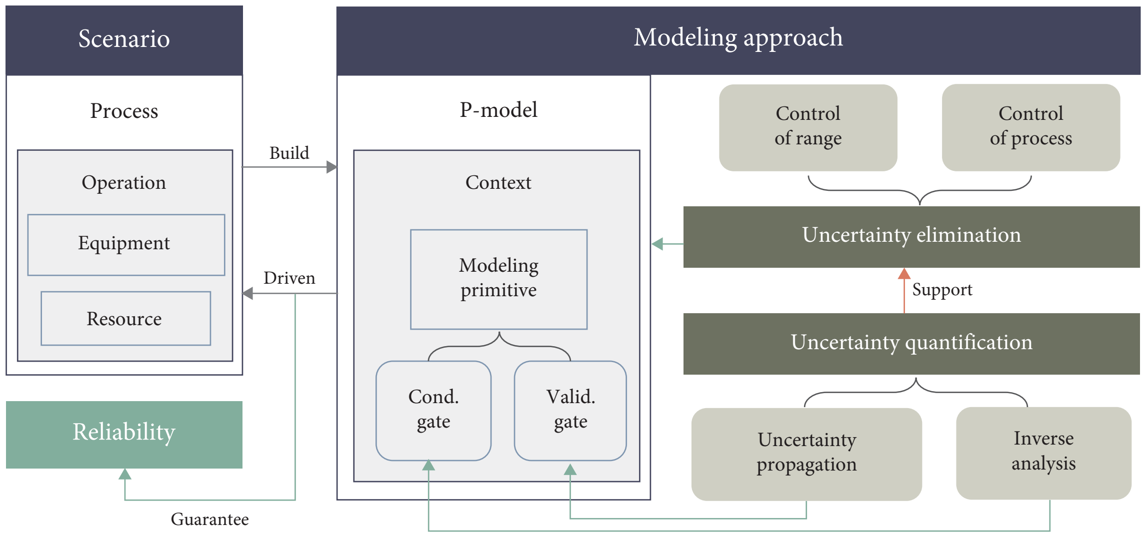

Figure 1: The idea of solving the problem in this paper.

is combined with modern information technology, and researchers are more concerned about the intelligence of decision-making [9]. Learning-based approaches are widely used in decision optimization and prediction for manufacturing processes. Such methods commonly bring automatic and efficient decisions for uncertainties in the process. Still, considering that uncertainties are already present at this time, they do not meet the industry's requirements for high reliability [10, 11]. In addition, the decision made by the machine cannot be completely accurate; the artificial-based and intelligence-assisted are still mainstream realizations and landing.

In software engineering, modeling is a common way to ensure the reliability of system design and testing by organizing knowledge and concepts with a standardized definition [12]. This paper aims to design an abstract meta-model structure that takes uncertainty into account, based on which models can be constructed and mapped to codes to drive reliable execution of the process.

Specifically, a meta-model architecture and uncertainty elimination (UE) approach for domain uncertainty is proposed. On the one hand, we propose a meta-modeling architecture centered on modeling primitive (MP) that represents one of the equipment executing the process, and this architecture serves as the basis for modeling. On the other hand, we design multiple structures in the meta-model to control and eliminate uncertainty, such as the Condition Gate (Con. Gate) and the Validation Gate (Valid. Gate), and an uncertainty quantification (UQ) framework is introduced to assist the verification of Con. Gate and Valid. Gate. The problem-solving idea of this paper is shown in Figure 1.

Compared with the existing methods to cope with uncertainty in the manufacturing field, we innovatively conduct research from the perspective of knowledge modeling, mainly describing how to eliminate uncertainty by the structural design of the model, and innovatively propose a set of corresponding UQ framework to provide more accurate support for model-based UE. The model constructed by our approach is highly deterministic, guaranteeing a reliable execution of the process. In addition, the approach is generic and can be applied to regular manufacturing processes.

The contributions of this paper are mentioned below:

(1) A knowledge model architecture based on MP is proposed, which fully considers the generic elements (including static and dynamic elements) of the manufacturing process. A specific model can be constructed for a specific process based on the meta-model.

(2) Two elimination strategies are incorporated in the structural design of the model, namely, range control and process control, to achieve the purpose of UE in advance [13].

(3) To achieve more accurate control for uncertainty, a UQ framework is introduced, and a generalized quantization framework based on MP is proposed.

(4) A modeling tool is used to model two manufacturing scenarios to demonstrate the proposed modeling approach, and a simulated production line and open-source dataset are used to illustrate the idea and results of UQ.

The remainder of this paper is organized as follows: Section 2 analyzes the existing work; Section 3 describes the meta-model architecture (elements and structure); Section 4 describes the model-based UE strategy and quantification framework; Section 5 illustrates the case study and experiment; and Section 6 concludes and prospects.

2. Related Work

Many standardized models are defined and applied in industrial manufacturing: packML and IEC61499, which are mainly used to solve the problems of information islands and production integration in industrial scenarios [14]. They are designed for different focuses and have limitations in describing the scenario elements; for example, PackML focuses on standardizing information about machine states and operation modes [15]. As an essential factor in manufacturing scenarios, uncertainty has not been studied using the domain modeling approach.

In the study of the definition of uncertainty, several researchers have analyzed uncertainty in different fields [16]: Hazır and Ulusoy [17] have investigated the sources and classification of uncertainty in project management, Smirnova [18] has studied the impact of uncertainty on the economy and proposed corresponding measures, Simankov et al. [19] have studied uncertainty in generic systems in various domains, and classified uncertainty as complete, stochastic, and fuzzy uncertainty.

In industrial manufacturing, uncertainty often refers to the unexpected situation caused by internal instability or external factors that can impact production activities during production [20]. Due to the different business concerns, different industries or fields have different definitions and classifications of uncertainty. A commonly accepted classification of uncertainty: aleatory uncertainty, which is usually caused by natural variability and randomness, and epistemic uncertainty, which is caused by inadequate or missing cognition and knowledge. Since new knowledge will emerge constantly, all aleatory uncertainties are epistemic in the final analysis. In this paper, these two kinds of uncertainties are summarized in a unified analysis [21].

Techniques commonly used to cope with manufacturing scenario uncertainty include scheduling optimization and data mining based on supply and production data, but these are often limited by the lack of effective organization and specification of knowledge and data [22, 23]. Moreover, UE based on prediction cannot be explained because the prediction model is a black box model [24]. This paper pioneers the integration of uncertainty reduction into the structural design of knowledge models, that is, uncertainty reduction through a model-based approach. The approach is interpretable, and the model is a product of the design phase. Generating code based on a reliable model and driving the process execution can achieve the purpose of precontrol of uncertainty and ensure the reliability of the process.

In addition, this paper introduces a probability-based UQ method to assist model-based UE [25, 26]. UQ methods usually include the following steps [27]:

(1) Characterize uncertainty in the system parameters and external environment.

(2) Propagate uncertainty by computing engineering models/surrogate models: Forward propagation of uncertainty addresses how uncertainty in model inputs is transformed into uncertainty in model outputs, and existing methods for propagating uncertainty include probabilistic and nonprobabilistic methods. Nonprobabilistic methods include interval analysis fuzzy theory, rough set theory, and evidence theory, which are usually not rigorous enough [28].

Probabilistic methods usually aim to provide distribution information (output means and variances, event probabilities) to support uncertainty assessment or decision-making. The most flexible method for estimating distributional information is Monte Carlo simulation, which draws random samples from a joint distribution of inputs and evaluates the output values corresponding to each input sample. However, this method consumes a lot of computational time [29]. Local expansion-based methods and polynomial chaos expansion (PCE) are essential and widely used alternatives to Monte Carlo simulation. PCE can provide higher accuracy and efficiency than Monte Carlo simulation for a moderate number of parameters by exploiting the regularity/canonicality of the input–output relationships induced by the model. With the development of deep learning, Bayesian neural networks are currently used for uncertainty propagation, which is suitable for scenarios with large amounts of data and high complexity [30]. In addition, there are agent-based methods, which have cheap and fast computing capabilities. Gaussian process is a commonly used agent model, mainly used in this paper for uncertainty propagation due to the careful consideration of speed and accuracy [31].

These methods are often used to propagate uncertainty for continuous input variables [32]. For discrete input variables, Nannapaneni and Mahadevan [33] studied the uncertainty method based on the Bayesian network (BN). BN allows the integration of various types of uncertainty that occur at different stages of the life cycle.

(3) Inverse analysis, which usually includes two kinds of problems, bias correction, and parameter correction; the most widely used method is Bayesian calibration [34].

(4) To identify the main variables affecting output uncertainty, Arriola and Hyman [35] introduced a global sensitivity analysis based on the variance in UQ.

(5) The results from the above steps can be used as indicators of UE during modeling. In this paper, we design a generic UQ framework based on the above steps and integrate it with the model structure.

In summary, this paper focuses on the strategy of UE from the modeling perspective and introduces UQ in the model to assist UE.

3. Meta-Model Architecture for Domain Uncertainty

"Human, machine, material, method, and environment" is the abbreviation of the five primary factors affecting product quality in total quality management theory. In this section, based on the scope division of these factors, a hierarchical meta-model architecture is designed for the process execution in the manufacturing scenario; that is, a process is normatively divided into multiple levels. The design of the meta-model architecture is shown in Figure 2. The left side of Figure 2 shows the general structure of the meta-model, which is unified by the P-model (the P-model is the largest and outermost structure of the meta-model we define. It represents a process, and constructing a P-model means

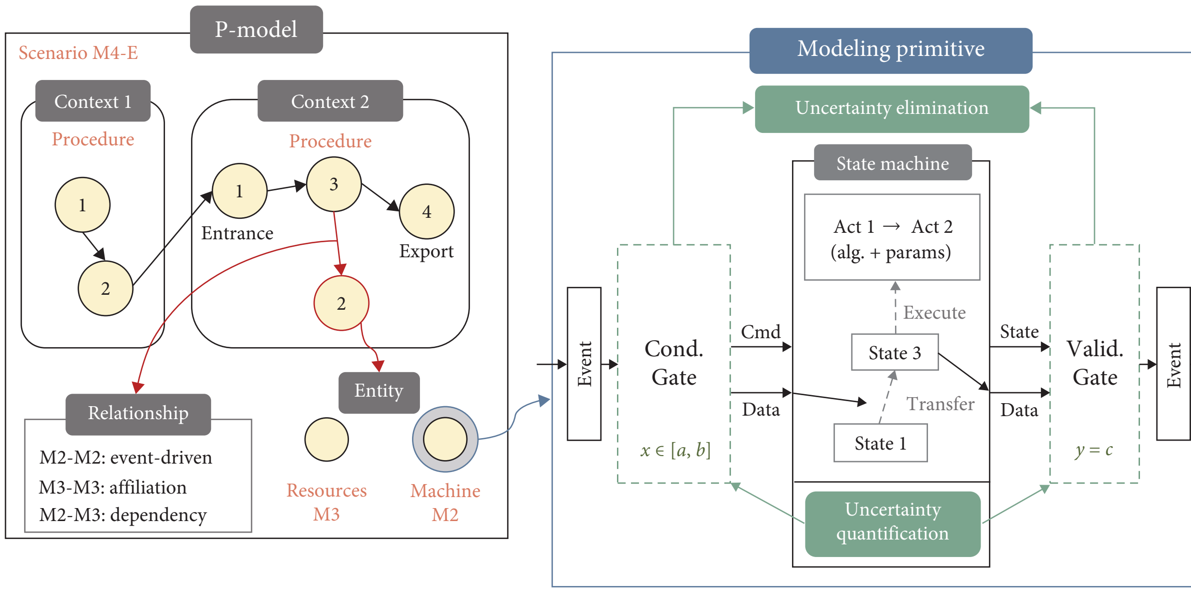

Figure 2: The meta-model architecture.

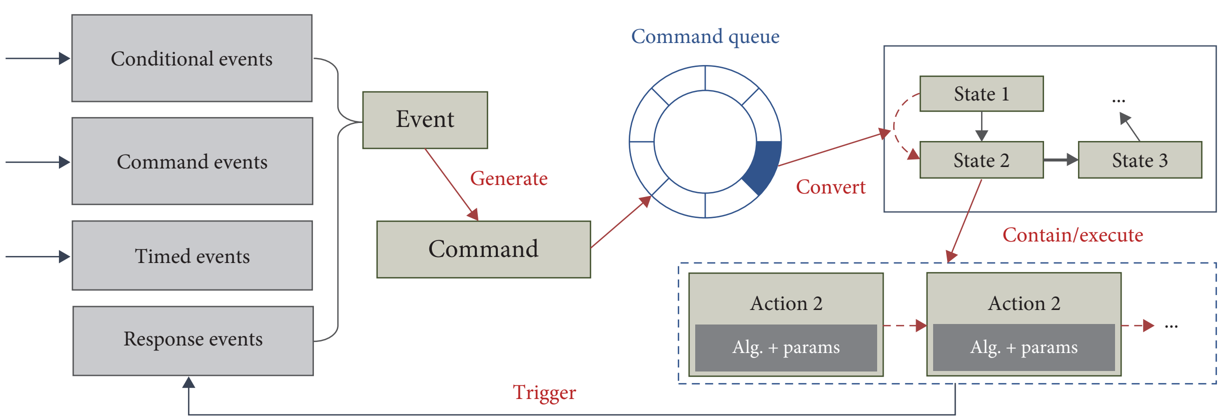

Figure 3: Relationship of elements in MP.

modeling for a process), and the right side shows the structure of the smallest unit of the meta-model—the MP.

3.1. P-Model. First, the P-model is specified as the outermost structure of the meta-model to define the process that carries the method (M1) and the environment (E). It contains all the static and dynamic elements that may appear in the process.

Second, a process is divided into procedures; each is modeled as a bounded context, and multiple procedures are considered interrelated contexts. The contexts communicate with each other through entities within the contexts. In addition, there is a glossary for each bounded context, providing a unified set of naming conventions for all elements. The glossary includes a "glossary-label" that provides a uniform naming convention for all elements and a "glossary-class" that defines inheritable abstract classes of entities and relationships.

Finally, the procedures are further divided, and each procedure (context) contains multiple machines (M2) and resources (M3), which are uniformly modeled as entities. The entities are associated with each other in three types as follows:

(1) The first is between machines, which are associated with events, called event-driven.
(2) The second is between resources, which are associated through dependencies and combinations, called direct affiliation.
(3) The third is between machines and resources, which usually appear as a certain machine depending on certain resources, called dependency.

3.2. MP. Resources are ordinary entities that contain only attributes, while machines are considered as entities with a special structure called the MP; MP itself contains multiple elements: the attribute, the event, the state, and the command (cmd). The relationship of these elements is shown in Figure 3, and each element is described as follows:

(1) The attribute refers to MP's properties, including generic and custom attributes that the user can extend. The constraints possessed by MP are part of the custom properties.
(2) The event refers to all possible events of MP, specifically the conditional event, the timed event, the command event, and the response event. The first three types refer to events that are interfered with by staff or triggered automatically by conditions, and the response event refers to the event that connects two machines (MP). The event will generate a command that leads to state transitions.
(3) The state refers to the state combination model that MP has in different modes. The command is used to drive the transition of states. Each machine can only be in one state at a time.
(4) The action is used to describe each state. Each state contains an ordered sequence of actions consisting of an algorithm and multiple parameters. The state is more abstract, and the action is more concrete; for instance, a "STARTING" state may include a "start" action of the mechanical arm. After the state transition occurs, the actions (algorithms) of the activated state are sequentially executed by the machine.

The above elements, combined with the Condition Gate and Validation Gate, make MP a dynamic and reliable model unit. As shown on the right side of Figure 2, the structure of each MP includes a Condition Gate, a Validation Gate, a state machine layer, and an uncertainty quantization module as follows:

(1) The entry of the MP is the event passed by the previous machine, and the exit is the event passed to the next machine, which indicates that the machines are associated with each other driven by the event.
(2) The entry event carries (input) variables and commands into the state machine layer. The (input) variables must be validated by a structure called "Condition Gate" before entering the state machine layer. In addition, the (input) variables also need to be passed to the uncertainty quantization module.
(3) The state machine layer handles the input variables and commands and outputs states and quantities of interest (QoI). Each state machine layer consists of a state transfer graph of the machine. The state transfers and executes the corresponding sequence of actions. After executing the sequence, the algorithm outputs QoI and state-carrying events.
(4) States and QoI are passed to the next MP carried by the output event after being verified by the Validation Gate.

MPs complete the process tasks that need to be performed by a single machine. Machines and resources work together to complete the process tasks required by a procedure. All the above meta-model structures are implemented as formal descriptions in XSD format.

4. UE

4.1. UE Strategy. The design of the meta-model structure described above fully considers the uncertainties existing in the process execution in the manufacturing scenario. Since most of the uncertainties in the process execution can be attributed to the process problems (effects) caused by various reasons (causes), this paper unifies various types of uncertainties into one concept for the convenience of analysis: process uncertainty from cause to effect [20]. As the smallest independent executing unit in process execution, the machine can be studied as the carrier object of process uncertainty.

For process uncertainty, we investigate the elimination approach in two aspects: the range control and the process control. The specific description is as follows:

(1) Control of uncertainty range: Eliminate a portion of the process uncertainty by controlling the range of uncertainty, which includes two strategies as follows:
   (i) Boundary restriction: Introduce the idea of modularity in the design of the bounded context and MP. Specify the boundaries of the bounded context and MP; the inputs within the boundary can be fuzzy or take values in a range, and the output QoI outside the boundary is deterministic. The uncertainty can be controlled within the bounded context and MP, and the reliability of the output is guaranteed eventually.
   (ii) Error tolerance: In some scenarios, unforeseen errors may occur due to strict limitations. We allow for controllable uncertainty to ensure reliability: when modeling, the fluctuation range of the attributes in the machine or process is appropriately expanded to allow uncertainty within a certain range in exchange for relative stability. The corresponding implemented model structure is the Condition Gate, in which the conditions for the input variable values are set to range values. The input variable values pass the validation as long as they are within the conditional range.
(2) Control of uncertainty process: Eliminate a portion of the uncertainty by ensuring the standardization and accuracy of data flow, which includes three strategies as follows:
   (i) Specification of machine and process parameters: During the model design, a glossary is defined for each context to describe all possible machine and process parameters so that they conform to a certain format specification.
   (ii) Functionalization: For the interaction between machines, a functional and responsive design idea from software engineering is used to ensure reliable information transfer. Specifically, the event-driven between MPs is expressed in the form of a function: the communication between primitives is realized by the cascading calls between functions,

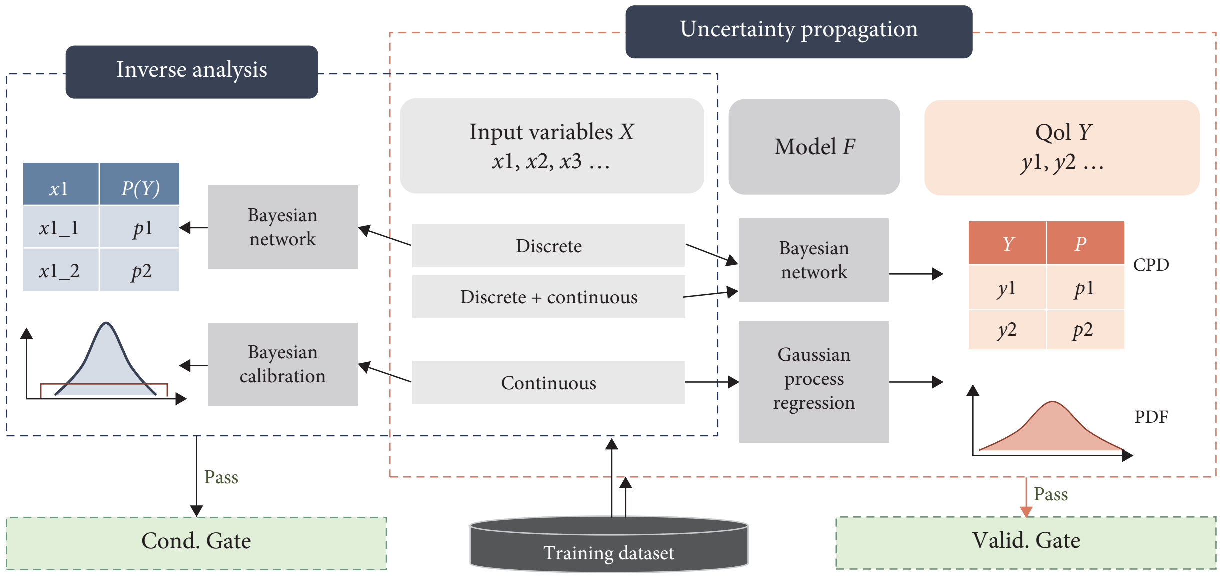

Figure 4: The idea of uncertainty quantification.

and the information is transferred by the passing of function parameters.

(iii) Standardization of data exchange: Accurate information exchange among machines (MPs) or contexts is an effective way to avoid process uncertainty. In the design of the MPs, a Condition Gate and a Validation Gate are set before and after each state machine layer. The data needs to be verified when entering and leaving a machine. The format specification of the data is verified by rule (XSD files), and the correctness of the data value is verified by a predefined fixed or range value. In addition, a machine can only be in one state at a time, and only events can drive the state transfer, which can ensure the machine's reliability.

4.2. UQ. We introduce UQ, using probabilistic methods to assist the above two UE strategies. The results of the UQ can be used as a reference when updating the validation conditions (the Condition Gate and Validation Gate) of the data; it can ensure the correctness of the data flow (process parameters and process results).

Process uncertainty in a machine, as the research object in this chapter, can be summarized in a paradigm of "input variable (X, θ) – model (F) – output QoI (Y)" as follows:

$$F(X, \theta) = Y. \tag{1}$$

The uncertainties in the process, such as problems with the machine itself, instability in resources or environment, and changes in requirements, can be represented as this paradigm for quantification [27]. The following research on UQ is based on this paradigm.

Purpose-oriented research ideas for UQ are grouped into two categories: passing the Validation Gate and passing the Condition Gate. The research ideas are shown in Figure 4.

4.2.1. Passing the Validation Gate. Passing the Validation Gate can also be called reliability verification of machine execution processes, which mainly uses uncertainty propagation to model multiple input variables to output QoI, followed by uncertainty analysis of the QoI.

Uncertainty propagation refers to transferring the uncertainty of the input variable through the model to the output QoI and evaluating the uncertainty of the impact on the output results. The steps and applications of uncertainty propagation are shown in the right-hand box of Figure 4 and are described as follows:

(1) Determination of parameters and models: The uncertain input variable is first determined, and a suitable mathematical model F is selected to map to the QoI. Since the process in this study cannot be modeled in general, a data-driven surrogate model is chosen as F. Two different surrogate models are selected according to the different types of values of the input variables (discrete and continuous): the Gaussian process regression (GPR) model and the BN model. The surrogate models are mainly used for uncertainty propagation.

(2) Uncertainty propagation: Then, the model is trained by training data, and the uncertainty (unstable value) of the input variables is propagated to the output QoI during the training process. The final predictive distribution on which the desired uncertainty depends specifically refers to the posterior distribution of the quantity of concern. A predictive distribution on which the final uncertainty relies refers specifically to the posterior distribution of QoI. For the two different surrogate models, the steps of uncertainty propagation are different.

(i) GPR is a nonparametric model used to establish the relationship between inputs and outputs, which can perform regression analysis of observed data based on Gaussian process priors and provide quantification of the uncertainty in the predicted results [36]. The steps of propagating uncertainty using GPR are as follows:

The input variable X and output QoI Y of the machine are assumed to be a prior Gaussian process sampling point, the mean function is initialized, and an appropriate Gaussian kernel function $k(X, X')$ is selected as follows:

$$Y(X) \sim N(\mu(X),\ k(X, X')). \tag{2}$$

The function distribution of the new observations (input variables) is still a Gaussian process during machine execution as follows:

$$\begin{bmatrix} Y \\ Y_* \end{bmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} K & K_*^T \\ K^* & K \end{bmatrix}\right). \tag{3}$$

The Bayesian formula is used to predict QoI (Y_*) to obtain the probability density function (PDF), and the uncertainty of QoI is analyzed based on the PDF as follows:

$$Y_* | Y \sim \mathcal{N}(K_* K^{-1} Y,\ K_{**} - K_* K^{-1} K_*^T). \tag{4}$$

The mean value of QoI is as follows:

$$\overline{Y_*} = K_* K^{-1} Y. \tag{5}$$

And the variance is as follows:

$$\mathrm{var}(Y_*) = K_{**} - K_* K^{-1} K_*^T. \tag{6}$$

The optimal hyperparameter of the Gaussian kernel function is found by maximizing Marginal Log-likelihood as follows:

$$\begin{aligned} \log p(Y|\sigma, l) &= \log \mathcal{N}(0, K(\sigma, l)) \\ &= -\frac{1}{2} Y^T K^{-1} Y - \frac{1}{2}\log|K| - \frac{N}{2}\log(2\pi). \end{aligned} \tag{7}$$

The newly observed data can continuously train the GPR model, which can reduce the uncertainty of the model.

(ii) BN is a graphical model that uses a directed acyclic graph to represent the dependencies between input and output variables [37]. These dependencies are represented by the conditional probability distribution (CPD), and BN can be expressed as a joint probability distribution of the variables as follows:

$$Pr_B(X) = \prod_{i=1}^{n} Pr_B\left(X_i | \prod_{x_i}\right), \tag{8}$$

where $\prod_{x_i}$ represents the set of parent nodes of X_i. In BN, uncertainty can be represented and propagated through CPD of discrete variables: first, the structure of the BN is specified, which usually uses a manual design with expert participation or automated structure learning. Second, the conditional probability of each edge is specified, and the prior knowledge is generally determined manually by experts, and the parameters are learned automatically from the data (Bayesian estimation). Finally, the posterior CPD of each variable is obtained.

The constructed BN can be sampled through its network structure and parameters to propagate uncertainty. For new input variables (evidence) of the machine, the inference process uses dependencies between nodes and CPD to calculate the posterior CPD (uncertainty) of the output QoI. In addition, the newly observed data can continuously update the BN model, which makes the model's performance more optimized.

(3) Passing the Validation Gate: The results obtained from uncertainty propagation are used to determine whether the Validation Gate in the corresponding MP can be passed. Given a set of input variable values, the output's uncertainty (PDF or CPD) can be inferred from the pretrained model. If the preset validation values are satisfied, the Validation Gate can be passed, and the subsequent process can be executed. The results of uncertainty propagation can continuously correct the preset validation values.

4.2.2. Passing the Condition Gate. It can also be called the feasibility verification of the process executed by a machine, which mainly adopts the method of inverse analysis. Inverse analysis refers to the evaluation of differences between models (bias correction) and uncertain parameters (parameter correction) by analyzing computer-simulated and experimentally observed data. Parameter correction is the main research goal of this paper.

As shown in the left-hand box of Figure 4, for discrete input variables using BN, the final output probabilities are directly inferred from the values of a single input variable, and the conditional gate can be passed if the probability is reliable (the conditional value is satisfied). For continuous input variables modeled by GPR, the Bayesian calibration method is used to study the posterior distribution for a single input variable [38]. The following mainly describes how Bayesian calibration is used to estimate the unknown parameters of the input variables to determine whether the Condition Gate can be passed.

The general updating formula of the model for bias correction is as follows:

$$y^e(x) = y^m(x, \theta^*) + \varepsilon. \tag{9}$$

The true distribution of θ is unknown, so it needs to be backward inferred from the experimental data $y^e(x)$. A common probabilistic inference method is Bayesian correction, that is, learning the posterior distribution of the unknown parameter from the observed data [39]. The specific steps are as follows:

(1) Define the prior distribution of the unknown input variables and construct the likelihood function: The unknown input variables' prior distribution (usually uniform) can generally be constructed using prior knowledge, expert experience, or historical data. A likelihood function for the unknown parameters is defined based on the observed experimental data. The likelihood function measures the probability of occurrence of the observed data given the parameter values.

(2) The posterior distribution inference is performed using the Bayesian formula as follows:

$$f(\theta|y_e) = \frac{f(y_e|\theta)f(\theta)}{f(y_e)} \propto f(y_e|\theta)f(\theta), \tag{10}$$

where $f(y_e|\theta)$ represents the likelihood function, $f(\theta)$ represents the prior, $f(y_e)$ represents the evidence, and $f(\theta|y_e)$ represents the posterior.

Analytic, sampling, and variational methods are commonly used for posterior distribution inference. We mainly choose the metropolis-Hastings sampling of MCMC, a sampling method based on probability distribution. We use metropolis-Hastings for sampling the posterior distribution and use many sampling results to approximate the posterior distribution.

(3) Passing the Condition Gate: The result of Bayesian calibration for a single input variable is the possible value range and distribution of the unknown parameter. Whether the Condition Gate can be passed is judged according to the confidence interval of the Bayesian correction value of the unknown parameter.

(4) Sensitivity analysis: Sensitivity analysis is used to estimate the contribution of each source (input) of uncertainty to the uncertainty of model output. Two types of sensitivity analysis are available—local and global. Global sensitivity analysis considers the influence of the input variable on its probability distribution (nonspecific value or range). This paper uses the Sobol global sensitivity analysis method to evaluate the coupling sensitivity of single and multiple input variables by calculating the variance between the input variable and the output response [40].

Consider a model with n random input variables X_1, $X_2, \ldots, X_n$ given by $Y = f(X)$, $f(X)$ may be decomposed in the following way:

$$\begin{aligned} Y = f_0 + \sum_{i=1}^{n} f_i(X_i) + \sum_{i<j}^{n} f_{ij}(X_i, X_j) + \cdots \\ + f_{1,2,\ldots,n}(X_1, X_2, \ldots, X_n). \end{aligned} \tag{11}$$

The total variance Var (Y) of $f(X)$ is defined to be as follows:

$$\mathrm{Var}\,(Y) = \sum_{i=1}^{n} V_i + \sum_{i<j}^{n} V_{ij} + \cdots + V_{12\ldots n}, \tag{12}$$

where

$$V_i = \mathrm{Var}_{X_i}(E_{\mathbf{X}\sim i}(Y|X_i)), \tag{13}$$

$$V_{ij} = \mathrm{Var}_{X_{ij}}\left(E_{\mathbf{X}\sim ij}\left(Y|X_i, X_j\right)\right) - V_i - V_j. \tag{14}$$

The $X_{\sim i}$ notation indicates the set of all variables except X_i. Based on the above, our specific analysis is as follows: we first determine the model input variables and the sampling range, and then we run the sampling function to generate the input samples from which the model (GPR) generates outputs. Finally, an analysis function was run to calculate (Monte Carlo simulation) the total sensitivity index S_i^T. The total sensitivity index represents the effect of an input parameter X_i on the result, including its interaction with other parameters $X_{\sim i}$. The calculation of S_i^T is as follows:

$$S_i^T = 1 - \frac{\mathrm{Var}_{\mathbf{X}_{\sim i}}\left(E_{X_i}(Y|\mathbf{X}_{\sim i})\right)}{\mathrm{Var}(Y)}. \tag{15}$$

The final sensitivity index can assist the judgment of the Condition Gate. The judgment condition of an input variable with a higher sensitivity index needs to be stricter (the variable value is constrained in a smaller range) to ensure a more reliable output.

5. Case Study and Data Evaluation

A corresponding modeling tool has been implemented for the above meta-model structure, which can be used to construct the model of a process that conforms to the meta-model structure, including the modeling and visualization for contexts, entities (MPs), entity attributes, events, and state machines. The constructed model can drive the process execution to achieve the purpose of eliminating uncertainty.

In addition, the UQ methods mentioned above and the implementation code are integrated and encapsulated in the entity modeling module of the modeling tool, as shown in Figure 5. Functions such as uncertainty propagation, inverse

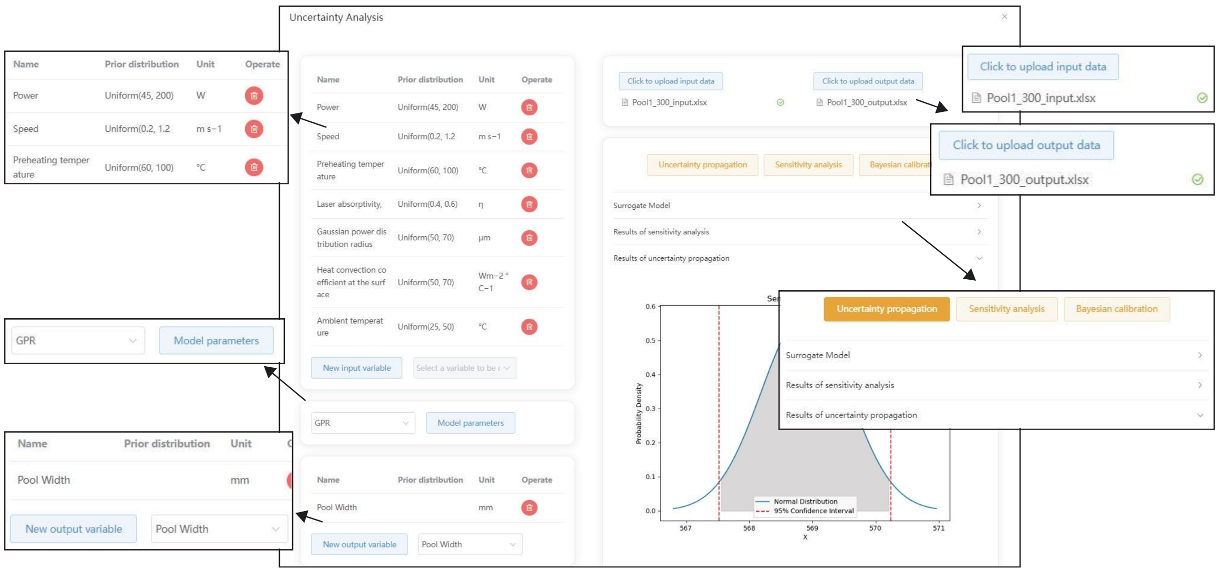

Figure 5: Uncertainty quantization module in the modeling tool.

analysis, and sensitivity analysis can be implemented by importing the dataset.

The following describes the use of the modeling tool to model two manufacturing process scenarios—welding and additive manufacturing, and the experiments and results on a simulated scenario and an open-source dataset using the UQ function. Case Study 1 is used to validate the feasibility of the modeling approach proposed, and Case Study 2 is used to illustrate the generalization of UQ.

5.1. Case Study 1—Welding. We use the case study to study the modeling and UQ of the welding process in a simulation scenario.

5.1.1. Case Study Design. The welding process is a traditional manufacturing process that combines two or more metallic or nonmetallic parts. There are many uncertainties in heating the welding material (such as wire, electrode) with the base material, forming a molten pool, and cooling using welding equipment. For example, during high-precision laser beam welding, the characteristics of the material (composition, thickness), the parameters of the laser (power, speed), and other factors will lead to uncertainty in the welding process and ultimately affect the welding quality [41, 42].

In general, the welding process contains multiple procedures. We built a simulation line for the welding process. To be more focused, "roof welding on Body-in-white (BIW)" was selected as the specific research scenario. The layout structure of the scenario is shown in Figure 6, which contains five procedures: assembling, welding, quality inspection, polishing, replenishment, and storage. Then, the corresponding model of the production line is constructed by the modeling tool to drive the operation of the production line. Relying on the reliable model, reliable process execution can be guaranteed.

The uncertainty of the welding quality problem is simulated in the welding procedure of the simulated production line. The welding quality under multiple input variables is simulated and observed on the welding manipulator in the welding procedure. The execution parameters and results of the welding manipulator are calibrated and adjusted using the input values and results of the open-source dataset [44], and 11 discrete input variables are set by combining with the preceding and following procedures.

5.1.2. Solution and Results.

(1) "Preparation" first, we use the modeling tool to accomplish two operations.

(i) Modeling the welding process: The welding scenario is modeled using the modeling tool. The welding process was divided into five contexts during modeling: the assembling context, the welding context, the inspection context, the polishing context, and the replenishment and storage context. The welding procedure is treated as a single context containing the entities (machines and resources) executing the welding. The welding manipulator is considered as an MP, which includes eleven input variables ($x1-x11$) and three output QoI ($y1-y3$): cracking in the weld metal, count of cracks, and average crack length. An implementation of the constructed model (Algorithm 1) is as follows:

After the modeling is completed, the model is mapped to code by mapping rules and deployed in the master controller (Raspberry Pi) of the production line.

(ii) Training the UQ model: The modeling tool is also deployed in the Raspberry Pi at the edge. The agent model is pretrained in the modeling tool using the training dataset for the equipment (welding manipulator) that needs to evaluate the uncertainty. Since there are nondiscrete value variables in the experimental data, we first discretize the nondiscrete value variables. Various discretization methods are integrated into the modeling tool, and two methods

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"entityList": [
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    }],
    "userAttr": [6],
    "state": [4]
  }}, …
]
}}
```

Algorithm 1: An implementation of the constructed model.

are mainly used in this case study: Equal Interval and K-means discretization. Next, BNs are applied to model the discrete variables: empirical knowledge is used to define BN's structure, as shown in Figure 7. The prior distribution of the variables is assumed to be the Dirichlet distribution, and the posterior distribution of the parameters is learned by Bayesian estimation when the BN structure is known. After the structure and parameter learning are completed, the BN model is constructed and can be used for inference.

(2) "Production line operation:" After constructing the model and mapping it to code, the code drives the production line to run, finishing the assembling, welding, quality inspection, and polishing in sequence. Uncertainty assessment is performed before the execution of the welding procedure: the production line feeds back to the Edge (Raspberry Pi) the current input parameters ($x1-x11$) of the welding manipulator, and the UQ Module of the modeling tool performs the inference automatically to reason out the probability distribution (uncertainty) of the output Qol using BN.

Table 1 shows the CPD of the output Qol given a set of input variable values. In this CPD table, the probability of successful welding is about 83%. If it is lower than the preset verification value, the Validation Gate will not be passed.

To test the accuracy of the proposed UQ framework in practical use, we divide three test groups from the dataset: Group 1 (all data with expected welding results) and Group 2 (all data with defective welding results) with 25 data volumes and Group 3 (contains both above welding results) with 50 data volumes. The welding process is simulated sequentially with 100 input variables three times on the simulated production line. The welding results are inspected by a vision camera. The inspection results are compared with the accurate results of the test set, and the comparison results are shown in Table 2. It can be found that the inference accuracy of the BN model reaches more than 98% accuracy, whether compared with the test set results or the visual detection results, and the time complexity of the inference algorithm is only about 5% of the welding process. The experimental results show that the uncertainty propagation algorithm can effectively evaluate uncertainty in simulated scenarios.

(3) "Inverse analysis:" The BN model can infer the reliability of the output Qol given a single input variable (evidence). The input variable can pass through the Condition Gate with a high reliability (success probability) of Qol, and the conditional range of the variable in this Condition Gate can be adjusted according to the situation (the success probability of Qol is above 95%). Table 3 shows the CPD of Qol given the values of the two input variables. The last row of the table shows the entropy calculated based on the conditional probability of the input variable. The higher the entropy, the higher the degree of uncertainty of the variable.

In addition, we conducted a comparative experiment on an input variable with a certain uncertainty, comparing the execution of the welding process after adjusting the conditional range of that variable in the Condition Gate. The comparison results are shown in Table 4, and it can be found that the uncertainty in process execution can be reduced by adjusting the Condition Gate through inverse analysis.

(4) "Totally:" We also experimented with the welding success rate and extra cost of the welding process under two situations: model-based pre-elimination and model-less postprocessing (tester coding directly, defects handled manually) in the production line, and the experimental results are shown in Table 5. We found that model-based UE can not only improve the success rate of welding but also save labor and time costs of manual repair welding.

5.2. Case Study 2—Additive Manufacturing. We use the case study to study the modeling and UQ of the welding process in an open-source dataset. In Case Study 2, we mainly validate the usability of the UQ framework on continuous input variables on the additive manufacturing open-source dataset,

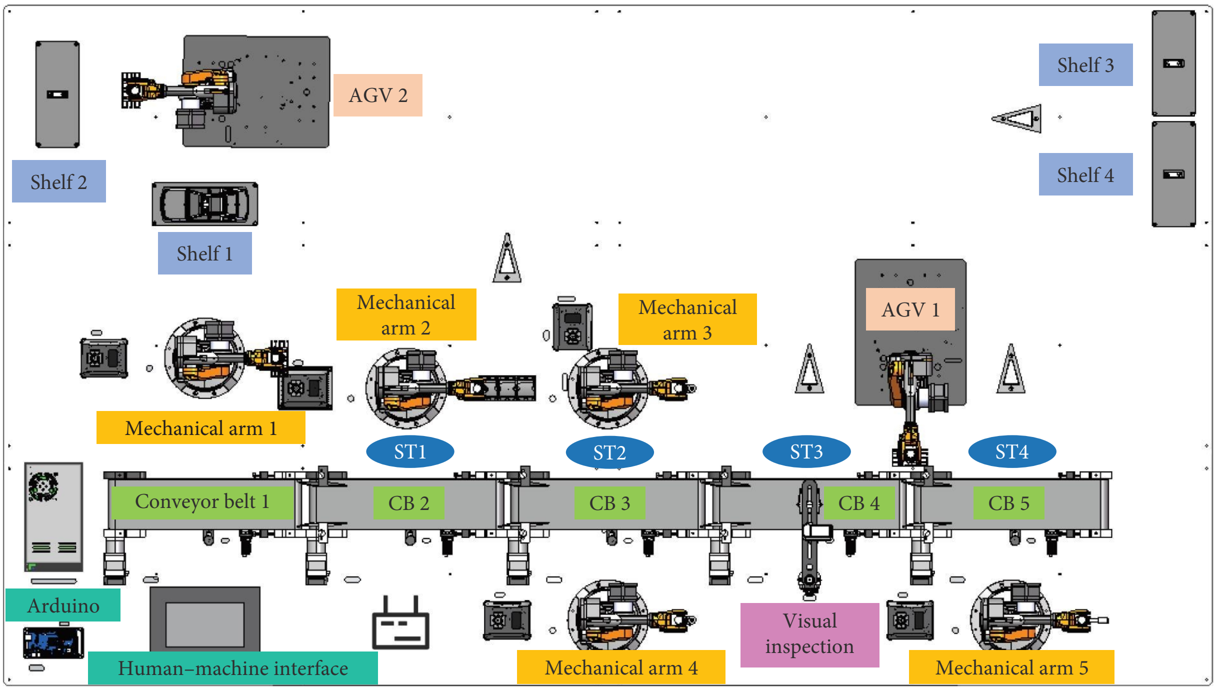

Figure 6: The layout structure of the simulation line (reproduced from Shi et al. [43], under the Creative Commons Attribution License/public domain).

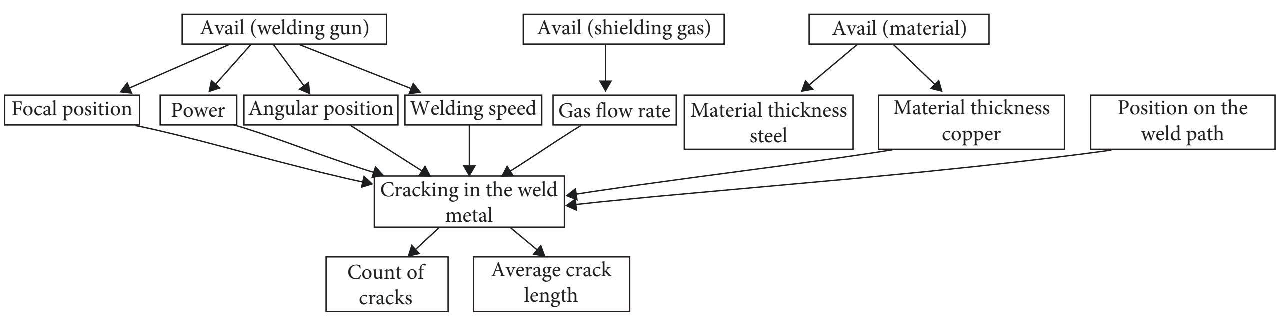

Figure 7: The structure of BN.

Table 1: The CPD of the output QoI given a set of input variable values.

Cracking in the weld metal	Given all parameter values
Cracking in the weld metal (0)	0.8395
Cracking in the weld metal (1)	0.0249
Cracking in the weld metal (2)	0.1356

which illustrates the generalizability of our proposed UQ framework.

5.2.1. Case Study Design. Additive manufacturing is an intelligent manufacturing process that adds materials layer by layer to produce 3D structural entities [45]. The complex layer-by-layer manufacturing process causes various uncertainties, such as natural changes in powder absorption rate, fluctuation in temperature boundary, and uncertainty in powder particle characteristics [46].

Metal 3D printing is a typical metal additive manufacturing process. Selective laser melting (SLM) is a common technique that usually includes multiple procedures: model design, material preparation and spreading, laser melting, postprocessing, and inspection and testing. Laser melting is the primary process of SLM, so we mainly perform parameter calibration for continuous input variables and quality control for QoI in a single laser melting machine.

The open-source data set includes seven input variables and three output QoI [47]. The input variables are continuous. The output QoI is the geometry of the melting pool, which determines the melting quality of the laser melting process.

5.2.2. Solution and Results. First, the modeling tool is used to model the metal 3D printing process, and then the open-

Table 2: Experiments on the accuracy of uncertainty propagation.

	Uncertainty inference accuracy (%)[1]	Uncertainty inference accuracy (%)[2]	Average inference time (s)[3]	Average welding process time (s)
Group 1	98.67	98.67	1.42	21.85
Group 2	98.67	100	0.97	20.77
Group 3	98.00	99.33	1.56	21.04

[1]Comparison with visual inspection results. [2]Comparison of results with results in the test set. [3]Algorithmic complexity.

Table 3: The CDP of QoI given the values of the two input variables.

Cracking in the weld metal	Evidence = (power: 3)	Evidence = (welding speed: 1.2)
Cracking in the weld metal (0)	0.7156	0.7306
Cracking in the weld metal (1)	0.1965	0.1800
Cracking in the weld metal (2)	0.0879	0.0894
Entropy	1.0860434629825808	1.0893897677340258

Table 4: Comparison results of adjusting the Gon.

Evidence = welding speed (multiple values)		Process continuation rate (PCR) (%)	Welding defect rate (based on PCR) (%)
The range of Gon. Gate	No adjustment	93.33	64.29
	Adjustment	56.67	0

Gate or not (30 simulations per group).

Table 5: Comparison of welding results under two uncertainty treatments (10 simulations per group).

	Total Takt time (average) (s)	Defect rate (%)	Extra costs
Pre-elimination	141.42	0	None
Postprocessing	186.87	30.00	Labor costs, workstation costs

Table 6: Physical meanings of input variables and output concerns.

Input variables	Unit	Range
Power (p)	W	49–195
Preheating temperature (Tpre)	°C	60–100
Laser absorptivity (eta)	\	0.4–0.6
Gaussian power distribution radius (Gau_rad)	μm	50–70
Heat convection coefficient at the surface (heat_conv_coeff)	$\mathrm{Wm^{-2}\,°C^{-1}}$	5–25
Ambient temperature (Ta)	°C	25–50
Output concerns	Unit	Range
Pool length	μm	\
Pool width	μm	\
Pool depth	μm	\

source dataset is used to conduct a UQ experiment in the laser melting machine (MP).

(1) Modeling and confirming input and output variables: The laser melting process can be modeled as a context, which contains the entities (machines and resources) executing the laser melting. The laser melting machine is regarded as an MP, which contains seven input variables ($x1$– $x7$) and three output concerns ($y1$– $y3$): Pool length, pool width, and pool height, as shown in Table 6.

(2) Uncertainty propagation: Since the dataset does not contain discontinuous variables, GPR can be directly modeled after data preprocessing. The kernel function is an essential configuration in GPR. The modeling tool integrates five kinds of kernel functions

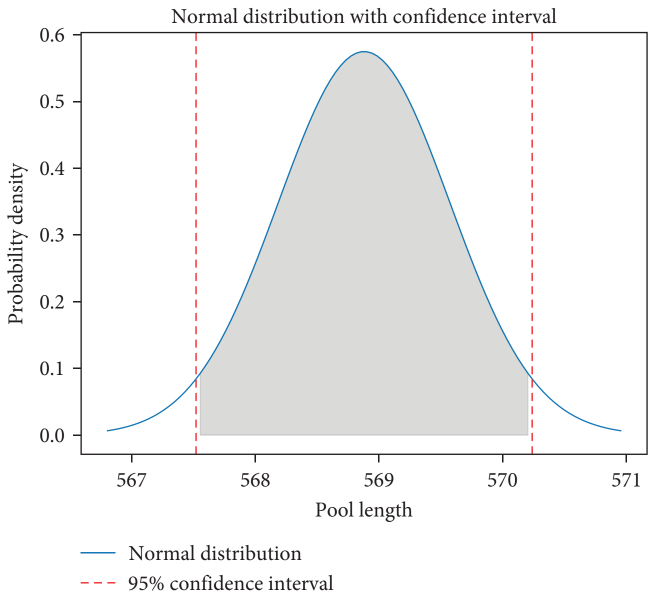

Figure 8: PDF of the pool length.

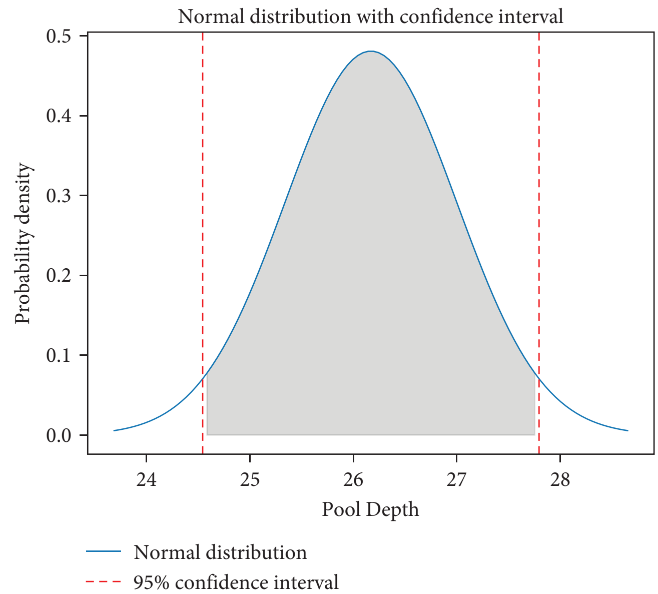

Figure 10: PDF of the pool height.

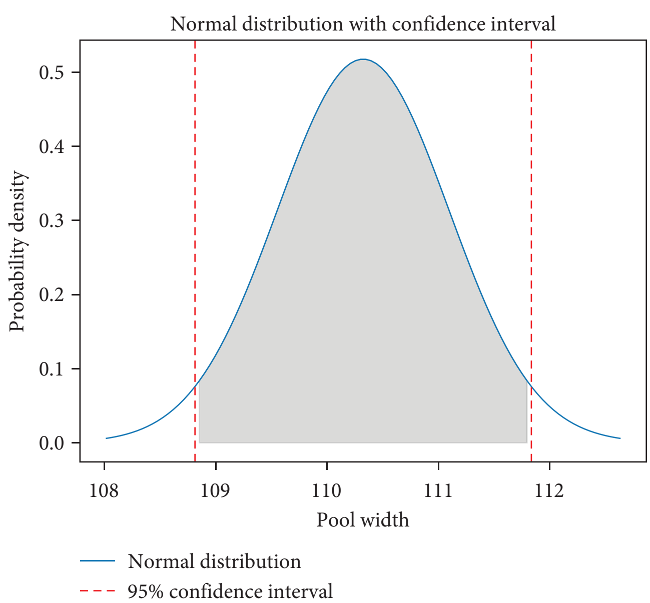

Figure 9: PDF of the pool width.

provided by Sklearn.gaussian_process: RBF kernel, Constant Kernel, Matern kernel, Rational Quadratic, and ExpSine Squared. In this example, these kernel functions are selected to construct the GPR to predict the test samples. Figure 8–10 show the prediction results of the GPR with the best test accuracy for the given samples. The result is the probability distribution of the output Qol, where the red dashed line is the 95% confidence interval; the Validation Gate can be passed if the preset validation value is within this confidence interval.

(3) Inverse analysis: In this example, the parameters of five variables ($x3$– $x7$) are uncertain, and their exact distribution is unknown. The modeling tool provides a Bayesian calibration method based on MCMC sampling. We first assume the prior distribution of parameters and then use the dataset to calibrate the parameters. The parameter calibration results of $x3$ are shown in Figure 11, where the right of Figure 11 is the sampling process of the dataset in the process of Bayesian calibration, and the left of Figure 11 is the final calibration result, which is the posterior distribution of parameters (mean and standard deviation). The mean value of the parameter is chosen to determine the posterior distribution of the variable, and the confidence interval is calculated to adjust the conditional range of the variable in the Condition Gate.

(4) Sensitivity analysis: The Sobol method is integrated into the modeling tool to sample the posterior distribution of input variables and analyze the sensitivity. The sensitivity analysis results on the above dataset are shown in Figure 12 (using the GPR model). It can be found that the variable named eta has the most minor influence on the final output results, and the conditional range can be appropriately relaxed during conditional verification.

For any process, indicators of the UQ result are not only used to determine whether the gate can be passed but also can update the Condition Gate and Validation Gate of MP. Parameter calibration of discrete input variables and quality control of Qol for a single machine can provide a reliable model, which can drive the process's execution and ensure a reliable process.

The above experimental results show that our proposed framework can give reasonable results in both uncertainty propagation and inverse analysis when facing equipment with continuous variables in the input parameters, and these

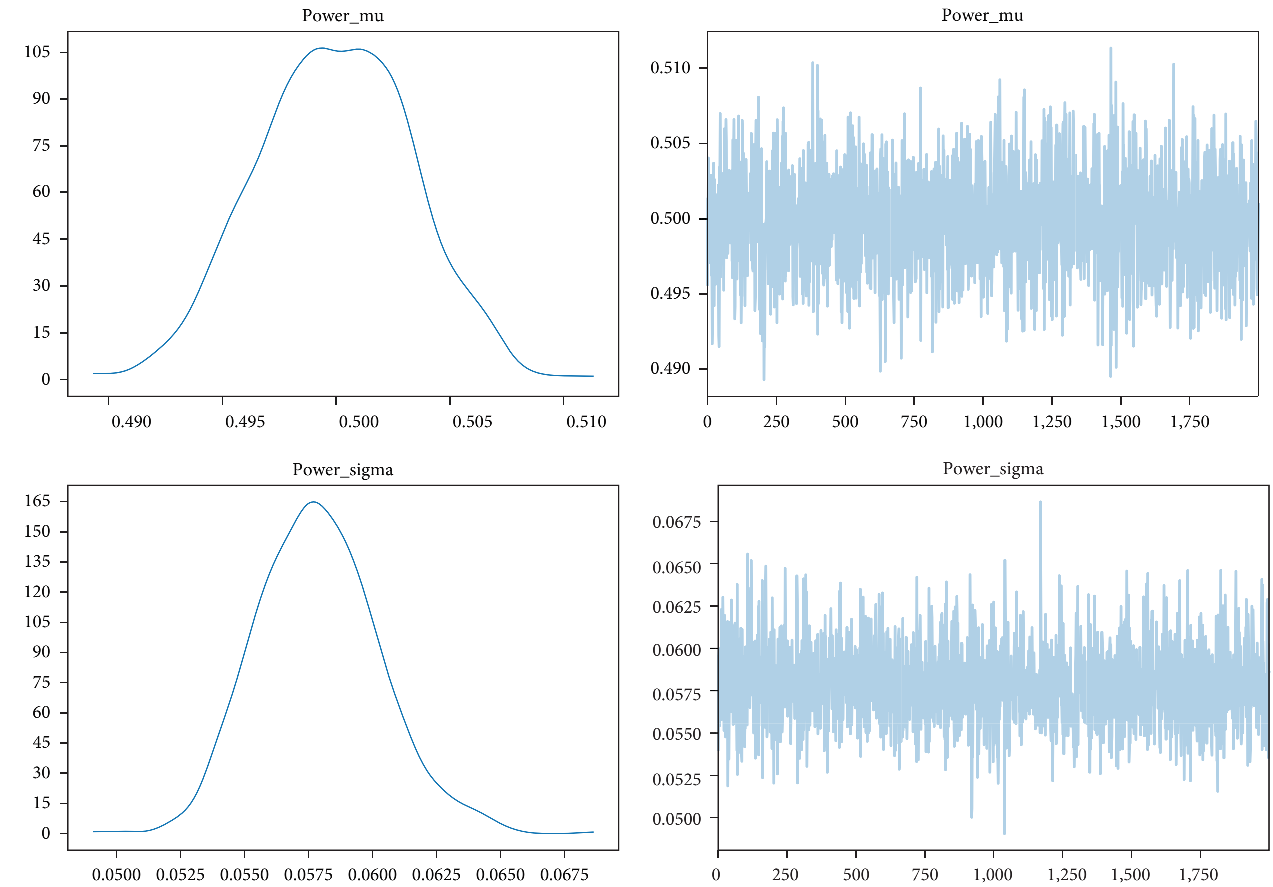

FIGURE 11: The results of Bayesian calibration.

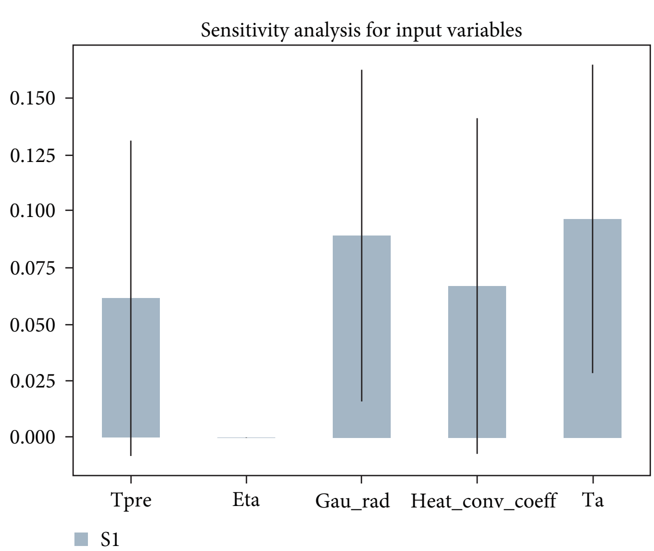

FIGURE 12: The results of sensitivity analysis.

result indicators can be used as the basis for updating the Condition Gate and Validation Gate of the model. Comprehensively analyzing Case Study 1 and Case Study 2, the proposed method is not only practically feasible but also generalizable to multiple scenarios.

6. Conclusions

In this paper, we propose a modeling approach for industrial manufacturing scenarios to support the reliable execution of processes. The approach defines a meta-model structure for abstractly describing various elements in a manufacturing scenario; then, the UE strategy is considered in the structural design of the meta-model, the UQ method is introduced, and the metrics of UQ can provide support for UE.

Unlike previous decision-making methods for uncertainty, the advantage of the proposed method is that control and elimination of uncertainty can be realized before the process execution, and the elimination metrics are continuously updated through UQ during the execution of the process. To support the effective use of the modeling approach in practice, we constructed a prototype tool and built simulation scenarios to validate the research approach, and the results validate the feasibility of applying the model in manufacturing scenarios to ensure process reliability.

Our study has several practical implications. The proposed method provides a general modeling basis for low-code techniques in manufacturing scenarios. The model structure is easy to understand, especially considering the reliability requirements, which are particularly concerning in manufacturing scenarios. Process engineers can build scenarios based on the model and easily realize reliable execution of processes through low code. In the future, process engineers can focus more on scenario design without much consideration of coding and uncertainty control.

The approach needs to be further optimized, and its application scenarios need to be further expanded. Specifically, there are three shortcomings:

(1) The UE strategy is still not comprehensive enough. This paper mainly focuses on the uncertainty in the process execution, and macro-uncertainties, such as some demand changes and environmental impacts, will be the focus of future work.
(2) In UQ, only the uncertainty of (input) variables is considered, but the surrogate model used also has uncertainty. In the future, we will focus on the bias analysis and calibration of the model.
(3) The proposed approach focuses on model design rather than low-code implementation. Only a simple code mapping design has been performed for the scenario we built, which is the focus of our future research.

Data Availability

Previously reported (.xlsx) data were used to support this study and are available at [44, 47].

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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