Twin Model-based Fault Detection and Tolerance Approach for In-core Self-Powered Neutron Detectors

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Abstract

The in-core self-powered neutron detector (SPND) acts as a key measuring device for the monitoring of parameters and evaluation of the operating conditions of nuclear reactors. Prompt detection and tolerance of faulty SPNDs are indispensable for reliable reactor management. To completely extract the correlated state information of SPNDs, we constructed a twin model based on a generalized regression neural network (GRNN) that represents the common relationships among overall signals. Faulty SPNDs were determined because of the functional concordance of the twin model and real monitoring systems, which calculated the error probability distribution between the model outputs and real values. Fault detection follows a tolerance phase to reinforce the stability of the twin model in the case of massive failures. A weighted K-nearest neighbor model was employed to reasonably reconstruct the values of the faulty signals and guarantee data purity. The experimental evaluation of the proposed method showed promising results, with excellent output consistency and high detection accuracy for both single- and multiple-point faulty SPNDs. For unexpected excessive failures, the proposed tolerance approach can efficiently repair fault behaviors and enhance the prediction performance of the twin model.

Full Text

Preamble

Twin Model-based Fault Detection and Tolerance Approach for In-core Self-Powered Neutron Detectors∗ Jing Chen,1 Yan-Zhen Lu,1 Hao Jiang,1, † Wei-Qing Lin,1 and Yong Xu2, 3 1College of Electrical Engineering and Automation, Fuzhou University, Fuzhou 350108, China 2The Department of Automation, Shanghai Jiao Tong University, Shanghai 200240, China 3Fujian Fuqing Nuclear Power Co., Ltd., Fujian 350318, China

The in-core self-powered neutron detector (SPND) serves as a key measuring device for monitoring parameters and evaluating operating conditions in nuclear reactors. Prompt detection and tolerance of faulty SPNDs are indispensable for reliable reactor management. To comprehensively extract the correlated state information of SPNDs, we constructed a twin model based on a generalized regression neural network (GRNN) that captures the common relationships among all signals. Faulty SPNDs were identified through the functional concordance between the twin model and real monitoring systems, which calculated the error probability distribution between model outputs and actual values. Fault detection is followed by a tolerance phase to reinforce the stability of the twin model during massive failures. A weighted K-nearest neighbor model was employed to reasonably reconstruct faulty signal values and guarantee data purity. Experimental evaluation of the proposed method showed promising results, with excellent output consistency and high detection accuracy for both single- and multiple-point faulty SPNDs. For unexpected excessive failures, the proposed tolerance approach can efficiently repair fault behaviors and enhance the prediction performance of the twin model.

Keywords: Self-powered neutron detector, Twin model, Fault detection, Fault tolerance, Generalized regression neural network, Nuclear power plant

INTRODUCTION

Neutron flux is a critical variable in nuclear reactors. Monitoring its variation and distribution is essential for maintaining power stability in nuclear reactors [1]. Currently, self-powered neutron detectors (SPNDs) are widely employed in core neutron flux measurement systems (CNFMS) of nuclear power plants (NPPs) to accurately measure neutron flux and provide highly reliable three-dimensional (3D) power distribution information. However, the risk of failure has increased with the growing scale and complexity of modern nuclear reactor control [2].

Faulty SPNDs that either completely or partially fail provide incorrect monitoring information, which may negatively affect both simple and advanced system functionalities, resulting in degraded overall system performance and increased risk levels [3]. Techniques to address these problems can be classified as hardware redundancy methods, model-based methods, and data-driven methods [4, 5]. Generally, hardware redundancy measures—where more than three SPNDs are installed to observe neutron flux within a spatial range—are employed in NPPs to improve CNFMS reliability. Assuming any single SPND in a neutron measurement channel fails, the additional SPNDs continue functioning and maintain high-accuracy measurements. Although this approach prevents occasional intermittent failures from negatively affecting the system, the inability to implement fault tolerance can lead to false perceptions of CNFMS performance when redundant SPNDs fail simultaneously. Moreover, redundant SPNDs incur high installation and maintenance costs, which adversely affect NPP economics [6].

Popular model-based methods (such as Kalman filtering [7], mixed Kullback–Leibler divergence and exponential weighted moving average [8], high-gain observer [9], Monte Carlo method [10], and extended state observer [11]) handle fault detection using simple mathematical models that formulate fault signatures. The results of these methods for specific nonlinear systems have been developed under various restrictive assumptions. Recently, data-driven methods [12–14] have been used for fault detection of key equipment in NPPs; the main principle is to establish an object model based on data analysis and achieve accurate detection using model outputs constrained by evaluation criteria [15]. Peng et al. [3] constructed mathematical models for various detectors using principal component analysis (PCA) and achieved fault detection and isolation for SPNDs through the square prediction error of linear models and a detector validity index based on reconstruction. Yellapu et al. [16] developed a method based on multiscale PCA with wavelet transform to reduce modeling costs and improve sensor fault diagnosis results by calculating wavelet approximation coefficients. An online multiscale data reconciliation scheme for detecting and isolating sensor faults in advanced heavy-water reactors was proposed in [17]; the scheme achieved high accuracy under different scenarios. Li et al. [18] employed two different fault identification methods to locate faults more accurately: an improved weighted contribution analysis method based on traditional sensor contribution analysis to Q statistics, and a method based on the sensor validity index obtained using the iterative reconstruction method. However, static linear models are typically unable to detect long-term SPND faults. To improve detection efficiency for practical time-varying faults, Chatterjee et al. [19] proposed using instantaneous cluster statistics to normalize measurements of each SPND in clusters and update the PCA model using normalized values. This approach yielded lower false alarm rates and higher detection rates for real-time fault changes than traditional static models. Experimental results demonstrate these approaches are useful for identifying faulty instruments. Yu et al. [20] proposed improvements to the traditional PCA model through a new corrected reconstruction algorithm to reconstruct the principal component and residual space. A cyclic PCA monitoring model was established to accurately detect different fault types and reconstruct fault data. Nageswara et al. [21] performed information fusion by combining an ensemble of trees with the support vector machine (SVM) algorithm to evaluate calculation errors of multiple sensors and the influence of complementary and redundant sensors. Most studies have failed to focus on the inherent correlation among all SPND signals in overall detector assemblies. For the dozens of SPNDs existing in neutron flux measurement channels, challenges in information integration and correlation analysis remain due to difficulties in handling large amounts of data simultaneously.

As an emerging enabling technology, digital twin (DT) can serve as a mirror of the real world by providing an integrated environment for simulating, decision-making, and optimizing physical system operations [22, 23]. Due to the powerful computing capabilities and cognitive intelligence of DT, developing more refined and scalable models for fault detection has become possible. Lin et al. [24] developed a nearly autonomous management and control (NAMAC) system for advanced nuclear reactors with DT technology. Cai et al. [25] proposed analytical techniques based on data and information fusion for modeling and developing DT virtual machine tools. DT applications in NPPs have proliferated recently [26–28]. The development of DT combined with advanced technologies for detection, control, and optimization can significantly improve system performance, reliability, availability, maintainability, and operational flexibility. Therefore, efficient in-core SPND fault detection and maintenance of monitoring systems using twin technologies are our major objectives. To continue this interesting exploration of SPND signal research, a twin model using DT technology was constructed for parameter analysis of an in-core nuclear reactor with large monitoring data and complex, changeable operating conditions.

In this context, the established twin model can extract rich values from isolated time-varying data without disturbing equipment on the real physical layer and can simulate the real-time state and dynamic characteristics of SPND entities through interactive data, overcoming the problem that traditional mathematical models [29] cannot effectively deduce the fault state of multidimensional signals in real time. In addition, several researchers have devoted attention to state analysis and the design of DT models for key nuclear reactor components. Hu et al. [30] comprehensively described the research status and development directions of DT technology in the field of advanced nuclear energy, proposed a multidimensional evaluation digital model suitable for application in nuclear reactors, and preliminarily established the fault diagnosis process. Wang et al. [31] proposed a DT system for the out-of-core detector assisted with an installation robot to perform real-time visualization monitoring of the detector installation and replacement process. Gong et al. [32] combined reduced-order models with machine learning to create physics-based DTs using real-time input parameters to rapidly reconstruct the neutron field in the core. Cancemi et al. [33] generated primary nuclear components through numerical simulation of different plant conditions, which may support predictive maintenance optimization based on plant condition and the development of a DT model for improving plant safety and availability.

Because the implementation of the twin model significantly depends on information transferred from valid data [34], the frequent and unexpected fault behaviors of SPNDs only provide unrepresentative data, leading to serious distortions in outcomes and even unprecedented collapse of the twin model. Decisions made after calculations based on large amounts of incorrect information fail to realize the entire purpose of maintaining normal system function. Most recent research methods have focused on fault detection, and only limited research has been conducted to simultaneously achieve fault tolerance in critical detectors at NPPs. This is one of the principal motivations for this work.

Designing a reasonable fault tolerance strategy that would work uninterruptedly with sufficient information-processing capabilities is practically challenging. Li et al. [35] suggested an active fault tolerance control method based on an improved BP neural network, which controls fault sensors through reconstruction. Kim et al. [36] developed a method for evaluating the fault detection coverage of a fault-tolerant technique using a fault injection experiment in a safety-critical digital I&C system for NPPs. They also proposed a probabilistic safety assessment model to observe the effect of fault detection coverage of fault-tolerant techniques. To enhance the stability of a modular high-temperature gas-cooled reactor system and the control rod drive mechanism, Hui et al. [37] proposed an adaptive fault-tolerant control scheme based on a radial basis function neural network, which has higher load tracking accuracy and better fault tolerance for systems. Li et al. [38] proposed an active fault-tolerant control scheme based on the deep Q-network algorithm of reinforcement learning to maintain the stability of the once-through steam generator control system. Rangegowda et al. [39] introduced a fault tolerance control framework to arrest performance degradation of conventional controllers in the presence of sensor bias. Clearly, appropriate fault tolerance operations are required to handle incorrect information provided by failed equipment, which can ensure data purity and no interference for normal performance of the twin model. Therefore, introducing an appropriate fault-tolerance strategy to SPND fault detection is advantageous for maintaining healthy interaction of data information and paving the way for reliable outputs of the twin model in the long term.

In this study, we propose an effective fault detection and tolerance approach for in-core SPNDs based on a twin model. The SPNDs are uniformly distributed in the reactor core; a generalized regression neural network (GRNN) [40] is employed to construct the twin model, which is consistent with the real system and represents the common relationship between overall signals. In this manner, the state correlation between SPND signals is completely considered, and the output characteristics of specific SPND individuals can be described using the joint feature information of surrounding SPNDs. State analysis and fault detection of the SPNDs were then realized by analyzing the probability distribution of errors between twin model outputs and real values. To achieve fault tolerance for unexpected faulty SPNDs, we used a weighted k-nearest neighbor (WKNN) [41] approach to recover and reconstruct faulty signals. Through troubleshooting, data substitution, and data verification of faulty SPNDs, the accuracy and rationality of detection results can be significantly improved. Compared with traditional single-signal analysis models, the proposed approach can detect multi-point faults more simply and efficiently.

The remainder of this paper is organized as follows: Section 2 provides a brief description of neutron flux measurement channel distribution and SPND composition. Section 3 describes the twin model construction scheme and specific framework for fault detection and tolerance. Experimental results and discussion are presented in Section 4. Finally, conclusions regarding the proposed framework are provided in Section 5.

II. BRIEF DESCRIPTION OF SPND

An in-core neutron instrument is one of the most important types of nuclear power equipment. SPNDs provide a crucial basis for neutron flux measurement for safe operation, treatment of abnormal working conditions, and post-accident monitoring of NPPs. In this study, an integrated core instrument casing assembly was used in a pressurized water reactor for third-generation NPPs. As shown in Fig. 1 [Figure 1: see original paper], the core contains 44 radially distributed measurement channels. In each channel, a core detector assembly installed in the instrument tube of a fuel assembly contains seven axially distributed SPNDs in equidistant layers.

SPNDs have been developed to meet requirements for small size, long life, and high tolerance to harsh environments. The composition of SPNDs is shown in Fig. 2 [Figure 2: see original paper], which mainly consists of an emitter, an insulator, and a collector. The communication line is constructed using a two-core cable in armor form and measures the currents generated by the emitter and noise currents caused by the background core. These currents are then transmitted to processing cabinets through the connector and transmission cable. Because noise currents are very small, they can be ignored. Generally, rhodium SPNDs are used in pressurized water reactor NPPs. The main generation process of SPND currents is determined by the radiation capture reaction, which proceeds in the emitter material 45Rh103 with the generation and subsequent disintegration of the induced beta-active isotope 45Rh104. The beta particles induced by disintegration then escape from the emitter with a certain probability and are collected by the collector, causing the emitter to become positively charged. Thus, the currents are proportional to the neutron flux absorbed at the SPND emitter location in the reactor.

III. METHODOLOGY

The purpose of this study is to use the twin model to enhance SPND detection performance. The main goal of the DT model is to create a mirror image of physical entities in the digital realm by observing data features and intrinsic correlation information among real SPND signals. In this study, we conducted further state analysis of current signals generated by radially distributed SPNDs on the reactor core plane of a specific NPP. As shown in Fig. 3 [Figure 3: see original paper], n SPNDs are uniformly arranged on the cross-section of the in-core vessel. Each SPND is responsible for the neutron radiation capture reaction in its relevant spatial range, resulting in n groups of recorded current signals. Each data-twinning procedure for an SPND requires signal analysis of a particular SPND by observing signal values of the other n-1 SPNDs. Therefore, the remaining n-1 SPND signals are used as model input characteristic variables, including a particular SPND label variable, prior to model training. We can obtain n sets of data patterns with related feature and label variables for each SPND. Subsequently, a GRNN is employed to train and learn the input variables in these data patterns, and the internal correlation among SPNDs can be explained through the adaptivity of the neural network. We can obtain n sets of sub-models, where features of the label SPND variable are related to features of neighboring SPNDs. By integrating n sub-models, we obtain an organic whole, which constitutes the SPND twin model. Using the twin model, errors between model outputs and actual signals are calculated to achieve SPND fault detection. The model identifies outliers in the error sequence in combination with the generalized extreme studentized deviate (ESD) statistical test [42], which provides rapid SPND fault detection results. A fault tolerance strategy should be introduced, the foundation of which is data recovery for fault variables in response to excessive fault variables that cause fault detection failure. Fault signals are replaced with normal values through constant troubleshooting, data substitution, and data validation, and the performance of the twin model is recovered. When all faulty SPNDs are successfully identified, detection results can assist in diagnostic decisions to maintain real detector assemblies.

A. Generalized Regression Neural Network

To deal with sample data comprising complicated multidimensional variables, prior research concentrated on PCA, clustering, and Kalman filter methods for signal analysis of individual SPND units. These techniques can rapidly establish models for axial SPNDs in the same detector assembly. In this study, we aimed to simultaneously analyze the spatial correlation between radially distributed SPND variables in the reactor core plane. The aforementioned techniques are not appropriate for large-scale and nonlinear data feature mining; however, the latest neural network algorithms that distribute information among neurons have significant robustness and can quickly analyze complex nonlinear relationships. As a typical radial basis neural network model based on nonlinear regression theory, GRNN can process high-dimensional data and mine mutual effects among multiple SPND current features due to its capabilities for nonlinear mapping and high learning speed. Unlike other types of artificial neural networks, GRNN has straightforward structures and training processes. Therefore, we used GRNN as the constituent architecture of the SPND twin model. As shown in Fig. 4 [Figure 4: see original paper], the GRNN is composed of the input, pattern, summation, and output layers. The input and output vectors of the corresponding network are $X = [x_1, x_2, ..., x_{n-1}]^T$ and $Y = [y_1, y_2, ..., y_k]^T$, where n-1 and k are the dimensions of X and Y respectively. The number of neurons in the input layer equals the dimension of the input vector, and each neuron is a simple distribution unit that directly transmits input to the pattern layer. The pattern layer is a radial basis layer, whose number of neurons equals the number of learning samples, n-1. The neuron transfer function P_i is typically a Gaussian function and can be written as $P_i = \exp[-(X - X_i)^T (X - X_i)/2\sigma^2]$, $i = 1, 2, ..., n-1$ where X_i is the training sample corresponding to the i-th neuron, T is the matrix transpose, and σ is a smoothing factor. The smaller σ is, the stronger the approximation ability of P_i for the samples.

There are two types of neuronal calculation formulas in the summation layer.

One sums the outputs of all neurons in the pattern layer. The connection weight between each neuron and the pattern layer is set to one. The transfer function can be expressed as $\sum$. The other type sums the outputs of all neurons in the pattern layer by weight. The transfer function can be described as $S_{M_j} = \sum w_{ij} P_i$, $j = 1, 2, ..., k$ where w_{ij} represents the weight of the i-th neuron in the pattern layer connected to the j-th neuron element in the summation layer, and S_{M_j} represents the summation value of the j-th neuron in the summation layer.

The output layer is calculated by dividing the values obtained using the two formulas in the summation layer based on the following equation: $y_j = \frac{S_{M_j}}{\sum P_i}$ where y_j is the output of the j-th output-layer neuron.

GRNN can be applied to construct different SPND regression submodels that are integrated to form a twin model that outputs twin data.

B. Construction of the Twin Model

State analysis of SPND signals with DT application can provide more efficient and intelligent service for monitoring neutron flux distribution and its rate. The premise of constructing a twin model is to extract sufficient and effective feature information from physical entities. The reactor core contains n sets of symmetrically distributed neutron flux measurement detector assemblies. Although SPNDs operate independently, the multidimensional currents they produce reveal a strong cooperative link in a shared environment. Features of nearby signals reflect characteristics of a specific SPND signal. The relationship between SPND signals can be explained by the following equations:

$S = \{s_1, s_2, ..., s_n\}$

$D = \{d_1, d_2, ..., d_n\}$

$U = \{U_1(S), U_2(S), ..., U_n(S)\}$

where S is the set of all SPND individuals at the same height in the reactor core, D is the set of sample values for each variable in S, and U is the set used to denote correlations between variables. $U_i(S)$ describes how signal characteristics of any variable in S are collectively represented by the remaining surrounding variables. As seen in Fig. 5 [Figure 5: see original paper], the reference network $U_i(S)$ is expressed as connectivity between the label variable and other variables. Data of the label variable can be twinned by analyzing the network of relationships among variables. By studying characteristics of the associated $\{s_1, s_2, ..., s_{n-1}\}$, inherent information of the label variables can be obtained. Thus, each variable in S can also be collectively described by the others. The twin model is built based on relationship networks, and GRNN is used to construct specific submodels to form a twin body. By dividing set D, the n-1-dimensional variables become features I_i and the remaining single variable becomes the training label T_i. After alternate division of n groups, data patterns between I_i and T_i are expressed as follows:

$$(I_i|T_i) = \begin{pmatrix} d_1 & d_2 & d_3 & \cdots & d_{n-2} & d_{n-1} \\ d_1 & d_2 & d_3 & \cdots & d_{n-2} & d_n \\ d_1 & d_2 & d_3 & \cdots & d_{n-1} & d_n \\ d_1 & d_3 & d_4 & \cdots & d_{n-1} & d_n \\ d_2 & d_3 & d_4 & \cdots & d_{n-1} & d_n \end{pmatrix}$$

The division result contains n rows of data patterns, and each dimensional variable of SPND signals in set D is designated as a label for its corresponding data pattern. For instance, SPND s_n is identified as the label of the first data pattern. Similarly, SPND s_i is considered the label of the (n+1-i)-th data pattern. To thoroughly explore correlation between any target variable and remaining variables in each pattern, GRNN was utilized to train submodels to learn state relationships between SPND features and labels. Subsequently, n groups of submodels were built after repeated training. An integrated organism M is combined as follows:

$$M = \{M_1, M_2, ..., M_n\}$$

where M_i represents the trained GRNN submodels for different data patterns. After the learning algorithm, each GRNN submodel outputs the predicted value of the target SPND when its inputs are (n-1)-dimensional feature vectors. All submodels are combined into M, which produces n groups of estimated data and explains the commonality of signal changes in all SPND components. Real SPND signals can be twinned using these virtual values. The residual between twin model output results and real values can be calculated in given operating scenarios to determine faulty SPNDs, after which status assessment and potential fault tolerance can be performed.

C. Fault Detection and Tolerance

Measuring the residual between twin model outputs and actual values allows us to ascertain whether faults exist in detector assemblies. Statistical tests can generally determine deviation points in a residual sequence. Traditional statistical techniques are sensitive to outlier presence because inaccurate data points can distort the mean and standard deviation of a data sequence. In this section, ESD was employed to detect possible outliers in the residual sequence and discriminate faults from original signals. ESD can maintain good elimination effects when several anomalies exist concurrently in data. We assumed outliers exist in the residual sequence. The maximum number of outliers was predetermined as r, and r rounds of separate tests were performed by calculating the statistical test variable using the following formula:

$$R_i = \max \frac{|E_i - \hat{E}|}{z}$$

where E_i is an observed point and $\widehat{E}$ and z denote the sample mean and standard deviation, respectively. The observed point that maximizes $|E_i - \widehat{E}|$ and deviates most from the mean should be located and eliminated during calculation. The aforementioned statistic is then recalculated using the remaining n-1 observed points. The process repeats until r observed points have been removed, resulting in r test statistics $R_1, R_2, ..., R_r$. Corresponding to these r test statistics, r critical values are calculated as follows:

$\lambda_i = \frac{(n-i)t_{p,n-i-1}}{\sqrt{(n-i+1+t^2_{p,n-i})(n-i+1)}}$

where $t_{p,v}$ represents the 100p percentage points from the t distribution with v degrees of freedom and $p = 1 - \frac{\alpha}{2(n-i+1)}$. α denotes the test confidence level. The number of outliers is determined by finding the largest i such that $R_i > \lambda_i$, and thus the initial hypothesis can be validated.

As mentioned above, simultaneous failures of excessive SPNDs in detector assemblies can lead to anomalously measured data that cannot accurately represent actual operational status. Judgments based on fault signals will prevent the system from reaching normal operating conditions and may even cause personnel to misoperate. The twin model's capacity to perform effective analysis suffers due to disordered input, and the reliability and validity of detection results cannot be demonstrated by residual information calculated from a broken model. For CNFMS to be dependable and secure, the fault detection function must be rehabilitated. In this case, we introduce an efficient fault-tolerant strategy implemented before multi-fault detection. The most important factor in designing a fault tolerance solution is that information available to the entire system after unexpected failure must be identical to information that would have been obtained if SPNDs were not faulty. The main objective was to achieve data recovery, including troubleshooting, data substitution, and data verification.

In the presence of multiple unknown fault sources, fault troubleshooting must be performed using multidimensional data. A possible selection approach involves selecting the vector with the largest calculated residual and performing data recovery first. When executing data substitution, values of faulty variables should be replaced with normal signals. To improve accuracy of replaced data, the KNN classifier was first used to select K instance points from the historical database in the nearest neighbor of the fault point's feature variable to form a new signal sample. The operating condition of K nearest-neighbor points was closest to that of fault signals, and their variable characteristics were in a division range similar to original signal characteristics. Weighted average operation was utilized for values of these K points, producing corrected signal values. Finally, fault signal values were entirely replaced by revised values.

After data substitution, Jensen–Shannon (JS) divergence [43] was employed to confirm modified data and guarantee replacement consistency. It can describe differences between probability distributions of variables, performing well in similarity measurement. For two probability distributions, the interval value of JS divergence is [0, 1]. The two distributions are more similar as the value decreases, and vice versa. The degree of JS divergence can fully evaluate suitability of modified data. Repeating the preceding steps for multi-fault samples can reduce the number of faulty SPNDs after recovery until detection results are satisfactory. When the satisfied sample is input into the twin model, output is stable and controlled within small error. In this case, the previous fault-detection approach is adequate and fault tolerance is no longer required.

IV. RESULTS AND DISCUSSION

In this section, the proposed method was evaluated using historical monitoring data collected from in-core detector assemblies in a third-generation pressurized water reactor. To build a reliable SPND twin model, a sufficient number of measurement datasets must be known in advance. The 44-dimensional SPND signals, distributed radially in a certain layer, were considered as experimental objects in this study. To improve twin model generalization, training data were derived from the reactor shutdown stage. As shown in Fig. 6 [Figure 6: see original paper], with control rod insertion, reactor core power gradually decreased from 100% FP to 0% FP, and all SPND currents decreased. Test set data were derived from SPNDs during steady operation.

A. Performance of the Twin Model

With continuous neutron flux reduction during shutdown, the number of neutrons captured by the emitter decreased, resulting in proportional decrease in currents generated by the 44 SPNDs. To extract valuable information from physical SPNDs under different power levels and build a twin model based on it, submodels for 44 dimensional signal variables were executed. First, the training set was segmented round after round, and 44 groups of data patterns with several feature variables I_i and label variable T_i were obtained as follows:

$$(I_i|T_i) = \begin{pmatrix} d_1 & d_2 & d_3 & \cdots & d_{42} & d_{43} & d_{44} \\ d_1 & d_2 & d_3 & \cdots & d_{42} & d_{44} & d_{43} \\ d_1 & d_2 & d_3 & \cdots & d_{43} & d_{44} & d_{42} \\ d_1 & d_3 & d_4 & \cdots & d_{43} & d_{44} & d_2 \\ d_2 & d_3 & d_4 & \cdots & d_{43} & d_{44} & d_1 \end{pmatrix}$$

Each data pattern in $(I_i|T_i)$ was input into GRNN for the model to learn correlation between signal variables, and the 44 submodels were well-trained. GRNN's superiority over other models is ascribed to convenient parameter setting. GRNN performance can only be changed by setting the smoothness factor σ in the kernel function. To improve model accuracy, root mean square error (RMSE) was employed as the loss function to optimize σ values for submodels. Twenty percent of the training set was selected as the verification set and a cross-validation approach was used to obtain accurate parameter optimization results. As shown in Table 1 , each submodel obtained minimum RMSE with corresponding optimal σ settings. Optimized parameters helped improve twin model performance in the verification set.

To demonstrate GRNN's superiority in modeling more clearly, we compared the proposed method with several typical approaches, including convolutional neural networks (CNN), multilayer perceptron (MLP), extreme gradient boosting (XGB), decision tree (DT), SVM, and Bayesian ridge (BR). All methods were implemented using the same data samples from the test set to compare output accuracies. As shown in Fig. 7 [Figure 7: see original paper], the twin model formed by GRNN had the lowest RMSE between model outputs and actual signal values. DT and XGBoost-based models, as common tree regression algorithms, had slightly larger errors than the GRNN-based model, which can easily overfit SPND signals and reduce precision. CNN and MLP models' learning abilities for SPND signal features were poorer than GRNN's. These models are suitable for dominant feature extraction but tend to ignore correlation between parts and the whole. SVR- and BR-based models are appropriate for handling small samples rather than analyzing larger multi-dimensional signals. Compared to typical machine learning algorithms, the twin model established based on GRNN can extract rich feature information from isolated time-varying data with lower errors and higher prediction ability. In subsequent fault detection phases, errors between model outputs and actual signals can be used to determine fault location. The twin model's estimated values can help improve in-core power measurement by avoiding interference from fault information.

B. Fault Detection Results Under Different Conditions

The novel contribution of this study is accurate identification of faulty SPNDs in numerous assemblies using a twin model. Signal characteristics analyzed by the twin model can help examine fault characteristics. In this section, single- and multi-point SPND fault signals were simulated through experiments to determine fault detection effectiveness under different conditions. Faulty SPND signals of diverse measurement channels were simulated by adding different percentages of bias to normal signals based on original operating conditions.

For single-point fault detection, as shown in Fig. 8 [Figure 8: see original paper], deviation between twin model output and actual normal value is very small before introducing faults into the test set, and data fit well. In simulation, a bias of 50% of normal signal value was introduced into SPND#12 at a time point after the normal signal. In this case, the twin model could maintain normal output, but failure of SPND#12 caused calculated RMSE to fluctuate significantly at this point. ESD test results show that RMSE of the 12th point deviates most, confirming existence of faulty SPND#12.

In reality, complex and changeable interference factors usually cause fault signals to vary. Different types of common fault behaviors mainly include bias, precision degradation, and complete failure, with abnormal states due to influence of external environmental factors. Signal deviation also varies at the same power level used to measure failure magnitude extent. Experiments (15 groups × 130 rounds) were conducted to compare fault-detection efficiency under different fault types and deviation rates. Mean accuracy, an evaluation index, is the proportion of successful detections in each experiment group to total experiments. Table 2 provides fault detection accuracy calculation results. Except for detection accuracy of 99.23% in "5% drifting", mean accuracies of other cases were 100%, indicating that fault variables identified by ESD test from errors are consistent with actual faulty SPNDs. Therefore, the proposed method can maintain extremely high correct detection rates for single-point SPND faults under various conditions.

Similarly, multiple SPNDs can fail simultaneously. The method for detecting multi-point faults is the same as for single-point faults. However, this remains challenging because multiple faulty signals can contaminate twin model input, leading to rising nondeterminacy of outputs. In this study, we analyzed impact of faulty SPND number on twin model output and fault detection accuracy. Because failure type and deviation rate had little influence on detection accuracy, added simulated fault signals were random. It was observed that multi-point fault detection accuracy remained at 100% when the number of faulty SPNDs was less than 26. In other words, the proposed method can perform relatively efficient detection when approximately half of the 44 SPNDs fail. As failure numbers continue increasing, accuracy gradually decreases and approaches 50%, meaning approximately half of faulty SPNDs detected by ESD are true. Unacceptable data deviating from normal range causes sharp accuracy decline. Excessive abnormal inputs strongly affect original twin model function and cause collapse, hindering subsequent detection realization. With ESD test calculation, multi-point fault detection accuracy of models based on other algorithms declined earlier than GRNN-based models under identical conditions. Their accuracies decreased at different rates with further failure expansion, finally becoming more stable along their tails. The method proposed in this study performs well for both single- and multi-point SPND fault detection.

C. Evaluation of Fault Tolerance

Previous analysis proved superiority of using the twin model to detect multiple faults. However, deficiency remains in dealing with excessive failures: detection accuracy decreases significantly when faulty signal numbers exceed the upper limit. Therefore, an efficient fault-tolerant solution is required to restore abnormal data. For multi-dimensional fault data points, the KNN algorithm can help search for K operating points closest to faulty signal features in the historical database. On this basis, WKNN regression was employed to obtain more accurate values by assigning greater weight to nearest neighbors. K value selection significantly impacts regression analysis results because smaller K can increase approximation error, make models more complicated, and likely lead to overfitting, resulting in larger estimation error. According to Fig. 10 [Figure 10: see original paper], WKNN has lower error than KNN without weighting. When K=8, WKNN has the smallest RMSE (2.2217μA). Hence, the hyperparameter K in WKNN used in this study was set to eight.

To verify feasibility of the fault tolerance scheme mentioned above, we selected 100 points of a continuous time sequence under full-power platform from the test set, and random faults were introduced into SPNDs from the 25th to 100th points in the example. In fault-tolerant processing, data recovery is first performed for the SPND variable with largest RMSE. Taking SPND#27 as an example, Fig. 11 [Figure 11: see original paper] shows that deviation between fault and original values is distinct (RMSE=0.0387μA), significantly affecting normal system monitoring. From the twin model perspective, deviation between predicted and original values was high (RMSE=0.0488μA), making it incapable of meeting high-precision control requirements. In WKNN implementation, deviation distance between regression value and original values was shortest (RMSE=0.0044μA), and data recovery accuracy was enhanced compared with the twin model. Through data recovery, WKNN can perform more reliable correction and maintain stable system operation.

For data verification, JS divergence was employed to prove probability distribution similarity of values. After calculation, divergence values of fault values, twin model predicted values, and WKNN regression values with original values were 4.3409×10^{-5}, 7.5058×10^{-7}, and 5.6829×10^{-7}, respectively. WKNN regression values have advantages in similarity measurement, which verifies remarkably similar probability distribution and high recovery performance.

We further evaluated fault-tolerant method performance on a sample filled with faulty signals. Impact of recovered variable number on average RMSE of model outputs and fault detection accuracy is illustrated in Fig. 12 [Figure 12: see original paper]. In multi-point fault detection, obtained detection accuracy with no data recovery measures was 52.18%, same as before. This is mainly attributed to twin model output error being much larger than normal range, providing completely false knowledge and leading to ESD test inability to determine that all SPND variables have failed. As data recovery progresses, faulty variables are substituted by recovered data. Subsequently, average RMSE decreases and detection accuracy increases gradually. When recovered variable number reaches approximately 18, accuracy increases to approximately 100%. Additionally, there is no additional need to recover from other failures in this case.

Finally, effects of fault tolerance strategy on improvement of twin-model-based SPND fault detection are discussed. As shown in Table 3 , faulty SPND number was divided into five intervals in multi-point fault detection experiment (150 groups): less than 25, 25–30, 30–35, 35–40, and more than 40. Without fault tolerance introduction, mean fault detection accuracies in the five intervals were 100%, 72.23%, 53.29%, 52.91% and 53.88%. After faulty data recovery, number of successfully detected faulty SPNDs increased, resulting in accuracies of 100%. This change confirms that provision of subsequent fault-tolerant measures to the twin model can efficiently enhance detection accuracy and improve model capacity to parse signal correlation, which is sufficient for maintaining healthy system monitoring.

V. CONCLUSION

In this study, we proposed a twin-model-based fault-detection method along with a tolerance strategy for in-core SPNDs. The twin model consists of submodels built by GRNN, which can extract inner correlation of multi-dimensional data through deep learning from historical SPND signals. Compared with other methods, the twin model can obtain higher prediction precision and help improve CNFMS measurements. The fault detection phase is based on calculating error probability distribution of model outputs that can determine existence of single- and multi-point faults. This technique can maintain detection accuracy of nearly 100%. To address decreased efficiency caused by excessive failures, a fault-tolerant phase was developed with WKNN, which could search for normal signal values with same operating conditions to replace faulty signals. Comprehensive steps including troubleshooting, data substitution, and data verification were conducted to achieve superior fault-tolerance performance. Experimental results show that the tolerance strategy is promising for delivering high detection quality with accuracy of more than 99%, suggesting that the proposed method can be considered adoptable. Furthermore, our work can be extended to other layers of in-core detector assemblies to achieve holistic condition-based maintenance of the monitoring system.

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