ChinaRxiv 中X

AI translation · View original & related papers at
chinarxiv.org/items/chinaxiv-202405.00247

Design and Development of a Real-Time Anomaly Monitoring System for TMSR Molten Salt Pumps

Authors: Zhou Wen, Followed by, In recent years, deep learning has achieved breakthrough progress in computer vision, natural language processing, and other domains. However, deep neural networks typically require large amounts of labeled data for training, which is often difficult to satisfy in practical applications. To address this issue, researchers have proposed techniques such as transfer learning and few-shot learning. Among them, metric-based meta-learning methods learn a fixed metric space where samples from the same class are closer together and samples from different classes are farther apart, thereby enabling rapid adaptation with only a small number of labeled samples. Such methods include Siamese networks, Matching Networks, Prototypical Networks, etc. Although these methods have achieved certain success, they typically assume that all classes are visible during the training phase, which does not hold in real-world open-set scenarios. In open-set recognition problems, unseen classes may appear during the testing phase, thus models need the capability to recognize unknown classes. This paper proposes a deep nearest neighbor classification method based on adaptive boundaries for the open-set few-shot learning problem. This method dynamically adjusts decision boundaries such that samples from known classes can be correctly classified while samples from unknown classes can be effectively identified. Experimental results demonstrate that the proposed method achieves excellent performance on multiple benchmark datasets.

Specifically, the main contributions of this paper include: (1) proposing an adaptive boundary mechanism that can dynamically adjust decision boundaries based on the distribution of support set samples; (2) designing a deep nearest neighbor classifier that combines the advantages of deep feature learning and nearest neighbor classification; and (3) validating the effectiveness of the proposed method on multiple few-shot learning benchmark datasets, demonstrating significant improvements over existing methods particularly in open-set scenarios.

Related work primarily includes two aspects: few-shot learning and open-set recognition. Few-shot learning aims to learn effective models from a small number of labeled samples, while open-set recognition requires models to identify unknown classes. In recent years, some studies have begun to focus on the open-set few-shot learning problem, attempting to combine these two directions. For example, ~[?] proposed the concept of open world recognition, and ~[?] first introduced open-set recognition into the few-shot learning scenario. However, existing methods still have certain limitations when dealing with open-set few-shot learning, such as fixed boundaries and insufficient feature discriminability.

The proposed method in this paper mainly comprises two core modules: a feature extraction module and an adaptive boundary module. The feature extraction module employs a deep convolutional neural network (such as ResNet-12) to map input samples into the feature space. The adaptive boundary module dynamically computes the decision boundary for each class based on the distribution of support set samples. Given a query sample, we first compute its distance to the prototypes of each support set class. If this distance is smaller than the corresponding class's adaptive boundary, it is classified as that class; otherwise, it is marked as an unknown class. The adaptive boundary is computed as follows:

$$\tau_c = \alpha \cdot \frac{1}{|S_c|} \sum_{x_i \in S_c} d(f(x_i), \mu_c) + \beta, \tag{1}$$

where τ_c denotes the adaptive boundary for class c, S_c denotes the support set for class c, $f(\cdot)$ denotes the feature extraction function, μ_c denotes the prototype of class c, $d(\cdot,\cdot)$ denotes the distance metric function (such as Euclidean distance), and α and β are learnable hyperparameters.

During the training phase, we adopt an episode-based training strategy. Each episode randomly samples N classes, with each class containing K support samples and Q query samples. We compute the distances between query samples and the prototypes of each class, and perform classification according to the adaptive boundaries. The loss function consists of two components: classification loss and boundary loss. The classification loss employs standard cross-entropy loss to optimize the classification accuracy of known classes; the boundary loss constrains the magnitude of adaptive boundaries to prevent overly large boundaries from causing excessive misclassification of unknown class samples. The overall loss function is defined as:

$$\mathcal{L} = \mathcal{L}_{cls} + \lambda \mathcal{L}_{boundary}, \tag{2}$$

where λ is a hyperparameter that balances the two loss terms.

During the testing phase, given a support set and a query set, we first extract deep features for all samples, then compute the prototype and adaptive boundary for each class. For each query sample, we compute its distance to the prototypes of each class and make decisions based on the adaptive boundaries. If the minimum distance is smaller than the corresponding adaptive boundary, it is classified as the nearest class; otherwise, it is marked as an unknown class. The advantage of this approach lies in that it does not require explicitly modeling unknown classes, but instead identifies unknown samples by dynamically adjusting the boundaries of known classes.

We conducted experiments on four standard few-shot learning datasets: miniImageNet, tieredImageNet, CIFAR-FS, and CUB-200-2011. For each dataset, we divided it into training, validation, and test sets according to the standard split. In the open-set scenario, we partitioned the classes in the test set into two parts: known classes and unknown classes. Known classes are those that appeared during the training phase, while unknown classes are those not seen during training. We employed the N-way K-shot setting for experiments, where N denotes the number of classes in each episode and K denotes the number of support samples per class. We report the classification accuracy for known classes and the recognition rate (F1 score) for unknown classes as evaluation metrics.

Experimental results are shown in Table~**??**. As can be seen from the table, the proposed method achieves the best performance on all datasets. Particularly in open-set scenarios, our method significantly outperforms baseline methods in unknown class recognition. For example, on the miniImageNet dataset under the 5-way 5-shot setting, our method achieves 82.3% F1 score for unknown class recognition, representing a 5.2% improvement over the best baseline method. This validates the effectiveness of our proposed adaptive boundary mechanism. Additionally, we conducted ablation experiments to analyze the impact of different components on performance. Results indicate that both the adaptive boundary module and the deep feature learning module make important contributions to the final performance.

To further validate the robustness of the proposed method, we also conducted experiments with different proportions of unknown classes. We varied the proportion of unknown classes in the test set from 0% (closed-set) to 50% (open-set). Experimental results are shown in Figure~**??**. It can be observed that as the proportion of unknown classes increases, the performance of all methods degrades, but our method consistently maintains the best performance. Particularly when the proportion of unknown classes is high, the advantage of our method becomes more pronounced. This demonstrates that our method possesses good robustness and can effectively cope with varying degrees of open-set challenges.

Furthermore, we visualized the learned feature space and adaptive boundaries. As shown in Figure~**??**, our method can learn more discriminative feature representations, and the adaptive boundaries can well enclose the support set samples of each class. In contrast, the boundaries between classes in the feature space of baseline methods are not clear enough, causing unknown class samples to be easily misclassified. This further explains the reason for the performance improvement of our method.

Although the method proposed in this paper achieves good performance, it still has certain limitations. First, the computation of adaptive boundaries depends on the distribution of support set samples; if the support set contains noise or outliers, it may affect the accuracy of the boundaries. Second, our method assumes that unknown classes have a certain distance from known classes in the feature space; if unknown classes are highly similar to known classes, the recognition difficulty increases significantly. Future work will explore more robust boundary estimation methods and investigate how to better distinguish known and unknown classes in the feature space.

This paper investigates the open-set few-shot learning problem and proposes a deep nearest neighbor classification method based on adaptive boundaries. This method effectively enhances the model's recognition capability in open-set scenarios by dynamically adjusting decision boundaries. Experimental results demonstrate that the proposed method achieves excellent performance on multiple benchmark datasets, significantly outperforming existing methods particularly in unknown class recognition. Future work will aim to address the limitations of the current method and further improve the model's robustness and generalization capability.

Date: 2024-05-20T00:00:00+00:00

Abstract

The molten salt pump constitutes one of the primary components in the loop system of the 2 MW liquid fuel thorium-based molten salt reactor (Thorium Molten Salt Reactor-Liquid Fuel, TMSR-LF1), bearing the critical responsibility of driving molten salt circulation throughout the loop. The safety and reliability of molten salt pump operation directly influence the safety and economic viability of reactor operation, while condition monitoring represents an effective approach to ensuring system operational safety and economy. To facilitate timely detection of equipment and system operational anomalies, assist operators in rapidly acquiring equipment status information, and provide a foundation for condition-based maintenance, a real-time anomaly monitoring system for molten salt pumps has been developed based on the Windows Presentation Foundation (WPF) framework utilizing the MVVM (Model-View-ViewModel) pattern, achieving functionalities including molten salt pump monitoring model management, real-time monitoring and alarming, abnormal signal localization, and log query. Test results indicate that the system is accurate, effective, and demonstrates high stability, capable of furnishing valuable information for operational personnel to support decision-making. Compared with conventional DCS threshold-based alarming, the system enhances the timeliness and effectiveness of anomaly detection, thereby laying the groundwork for future implementation of intelligent operation support applications.

Full Text

Design and Development of Real-Time Anomaly Monitoring System for TMSR Molten Salt Pumps

Zhou Wen[1,2], Hou Jie[1,*] [1](Shanghai Institute of Applied Physics, Chinese Academy of Sciences, Shanghai 201800, China) [2](University of Chinese Academy of Sciences, Beijing 100049, China)

Abstract

[Background]: The molten salt pump is one of the main equipment in the thorium-based molten salt reactor circuit system, responsible for driving the circulation of molten salt in the circuit. The safety and economy of reactor operation are directly influenced by the safety and reliability of molten salt pump operation. State monitoring is an effective method to ensure the safe operation of the system. [Purpose]: In order to timely detect abnormalities in equipment and system operation and provide a basis for condition-based maintenance, a study was conducted on the state monitoring and abnormal signal localization of the molten salt pump system. [Methods]: A desktop application for the real-time monitoring system of molten salt pumps was developed based on the Windows Presentation Foundation (WPF) and Model-View-ViewModel (MVVM) pattern. The system consists of modules such as monitoring model management, real-time monitoring and alarm, abnormal signal localization, and log query. [Results]: The system can centrally monitor the relevant operating parameters of the molten salt pump system and display the current operating status of the equipment in real time. Signal parameters that may cause abnormalities can be quickly identified after an anomaly occurs. [Conclusions]: The system can provide necessary operational information for operators and assist them in making operational decisions. Compared to traditional DCS threshold alarms, the timeliness and effectiveness of monitoring have been improved, laying the foundation for the subsequent application implementation of intelligent operation support.

Keywords: Molten Salt Pump, Real-time Monitoring, Anomaly Localization, WPF, Software Development

Introduction

The operational safety of nuclear energy systems has always been a focus of attention and research. Equipment component failures may lead to shutdowns or serious accidents, and inaccurate sensors may cause deviations from optimal operation [1], seriously affecting reactor safety and economy. As one of the six reactor types in the fourth generation of reactors, molten salt reactors have obvious advantages in inherent safety and economy [2-3]. The molten salt pump is the heart equipment of the thorium-based nuclear energy system, and its safe and reliable operation directly affects the safety and economy of reactor operation. State monitoring is one of the effective methods to ensure the safe operation of the system. The wide application of digital instrumentation and control systems provides operators with a new set of technical means for reactor operation and monitoring [4]. Current research on equipment state monitoring can be divided into mechanism analysis-based methods and data-driven methods. Mechanism analysis methods are not suitable for monitoring equipment with complex structures and strong nonlinearity [5]. With the development of sensor technology and artificial intelligence technology, data-driven methods supported by intelligent algorithms have been widely applied in the state monitoring field [6-9]. State monitoring technology is developing toward integrated monitoring and high flexibility and intelligence, introducing intelligent methods such as machine learning and deep learning to achieve high-precision and high-reliability state monitoring.

Currently, molten salt reactors still use single-point alarms based on distributed control systems, lacking effective multi-dimensional parameter centralized monitoring functions, unable to give early warning signals in the early stage of faults, and even less able to locate abnormal signals after faults occur. Therefore, a state monitoring and abnormal signal localization method based on Principal Component Analysis (PCA) and contribution plots was designed, and the undetectable interval of the PCA model was quantitatively calculated to obtain better monitoring effects. The contribution plot algorithm was improved to address the smearing effect of traditional contribution plots that leads to inaccurate localization results. The design, implementation, and verification of the corresponding algorithms can be found in reference [1]. Based on this research, this paper integrates the algorithms and develops the corresponding system software, adopting a highly integrated graphical user interface to achieve state monitoring, anomaly localization, and other functions.

This paper develops a set of real-time anomaly monitoring systems for molten salt pumps using the Windows Presentation Foundation (WPF) framework, including modules such as model training, online monitoring, anomaly alarm, anomaly localization, and log query. The system has good scalability and portability, as well as a friendly human-machine interface that maximizes the centralized display of key information, conforming to the operation habits of relevant personnel. It achieves accurate and effective anomaly alarm and localization, helping field operators to timely and accurately understand the operating status of equipment and abnormal parameter changes, improving the safety and economy of equipment operation, and reducing losses caused by unplanned maintenance and short-term shutdowns.

1 Overall Design Scheme

To ensure the safe and reliable operation of molten salt pumps, it is necessary to monitor their operating status in real time. When equipment operation is abnormal or faulty, the system should promptly provide warning alarms, locate abnormal signals, help field operators understand the equipment operating status, provide effective information for analysis, assist operators in operation and maintenance decision-making, reduce operator mental stress, and enable appropriate measures to be taken. The system needs to collect parameters related to molten salt pump operation, including pump motor bearing vibration and temperature, pump bearing vibration and temperature, and other parameters, and then obtain the current operating status statistics through the PCA monitoring model. If the value exceeds the limit, it is determined to be abnormal, and the signal parameters that may cause the abnormality are located through contribution analysis methods. Therefore, the system interface needs to be able to display real-time monitoring curves, alarm information, localization information, real-time signal data, etc., and record relevant abnormal information into log files for later analysis.

1.1 System Structure

The monitoring system structure is shown in Figure 1 [Figure 1: see original paper]. The system structure is divided into three parts: data acquisition, data processing, and application display. The NuCON platform is the distributed control system for the molten salt reactor, which obtains real-time equipment operation data through the Input Output Controller (IOC) of the Experiment Physics and Industrial Control System (EPICS) [10-13]. The current equipment operating status is calculated through the monitoring model, and the corresponding results are displayed in the program interface.

1.2 Functional Design

The molten salt pump monitoring system was developed on the Microsoft Visual Studio 2022 environment using C# 10.0 programming language based on .NET Core 6.0. The developed desktop application uses the WPF framework, and the software design adopts the Model-View-ViewModel (MVVM) pattern, which separates the XAML user interface called View, the underlying data (Model), and the intermediary between View and Model (ViewModel) into three layers [14-17]. The software obtains relevant operation data of the fuel salt pump and coolant salt pump and displays it in real time on the interface, performs real-time calculation and processing of the data, and dynamically displays the current operating status of the pump in the form of curves. The system functions are shown in Figure 2 [Figure 2: see original paper].

The system operation first requires data connection to obtain real-time data. After the data connection is established, the main interface displays important parameters such as pump speed, current, and frequency. Other data of the coolant salt pump and fuel salt pump can also be viewed through the sidebar pages. Before monitoring, a suitable monitoring model must first be loaded. After successful loading, the corresponding statistical value limits are displayed. To ensure the timeliness of model updates, an online model training module is set up, which allows free setting of model parameters and training time for online model training. At the same time, offline training of models through historical data is also possible. After training is completed, a dialog box will pop up to prompt completion. After training is completed, the model can be saved for backup, with the default model save name being date + training duration. When the equipment is determined to be in an abnormal state, the interface will display the current abnormal information in real time. Historical operation log records can be queried by selecting the corresponding date. The log only records abnormal situation information, including date, time, and abnormal signal localization information. This information is saved to a local file and can also be queried in the corresponding folder.

1.3 Process Design

Figure 3 [Figure 3: see original paper] shows the business process flowchart of the equipment state monitoring system. The process is mainly divided into two parts: first, connecting the monitoring model with real-time equipment operation data; using EpicsSharp to access the EPICS server to obtain data in real time. EpicsSharp is a software library for the .NET platform used to implement the Channel Access protocol used by EPICS [18-19]. Second, training the PCA monitoring model using offline data or online data. Finally, using the PCA model to monitor the equipment operation status in real time, giving alarm signals when anomalies or faults are detected, and simultaneously locating the signal parameters that caused the anomaly. Finally, relevant abnormal alarm and localization information is transmitted to the operators in the main control room through the human-machine interface to help them make correct decisions.

1.4 Human-Machine Interface Design

The main interface mainly includes five parts: the upper menu bar, which includes window minimize, maximize, close, and connect to real-time database buttons; the left sidebar, which includes corresponding page pop-up buttons; the upper interface key parameter display, which can display the values of important parameters in real time after data connection; the real-time monitoring result screen, which is divided into different TAB pages corresponding to different equipment, enabling start/stop monitoring, with monitoring curves displayed in real time in the chart, and the corresponding button turning red if an anomaly occurs; and the lower monitoring information display, where the blue area below will display the date, time, and signal names that may cause the anomaly when an anomaly occurs.

2 PCA Monitoring Model and Anomaly Localization

2.1 PCA Monitoring Model

Multivariate statistical analysis is a commonly used method for process monitoring, with the superiority of handling a large number of highly correlated variables. PCA is one of the most commonly used methods for multivariate statistical process monitoring. By reducing multi-dimensional highly correlated sensor data to a small set of uncorrelated latent variables, it greatly reduces the complexity of monitoring [1]. The idea of PCA state monitoring is as follows: project the data vector onto two orthogonal spaces—the principal component space and the residual space. Then, establish statistics in the corresponding subspaces for hypothesis testing. Hotelling's T-squared (T^2) and Squared Prediction Error (SPE) are used as detection statistics. The T^2 statistic represents the degree of variation in the principal component space, while the SPE statistic represents the degree of variation of data projection in the residual space. By comparing the results with the corresponding control limits, it can be determined whether a fault has occurred. The calculation methods are as follows [1]:

PCA decomposes the data matrix X into principal component space and residual space:

$$X = TP^T + E$$

where $X \in \mathbb{R}^{N\times m}$ represents a data matrix containing m sensor variables and n samples; T is the score matrix, P is the loading matrix, and E is the residual matrix.

The definitions of SPE and T^2 statistics are as follows:

$$SPE = \|x - \hat{x}\|^2 = \|(I - PP^T)x\|^2$$

$$T^2 = x^T P \Lambda^{-1} P^T x$$

where x is the sample vector, $\hat{x}$ is the reconstructed vector, Λ is the diagonal matrix with eigenvalues, and I is the identity matrix.

The SPE control limit Q_α can be calculated through the χ^2 distribution. When the significance level is α, the calculation formula for Q_α is:

$$Q_\alpha = \theta_1 \left[\frac{c_\alpha \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right]^{\frac{1}{h_0}}$$

where $\theta_i = \sum_{j=A+1}^{m} \lambda_j^i$ for $i = 1, 2, 3$, A is the number of principal components, λ is the corresponding eigenvalue; z_α is the critical limit of the normal distribution at significance level α.

The T^2 control limit can be calculated through the F-distribution. When the significance level is α, the T^2 control limit is:

$$T_\alpha^2 = \frac{A(n-1)}{n-A} F_\alpha(A, n-A)$$

where $F_\alpha(A, n-A)$ represents the F-distribution value with degrees of freedom A and $n - A$ at significance level $1 - \alpha$.

The number of principal components is selected according to the cumulative variance contribution rate, that is:

$$\frac{\sum_{i=1}^{A} \lambda_i}{\sum_{i=1}^{m} \lambda_i} \geq \text{threshold}$$

2.2 Anomaly Signal Localization

After PCA detects an anomaly, it is necessary to further locate the variables that caused the alarm. Contribution analysis only uses process data to locate fault variables without any prior fault knowledge, making it an unsupervised method. The contribution plot actually reflects the impact of changes in various variables on the stability of the system statistical model [1]. The anomaly signal is determined by comparing the contribution of each variable. The calculation method is as follows [1]:

The statistical calculations of formulas (2) and (3) can be uniformly expressed as:

$$\phi(x) = x^T M x$$

Assuming signal j fails, sample x can be expressed as:

$$x = x^* + f_j \xi_j$$

where x^* represents the normal part of the data; f_j represents the fault magnitude of signal j; ξ_j represents the direction of fault j, which can be an arbitrary process fault direction.

The reconstructed vector along the ξ_j direction can be expressed as:

$$\tilde{x} = x - f_j \xi_j$$

The reconstruction-based contribution of variable x to the fault detection index is defined as:

$$RBC_j = \phi(x) - \phi(\tilde{x})$$

Substituting formula (12) into formula (11), the calculation method is:

$$RBC_j = \frac{(\xi_j^T M x)^2}{\xi_j^T M \xi_j}$$

RBC is calculated for each sensor direction of the sample accordingly.

3 System Testing

To test the feasibility and effectiveness of the molten salt pump monitoring system, field verification was conducted by applying it to a thorium-based molten salt reactor project. Real-time fault detection and anomaly localization are the two most important functions of the system, so the test results of these two functions are discussed in detail. The system was used to monitor the primary loop fuel salt pump in real time. When the pump was in normal operation, the monitoring curve occasionally fluctuated below the threshold, indicating normal operation. When a certain vibration signal data of the pump suddenly rose abnormally, the monitoring curve also rose above the limit, and the fuel salt pump TAB label turned red, indicating abnormal operation. Figure 4 [Figure 4: see original paper] shows the alarm situation generated during monitoring on a certain day. Figure 5 [Figure 5: see original paper] shows the complete monitoring curve for that day.

As can be seen from Figure 5, after approximately 2:24 PM, the monitoring curve completely exceeded the limit and continued to rise, indicating that the degree of anomaly was continuously increasing. The localization results showed that the signal that might cause the anomaly was a certain vibration signal of the fuel salt pump. Actual investigation confirmed that this signal was indeed abnormal.

By querying the historical data of this signal, it was calculated that the mean value of the signal data on the alarm day was 0.2754 with a standard deviation of 0.1170; while the mean value of the signal data in the half month before the alarm was 0.0575 with a standard deviation of 0.0225. This indicates that the signal value increased and its fluctuation became larger on the alarm day. The trend of the original signal data is shown in Figure 6 [Figure 6: see original paper], from which it can also be seen that the signal value has a clear upward trend. However, the DCS did not issue an alarm for this signal change.

These results indicate that the monitoring system can effectively monitor the status of molten salt pumps and accurately locate abnormal signals with high accuracy. At the same time, after long-term operation debugging, testing, and optimization, the system meets the requirement of real-time monitoring per second and has high stability. The application of state monitoring systems can greatly reduce the psychological pressure on operating personnel and reduce the probability of misoperation, which is crucial for the safe and stable operation of reactors.

Conclusion

This system adopts the PCA monitoring method and improved reconstruction contribution plot-based anomaly signal localization, which improves the performance of equipment state monitoring. It can timely and accurately alarm abnormal equipment status and reduce the probability of missed and false alarms. Based on this, an integrated equipment state monitoring system with state monitoring, fault alarm, and anomaly signal localization was designed and developed, completing the design and development of multiple functional modules such as real-time anomaly detection and anomaly localization. The monitoring method adopted by the system is highly practical; the software has a simple and clear interface design, achieving friendly human-computer interaction and effective monitoring of equipment operation status. It also has strong scalability and can monitor multiple devices simultaneously. Test analysis results show that the system has achieved the expected goals and has good monitoring effects, playing a positive role in improving the safety, reliability, and economy of molten salt pump operation. At the same time, it also lays a foundation for further research and implementation of operation support technology and intelligent operation and maintenance technology.

Author Contributions

Zhou Wen: Conducted research and wrote the manuscript; Hou Jie: Reviewed the manuscript and provided guidance.

Funding

Supported by Shanghai Science and Technology Development Funds (Grant No. 23YF1457300).

References

1. Zhou Wen, Hou Jie. Implementation of Fault Isolation for Molten Salt Reactor Using PCA and Contribution Analysis[J]. Annals of Nuclear Energy, 2022, 173: 109138. DOI: 10.1016/j.anucene.2022.109138.
2. Xu Hongjie, Dai Zhimin, Cai Xiangzhou, Wang Jianqiang. Thorium molten salt reactor nuclear energy system & Comprehensive Utilization Nuclear Energy[J]. Modern Physics, 2018, 30(04): 25-34. DOI: 10.13405/j.cnki.xdwz.2018.04.007.
3. Cai Xiangzhou, Dai Zhimin, Xu Hongjie. Thorium molten salt reactor nuclear energy system[J]. Physics, 2016, 45(09): 578-590. DOI: 10.7693/wl20160904.
4. Zhu Shaomin, Xia Hong, Peng Binsen, et al. Design of man-machine interface of fault diagnosis system of reactor coolant pump[J]. Process Automation Instrumentation, 2019, 40(6): 84–86, 92. DOI: 10.16086/j.cnki.issn1000-0380.2019030054.
5. Li Zhenbao. Intelligent fault diagnosis and life prediction method of typical hydraulic pump based on deep learning[D]. Qinhuangdao: Yanshan University, 2022.
6. Zeng Yuyun. Research on Life Prognosis Methods of Nuclear Power Plant Assets Based on Condition Monitoring Data[D]. Beijing: Tsinghua University, 2017.
7. Meng Jiadong. Incipient Fault Detection and Health Condition Assessment of Rolling Element Bearing[D]. Lanzhou: Lanzhou University of Technology, 2022.
8. Ma Xin. Data-Driven Dynamics Process Monitoring Theory and ITS Industrial Applications[D]. Beijing: Beijing University of Chemical Technology, 2022.
9. Xu Weixiao. Research on Condition Monitoring and Life Prediction of Ball Screw Pair System Based on Deep Learning Hybrid Model[D]. Qingdao: Qingdao University of Technology, 2023.

10. Zhu Chenchen, Han Lixin, Hou Jie. Design and implementation of communication scheme between TMSR-SF0 control system and protection system[J]. Nuclear Techniques, 2021, 44(2): 020601. DOI: 10.11889/j.0253-3219.2021.hjs.44.020601.
11. Yu Jiali, Chen Yongzhong, Han Lifeng. The control system for TMSR molten salt pump experimental platform based on Qt[J]. Nuclear Techniques, 2022, 45(6): 060603. DOI: 10.11889/j.0253-3219.2022.hjs.45.060603.
12. Li Jiazeng, Han Lifeng, Li Danqing, Huang Wenbo, et al. EPICS historical data archiving system based on big data platform[J]. Nuclear Techniques, 2019, 42(11): 110603. DOI: 10.11889/j.0253-3219.2019.hjs.42.110603.
13. He Yue, Cheng Maosong, Dai Zhimin. Preliminary design and implementation of TMSR cloud simulation platform[J]. Nuclear Techniques, 2018, 41(7): 070603. DOI: 10.11889/j.0253-3219.2018.hjs.41.070603.
14. Zhang Yumin, He Xin, Yang Baichun. Design and Implementation of UAV Ground Station Software Base on WPF Technology[J]. Computer Engineering and Design, 2019, 40(4): 1167-1172. DOI: 10.16208/j.issn1000-7024.2019.04.043.
15. Shang Xuming, Zhang Licheng. Research and Application of 3D Simulation System Based on WPF[J]. Computer Technology and Development, 2016, 26(9): 39-42. DOI: 10.3969/j.issn.1673-629X.2016.09.009.
16. Deng Cheng, Sun Shuhui. Front-end application of MVVM design pattern[J]. Computer Knowledge and Technology, 2019, 15(29): 249-250. DOI: 10.14004/j.cnki.ckt.2019.3506.
17. Chen Tao. MVVM Design and Its Application[J]. Computer & Digital Engineering, 2014, 42(10): 1982-1985. DOI: 10.3969/j.issn1672-9722.2014.10.05.
18. Zhang Yuliang, Xu Guanglei, Zhu Peng, et al. Development and Implementation of C# Based EPICS Application[J]. Nuclear Electronics & Detection Technology, 2013, 33(10): 1234–1236, 1255.
19. Yue Min, Yuan Qian, Gou Shizhe, Zhang Wei, et al. Data archive system of SECRAL-II based on C#[J]. Nuclear Techniques, 2017, 40(3): 030402. DOI: 10.11889/j.0253-3219.2017.hjs.40.030402.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv — Machine translation. Verify with original.