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Research Article

Multidisciplinary Reliability Design Considering Hybrid Uncertainty Incorporating Deep Learning

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Multidisciplinary reliability design optimization is considered an effective method for solving complex product design optimization problems under the influence of uncertainty factors; however, the high computational cost seriously affects its application in practice. As an important part of multidisciplinary reliability design optimization, multidisciplinary reliability analysis plays a direct leading role in its computational efficiency. At present, multidisciplinary reliability analysis under mixed uncertainty is still nested or sequential execution mode, which leads to the problem of poor disciplinary autonomy and inefficiency in the reliability analysis of complex products. To this end, a multidisciplinary reliability assessment method integrating deep neural networks and probabilistic computational models under mixed uncertainty is proposed for the problem of multidisciplinary reliability analysis under mixed uncertainty. The method considers the stochastic-interval-fuzzy uncertainty, decouples the nested multidisciplinary probability analysis, multidisciplinary likelihood analysis, and multidisciplinary interval analysis, uses deep neural networks to extract subdisciplinary high-dimensional features, and fuses them with probabilistic computational models. Moreover, the whole system is divided into several independent subsystems, then the collected reliability data are classified, and the fault data are attributed to each subsystem. Meanwhile, the environmental conditions of the system are considered, and the corresponding environmental factors are added as input neurons along with each subsystem. In this paper, the effectiveness of the proposed method is verified on numerical calculations and real inverter power failure data.

1. Introduction

Multidisciplinary design optimization (MDO) can be used to design complex systems and subsystems by fully exploring and exploiting the synergistic mechanisms of interactions in the system and to optimize the design from a system-wide perspective to achieve improved product performance and shorter design cycles. MDO is considered an effective approach to solve complex product design optimization problems [1]. Early MDO design methods generally consider only the optimization of design solutions in deterministic cases. This deterministic optimization approach pushes the design results to the edge of performance constraints, leaving little or no room for uncertainty in engineering, which can easily lead to product design failure. In order to achieve a comprehensive improvement of the stability and reliability of the design solution while pursuing the optimal performance of complex products, reliability-oriented multidisciplinary design optimization has become a hot issue in MDO at present. This paper is motivated by the fact that multidisciplinary reliability analysis under mixed uncertainties still uses nested or sequential execution models, which leads to poor disciplinary autonomy and inefficiency in the reliability analysis of complex products.

Reliability-based multidisciplinary design optimization (RBMDO) is an organic combination of reliability analysis and multidisciplinary design optimization to obtain the optimal design of complex products while meeting reliability requirements. It is considered an effective method to solve the problem of optimizing complex product design under the influence of uncertainties [2]. Since RBMDO requires both multidisciplinary design optimization and multidisciplinary reliability analysis, the computational cost is very high, which seriously affects its application in practice. As an important part of RBMDO, multidisciplinary reliability analysis has a significant impact on its computational cost. Studies have shown that the efficiency of multidisciplinary reliability analysis directly dominates the computational efficiency of the entire RBMDO. It is easy to see that improving the computational efficiency of multidisciplinary reliability analysis can effectively improve the efficiency of RBMDO solution and help promote the engineering application of RBMDO technology. RBMDO should fully consider the various uncertainties that exist in the design to ensure that the designed complex products can have sufficient reliability under the fluctuation of uncertainties. RBMDO has undergone more than a decade of development since its introduction. In 2002, NASA published a white paper, "*Opportunities and Challenges of UMDO for Aircraft Design*," in which the importance and urgency of multidisciplinary design optimization considering reliability was emphasized. Subsequently, RBMDO has become the focus of attention in the field of complex product design and MDO.

Although RBMDO has a history of more than ten years so far, the development of RBMDO still faces many challenges and difficulties at present. The main problems are as follows: (1) the limitation of dealing with uncertainty. For a long time, RBMDO has mostly considered only the cases where there is random uncertainty. Or only consider the case of cognitive uncertainty. And the RBMDO method for mixed uncertainty has not yet truly and comprehensively considered the large variety of different uncertainty effects that exist in actual engineering. (2) In computational complexity, in the process of multidisciplinary reliability design optimization when only a single uncertainty is considered, deterministic multidisciplinary design optimization, reliability analysis, and multidisciplinary analysis are involved. These links together form a three-level nested cycle, making the computation very complex. Further, considering the mixed uncertainty may bring RBMDO from a three-layer nested cycle to four or even more layers, and its computation is unacceptably large. Therefore, how to reasonably mitigate the computation of RBMDO under mixed uncertainty is also a pressing issue at present [3].

In the process of establishing a reliability model or optimization model, a primary prerequisite is the need to obtain mathematical expressions for certain performance responses (strength, stiffness, velocity, displacement, etc.) of a mechanical product. For a complex mechanical product, the expressions of these performance responses are often implicit, and it is very difficult to derive their mathematical expressions directly. To solve this problem, researchers have proposed the concept of agent models. The basic idea of the proxy model is to connect discrete performance response points by data interpolation or fitting to make a continuous differentiable response surface. These discrete performance response points can be obtained by means of real tests or computer simulations, but both real tests and computer simulations have the problems of high cost and low efficiency. Therefore, how to obtain the most accurate proxy model with the least number of design points becomes a critical issue. At present, the commonly used agent models include polynomial response surface model, neural network model, Kriging model, neural network model, and radial basis function model. Each of these models has its own characteristics, but their common feature is that they are only an approximate expression of the real model. So, there is always a certain error between the proxy model and the real model, and this error is uncertain. A question that arises is how to evaluate this error and how to quantify the uncertainty of this error.

A large number of uncertainties exist in actual engineering. To ensure that products can be safe and reliable under these uncertainties, RBMDO dealing with uncertainty factors has been a popular issue in research. Uncertainty in complex engineering systems can be divided into two categories, random and cognitive uncertainty, from the perspective of human cognitive ability, which affects reliability. Random uncertainty, also known as chance uncertainty, nonparsimonious uncertainty, and inherent uncertainty, describes the variation within a physical system with sufficient experimental data and perfect information. Random uncertainty is generally treated and measured using a probabilistic approach [4]. Cognitive uncertainty, on the other hand, is the lack of knowledge and imperfect information caused by negligence, experimental conditions or other cognitive ability limitations, so it is also known as parsimonious uncertainty, subjective uncertainty, etc. [5]. There are two main typical forms of cognitive uncertainty that are common in engineering. One is the fuzzy uncertainty due to the complexity of the thing itself, and it is difficult to obtain sufficient data information to describe it accurately. The other is the interval uncertainty that can only obtain the magnitude or boundaries of its variation using limited data due to the limitation of experimental conditions and cost in actual engineering, where sufficient information is not easily available to describe the uncertainty. Fuzzy uncertainty is usually handled and measured using fuzzy sets, likelihood theory, etc. While interval uncertainty is usually treated and measured using convex models, evidence theory, interval analysis, etc. RBMDO, which considers the influence of uncertainty, has undergone a development process from single uncertainty to mixed uncertainty, and a series of results have been achieved.

The main contributions of this paper are summarized as follows. Most of the studies on multidisciplinary reliability analysis methods for single uncertainty have focused on parallel collaborative strategies. This fully reflects that parallel collaborative solving is an effective means to improve the efficiency of multidisciplinary reliability analysis. In this paper, a reliability analysis method considering stochastic-fuzzy-interval uncertainty is investigated. The reliability is evaluated by integrating probabilistic computation and deep learning models. It is also validated by arithmetic examples and inverter power supply reliability.

2. Related Works

2.1. Research Status of Reliability Theory. In the middle of the 20th century, the idea of probabilistic design was introduced into the field of engineering design, which laid the theoretical foundation of structural reliability design. The reliability design method is a combination of probabilistic statistical theory and traditional mechanical design theory. All uncertainty phenomena are regarded as random phenomena, and probability distribution is used to quantify uncertainty, through a certain calculation method to quantitatively evaluate the probability of mechanical parts or components not to fail (i.e., reliability) [6]. This design method not only can solve the problems that cannot be solved by traditional design methods in the past but also can effectively improve the comprehensive performance index of mechanical products. After more than half a century of development, the probability-based reliability design method has become more and more mature. Whether it is theoretical research or engineering application, there are many achievements related to it. At present, this method has become the most common and successful method to deal with uncertainty factors.

With the in-depth understanding of the uncertainty phenomenon, it is gradually found that the probability-based reliability design also has certain limitations. The literature [7] points out that four prerequisites must be satisfied when using probability theory to deal with problems: the event is well defined; there exist a large number of samples; the samples are probabilistically repetitive and have a good distribution law; and they are not affected by human factors. In the early design stage of mechanical systems, especially for mechanical equipment with complex structures and harsh working conditions, it is often difficult for engineers to obtain sufficient statistical data. And by the limitation of objective or subjective factors such as statistical methods, observation means, personnel quality, and resource cost, it is almost impossible to require all the statistics to meet the above four conditions at the same time, which makes the probability-based reliability design cannot effectively deal with such problems.

The core idea of probability theory is to determine several metrics such as likelihood, likelihood distribution, likelihood distribution function, marginal likelihood distribution function, and the relationship between them, as well as the conversion rules of various fuzzy propositions and the inference rules of imprecise propositions. Probabilistic reliability theory can be regarded as a complement of probabilistic reliability theory and fuzzy reliability theory, which integrates various methods such as statistical analysis, logical reasoning, and probabilistic modeling. It is especially suitable for dealing with the situation of fuzzy information and incomplete information.

Nonprobabilistic reliability theory requires less data and information and has good prospects for engineering applications. At present, nonprobabilistic reliability theory has started to be applied in various fields such as civil engineering, transportation, computational mechanics, military, energy, automatic control, and aerospace and has become one of the important tools for dealing with uncertainty in mechanical engineering [8, 9]. However, compared with the mature probabilistic reliability theory, the nonprobabilistic reliability theory is still in the stage of development and improvement. Therefore, probabilistic reliability theory is still the mainstream tool for reliability engineering. The nonprobability reliability theory can only be a useful supplement to the probabilistic reliability theory and cannot completely replace the probabilistic reliability theory.

Although reliability design can ensure that the designed mechanical products meet the reliability requirements, it cannot guarantee that the products have the best working performance and parameter matching, for example, the products have the smallest structural size, the lowest production cost, and the greatest economic efficiency [10]. To make the product meet the reliability requirements under uncertainty conditions and also have the optimal design results, it is necessary to combine uncertainty theory with optimization techniques, i.e., to adopt the optimization method of reliability design under uncertainty conditions. Uncertainty optimization design is a design decision method that incorporates uncertainties into an optimal design model. This approach considers the design variables, design parameters and constraints in the model, and even the model itself, to have a certain degree of uncertainty. The impact of these uncertainties on product performance can be effectively avoided through rational planning decisions. At present, the typical uncertainty optimization design methods are mainly reliability optimization design and robust optimization design. Reliability design optimization is mainly to find the optimal design solution under the condition of ensuring system reliability. Robust design optimization, on the other hand, is to find the design solution whose system performance is least sensitive to uncertainty factors. Both of these design ideas are increasingly being studied or applied.

Uncertainty analysis focuses on how to use effective methods to analyze the process of uncertainty propagation in a system model and to quantitatively evaluate the uncertainty on the system output information based on the uncertainty of the system input information. In the case of reliability of mechanical systems, it is to analyze the influence of uncertainty on the reliability of mechanical products. At this point uncertainty analysis can also be called reliability analysis [11]. Depending on the basic theory, reliability analysis can be divided into probabilistic reliability analysis and nonprobabilistic reliability analysis.

The numerical simulation method, represented by Monte Carlo method, calculates the reliability of the system by simulating the random sampling process, which has the characteristics of high precision and low efficiency [12]. In order to improve the computational efficiency, some improved Monte Carlo methods have also appeared, such as the significant sampling method, the directional sampling method, the subset simulation method, and the line sampling method. These methods can improve some computational efficiency under certain conditions, but they can never avoid the requirement of multiple repetitions of sampling. As a result, the total computational efficiency is not too high. Deterministic optimization, on the other hand, is mainly concerned with optimization strategies, optimization algorithms, optimization models, etc. Optimization strategy refers to how to arrange deterministic calculation and uncertainty analysis under the same model in order to improve the efficiency and accuracy of optimization calculation. Sequential Optimization and Reliability Assessment (SORA) [13] is a representative optimization strategy. The SORA method decouples the traditional two-layer cycle into a single-layer cycle, which can greatly improve the computational efficiency. The SORA method was first used for probabilistic models, but later it was used for possible reliability models and also achieved good results.

2.2. Research Status of Multidisciplinary Design Research. In the past, many studies have been conducted to optimize the design of mechanical systems, often focusing only on one part of the system. However, a mechanical system is a large engineering machine with complex structure and close interactions between mechanisms, and its subsystems interact with each other. The parameters changed by the optimization of one mechanism will affect not only the mechanism under study but also other mechanisms [14]. In other words, the design parameters adjusted for the optimization of a subsystem, although making the performance of the studied subsystem better, may cause the performance of other subsystems to decline. Therefore, for complex systems, it is necessary to consider it whole and perform multidisciplinary optimization design. Multidisciplinary design optimization (MDO) in the discipline can refer to both mechanical, electrical, structural, and other general sense of the discipline but also can refer to the decoupling of the system after the subsystem [15]. MDO can be used to design complex systems and subsystems by fully exploring and exploiting the synergistic mechanisms of interactions in the system and to optimize the design from a global perspective to improve product performance and shorten the design cycle. A white paper published by the American Institute of Aeronautics and Astronautics introduces the MDO method, which has been applied in many fields [16]. Sun et al. [17] introduce the application of MDO method in mechanism design. Park et al. [18] apply the MDO method to the optimal design of magnetorheological brakes for automobiles. Hart and Vlahopoulos [19] proposed a prototype tool for the MDO method for ships, and many scholars have done work in the optimal design of mechanical systems using the MDO method. After decoupling the system, it is easier to obtain reliable optimization results by considering the mutual coupling relationship between subsystems for design optimization using the MDO optimization design method.

The multidisciplinary reliability studies mentioned above are for the case of random uncertainties, while in practical engineering, there are usually a mixture of uncertainties at the same time. For complex multidisciplinary systems, the existence of mixed uncertainties is more obvious and common. The multidisciplinary reliability analysis under mixed uncertainties depends on the development of single-disciplinary reliability analysis techniques. With the development of some single-disciplinary reliability analysis methods under mixed uncertainty, scholars have integrated these methods with MDO optimization strategies to form some multidisciplinary reliability analysis methods under mixed uncertainty. Meng et al. [20] proposed three efficient multidisciplinary reliability analysis methods under random-interval uncertainty for multidisciplinary reliability problems containing random-interval uncertainty at the same time, combining the FORM-URA method for hybrid reliability analysis under single discipline and the MDO optimization strategy MDF, and gave the applicability of the three methods.

In summary, the research of multidisciplinary reliability analysis methods is based on the research of single-discipline reliability analysis and deterministic MDO methods, and the research is mainly carried out by combining some methods. In the multidisciplinary reliability analysis under mixed uncertainty, the coupling of multiple types of disciplines and multiple uncertainties is involved, which makes its computational efficiency low. Therefore, in the research of multidisciplinary reliability analysis methods under mixed uncertainty, how to improve the computational efficiency has been the main problem faced by its development. At present, some very effective methods have been developed for multidisciplinary reliability analysis under random-fuzzy and random-interval uncertainties. However, with the increase of the types of uncertainties considered, it will further increase the computational power of multidisciplinary reliability analysis, which is bound to bring new challenges to the research of multidisciplinary reliability analysis methods. With the development of deep learning technology, the technology provides new ideas for the research of parameter estimation and model prediction [21]. Combining deep learning methods is a potential solution.

3. Algorithm Design

3.1. Random-Fuzzy-Interval Uncertainty Modeling. The multidisciplinary design problem involves several different disciplines. The different design situations in each discipline, as well as the different background knowledge and preferences of the experts performing the design in each discipline, make the uncertainties in the inputs from each discipline different. These uncertainties input by different disciplines are propagated through interdisciplinary coupling, making the whole multidisciplinary system contain a mixture of uncertainties. It is easy to see that for the coupled multidisciplinary system, the uncertainty of the input of each discipline directly determines the uncertainty contained in the whole system. When each discipline contains three different types of uncertainty, it can be classified into various cases depending on the type of uncertainty of each discipline's input.

(1) Each discipline contains a different kind of uncertainty. This situation is characterized by the fact that each discipline contains only one type of uncertainty, and each discipline contains a different type of uncertainty, which is fed into the total system by different disciplines

(2) Each discipline contains both types of uncertainty. This case is characterized by the fact that each

discipline contains only two types of uncertainty, and at least two disciplines contain different types of uncertainty, which are entered into the total system by different disciplines

(3) Each discipline contains all three types of uncertainty at the same time. This case is characterized by the fact that each discipline contains three types of uncertainty at the same time: random, fuzzy, and interval. These uncertainty variables are entered into the total system by different disciplines

(4) A combination of single, two, and three types of uncertainty. This case is characterized by the fact that each discipline may contain one or two or three types of uncertainty, each discipline contains different ones, and the uncertainties of each discipline are combined together and input into the total system, as shown in Figure 1. From Figure 1, it can be found that for the three different inputs to Discipline 2 and Discipline 3, respectively, the three disciplines are finally fused together through the interaction of the three disciplines

3.2. Integrating Probabilistic and Deep Learning for Reliability Assessment. There are many indicators for product reliability evaluation. Among them, reliability, i.e., the probability of no failure calculated by probability method, is the most commonly used index in product design. The probability-based reliability evaluation considers various random uncertainties in the design, calculates the probability of failure caused by these uncertainties using the probability theory method, and evaluates the degree of safety based on the magnitude of the calculated value.

Probability-based reliability evaluation has a long history of research and mature technical methods. The early reliability calculation was implemented by its definition. Based on the basic principles of probability theory, when the distribution density function of the input random variable is known, the reliability is calculated as the multiple integrals in the reliability domain $\Omega_R = \{g(\mathrm{X}_r) \geq 0\}$, which is calculated by the equation:

$$R(g) = P\{g(\mathrm{X}_r) \geq 0\} = \int_{g(\mathrm{X}_r)\geq 0} f_{\mathrm{X}_r}(\mathrm{X}_r) d\mathrm{X}_r, \tag{1}$$

where subscript n represents the number of random vectors and $f_{\mathrm{X}_r}(\mathrm{X}_r)$ is the joint probability density function of random variables.

Reliability R and failure probability F are a pair of relative indexes for reliability evaluation. For the probability of the same events, they have the following relationship:

$$R(g) = 1 - F(g). \tag{2}$$

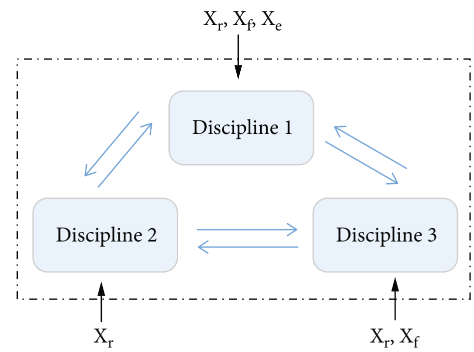

Figure 1: Combination of single, double, and three uncertainty cases.

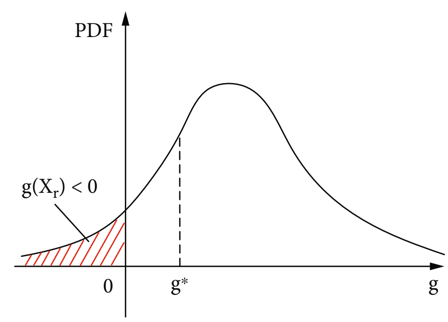

Figure 2: Percentage performance of reliability assessment.

The failure probability is calculated by the equation:

$$F(g) = P\{g(\mathrm{X}_r) < 0\} = \int_{g(\mathrm{X}_r)<0} f_{\mathrm{X}_r}(\mathrm{X}_r) d\mathrm{X}_r. \tag{3}$$

For the calculation of Equations (1) and (3), the integration domain of the actual engineering problem is very complex, resulting in almost impossible to solve. For this reason, the reliability index knife of simple form and easy to solve is often used as a solution alternative, and its calculation equation is:

$$F(g) = \Phi(-\beta). \tag{4}$$

The calculation method used in Equation (4) is also known as Reliability Index Approach (RIA), which is aimed at obtaining the magnitude of the failure probability and thus making a judgment on whether it is reliable or not. To further improve the efficiency and accuracy of reliability assessment using reliability index, this paper uses the percentage performance measure approach (PMA) for reliability assessment. Different from RIA, PMA directly evaluates whether the current design point is safe and reliable under the specified reliability index β_t, and its calculation equation is:

$$g^* = F^{-1}(\Phi(-\beta_t)), \tag{5}$$

where g^* is the target probability percentage performance and the upper corner -1 represents the inverse operation.

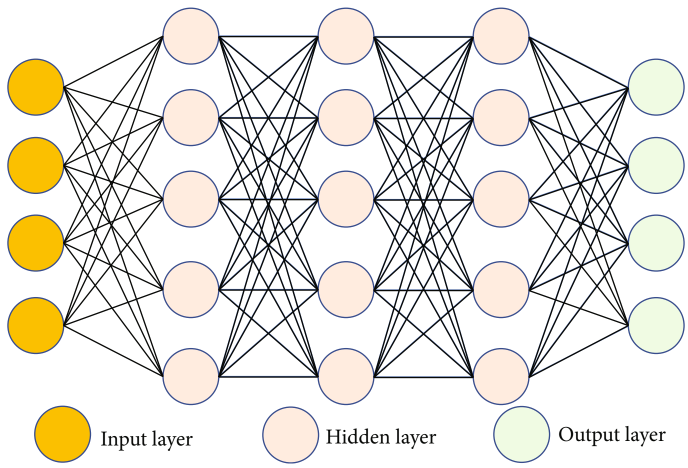

Figure 3: Deep neural network structure diagram.

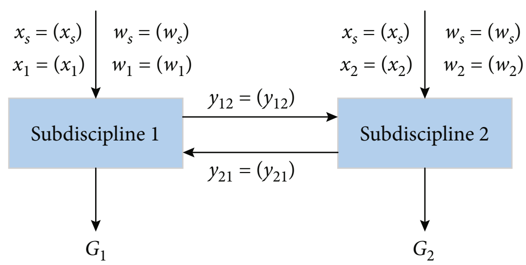

Figure 4: Coupling structure diagram of numerical example.

Table 1: Distribution parameters of uncertain variables for numerical examples.

Random variables				Interval variables	
Variables	Distribution	Average μ	Standard deviation σ	Variables	$[w^l, w^u]$
x_s	Normal	01.2	1	w_s	[2.065, 2.075]
x_1	Normal	1.4885	0.1	w_1	[0.7714, 0.7814]
x_2	Normal	3.3227	0.1	w_2	[0.14, 0.16]

A schematic diagram of PMA method to evaluate reliability is shown in Figure 2.

From the figure, it can be seen that if the value of g^* is greater than or equal to zero, it indicates that the design point is satisfying the reliability requirement under the current β_t, and vice versa. From the formula of the PMA method and its way of reliability assessment, it can be seen that the PMA method is just opposite in form to the RIA method. For this reason, the analysis method that uses the RIA method to solve the reliability directly is often called positive reliability analysis, while the party that uses the PMA method for reliability analysis is called inverse reliability analysis.

In addition to probabilistic calculations, this paper incorporates deep neural networks to assess multidisciplinary reliability. The main idea of the reliability prediction model based on deep neural network is as follows: the whole system is divided into several independent subsystems, and then the collected reliability data are classified and the failure data are attributed to each subsystem. At the same time, the environmental conditions of the system are considered, and the corresponding environmental factors are added as input neurons together with the subsystems. The failure rate of the whole system is taken as the output neuron to build a deep neural network with multilayer structure. The neural network structure used in this paper is shown in Figure 3. The neural network structure in Figure 3 contains three different modules: the input layer, the hidden layer, and the output layer. The hidden layer is composed by three fully connected networks.

Environmental factors include natural environmental factors and anthropogenic environmental factors, which are calculated by the equation:

$$\beta = \frac{1}{2}\beta_1 + \frac{1}{2}\beta_2, \tag{6}$$

where β_1 is the natural environmental factor and β_2 is the anthropogenic environmental factor.

Table 2: Results of different methods of numerical examples.

Method	G_1		G_2	
	P_f	Funcall	P_f	Funcall
Proposed	0.1799	856	0.1091	654
	0.1822	831	0.1124	636
SDL	0.1797	(1231, 1115)	0.1092	(7810, 8650)
	0.1823	(1221, 1105)	0.1124	(13185, 14621)
SSL	0.1797	(2084, 2084)	0.1092	(380, 380)
	0.1823	(2540, 2540)	0.1124	(380, 380)
SSSL	0.1797	(506, 410)	0.1092	(785, 977)
	0.1823	(506, 410)	0.1124	(785, 977)
MCS	0.1806	10^6	0.1093	10^6
	0.1823	10^6	0.1129	10^6

In this paper, the algorithm uses the system failure rate as the input data. The system failure rate data are statistically collected and attributed to each functional module. The failure rate of each module is used as an input neuron data, respectively. The system failure rate is used as the neural network output. The system failure rate is:

$$\lambda_i = \sum_{i=1}^{n} r_i / \sum_{i=1}^{n} t_i = N_0/T, \tag{7}$$

where n is the number of sampled units. t_i is the actual working time of the ith product in the evaluation period in hours. r_i is the failure frequency of the ith product in the evaluation period. N_0 is the accumulated failure frequency of the system in the evaluation period. T is the total working time in the evaluation period. The failure rate of the input neuron is:

$$\lambda_j = \frac{N_j}{T}, \tag{8}$$

where N is the number of faults of the jth input neuron during the rating period and T is the total working time of the rating cycle.

4. Experiments

4.1. Numerical Example. This numerical example consists of two subdisciplines, as shown in Figure 4. The numerical example contains two independent random variables x_1 and x_2 and one shared random variable x_s and two independent interval variables w_1 and w_2 and one shared interval variable w_s. The limit state functions and coupling equations of each discipline are shown in Equations (9)–(12), and the distribution of each uncertainty variable is shown in Table 1.

Subdiscipline 1:

$$G_1 = (x_s + 0.5w_s)2 + 2w_1 + x_1 + w_1 e^{-y_{21}} - 7.65, \tag{9}$$

$$y_{12} = (x_s + 0.5w_s)2 + 2w_1 - x_1 + 2\sqrt{y_{21}}. \tag{10}$$

Table 3: Experimental environment.

Name	Versions
Python	3.7
Tensorflow-gpu	2.0.0rc0
CUDA	10.0
CUDNN	V7.5.0
Opencv-python	4.4.0.46
Keras	2.3.1

Subdiscipline 2:

$$G_2 = \sqrt{x_s + 0.5w_s} + w_2 + 0.4x_2(x_s + w_s) + 0.2y_{12} - 9.3, \tag{11}$$

$$y_{21} = (x_s + 0.5w_s)w_2 + w_2^2 + x_2 + y_{12}. \tag{12}$$

When solving, the limit state function and coupled equations are first transformed into the U-space. The results of the multidisciplinary reliability analysis are shown in Table 2 for each of the two disciplines using the method proposed in this paper. SDL denotes sequential double loops; SSL denotes sequential single loops; SSSL denotes sequential single-single loops; MCS denotes Monte Carlo simulation; Funcall denotes the number of function evaluations. The results obtained by SDL, SSL, SSSL, and MCS methods are from the original literature. As can be seen from Table 2, the failure probabilities obtained by the proposed method are close to those obtained by the three methods of SDL, SSL, and SSSL and the MCS method and meet the accuracy requirements. However, the other three methods involve random uncertainty solution and interval uncertainty cycle in solving, so their total number of function evaluation is the sum of the evaluation times in probability analysis and interval analysis. For example, for function G_1, the least number of function evaluations is the SSSL method. The number of function evaluations for solving the minimum and maximum values of failure probability is $506 + 410 = 916$. For function G_2, the least number of function evaluations is the SSL method. The number of function evaluations

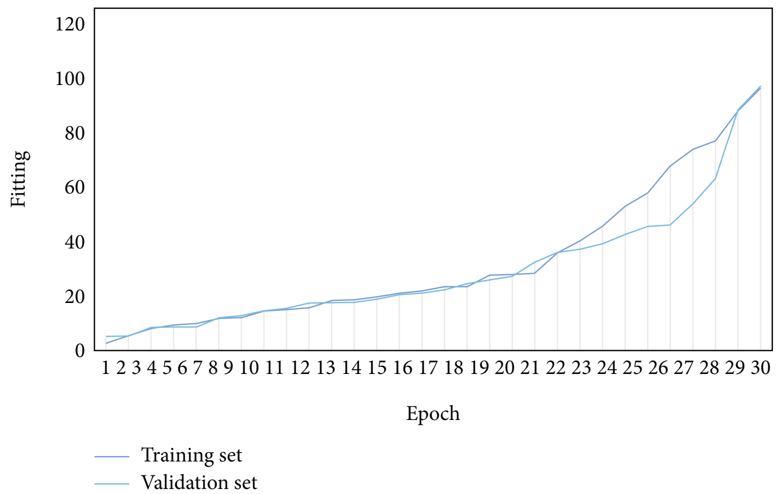

Figure 5: Schematic diagram of training process performance improvement.

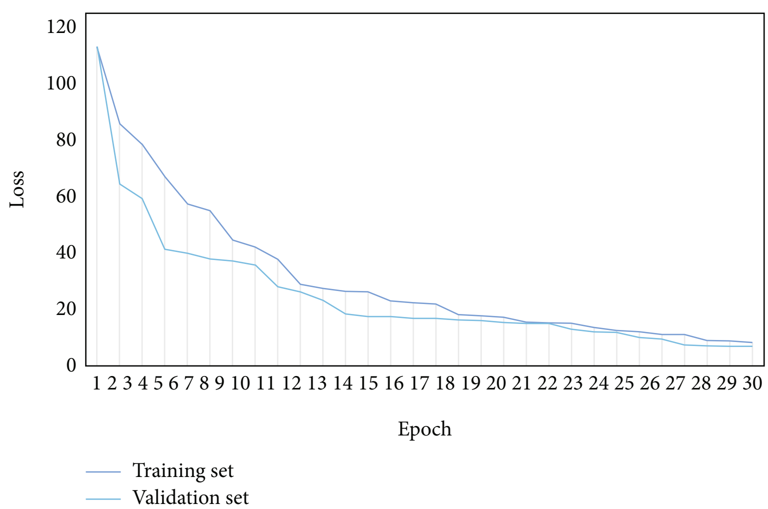

Figure 6: The training process loss convergence schematic.

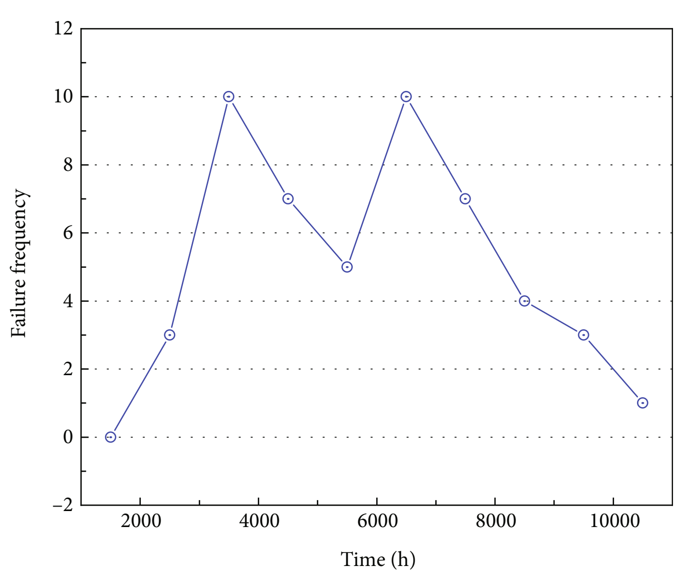

Figure 7: Failure statistics of inverter power.

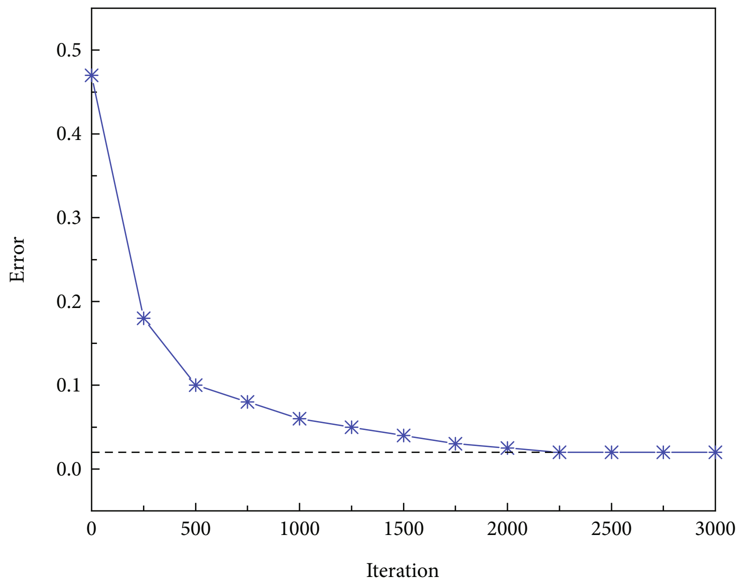

Figure 8: Performance curve of training error.

Table 4: Reliability prediction results.

Method	Sample	Test results	Prediction	Error	Average error rate
Probability calculation	9	0.1589	0.1377	0.0212	13.33%
	10	0.1634	0.1416	0.0248	
DNN	9	0.1589	0.1513	0.0076	5.91%
	10	0.1634	0.1519	0.0115	
Fusion method	9	0.1589	0.1527	0.0062	3.85%
	10	0.1634	0.1696	0.0062	

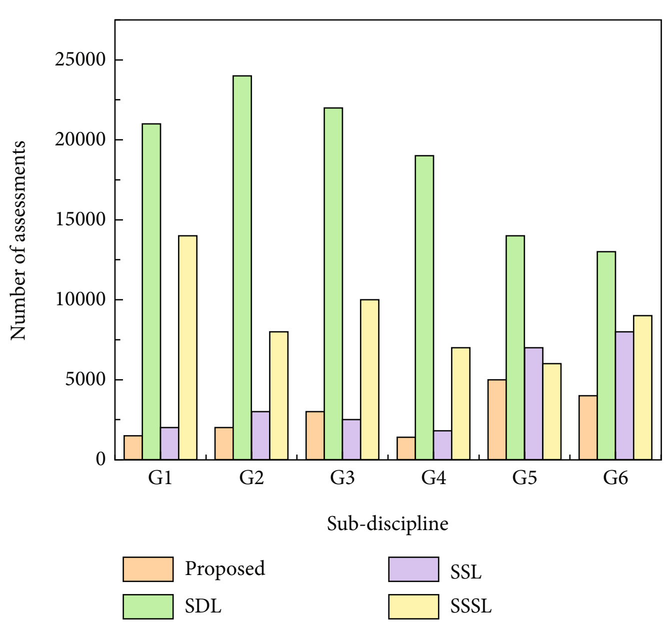

Figure 9: Comparison of the number of function evaluations when solving for the failure probability of inverter power by different methods.

for solving the minimum and maximum values of failure probability is $380 + 380 = 760$. When using the proposed method, the function evaluation times are 856 and 831 for solving the minimum and maximum values of failure probability for function G_1, and 654 and 636 for solving function G_2, respectively, which are less than the function evaluation times of the original method.

4.2. Inverter Power Reliability Test. Inverter power supplies have been sold in the process of development and improvement of products. The data used in this paper comes from an internal nonpublic dataset of a Chinese machinery and equipment research center. The data includes the first failure time of the product collected and compiled on the returned product quality feedback form. These data come from real working environment and contain field information, which are important data to reflect the product life distribution pattern and evaluate the reliability of inverter power supply. The model parameters are set as follows, the feature vector dimension is 256, the learning rate is 0.005, and the filter windows are selected as 3, 4, and 5; the dropout is 0.5, and the batch size is 128. The experimental environment is shown in Table 3. The training process performance enhancement and loss convergence are shown in Figures 5 and 6.

The inverter power supply failure statistics chart is shown in Figure 7, the horizontal coordinate is the lifetime period of the failure, and the vertical coordinate is the number of failures occurred in the time period. As can be seen from the graph, the number of failures is mainly concentrated in the time period of 3000-7000 hours.

In this paper, the inverter subsystem, drive subsystem, sampling subsystem, supply electronics system, feedback subsystem, protection subsystem, sine wave generation subsystem, PWM control subsystem, and environment factor are selected as the input vectors of the network, and the neural network established in this paper is determined according to the above discussion as: initial weights of $-1 \sim 1$; learning factor $\eta = 0.05$; impulse factor $\alpha = 0.9$; iteration accuracy $\varepsilon = 0.00001$. The error variation during the training of the deep neural network is shown in Figure 8. As can be seen from Figure 8, the model reaches convergence at 2500 iterations during the training process.

After the neural network prediction model was established, the sample data were brought in for reliability prediction, and the evaluation results were compared and analyzed with the results of the prediction method using probability calculation only, and the comparison of the prediction results is shown in Table 4. It can be seen that the deep neural network method can reduce the larger errors brought in data processing and improve the prediction accuracy compared with the probability calculation model prediction method. This is because neural networks can achieve arbitrary nonlinear mapping and can represent complex relationships between reliability variables.

In Figure 9, the horizontal coordinates represent the item categories. The bar graphs indicate the number of function evaluations used by different methods when solving the failure probability of each constraint function, respectively. The methods are, from left to right, the probability calculation fused with deep learning proposed in this paper, the SDL method, the SSL method, and the SSSL method. From Figure 9, it is clear that the number of function evaluations required by using the methods in this paper is all less than those of the remaining methods.

The results of both the numerical example and the inverter power example show that the reliability analysis under uncertainty using the method of this paper can achieve fast solution of reliability analysis and improve the solution efficiency while meeting certain computational accuracy requirements. The probability calculation method with the fusion of deep learning models can effectively reduce the evaluation error. It shows that the proposed multidisciplinary collaborative reliability analysis method with mixed uncertainties can effectively deal with the reliability analysis problems when random uncertainties, interval uncertainties, and fuzzy uncertainties exist simultaneously.

5. Conclusions

The paper addresses the problems of limited types of handling uncertainty and computational complexity faced by the current development of multidisciplinary reliability design optimization and carries out research on multidisciplinary reliability design optimization methods considering mixed uncertainty with the aim of expanding and improving the theoretical system of multidisciplinary reliability design optimization under mixed uncertainty. Based on probability theory and deep learning theory, the reliability analysis and multidisciplinary reliability design optimization modeling under random-fuzzy-interval uncertainty are thoroughly studied. In this paper, the proposed method is validated using numerical arithmetic examples and inverter power supply failure data. The results show that the proposed method is able to consider multiple uncertainties and surpasses other methods in terms of computational speed and evaluation accuracy. The reliability prediction model incorporating deep neural networks can effectively improve the evaluation performance and has a greater potential for application in multidisciplinary reliability optimization design. In the future, we plan to conduct multidisciplinary reliability design research based on reinforcement learning.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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