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Research Article

A Multisource Uncertainty Fusion Reliability Evaluation Method for the Control Rod Drive Mechanism of Nuclear Power Plants

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The reliability of a pressurized water reactor power plant's control rod drive mechanism (CRDM) is affected by many factors, such as operation states, unit performance, and dynamic environments. Multiple sources of uncertainties, including random, interval, and fuzzy, exist when analyzing the reliability of CRDMs. Modeling reliability without considering the fusion of multisource uncertainties may result in model distortion and may not provide realistic assessment results. This paper proposes a multisource uncertainty fusion method powered by the margin-based variable transformation and the Bayesian network propagation. The interval and fuzzy variables are transformed into random variables to obtain the corresponding generalized probability density function of the CRDM's feature parameters. After that, the CRDM's reliability can be evaluated via probability quantization of the Bayesian network inference result through sampling algorithms. A magnetic-jack type CRDM case is presented to verify the proposed method, and the results show that this method can fuse three types of uncertainty variable in a unified way and effectively obtain reliability evaluation results.

1. Introduction

Nuclear energy is sustainable clean energy and has been recognized as the only alternative energy that can replace conventional energy on a large scale [1]. The pressurized water reactor (PWR) is the most commonly used reactor for the third-generation nuclear power plant [2]. The power generation of PWR is fine-tuned by the control rods' insertion height into the reactor core, which is adjusted by the control rod drive mechanism (CRDM) [3]. That makes CRDMs crucial to ensuring the reliability and safety of nuclear power plants [4]. At the same time, due to the harsh working environment of CRDMs, their maintenance is complex and generally needs to shut down the reactor, which costs a lot. Therefore, it is vital to analyze and evaluate the reliability of CRDM to ensure the safe, reliable, and economical operation of a nuclear power plant system [5–7].

There are various types of CRDM for different nuclear reactors, most specially made electromechanical products composed of multiple components. In CRDM, many components, such as rotating machinery, have performance degradation under long-term use that is non-negligible [8]. The complex structure of CRDM means that their reliability is affected by diverse uncertain performance variables [9]. Owing to the diversity of knowledge, sensing techniques, and data acquisition methods, the uncertainty types of these variables are also diverse. A general taxonomy categorizes uncertainty into three types: random, interval, and fuzzy [10]. The random type is the most general variable among these three types and has been well-studied with efficient quantification techniques. However, because of the lack of samples or knowledge, the interval and fuzzy types of uncertainty are hard to invite in reliability evaluation practice. Rahman et al. [11] discussed the optimization problem with type-2 interval uncertainty and provided a theoretical framework. In countering the multiple uncertainties, the main challenge lies in the synthesis quantification method of these three types of uncertainty, i.e., the multisource uncertainty fusion.

Multisource uncertainty fusion technology reduces information uncertainty by combining, processing, filtering, and verifying information from multiple data sources, which is beneficial for obtaining accurate feature information. Given that the fuzzy and interval variables are hard to invite in reliability evaluation practice, people usually transform them into the random type and then use the probability theory to evaluate reliability. The conversion modes between different uncertain variables are detailed in the literature review (see Section 2). After the transformation, the multisource uncertainty fusion problem turns into the fusion task of the random variables gathered from multiple data sources, i.e., the multisource signal processing. Rehman and Mandic [12] proposed a multivariate empirical mode decomposition (EMD) method, which allows for the simultaneous processing of multivariate signals. Based on this, Lv et al. [13] verified the theoretical effectiveness of the multivariate EMD method and its sensitivity to noise. Yuan et al. [14] proposed a multivariate intrinsic multiscale entropy (MIME) analysis based on multivariate variational mode decomposition (MVMD). Zhang et al. [15] proposed a multidimensional dynamic mode decomposition (MDMD), which solves the problem of mixed-mode characteristics and possible loss of critical fault feature information when processing multivariate signals.

There are two main methods for analyzing the reliability of CRDM: the method based on degradation simulation and the method based on reliability modeling. Degradation simulation methods mainly focus on the components' performance deterioration during the operation of CRDM. Yu et al. [16] built a multiphysics coupling simulation for the key structure of the magnetic-jack type CRDM and then used the Monte Carlo method to calculate its time-dependent reliability. As presented in Yu et al.'s work, multiple compute-intensive simulations are needed during the simulation-based method to maintain the accuracy of reliability calculating. Moreover, building a high-fidelity simulation for the whole structure of the CRDM is challenging, which constrains the application of simulation-based methods [17]. Model-based methods can establish a formalized reliability model for the entire system of CRDM to describe the propagation of failures or defects and then evaluate the reliability. Specific methods, such as the reliability block diagram (RBD), failure tree analysis (FTA), and event tree analysis (ETA), are widely used in the practice of nuclear power plants. Wang et al. [18] applied the RBD method to model the reliability of a CRDM control system for the thorium molten salt reactor (TMSR). As presented in Wang et al.'s work, the model-based method relies on probability calculation rather than statistical simulation to quantify the uncertainty. However, conventional model-based methods mainly rely on the designer's prior knowledge or historical data to determine the implicit probability propagation pattern within the CRDM system. These methods are inconvenient for handling multisource uncertainties. Apparently, neither the simulation-based method nor the model-based method can solve the multisource uncertainty fusion task in CRDM reliability evaluation separately.

Informed by the literature review (see Section 2), this paper proposes a multisource uncertainty fusion reliability evaluation method for the CRDM. A physics simulation is constructed first, and then, a model-based response surface is built for the simulation model as a lightweight surrogate. With this surrogate, the multiple types of uncertainty are transformed and fused through a margin-based method to evaluate the reliability of CRDM. This paper details how

(1) multisource uncertainties are fused for reliability evaluation based on the margin theory

(2) the reliability of CRDM performance is evaluated with a joint approach of physics simulation and a model-based method considering multiple types of uncertainty

(3) the reliability of a practice CRDM's latch assembly performance is evaluated based on the proposed method

The rest of this paper is organized as follows. Section 2 introduces related works, in the multisource uncertainty fusion method, and Section 3 provides the methodology for the proposed method. In Section 4, the application results of the proposed method are demonstrated. Section 5 and Section 6 discusses and summarizes the article.

2. Literature Review

The multisource uncertainty fusion method fuses random, fuzzy, and interval variables converting different types of uncertainty into the same. In recent years, various approaches have been used to transform different types of uncertainty. The related literatures are listed in Table 1.

The literature regarding the reliability of fusing random and fuzzy variables can be summarized as follows: fuzzy variables are usually transformed into random variables, and then, probability theory is used to evaluate the reliability. The commonly used conversion methods include the formula method, the equivalent density function method, and the information entropy method. The equivalent probability density function method uses the distribution probability of artificially given random variables [19, 20] that deviate from reality. Valdebenito et al. [21] proposed a method for the approximate calculation of fuzzy failure probability, but this method is only used to solve the problem of the medium nonlinear performance function. You et al. [22] used envelope distribution to describe fuzzy random variables. The information entropy method uses the invariance of entropy to equate the fuzzy entropy of the original fuzzy variable to the probability entropy of the random variable so that the fuzzy variable can be transformed into a normal random variable. The effectiveness of this method has been confirmed in two cases [23]. However, this method also has

Table 1: A summary of closely related literature and the present work.

Fusing uncertainties	Authors	Method description
Random and fuzzy	Dong and Wang [19]	Equivalent probability density function
	Guo et al. [20]	Equivalent probability density function
	Valdebenito et al. [21]	Approximate calculation
	You et al. [22]	Envelope distribution
	Zhang et al. [23]	Information entropy
Random and interval	Elishakoff and Colombi [24]	Convex model theory
	Du [25]	Evidence theory
	Deng [26]	Mixed reliability index
	Li et al. [27]	Normal and standard variable conversion
	Wang et al. [28]	Upper and lower bounds
	Yang et al. [29]	Kriging model and Monte Carlo simulation
	Yang et al. [30]	Kriging model and Monte Carlo simulation
	Zhang et al. [31]	Kriging model and Monte Carlo simulation
	Liu and Elishakoff [32]	Kriging model and Monte Carlo simulation
Fuzzy and interval	Gao and Zhang [39]	Information entropy
	Wang and Matthies [40]	Two-stage analysis framework
	Lü et al. [41]	Interval variables with fuzzy limits
	Li and Nie [42]	Fuzzy decomposition theorem
Random and fuzzy and interval	An et al. [43]	Iterative first-order reliability method
	Tang et al. [44]	Subintervals and evidence theory
	Zhang et al. [45]	Uniformity variable conversion

shortcomings. Using this method loses the original distribution information, resulting in the nonunique distribution probability of transformed random variables.

The literature regarding the reliability of fusing random and interval variables can be summarized as follows: in [24], the authors proposed an analysis method to solve the mixed reliability problem based on the convex model theory. In [25], the authors performed the reliability evaluation under the condition, based on evidence theory, that interval and random variables exist at the same time. Taking the truss structure as an example, Deng [26] proved that when the interval variable reaches the extreme value, the extreme value of the mixed reliability index can be obtained. Li et al. [27] converted random variables into normal variables and interval variables into standard variables, which solved the problem of static system reliability with mixed uncertain variables. Wang et al. [28] deduced the relationship between the upper and lower bounds of failure probability and the upper and lower bounds of the product, the interval variable function, which avoided the optimization analysis process and improved the calculation efficiency. A hybrid reliability method based on an active learning Kriging model and a Monte Carlo simulation (MCS) was proposed in [29–31], which improved the accuracy of failure-probability-limit estimation, but this method was not suitable for estimating small failure probability. Liu and Elishakoff [32] proposed a combined importance sampling and active learning Kriging reliability method to accurately evaluate the limit of small-fault probability relative to interval variables.

For the reliability of fusing fuzzy and interval variables, the existing research evidence on fuzzy theory mainly focuses on decision analysis and uncertain reasoning [33–38], whereas there is less research on reliability analysis. Gao and Zhang [39] evaluated the conservative value of structural reliability by calculating the worst reliability under the condition of interval variables and combining the information entropy method. Wang and Matthies [40] proposed a two-stage analysis framework for the reliability evaluation of a mixed cognitive uncertainty system, which successively introduced evidence information and fuzzy information to quantitatively evaluate the system's reliability. In [41], the authors proposed a reliability analysis method to solve the problem that the uncertain parameters are interval variables, and the lower and upper limits of interval variables can only be modeled as fuzzy variables. Li and Nie [42] converted fuzzy variables into interval variables according to the fuzzy decomposition theorem and then obtained the interval value of structural reliability by using the error transfer principle.

When all three types of uncertainty exist, most processing methods are based on adding a third uncertainty variable into the method of fusing two uncertain variables. In [43], fuzzy variables and random variables were transformed into interval variables and then solved by an iterative first-order reliability method. In [44], random variables and fuzzy variables (equivalent to random variables) were discretized into subintervals, and finally, the reliability analysis was completed by using evidence theory. Based on the cut set optimization theory, Zhang et al. [45] converted fuzzy variables into random variables and interval variables into random variables by the uniformity method and then used the FORM method to solve the structural reliability.

3. Method

The proposed multisource uncertainty fusion reliability evaluation method is a joint method that combines the simulation and model-based methods that can assess reliability considering random, fuzzy, and interval uncertainties. The framework of the proposed method is demonstrated in Figure 1. A dynamic simulation of CRDM is first built to analyze the force and mutual motion between parts. The relationship of velocity, displacement, and mass of the key parts to the performance of CRDM is simulated. Then, based on the dynamic simulation, a Bayesian network is constructed as a surrogate of CRDM performance in relation to the state of the parts. Meanwhile, the multiple types of uncertainty variables are transformed into random variables that are the uncertainty propagation inputs of the surrogate. After that, the margin-based theory models the reliability of the CRDM and calculates the probability of failure and reliability.

As shown in Figure 1, the dynamic simulation part of the proposed method only provides the data upon which the subsequent analysis is based. In practice, researchers can use the actual measured data during CRDM operation instead of the simulation model. Therefore, the dynamic simulation part is not the primary point of this paper.

3.1. Multisource Uncertainty Transformation. For the interval variable X_I, the only information known by users is the upper and lower bounds of a single interval or the upper and lower bounds of multiple intervals and their corresponding basic probability distribution. The conversion of interval variables to random variables can be based on the Laplace criterion. The Laplace criterion is also called the equivalent probability principle. The basic assumption of the principle is that since the probability of each natural state cannot be determined, the probability of each state is considered to be the same.

For interval variables, the distribution state in the interval is unknown, and there may be a variety of distribution forms. It can be assumed that the variable obeys uniform distribution in the interval, which adds to the minimum assumption under limited knowledge. If there is more information or knowledge, it can be used to characterize the distribution of interval variables, and the corresponding distribution function can be used to correct the distribution probability of the variables.

The interval variable X_I, containing only one interval number, namely, $X_I \in [a, b]$, is considered to be uniformly distributed in the interval. The generalized probability density function $\widehat{f}_{X_I}(x)$ is shown in

$$\widehat{f}_{X_I}(x) = \frac{1}{b-a}, a \le x \le b. \tag{1}$$

Fuzzy variables can usually be represented by membership functions. Common membership functions have similar types to probability density functions, which are mainly used to characterize the possibility of variables appearing at different values. The biggest difference between the two is that the area under the distribution curve of the probability density function is 1, whereas the area under the membership function curve is not 1. In order to solve the problem of reliability calculation with fuzzy variables, some researchers have proposed the method of transforming membership functions into probability density functions to realize the transformation of fuzzy variables into random variables; these methods mainly include the generalized density function method, equivalent density function method, and information entropy method. The generalized density function method converts the original membership function of fuzzy variables into a similar probability density function based on the normalization principle and then completes the conversion from fuzzy variables to random variables.

A fuzzy variable is denoted as X_F, the membership function of which is $\mu_{X_F}(x)$; the generalized probability density function can be obtained with the normalization method, which equals the quotient of the membership function divided by the integral of the membership function, as shown in

$$\widehat{f}_{X_F}(x) = \frac{\mu_{X_F}(x)}{\int_{-\infty}^{+\infty} \mu_{X_F}(x)dx}. \tag{2}$$

$\widehat{f}_{X_F}(x)$ is the generalized probability density function after the membership function $\mu_{X_F}(x)$ of fuzzy variable X_F is transformed into a random variable.

This method applies to the situation where the area of membership function curve is bounded, and most of them belong to this situation in practical engineering. Therefore, the above-mentioned conversion method has good applicability. It should be noted that there is no inevitable connection between the probability distribution of fuzzy variables and the probability distribution of variables, but in practice, the possibility of events can transmit information about the probability of events. According to the possibility/probability consistency principle in fuzzy mathematics, if the probability of an event is greater, the possibility of its occurrence is bound to be greater; if the event is less likely to occur, the probability of occurrence is bound to be smaller.

The generalized density function obtained by equation (2) not only retains the distribution state described by the membership function of the original fuzzy variable but also meets the completeness and non-negative requirements of the probability density function. In addition, the relative magnitude of the transformed random variables does not change in the value range. Therefore, the generalized probability density function $\widehat{f}_{X_F}(x)$ still contains the ambiguity of the original fuzzy variable.

Since the density function of interval variables and fuzzy variables is usually not the commonly used probability density function, the commonly used random sampling algorithm may not be able to extract the sample data that conform to the variable distribution and cannot truly reflect

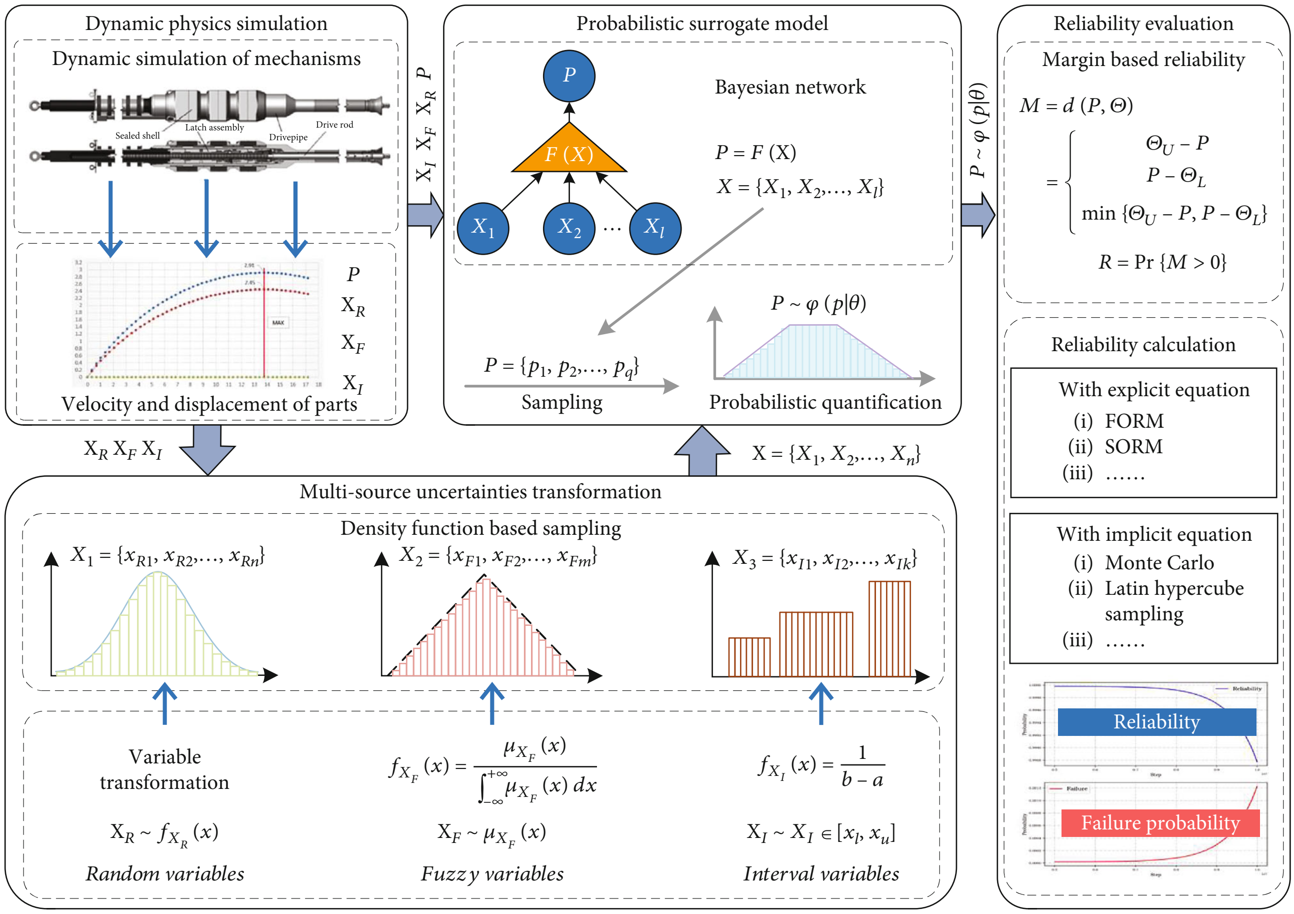

Figure 1: The multisource uncertainty fusion reliability evaluation framework.

the uncertainty of the variables. In this paper, a sampling method for arbitrary probability density function is proposed, which is used to sample the generalized probability density function obtained after the transformation of interval variables and fuzzy variables so that we can study the uncertainty propagation problem under fused uncertainty.

For any random variable with a probability density function $f(x)$, the cumulative distribution function of which is $F(x)$, and the sample interval to be extracted is $[a_1, a_{m+1}]$; the distribution of variables in the interval can be represented by $f(x)$.

The sampling interval is divided into m subintervals, denoted as $I_1 = [a_1, a_2]$, $I_2 = [a_2, a_3], \ldots, I_i = [a_i, a_{i+1}], \ldots,$ and $I_m = [a_m, a_{m+1}]$. In each subinterval, the frequency of random variables is denoted as $P_1, P_2, \ldots, P_m$, and $\sum_m P_i = 1$. The frequency for the ith subinterval is calculated by

$$P_i = F(a_{i+1}) - F(a_i), 1 \le i \le m. \tag{3}$$

The number of the sample is set as N, the sample frequency in each subinterval is denoted as $n_1, n_2, \ldots,$ and n_m, and apparently, $\sum_m N_i = N$. The sample number in the ith subinterval is calculated by

$$n_i = P_i N. \tag{4}$$

The samples in each subinterval are denoted as X_1, $X_2, \ldots,$ and X_m, which can be sampled using the uniform sampling method, as shown in

$$X_i = unirnd(a_i, a_{i+1}, n_i), 1 \le i \le m, \tag{5}$$

where (a_i, a_{i+1}, n_i) denotes the extraction of n_i uniformly distributed samples within interval $[a_i, a_{i+1}]$.

Finally, the sample $X = \{X_1, X_2, \cdots, X_m\}$ is obtained, which obeys the distribution characteristics represented by the probability density function $f(x)$. The sampling process is a numerical approximation of the density function, and the approximation accuracy depends on the interval division and the sampling number. The larger the number of subintervals m and the total number of samples N, the closer the extracted samples are to the variable characteristics represented by the probability density function.

After variable transformation for each input uncertainty variable, the corresponding probability density function or generalized probability density function of each variable can be obtained. Then, using the sampling algorithm shown in equations (3)–(5), we can extract N groups of samples with different types of uncertainty characteristics of the variables. The Monte Carlo or Latin hypercube sample combination method can be used to obtain the corresponding N groups of feature output variable samples, and the

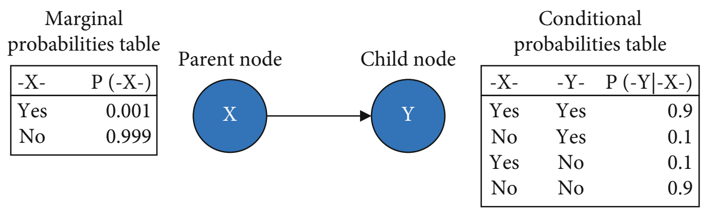

Figure 2: The structure of Bayesian network.

probabilistic quantification of feature variables can be obtained using the probabilistic method.

3.2. Probabilistic Surrogate Model. The Bayesian network is a classical method for constructing a surrogate model to quantify uncertainty propagation. Its simple modeling and convenient calculation characteristics make it suitable for CRDM reliability evaluation. Bayesian networks consist of nodes and directed edges. Nodes represent random events, and directed edges denote the correlation between random events. Uncertainty is propagated by conditional probabilities between nodes connected by directed edges.

The simplest Bayesian network, consisting of two nodes and one edge, is shown in Figure 2. The marginal probability table expresses the probability of node X's state (yes or no), and the state of the child node Y is affected by the parent node X, so it is expressed by the conditional probability table.

When the structure of the Bayesian network is determined, the Bayesian network can act as a probabilistic surrogate that inference each node's probability based on posterior knowledge, i.e., the evidence. The basic algorithm of Bayesian network inference is the variable elimination algorithm [44].

Let X be the set of all variables in the Bayesian network Θ and Γ be the set of all probability distributions in Θ. By definition, Γ is a decomposition of the joint probability distribution of $\Pr(X)$. Suppose evidence $E=e$ is observed, in the factor of Γ; each evidence variable is set as its observed value, and a set of functions is obtained, denoted as Γ'. Γ' is a decomposition of $\Pr(Y, E=e)$, in which $Y=X-E$. Let Q be a subset of Y, eliminate the subsets in Γ' that are contained in Y yet not contained in Q, and then generate a subset Γ''. Γ'' is a decomposition of $\Pr(Q, E=e)$. Therefore, $\Pr(Q, E=e)$ can be obtained by multiplying all the factors of Γ''. Given the conditional probability formula, we can obtain $\Pr(Q|E=e)=\Pr(Q, E=e)/\Pr(E=e)$, in which $\Pr(E=e)=\sum_Q \Pr(Q, E=e)$. Thereby, the probability of each node can be evaluated when evidence is given.

3.3. Reliability Evaluation. It is necessary to analyze the functional principles of the product first to model and analyze the product's reliability and then determine the corresponding performance parameters and their failure criteria. Failure criteria can usually be divided into three categories: upper limit type, lower limit type, and interval type. Then, the product's reliability can be obtained by calculating the probability of the feature performance parameter not exceeding its failure criterion.

The performance margin is employed to characterize the distance between feature performance parameters and failure criteria [46]. For different failure criterion types (upper limit type, lower limit type, and interval type), the performance margin M is calculated as shown in

$$M = d(P, \Theta) = \begin{cases} \Theta_U - P, \\ P - \Theta_L, \\ \min \{\Theta_U - P, P - \Theta_L\}. \end{cases} \quad (6)$$

The form of d depends on the form of product failure criteria. P represents the feature performance parameters of products, and Θ represents the failure criterion corresponding to the performance parameters (Θ_U represents the upper limit of failure criterion and Θ_L for the lower limit of failure criterion).

The reliability of the product is the probability that its feature performance parameters do not exceed its failure criterion, which is the probability that the performance margin is greater than 0, as shown in

$$R = \Pr\{M > 0\}, \quad (7)$$

where $\Pr\{A\}$ denotes the probability of event A occurring.

For the performance margin equation with explicit expression, the corresponding reliability can be directly solved by analytical methods such as first-order reliability method (FORM) [45] or second-order reliability method(-SORM). The explicit expression of the product performance margin is denoted as $f_X(X)$, where X is the variable vector of the internal and external factors of the product, as shown in

$$M = d(P, \Theta) = f_X(X). \quad (8)$$

According to the FORM method, the corresponding reliability can be calculated by

$$R_M = \phi\left(\frac{\mu_M}{\sigma_M}\right), \quad (9)$$

where $\phi(\cdot)$ represents the cumulative probability density function of standard normal distribution, μ_M denotes the

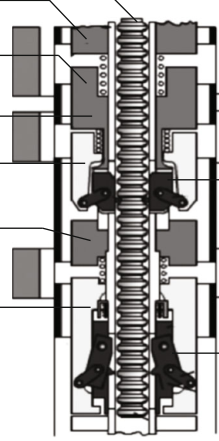

Figure 3: The structure diagram of CRDM latch assembly.

mean, and σ_M represents the standard deviation of the margin equation. Their approximate formula is shown in

$$\mu_M \approx f_X(\mu_X)$$
$$\sigma_M \approx \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\partial f_X(\mu_X)/\partial X_i\right)\left(\partial f_X(\mu_X)/\partial X_j\right)\rho_{X_iX_j}\sigma_{X_i}\sigma_{X_j}}, \quad (10)$$

where $\rho_{X_iX_j}$ represents the correlation coefficient between variables X_i and X_j. It is necessary to calculate the mean and standard deviation of each variable after converting them into random variables and the partial derivative of the margin equation for each variable.

For the margin equation without explicit expression, the numerical method is adopted to realize the fusion of multisource uncertainty variables so as to obtain the probability quantification of the feature performance parameter P or the corresponding threshold Θ in the margin equation. With the corresponding probability density function of each parameter obtained, the reliability of the product can be evaluated using

$$R = \begin{cases} \iint_{P<\Theta_U} f_P(x) f_{\Theta_U}(y)\,dxdy, \\ \iint_{P>\Theta_L} f_P(x) f_{\Theta_L}(y)\,dxdy, \\ \iiint_{\Theta_L<P<\Theta_U} f_P(x) f_{\Theta_L}(y) f_{\Theta_L}(z)\,dxdydz. \end{cases} \quad (11)$$

4. Results

In order to verify the generality of the proposed method, a practical engineering case of a magnetic-jack type CRDM was studied. This case evaluates the reliability under multisource uncertainties for a magnetic-jack type CRDM, and the margin equation of which is implicit. The function of the CRDM depends on the cooperation of the components in latch assembly [47], and the structure of which is shown in Figure 3.

As shown in Figure 3, the magnetic-jack type CRDM utilizes the insertion (and withdrawal) of the movable gripper (MG) to control the depth of the control rod. The insertion of the MG is driven by the MG plunger magnet, which moves as the MG coil is energized. Therefore, the insertion time of the MG depends on the movement of the MG plunger magnet. Moreover, the position of the control rod is held by the stationary gripper (SG) with the SG plunger magnet and SG coil. That makes the coordination of movement of the MG and SG requires that the MG plunger magnet has completed its movement by the time the SG coil is de-energized, as shown in Figure 4.

The margin equation for the cooperation between MG and SG can be expressed as

$$\text{Margin} = \Theta_T - T_{\text{MG}}, \quad (12)$$

where Θ_T represents the off time of the SG coil and T_{MG} represents the time of MG plunger magnet completing its movement. The reliability R of the corresponding MG's insertion action is

$$R = \Pr\{\text{Margin} > 0\}. \quad (13)$$

The movement of the MG plunger magnet is a multibody dynamic coupling process with many units coordinated, which makes the T_{MG} an uncertain variable that is affected by multiple uncertain variables that may be time-variant. The complexity of the MG plunger magnet's movement makes the reliability of CRDM a multisource uncertainty fusion problem with an implicit margin equation. In [48], the authors established a simulation model, as shown in Figures 5 and 6, to obtain the T_{MG} and determine the crucial variables that may affect the T_{MG}, as shown in Table 2. Owing to the limitation of vertical displacement in the CRDM, the T_{MG} is when the plunger magnet moves 8.6 mm in the vertical direction. In Table 2, m_{MG} denotes the mass of the MG plunger magnet, s denotes the cross-

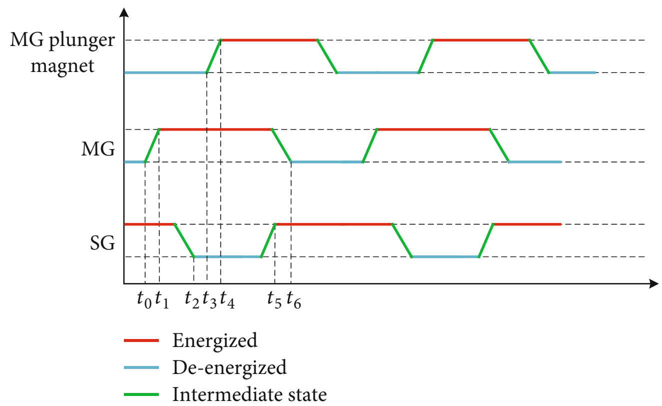

FIGURE 4: Action timing relationship of CRDM (partial).

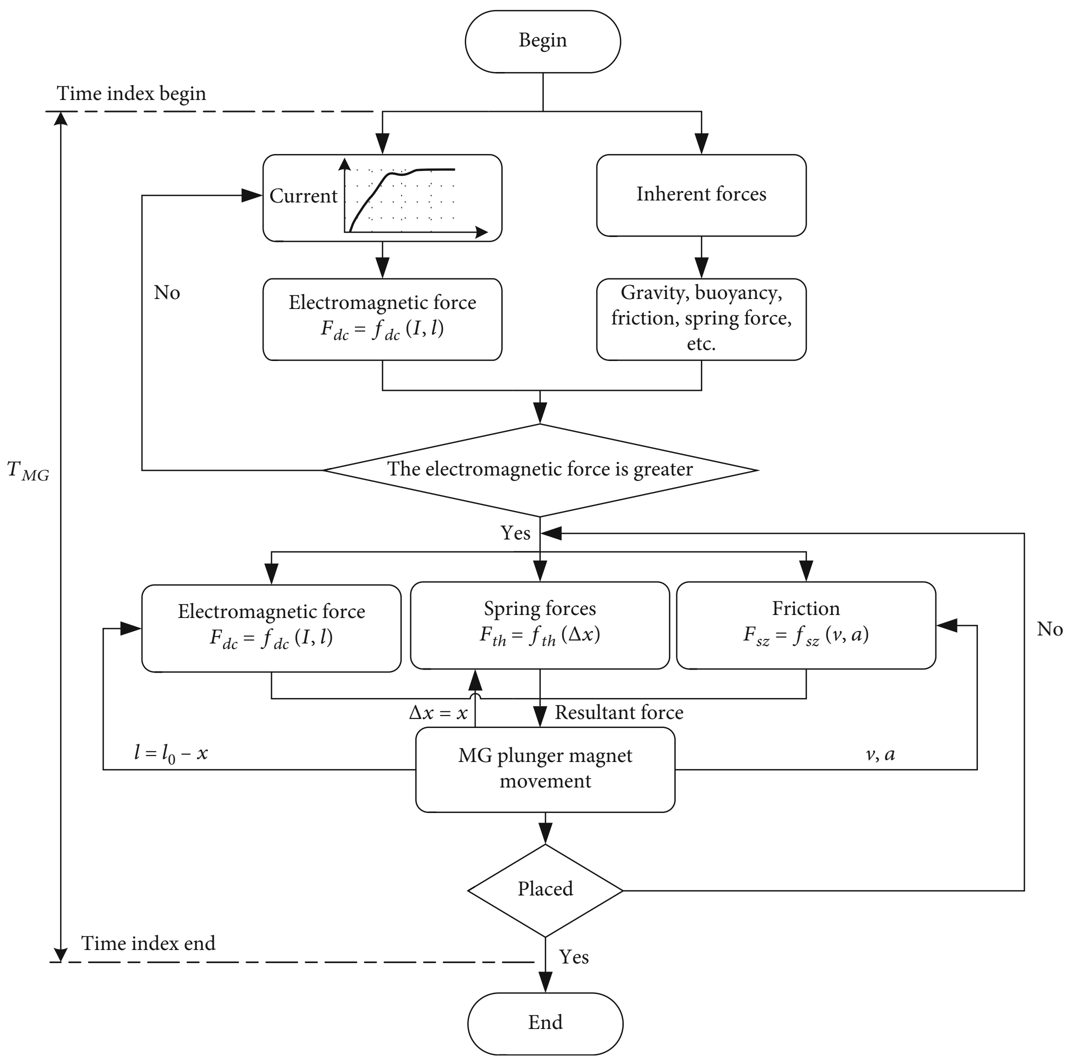

FIGURE 5: The simulation process of the CRDM.

sectional area of the MG plunger magnet, F_μ denotes the frictional force, k denotes the elastic coefficient of the spring, and α and C denote the buoyancy and spring force coefficients.

In order to enhance the uncertainty quantification efficiency, a Bayesian network-based surrogate can be made to analyze the uncertainty propagation between these variables as proposed. The structure of the Bayesian network is shown

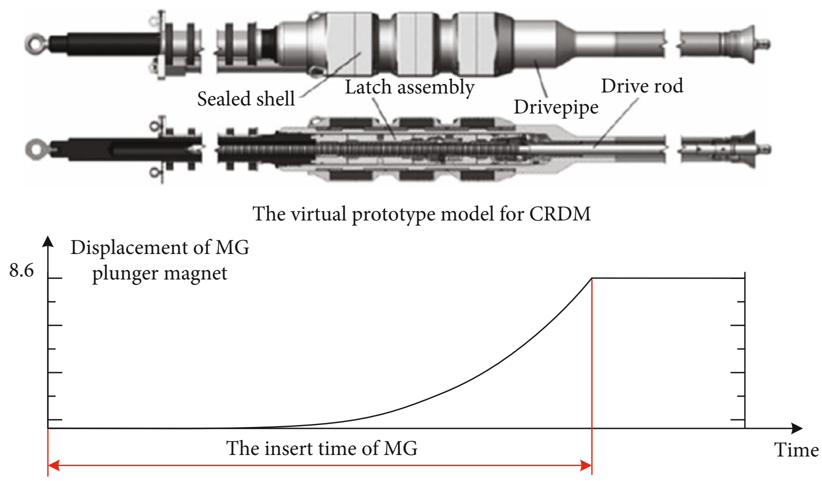

Figure 6: Displacement curve of MG plunger magnet and insert time of MG.

Table 2: The uncertainty information of feature variables in the MG plunger magnet.

Variable	Uncertain information		
	Type	Feature	Quantified expressions
m_{MG}	Random variable	Normal distribution	$N(5.6, 0.05^2)$
s	Random variable	Normal distribution	$N(0.005, 0.00005^2)$
F_μ	Interval variable	Interval number	[148,152]
k	Interval variable	Interval number	[950, 1050]
α	Fuzzy variable	Isosceles triangle	$\mu(x)=\begin{cases}1-\frac{0.25-x}{0.01}, 0.24\le x\le 0.25\\ 1-\frac{0.25-x}{0.01}, 0.24\le x\le 0.25\end{cases}$
C	Fuzzy variable	Isosceles triangle	$\mu(x)=\begin{cases}1-\frac{3.5-x}{0.1}, 3.4\le x\le 3.5\\ 1-\frac{x-3.5}{0.1}, 3.5\le x\le 3.6\end{cases}$

in Figure 7. It contains seven nodes, six parent nodes, and one child node.

In which, each parent node denotes a parameter in Table 2, and the child node is the simulated T_{MG}. With this Bayesian network as the surrogate, the insert time of the MG can then be described, as shown in

$$T_{MG} = \text{Surrogate}_{MG}(m_{MG}, s, F_\mu, k, a, C). \quad (14)$$

However, with the multiple uncertainties existing, this equation cannot be directly employed to evaluate the reliability of the CRDM. As shown in Table 2, these six variables are uncertain variables of different types. We utilized the method proposed in Section 3.1 to transform the fuzzy and interval variables into random variables through the generalized probability density function. The transformation results of F_μ, k, α, and C are listed in Table 3.

According to the transformed generalized density function, using the sampling method described in Section 3.1, the variables, such as m_{MG}, s, F_μ, k, α, and C, can be sampled, and the sampling number is set to 10000 times to obtain samples that meet the uncertainty characteristics of

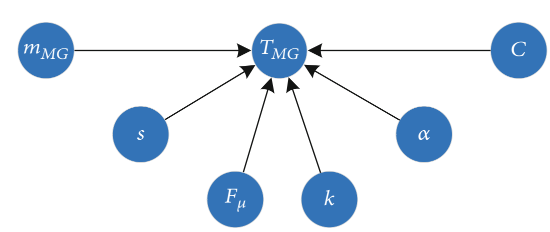

Figure 7: The structure of Bayesian network for T_{MG}.

Table 3: The transformation results of fuzzy and interval variables.

Variable	Generalized probability density function
F_μ	$\hat{f}_{F_\mu}(x)=\frac{1}{4}, 148\le x\le 152$
k	$\hat{f}_k(x)=\frac{1}{100}, 950\le x\le 1050$
α	$\hat{f}_\alpha(x)=\begin{cases}100\left(1-\frac{0.25-x}{0.01}\right), 0.24\le x\le 0.25\\ 100\left(1-\frac{x-0.25}{0.01}\right), 0.25< x\le 0.26\end{cases}$
C	$\hat{f}_C(x)=\begin{cases}10\left(1-\frac{3.5-x}{0.1}\right), 3.4\le x\le 3.5\\ 10\left(1-\frac{x-3.5}{0.1}\right), 3.5< x\le 3.6\end{cases}$

Table 4: The deterministic value of variable.

Variable	Value
F'_{μ}	150
k'	1000
α'	100
C'	10

each variable. After that, the Monte Carlo sample combination method is used to combine the extracted samples to form 10000 sets of simulation input samples. Then, the input samples are brought into the surrogate model, $\mathrm{Surrogate}_{\mathrm{MG}}$, and a set of 10000 samples of the insert time of the MG is obtained, called $\mathrm{data}_{\mathrm{fusion}}$.

In addition, there are many other uncertainty quantification methods that provide reference for this paper. Xiao et al. [49] constructed a linearized tangent function to quantify the uncertainty, through which the reliability index interval was efficiently calculated. Hurtado et al. recently developed several new probability-interval hybrid reliability analysis methods with acceptable accuracy and low computational cost, based on their own concept of reliability plot [50–52]. Qiu et al. [53] treated the mean values and variances of structural intensity and stress as interval parameters and provided the solution of the upper and lower bounds of reliability index, based on which they analyzed the variation trend of the reliability index interval when the interval parameters change. Therefore, in order to demonstrate that the method proposed in this paper has higher accuracy, we conducted a comparative experiment by using the mean method to quantify uncertainty and made the assumptions shown in Table 4. Then, the new parameter values from Table 4 are substituted into the surrogate model, $\mathrm{Surrogate}_{\mathrm{MG}}$, and a new set of 10000 samples of the insert time of the MG is obtained, called $\mathrm{data}_{\mathrm{mean}}$.

The distribution of all obtained samples is drawn as a histogram with a normal fit curve, as shown in Figure 8 [54].

The probabilistic method is employed to obtain the T_{MG} from the $\mathrm{data}_{\mathrm{fusion}}$ and T'_{MG} from the $\mathrm{data}_{\mathrm{mean}}$. It can be concluded that both T_{MG} and T'_{MG} obey the normal distribution, i.e., $T_{\mathrm{MG}} \sim N(127.925, 7.155^2)$, and $T'_{\mathrm{MG}} \sim N(130.835, 8.665^2)$. Therefore, the reliability of the MG is evaluated with the following equations:

$$R = \Phi\left(\frac{150 - 127.925}{7.155}\right) = 0.9989831, \quad (15)$$

$$R' = \Phi\left(\frac{150 - 130.835}{8.665}\right) = 0.9867628. \quad (16)$$

The comparison of the results obtained from Figure 8 and Equations (15) and (16) reveals that the method described in the paper, which considers various uncertainties, leads to a significant improvement about 0.0122203 in reliability compared to the case where uncertainties are

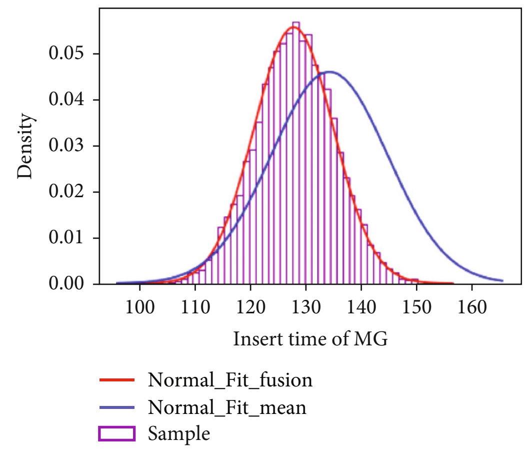

Figure 8: Frequency histogram of MC sampling results.

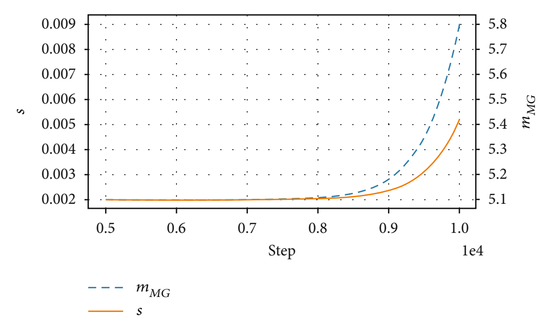

Figure 9: The dynamic mean of m_{MG} and s.

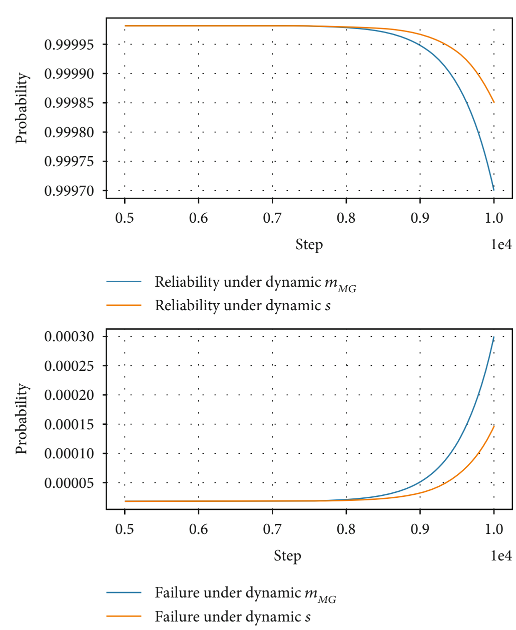

Figure 10: The reliability and failure probability under dynamic parameters.

Table 5: The change rate of the reliability.

Variable	Rangeability	Rate	Reliability rangeability	Reliability rate
m_{MG}	[5.1, 5.8]	13.7%	[0.9999816, 0.9997008]	0.028%
s	[0.002, 0.005]	150%	[0.9999816, 0.9989004]	0.013%
m_{MG}	[5.1, 6.12]	20%	[0.9999816, 0.9996717]	0.041%
s	[0.002, 0.0024]	20%	[0.9999816, 0.9999813]	0.00003%

not considered. The fitting to real data is better, and the accuracy is higher.

5. Discussion

In order to further discuss the impact of dynamic parameters on the performance of CRDM, the mean of the mass of the MG plunger magnet (m_{MG}) and the cross-sectional area of the MG plunger magnet (s) are gradually increasing during the operation step of CRDM (this represents the degeneration of the plunger magnet clamping or stagnation), as shown in Figure 9, and the other parameters are set to constants. With the proposed method, the reliability and failure probability of the CRDM latch assembly can be obtained at each step.

As shown in Figure 10, the reliability gradually decreases during operation from 5000 to 10000 steps, and the failure probability gradually increases. However, the impact of m_{MG} and s on the reliability of the CRDM latch assembly is different. As listed in Table 5, when the m_{MG} increases from 5.1 to 5.8 (increases 13.7%), the reliability of CRDM decreases from 0.9999816 to 0.9997008 (decreases 0.028%), whereas when the s increases from 0.002 to 0.005 (increases over 150%), the reliability decreases from 0.999816 to 0.9998542 (decreases 0.013%). What is more, Xia et al. proposed a sensitivity calculation method for reliability, which is shown in the following equation [55]:

$$\text{Sensitivity} = \left| \frac{df(x_2) - df(x_1)}{x_2 - x_1} \right|, \quad (17)$$

where x_1 and x_2 are the value of variables and $f(x_1)$ and $f(x_2)$ are the reliability functions about variables x_1 and x_2. Therefore, the paper used equation (17) to calculate the sensitivity of m_{MG} and s, as shown in

$$\text{Sensitivity of } m_{MG} = \left| \frac{0.9996717 - 0.9999816}{6.12 - 5.1} \right| = 0.00106, \quad (18)$$

$$\text{Sensitivity of } s = \left| \frac{0.99999813 - 0.9999816}{0.0024 - 0.002} \right| = 0.00075. \quad (19)$$

As shown in Table 5, when both m_{MG} and s are increased by 20%, the sensitivity value of m_{MG}, 0.00106, is greater than the sensitivity value of s, 0.00075. Hence, the reliability is more sensitive to m_{MG} than s.

6. Conclusion

This paper provides a fusion reliability evaluation method for the CRDM of nuclear power plants when random, fuzzy, and interval uncertainty variables exist simultaneously. The multisource uncertainties are fused by transforming the interval and fuzzy uncertainty variables into random variables and then propagating these in a Bayesian network model. The variable transformation is performed based on the generalized density function while retaining the original uncertainty characteristics of the variable. The Bayesian network model is built as a lightweight surrogate for the dynamic simulation of CRDM. After the fusion of multisource uncertainties, the probability quantification of feature variables can be conducted and so can the reliability evaluation. The margin equation is modeled to evaluate the reliability with either explicit or implicit expressions. The proposed method contains the following features:

(1) The method can realize the unified processing of various uncertain variables and the probability quantification of critical parameters in the reliability model and so can directly obtain product-reliability probability measurement results

(2) The proposed method can handle either explicit or implicit margin reliability equations, making it suitable for both simulation-based and model-based CRDM reliability evaluation

(3) A practice CRDM with an implicit margin equation was used to illustrate the reliability evaluation process under multisource uncertainties. The results show that the proposed method can efficiently evaluate the product's reliability under multisource uncertainties, affirming its potential for practical applications in the nuclear power industry

However, the Bayesian network model established in this study can only analyze the reliability of one function of CRDM. In practice, the functions of CRDM are relatively complex, and there are sequential relationships or correlation connections between different functions. Therefore, it is necessary to explore further the reliability analysis method of CRDM's multifunctional synthesis in future studies. In addition, the method proposed in this study has good application prospects in situations where other systems face similar problems, such as cantilever beams and transmission shafts. After conducting targeted analysis combined with specific cases, the corresponding reliability calculation process is similar.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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