Real-time Evaluation of Relay Protection System Status for Smart Grid: A Fusion Model of Digital Twin and Deep Transfer Learning

Zhong-liang Xie[1,*] and Tian-xiong Huang[2]

[1]*GuangZhou DongKe Electric Limited Company, Guangzhou, Guangdong 510700, China*
[2]*China Yangtze Power Co., Ltd. Wudongde Hydropower Plant, Yunnan Kunming, 651580 China*
E-mail: Xie_ZLwork@outlook.com
[*]*Corresponding Author*

Received 09 January 2026; Accepted 19 February 2026

Abstract

To address issues in traditional relay protection system state evaluation, such as insufficient training samples, lagging results, and manual setting management, this study proposes a real-time state evaluation model integrating digital twin and deep transfer learning. A high-fidelity digital twin system is constructed to establish bidirectional mapping and dynamic updates between the physical system and virtual twin. A sparse stacked autoencoder extracts discriminative features, and an online adaptation strategy based on deep transfer learning enables continuous self-optimization with streaming data. Experimental results show an overall accuracy of 98.2%, weighted F1-score of 0.978, and average evaluation delay reduced to 1.5 minutes. The intelligent setting management platform improves verification and download efficiency

Strategic Planning for Energy and the Environment, Vol. 45_2, 589–614.
doi: 10.13052/spee1048-5236.45212

by 60% and 40% respectively, with error rate decreasing from 10.2% to 0.22%. The framework enables minute-level real-time evaluation, predictive maintenance, and closed-loop operation, providing a reliable approach for building resilient and smart grids.

Keywords: Relay protection, digital twin, deep transfer learning, sparse autoencoder, real-time state evaluation, intelligent setting management.

1 Introduction

With the large-scale grid integration of renewable energy and increasingly complex load characteristics, modern power systems are undergoing profound transformation, and their safe and stable operation puts forward higher requirements for the reliability, quickness and adaptability of relay protection systems. As the first line of defense for power grid security, the relay protection system's condition evaluation and intelligent operation and maintenance have become core issues in constructing smart grids and power grid modernization [1]. The traditional operation and maintenance model is highly dependent on regular maintenance and manual experience. It has problems such as lagging status perception, low efficiency of fixed-value management, and difficulties in cross-system collaboration. It is difficult to meet the needs of real-time dynamic regulation and lean management of the power system. In recent years, digital twin technology and artificial intelligence methods have shown great potential in the field of power equipment condition monitoring. Yao Z et al. proposed a relay protection mirror operation scheme based on digital twins to solve the high cost of relying on physical devices in traditional relay protection research, as well as the shortcomings of existing digital twin applications in real-time interaction, logical transparency, interface standardization, and human-computer interaction. Taking the 110 kV double-bus double-section busbar protection as an example for verification, the twin protection in this scheme had the same action behavior and external characteristics as the actual protection device [2]. Khan M M S et al. proposed a real-time network attack location method based on digital twins to solve the rapid location of false data injection attacks in distribution networks. This method used digital twins to build a reference model and combined it with the radial physical characteristics of the distribution network to accurately locate the location of the attack. The results showed that this method could effectively locate attacks in various operating scenarios [3]. Mani D et al. proposed a closed-loop relay protection test solution based on digital twin technology to solve traditional relay protection test methods that are time-consuming, high-cost and dependent on on-site personnel. The results showed that this method significantly shortened the test time and improved the verification accuracy compared with traditional methods, while providing a new standard for remote diagnosis and integrated applications [4]. Najar A et al. proposed a microgrid fault protection scheme that combined multi-agent protection and deep learning to solve the failure problem of traditional protection methods caused by the randomness and topological variability of distributed power sources. This solution used multi-agent to quickly detect and isolate faults, and used discrete wavelet transform and deep neural network to locate faults. The results showed that this method could achieve high-precision fault detection, location and isolation under various operating conditions of microgrids [5].

Existing research demonstrates the potential of digital twin and AI in specific relay protection applications, yet it primarily focuses on isolated scenario-based implementations without establishing a systematic data fusion and interaction framework for panoramic secondary systems and multi-device coordination. It also fails to address cross-system collaboration challenges caused by data silos and protocol heterogeneity. Moreover, most methods rely on offline historical or simulated data, lacking mechanisms for continuous model updating with real-time streaming data, which hinders adaptation to dynamic environments and genuine real-time state awareness and collaborative decision-making. In addition, in the field of relay protection, existing research mostly focuses on fault diagnosis of a single device or off-line verification of fixed-values. Although it has improved operation and maintenance efficiency, the following limitations still exist: (1) Models mostly rely on historical offline data training, making it difficult to achieve real-time evaluation and dynamic update of status; (2) There is a lack of multi-device, cross-level panoramic data fusion and unified modeling framework for secondary systems; (3) Insufficient attention is paid to sample imbalance, resulting in limited identification performance for minority states. Therefore, the study proposes a fusion model combining digital twin-driven real-time status evaluation and Deep Transfer Learning (DTL) for relay protection system status. It aims to build a technical system that can accurately assess the status of the relay protection system in real-time and support predictive maintenance and intelligent decision-making to improve the resilience and reliability of the power grid in complex operating environments. The innovation points of the research are: (1) realizing panoramic data aggregation and closed-loop control by building a unified data architecture and fixed-value intelligent operation and maintenance platform for secondary systems; (2) designing a state evaluation model based on Stacked Sparse Auto-Encoder (SSAE), introducing a DTL strategy, and using real-time data to dynamically update the model to achieve two-way interaction and continuous optimization of physical entities and digital twins.

2 Methods and Materials

2.1 Construction of Relay Protection System Data Architecture and Fixed-value Intelligent Operation and Maintenance Platform

The relay protection system data of smart substations is characterized by multi-source heterogeneity and rapid growth, covering multiple independent systems such as factory data, configuration files, operation management, online monitoring, and team records. The data formats are diverse and the correlations are complex. The traditional decentralized management model is difficult to effectively integrate information, which restricts the development of advanced services such as fixed-value closed-loop management and real-time status sensing. To solve the above problems, it is necessary to build a unified relay protection system data architecture. A fixed-value intelligent operation and maintenance platform is designed. The core of the data unified architecture is to establish a panoramic data model with secondary equipment as the main body, as shown in Figure 1.

As shown in Figure 1, the panoramic data model integrates multi-dimensional data modules such as equipment ledgers, topological relationships, defect records, and operation information to provide a standardized data basis for upper-layer applications. A corresponding data collection system is designed, which is deployed at the station control layer. Through the front-end collection, message collection and secondary loop collection modules, the device and link status, online message verification and smart substation configuration description file analysis are respectively obtained to achieve all-round data coverage of the protection system from physical to network, from static to dynamic [6, 7]. To enhance the automation and closed-loop control capabilities of fixed-value management, the research further designs and implements an operation and maintenance platform relying on cloud-edge collaborative architecture. Its composition structure is shown in Figure 2.

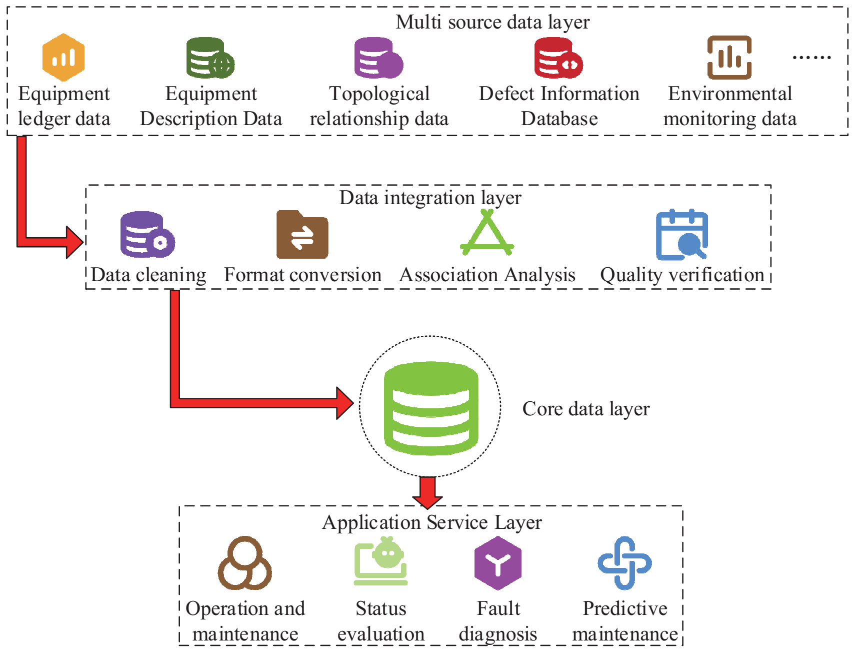


Figure 1 Schematic diagram of panoramic data model.

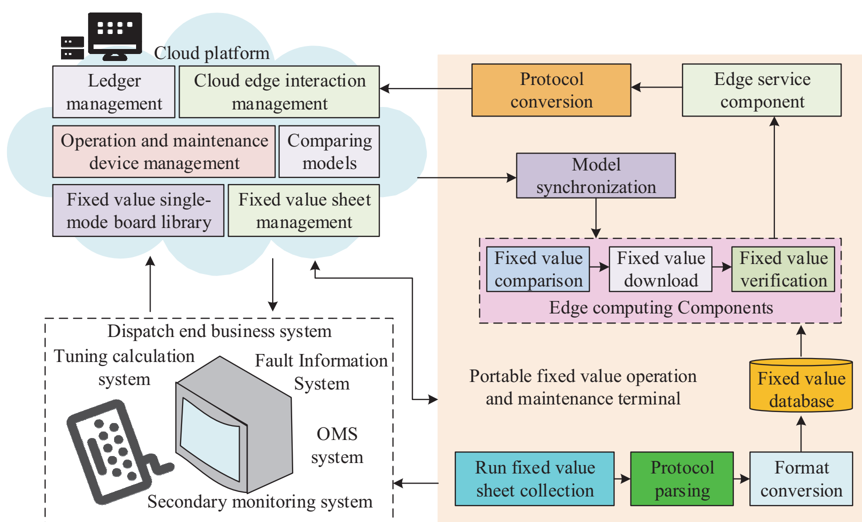


Figure 2 Schematic diagram of fixed-value intelligent operation and maintenance platform.

As shown in Figure 2, the platform architecture is divided into two parts: the cloud and the edge. The cloud-integrated dispatching end business system is responsible for setting value template management, comparison model maintenance, and task issuance and aggregation. The edge side uses portable operation and maintenance terminals as carriers to connect the cloud and on-site protection devices, forming a closed-loop management and control model of "scheduling end-cloud platform-portable terminal-protection equipment" [8]. The terminal adopts a modular design and has functions such as data collection, protocol analysis, edge computing and secure interaction. It can read the device setting value through the network or serial port, or enter the paper setting value sheet through a high-speed camera, and uniformly convert it into a standard format [9, 10]. During fixed-value comparison, the terminal compares the source order and the on-site order according to the standard fixed-value order format. If inconsistencies are found and need to be downloaded, the download will be executed and reviewed after confirmation to ensure that the on-site settings are consistent with the dispatch instructions. All operation logs are sent back to the cloud, making the entire process traceable and auditable.

2.2 Design of State Evaluation Model Based on Digital Twin

On the basis of uniformly aggregating relay protection system data and fixed-value intelligent closed-loop management and control, to further extend the value of data to the field of equipment health management, an intelligent analysis model that can accurately reflect the system operating status in real-time and support predictive maintenance is built. Therefore, the study proposes a state evaluation model based on digital twin drive, as shown in Figure 3.

As shown in Figure 3, the core of this model is to build a high-fidelity digital twin of the physical protection system. Through data fusion and simulation optimization capabilities, a deep feature extraction and status classification framework is designed to overcome the evaluation lag problem caused by traditional methods relying on offline data. The model is constructed based on a set of evaluation indicators that comprehensively reflect the health of the system. It focuses on the core functions and monitoring feasibility of the secondary system of the substation, and selects indicators from multiple dimensions such as reliability, performance, familial defects, operating years, and environmental adaptability to form a normalized multi-dimensional state vector as input. The system operating status

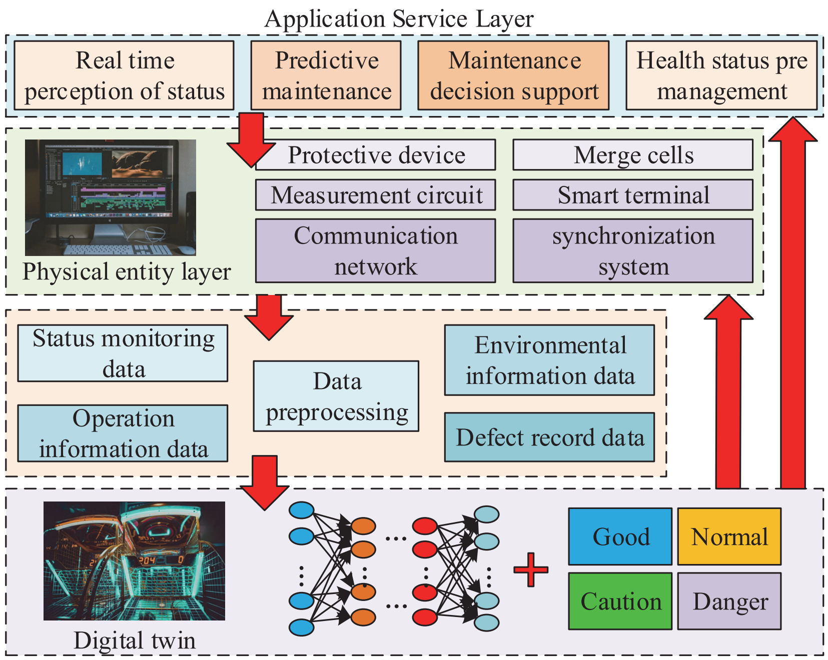


Figure 3 Schematic diagram of state evaluation model (Image source: https://colorhub.me/photos/3VEO2;https://colorhub.me/photos/wGOla).

is divided into four levels: "good", "normal", "attention" and "danger", as classification targets [11, 12]. To automatically extract effective features from high-dimensional nonlinear noisy data, the study uses SSAE as the basic deep learning architecture, as shown in Figure 4.

From Figure 4, SSAE is composed of multiple Sparse Auto-Encoder, (SAE) stacked layer-by-layer. Its basic unit learns the compressed feature representation of the input data through the encoding and decoding process. The encoding and decoding process can be expressed as formula (1).

$$\begin{cases} \mathbf{h} = \sigma(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}) \\ \hat{\mathbf{x}} = \sigma(\mathbf{W}^{(2)}\mathbf{h} + \mathbf{b}^{(2)}) \end{cases} \tag{1}$$

In formula (1), $\mathbf{x}$ is the input state vector. $\mathbf{h}$ is the hidden layer feature vector. $\hat{\mathbf{x}}$ is the reconstruction vector. $\mathbf{W}^{(1)}$, $\mathbf{b}^{(1)}$, $\mathbf{W}^{(2)}$ and $\mathbf{b}^{(2)}$ are encoding and decoding parameters, respectively. σ is the nonlinear activation function [13]. A sparsity penalty term is introduced in the loss function of each SAE, which can constrain the average activity of hidden layer neurons,

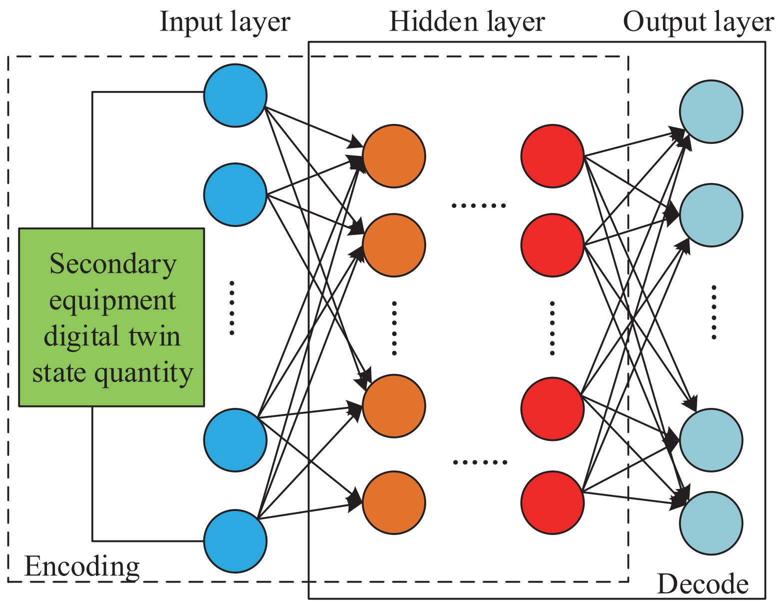


Figure 4 Schematic diagram of SSAE.

allowing the network to learn more discriminative sparse features in the data. The sparsity penalty term is implemented by adding a constraint based on the KL divergence between the average neuron activation and a target sparse value to the loss function. This encourages only a subset of key neurons to activate during training, leading to sparse data representation. This mechanism not only mimics efficient biological neural processing but also forces the network to learn more discriminative features while suppressing noise and redundancy, thereby improving feature representation, reducing overfitting, and enhancing model generalization [14].

Multiple pre-trained SAEs are stacked layer by layer, and the output of the bottom SAE is used as the input of the upper SAE, ultimately forming a deep feature extraction network. In SSAE design, the choice of sparsity penalty coefficient critically influences feature discriminability and model generalization. Sensitivity analysis via grid search over $\{0.01, 0.05, 0.1, 0.2, 0.5\}$ showed that overly small coefficients lead to redundant features and poor minority-class recognition, while excessively large coefficients suppress meaningful feature learning. A coefficient of 0.05 achieved the best balance on the validation set. After completing the unsupervised layer-by-layer pre-training of SSAE, a Softmax classifier is connected to the top to form a

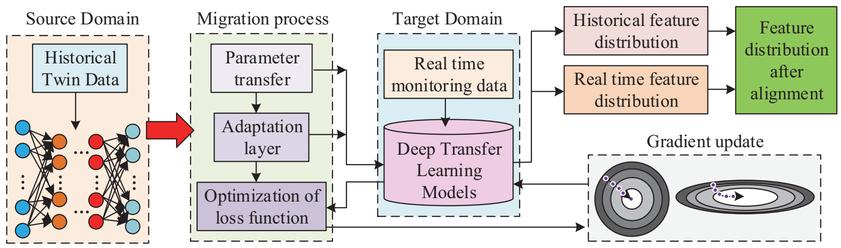


Figure 5 Schematic diagram of DTL strategy.

complete deep state evaluation model. At this time, the historical status data judged by experts are used to perform supervised global fine-tuning of the network. All weight parameters of the network are optimized by minimizing the cross-entropy loss between the predicted state probability distribution and the true label. Finally, when the model is deployed in the digital twin, it can achieve deep feature abstraction of the input status indicator vector, output the probability that it belongs to each status level, and complete the preliminary status evaluation.

2.3 Real-time Update Strategy Based on DTL

Although the digital twin state evaluation model based on SSAE has powerful feature extraction capabilities, its essence is a static model trained based on historical data, which is difficult to adapt to the dynamic changes in working conditions and the gradual deterioration of equipment status in the actual operation of the relay protection system. In addition, most protective equipment is in a normal state during actual operation, and samples of abnormal states such as "attention" and "danger" are extremely rare, resulting in serious class imbalance in real-time monitoring data. Directly using these data to retrain the model can easily lead to overfitting, thereby weakening the model's ability to identify minority class states. In this regard, the study introduces the DTL strategy to build a model online update mechanism that uses twin historical data as the knowledge source and physical entity real-time data as the driving target, as shown in Figure 5.

As shown in Figure 5, the core of this strategy is to transfer the SSAE model knowledge trained on historical twin data (source domain) to a new model oriented to real-time monitoring data (target domain), and achieve rapid model adaptation by minimizing the distribution difference between the source domain and the target domain. The specific method is to introduce an adaptation layer between the top feature layer of pre-trained SSAE and the

Softmax classification layer, learn the feature mapping transformation, and align the feature distribution of real-time data with historical data [15, 16]. To measure and reduce distribution differences, the Maximum Mean Difference (MMD) is used as the distribution distance measurement criterion. The MMD square distance between the source domain sample set $\mathbf{X}_s$ and the target domain sample set $\mathbf{X}_t$ can be estimated by formula (2).

$$\mathrm{MMD}^2(\mathbf{X}_s, \mathbf{X}_t) = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(\mathbf{x}_i^s) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(\mathbf{x}_j^t) \right\|_{\mathcal{H}}^2 \tag{2}$$

In formula (2), X_t is the nonlinear transformation that maps the original features to RKHS. n_s and n_t are the number of samples in the source domain and target domain, respectively [17]. By introducing the MMD term into the overall loss function of the model, the model is forced to reduce the distribution difference between historical and real-time data in the deep feature space while optimizing the classification accuracy [18]. The overall loss function J_{DTL} to construct the DTL model for real-time updating can be defined as formula (3).

$$J_{\mathrm{DTL}}(\Theta) = L_c(\mathbf{X}_L, \mathbf{Y}) + \lambda \cdot \mathrm{MMD}^2(\mathbf{X}_s, \mathbf{X}_t) \tag{3}$$

In formula (3), L_c represents the classification cross-entropy loss calculated based on a small amount of labeled data $(\mathbf{X}_L, \mathbf{Y})$ in the source domain, which is used to maintain the original state discrimination ability of the model [19]. Θ represents all trainable parameters in the model. λ is a positive trade-off parameter used to adjust the relative importance between classification loss and distribution adaptation loss. During the update process, the real-time monitoring data stream generated by the physical entity is continuously input into the DTL model, as shown in Figure 6.

From Figure 6, the model extracts features and calculates losses through forward propagation, and then updates the adaptation layer and upper network parameters through the back propagation algorithm. The underlying feature extraction parameters in SSAE carry general feature knowledge related to device status and can be fine-tuned or partially frozen using a smaller learning rate to prevent catastrophic forgetting on a small amount of unbalanced real-time data. Based on this process, the model can complete progressive online learning and parameter updates driven by real-time data. Ultimately, through the DTL strategy, the state evaluation model in the digital twin is no longer static, but becomes an intelligent agent that can dynamically

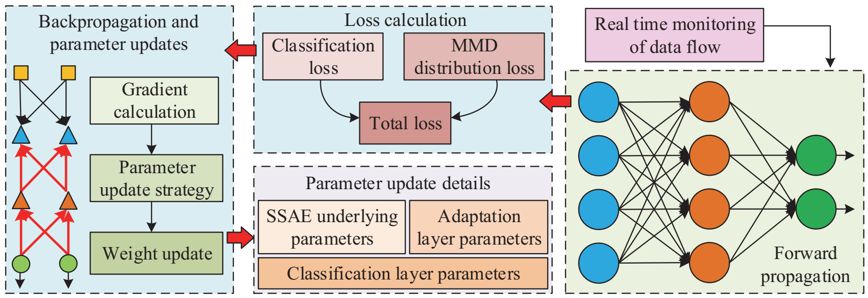


Figure 6 Schematic diagram of the update process.

evolve and self-adjust as the physical entity's operating data continues to flow in.

3 Results

This section validates the proposed SSAE+DTL fusion model and compares its performance using public datasets and a digital twin simulation platform. Through controlled operational conditions, the model's feature extraction, real-time updating, and robustness are systematically evaluated. It should be noted that simulation focuses on algorithmic logic verification, reflecting the method's potential under ideal data conditions; actual deployment performance may differ due to engineering factors such as hardware capability, network latency, data quality, and device heterogeneity. Section 3.2 will further assess the system's comprehensive performance based on real substation deployment data.

3.1 Verification of Synergistic Effectiveness of State Evaluation and Transfer Learning Models

To verify the synergistic effectiveness of the proposed model (hereinafter referred to as SSAE+DTL), the research builds an experimental environment based on public data and simulation platforms. Historical data comes from the IEEE PES test data set and the UCI power transformer fault data set, which are used to construct about 150,000 samples, and the "attention" and "danger" category samples are enhanced through the NASA bearing fault data set to alleviate the imbalance problem. To enable effective use of multi-source heterogeneous data within a unified evaluation framework, this study performed standardized preprocessing on all raw data: first, extracting raw features (e.g., electrical waveform characteristics, operating temperature, historical defect frequency, operation year coefficient) based on the panoramic data model and evaluation index set; next, applying min-max normalization to scale all features to the [0,1] range, eliminating unit and magnitude differences; finally, combining processed multidimensional features into a state indicator vector reflecting dimensions such as “reliability,” “performance,” “familial defects,” “operation years,” and “environmental adaptability,” in line with system logic and expert knowledge. Although the data originate from different devices and operating contexts, the health degradation mechanisms and state evolution patterns they reflect share commonality in secondary system state evaluation. By aligning data distributions and focusing on system-level health representation, this cross-source fusion strategy not only expands sample diversity – especially for key minority classes – but also provides a foundation for models to learn more generalizable discriminative features. Subsequent deep transfer learning will further calibrate potential domain shifts caused by data source differences, ensuring the model’s generalization in real target scenarios.

Real-time data is generated by the digital twin platform jointly built by OpenDSS and PandaPower to simulate dynamic working conditions including distributed energy sources and load fluctuations. The injection frequency is once per minute. In terms of model, SSAE uses three hidden layers (128-64-32), a sparsity penalty coefficient of 0.05, and the Adam optimizer (learning rate 0.001) for initial training. The DTL stage introduces an adaptation layer with a dimension of 16, based on the Gaussian kernel MMD alignment distribution, with a trade-off parameter $\lambda = 0.3$. An incremental update is triggered every 100 pieces of real-time data received, and the underlying parameters are partially frozen to avoid catastrophic forgetting. The optimal model update frequency was determined by evaluating intervals of 50, 100, 200, and 500 data entries. Too frequent updates (every 50 entries) increase susceptibility to noise and parameter oscillation, while longer intervals (every 500) introduce unacceptable latency. Balancing responsiveness and stability, an interval of 100 entries was selected for incremental updates. Future work will explore adaptive triggering based on data distribution changes to handle abrupt operational shifts. The experiment first tested the classification accuracy of different state evaluation models, as shown in Table 1.

From Table 1, the recognition accuracy of the SSAE static model in the four status categories of “good”, “normal”, “attention” and “danger” was 98.8%, 97.5%, 80.2% and 73.4%, respectively, the overall accuracy was 96.1%, and the weighted F1-score was 0.958, which were better than those

Table 1 Comparison of classification accuracy of different state evaluation models

Model Category	Good (%)	Normal (%)	Attention (%)	Danger (%)	Overall Accuracy (%)	Weighted F1-Score
Logistic Regression	96.5	94.2	65.3	52.1	92.8	0.912
SVM	97.1	95.8	68.4	56.7	93.5	0.924
RF	98.0	96.5	72.1	61.3	94.7	0.938
Deep Auto-encoder	98.3	97.0	76.5	68.9	95.2	0.946
SSAE	98.8	97.5	80.2	73.4	96.1	0.958
SSAE+DTL	99.1	98	84.6	79.8	98.2	0.978

Table 2 Performance metrics comparison for key minority classes (%)

Model Category	State	Recall	Precision	Specificity
Logistic Regression	Attention	65.3	70.1	99.2
	Danger	52.1	58.6	99.4
Support Vector Machine	Attention	68.4	72.9	99.3
	Danger	56.7	62.3	99.5
Random Forest	Attention	72.1	76.8	99.4
	Danger	61.3	68.4	99.6
Deep Autoencoder	Attention	76.5	80.2	99.5
	Danger	68.9	75.1	99.7
SSAE	Attention	80.2	83.6	99.6
	Danger	73.4	79.5	99.8
SSAE+DTL	Attention	84.6	88.9	99.7
	Danger	79.8	85.2	99.9

of traditional logistic regression, Support Vector Machine (SVM), Random Forest (RF) and ordinary deep auto-encoder and other comparative models. After further introducing the DTL dynamic update mechanism, the model's recognition performance in each state category was further improved, with an overall accuracy of 98.2% and a weighted F1-score of 0.978, indicating that the SSAE+DTL has obvious advantages in handling sample imbalance problems and can adapt to changes in real-time data distribution through continuous learning.

Due to the extremely low tolerance for false negatives and false positives in relay protection systems – especially for "Attention" and "Danger" states – overall accuracy and weighted F1 score are insufficient for evaluating model performance under class imbalance. Therefore, this study further computed recall, precision, and specificity for these two key minority classes across SSAE+DTL and comparative models, as shown in Table 2.

Table 3 Quantitative comparison of inter-domain distribution differences before and after deep transfer learning

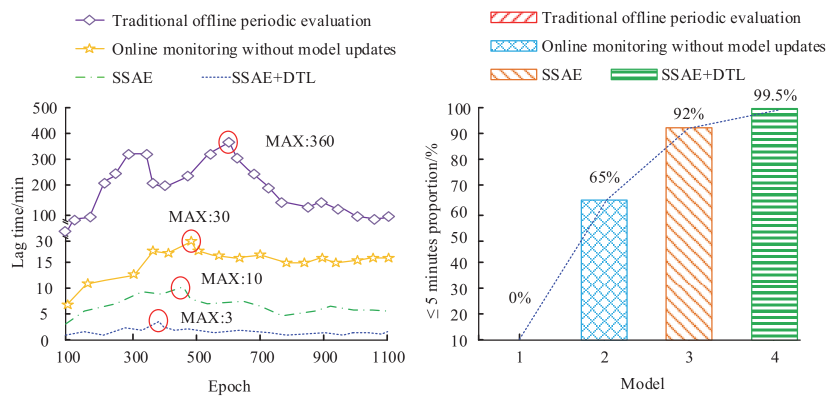
Evaluation Stage	MMD Distance	Qualitative Description of Feature Space Alignment
Before Transfer	0.152	Significant separation between source and target domain feature distributions, indicating notable domain shift.
After Transfer	0.038	Highly overlapping feature distributions between domains, demonstrating significant alignment effect.

As shown in Table 2, the SSAE+DTL model achieved superior recall (79.8%) and precision (85.2%) for the "Danger" state compared to other models, benefiting from enhanced feature extraction and domain adaptation for minority classes. Additionally, the model demonstrated high specificity (above 99.5%) for both abnormal states, effectively reducing false alarms and unnecessary equipment outages by avoiding misclassification of normal conditions. These results indicate that the proposed model achieves a better balance between minority-class detection and false alarm control, aligning with the high reliability and safety requirements of relay protection systems.

To quantify the distribution difference between source and target domains and evaluate the feature alignment effect of DTL, this study used Maximum Mean Discrepancy (MMD) as the distance metric, calculating MMD before and after alignment (Table 3). t-SNE visualization of high-level features further revealed that, before DTL, feature points from the two domains were clearly separated; after DTL, they exhibited significant overlap, demonstrating effective alignment.

The above quantitative and visual evaluation results show that the DTL strategy effectively reduces the distribution difference between historical data and real-time data in the deep feature space, providing direct evidence that the strategy can significantly improve the generalization performance and state recognition accuracy of the model in the target domain. Next, the experiment tested the real-time performance of the model, as shown in Figure 7.

From Figure 7, the maximum lag time of the traditional offline periodic evaluation method was 360 min and the average lag time was 180 min, which cannot achieve minute-level response. The maximum lag time of the online monitoring without model updates was 30 minutes, the average lag time was 15 minutes, and the minute-level achievement ratio was 65%. The maximum lag time of the SSAE-based state model was 10 minutes, the average lag time was 5 minutes, and the minute-level achievement ratio was 92%. In contrast, the proposed SSAE+DTL performed best in real-time performance, with a



(a) Lag time of status evaluation results (b) Minute-level achievement ratio

Figure 7 Comparison of the average lag time and the percentage of minutes achieved by different evaluation methods.

maximum lag time of only 3 minutes, an average lag time of 1.5 minutes, and a minute-level achievement ratio of 99.5%, achieving minute-level real-time feedback. This result shows that the SSAE+DTL has obvious advantages in the timeliness of condition evaluation. In addition, the study also tested the robustness performance of the model under different working conditions, as shown in Figure 8.

The operational conditions in Figure 8 are defined as follows: (1) Normal load fluctuation: load varies within $\pm 15\%$ of rated capacity with no distributed generation; (2) High renewable energy penetration: PV and wind power account for 60% of total load, with PV output following a typical solar curve and wind power based on Weibull-distributed randomness, both integrated via inverters; (3) Transient communication anomalies: random packet loss (5%–10%) or short interruptions (30–60 s) in the station control network; (4) Concurrent mild multi-device faults: injection of three independent minor abnormal signals (e.g., sampling deviations, contact jitter) into busbar, line, and transformer protection circuits to simulate multiple soft faults. From Figure 8, under normal load fluctuations, the accuracy of the SSAE+DTL reached 98.0%, which was better than that of traditional SVM (93.2%), RF (94.5%) and standard auto-encoder (95.0%). In high renewable energy penetration scenario, the accuracy of the SSAE+DTL was 95.8%, which was 5.7%–8.2% higher than that of comparison methods. When an instantaneous instantaneous abnormality occurred in the communication network, the SSAE+DTL still maintained an accuracy of 94.2%, which was higher

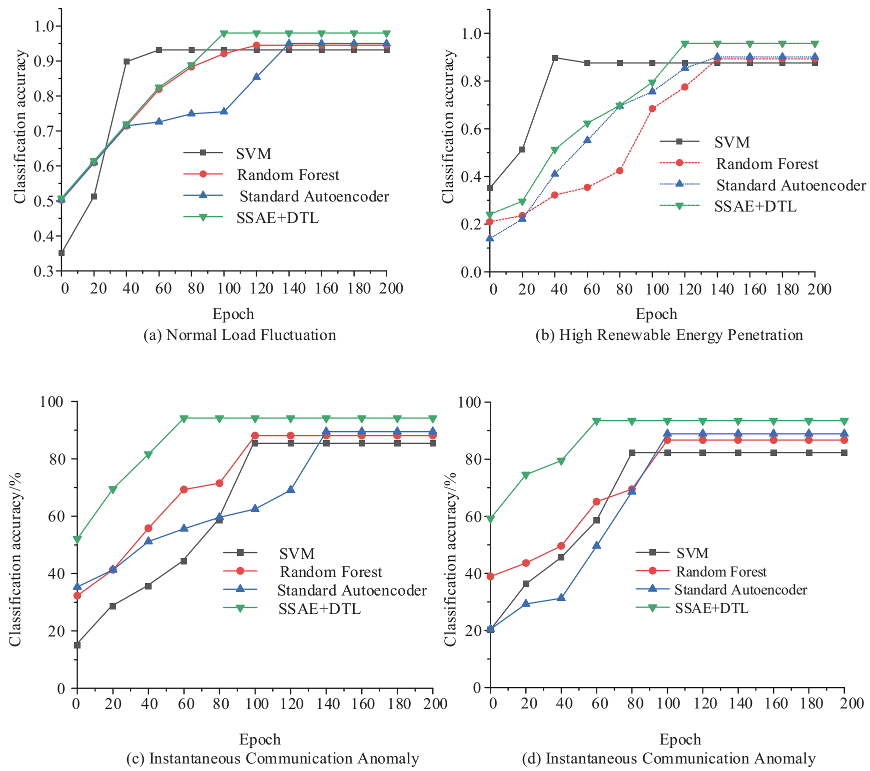


Figure 8 Comparison of state evaluation accuracy of various models under complex working conditions.

than that of other methods. Under complex working conditions where multiple devices have concurrent mild failures, the model accuracy was 93.5%, 11.2% higher than that of traditional SVM, reflecting stronger environmental adaptability and system resilience. In summary, the SSAE+DTL shows better accuracy and robustness under different complex working conditions. Finally, the experiment tested the efficiency improvement of the fixed-value intelligent operation and maintenance platform, as shown in Table 4.

From Table 4, the fixed-value intelligent operation and maintenance platform increased the efficiency of fixed-value single verification by 60%, the efficiency of on-site entry and verification settings by 60%, and the efficiency of fixed-value download execution and confirmation by 40%. The review and feedback efficiency increased by 73.3%, and the whole-process logging and archiving efficiency increased by 86.7%. The average error rate in each

Table 4 Comparison of efficiency improvement of fixed-value intelligent operation and maintenance platforms

Operation Process	Traditional Manual Average Time (min)	Intelligent Platform Average Time (min)	Efficiency Improvement (%)	Manual Error Rate (%)	Platform Error Rate (%)
Manual Verification of Setting List	25	10	60	8.2	0.5
On-site Entry and Verification Settings	20	8	60	12.5	0.3
Download Execution and Confirmation	30	18	40	5.8	0.2
Review and Feedback	15	4	73.3	6.4	0.1
Whole-process Logging and Archiving	15	2	86.7	18.3	0

link dropped from 10.2% for manual operations to 0.22% for the platform. The platform achieves synergistic improvements in efficiency and reliability. Based on this result, it can be considered that the SSAE+DTL has greatly optimized the efficiency and accuracy of the entire fixed-value operation and maintenance process.

3.2 Practical Application Effects of Relay Protection Systems

The study deployed experimental systems in three 220 kV smart substations affiliated to a provincial electric power company, and carried out a six-month on-site operation verification. The experimental system covers 12 sets of mainstream relay protection devices including line protection, transformer protection and busbar protection, and is connected to secondary equipment such as station merging units, intelligent terminals and synchronized clocks. During the test, the system continuously collected equipment status monitoring data, network messages and fixed-value operation logs, and synchronized the data to the cloud digital twin platform in real-time through the power private network. The on-site operating conditions cover multiple time periods including normal working conditions, spring maintenance period, summer load peak, and high renewable energy penetration in autumn to fully reflect the performance of the model in actual complex environments. In the evaluation, the study used the manual inspection and regular calibration data of the same period one year before deployment as the baseline, and conducted

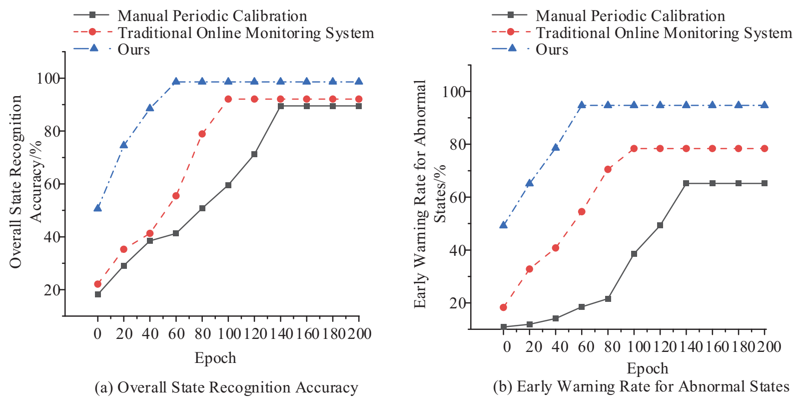


Figure 9 Comparison between the accuracy rate of state identification and the abnormal early warning rate in field operation.

comparative statistics within the same time window. The results are shown in Figure 9.

Figure 9(a) shows the accuracy results of the operating status evaluation. The overall state recognition accuracy of the system integrating the SSAE+DTL reached 98.6%, which was 9.1% and 6.5% higher than that of the manual periodic calibration (89.5%) and the traditional online monitoring system (92.1%), respectively. Figure 9(b) shows the results of the abnormal status early warning rate. The abnormal status early warning rate of the SSAE+DTL was 94.7%, which was significantly higher than that of the manual periodic calibration (65.2%) and the traditional system (78.4%). It shows that after integrating SSAE+DTL, the system has better status sensing and early warning capabilities in practical applications. Next, the on-site value-setting operation and maintenance efficiency was collected, as shown in Figure 10.

From Figure 10, in terms of efficiency and reliability of fixed-value operation and maintenance, the average time consumption of a single fixed-value check of the SSAE+DTL was only 9 minutes, which was better than that of the traditional manual method and the rule-assisted automation system. It only took 16 minutes on average to download a fixed-value order, which was significantly shorter than that of the traditional method and the rule-assisted automation system. The fixed-value closed-loop execution completion rate reached 99.1%, which was higher than that of the traditional method (82.4%) and the automated system (93.7%), indicating that the SSAE+DTL has obvious advantages in improving operation and maintenance efficiency and

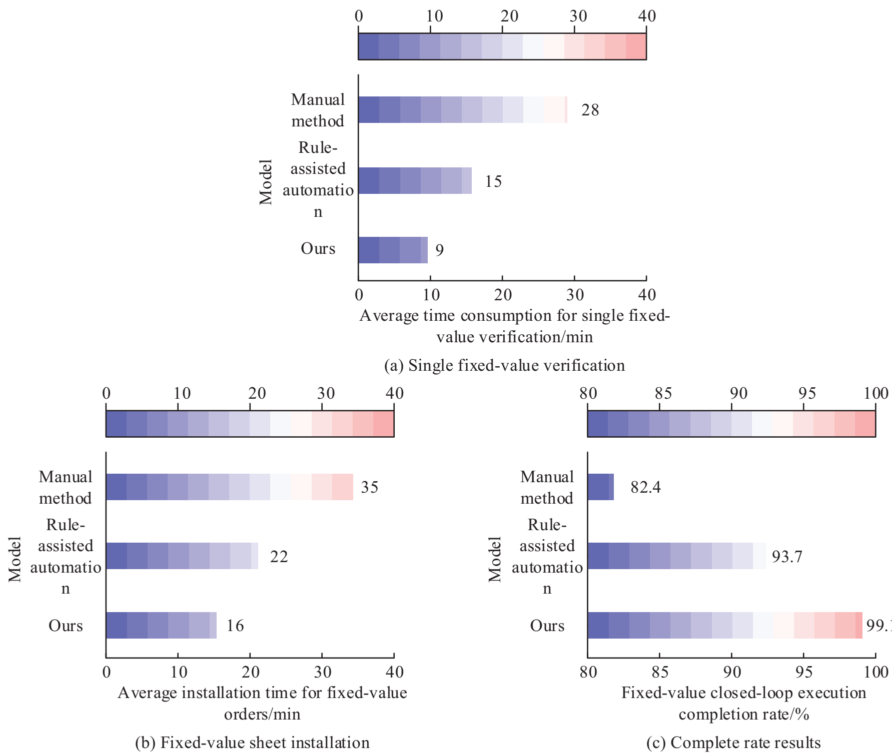


Figure 10 Comparison of fixed value verification, download time and closed loop execution integrity rate.

execution reliability. Finally, the study examined the overall performance of the system. The results are shown in Table 5.

From Table 5, the SSAE+DTL showed comprehensive advantages, including an average failure-free time of 2,500 h, a fault recovery time of 18 minutes, an annual comprehensive operation and maintenance cost of 160,000 yuan, an action accuracy rate in renewable energy scenarios of 97.3%, and a system self-recovery success rate of 96.9%, which were better than those of traditional modes and IoT monitoring systems.

4 Discussion

To overcome challenges such as insufficient training samples, lagging evaluation results, manual value management, and difficulty in cross-system

Table 5 Multi-dimensional comparison of system core performance

Performance Dimension	Traditional	IoT Monitoring	Ours	Ours vs Traditional	Ours vs IoT
Mean Failure-free Time/h	720	1,500	2,500	247.2	66.7
Mean Fault Recovery Time/min	120	45	18	−85	−60
Annual Comprehensive Maintenance Cost/10K CNY	24	22.7	16	−33.3	−29.5
Action Accuracy Rate in Renewable Energy Scenarios/%	88.5	92.7	97.3	9.9	5
System Self-Recovery Success Rate/%	68.3	84.5	96.9	41.9	14.7

collaboration in traditional relay protection system status evaluation methods, a fusion model that combines digital twin-driven real-time status evaluation and DTL fusion model is proposed to support the real-time perception and intelligent operation and maintenance capabilities of smart grids. The results showed that the overall accuracy of status evaluation reached 98.2%, the weighted F1-score was 0.978, and the average lag was only 1.5 minutes. The built-in fixed-value intelligent operation and maintenance platform increased the verification and downloading efficiency by 60% and about 40%, respectively, and the average error rate dropped from 10.2% to 0.22%. During on-site deployment, the system status identification accuracy rate reached 98.6%, the abnormality warning rate reached 94.7%, the average time for a single fixed-value check was reduced to 9 minutes, and the closed-loop execution completeness rate reached 99.1%. Compared with other research in the same field, the fusion model that integrates digital twin-driven and DTL shows obvious advantages in real-time evaluation of relay protection system status and intelligent operation and maintenance. Önder M et al. [20] proposed a multi-stage cascade machine learning model for smart grid stability prediction and achieved a high accuracy of 99.9%. However, this method relies on offline multi-stage processing and is difficult to adapt to the strong real-time and dynamic evolution requirements of relay protection. In contrast, the study introduced a DTL mechanism to achieve real-time data-driven online dynamic updates, which greatly improved the timeliness of status evaluation and the ability to adapt to imbalanced samples. Mendoza M A T et al. [21] proposed a voltage collapse adaptive control scheme based on digital twins, which improved the voltage stability of the primary system. Although this work reflects the potential of digital twins in power regulation, it does not go into the status evaluation and closed-loop operation and maintenance of the secondary protection system. On this basis, this study combines digital twins with DTL to build a real-time status evaluation system for the entire relay protection chain, realizing fixed-value cloud collaborative closed-loop management, and providing more comprehensive support in system resilience, operation and maintenance efficiency, and real-time performance. In summary, the model proposed in this study provides key technical support for constructing power grid modernization and intelligent operation and maintenance systems.

While field validation of this study showed positive results, limitations remain. The validation was conducted in only three 220 kV substations, with limited device types, manufacturer models, and operational scenarios, resulting in a relatively small sample size. Consequently, the model's adaptability and robustness across broader voltage levels, heterogeneous equipment, and extreme or rare conditions have not been fully verified. Therefore, extrapolating current findings to grid-wide, all-type protection systems requires caution. Future work should include large-scale validation across more voltage levels, device types, and extended real-world operation to further confirm generalizability and engineering practicality, facilitating broader technology adoption.

5 Conclusion

The fusion model that integrates digital twin-driven and DTL for relay protection status evaluation has successfully achieved real-time accurate perception and closed-loop intelligent operation and maintenance. By constructing a two-way interaction mechanism and a continuous adaptive learning process between physical entities and digital twins, the model can greatly improve the dynamic adaptability and operational resilience of the system in complex scenarios such as high renewable energy penetration and severe load fluctuations. This achievement not only promotes the intelligent paradigm shift of the relay protection operation and maintenance model from "regular maintenance and manual intervention" to "data-driven, real-time warning, and active protection", but also provides key theoretical support and technical implementation path for constructing a modern smart grid with high reliability, strong self-healing ability and wide compatibility, and has important engineering application value and industry promotion prospects.

References

[1] Qin B, Pan H, Dai Y, Si X, Huang X, Yuen C. Machine and deep learning for digital twin networks: A survey[J]. IEEE Internet of Things Journal, 2024, 11(21): 34694–34716. DOI:10.1109/JIOT.2024.3416733.

[2] Yao Z, Li D, Li Z, Zhou P, Li L. Relay protection mirror operation technology based on digital twin[J]. Protection and Control of Modern Power Systems, 2023, 8(4): 1–14. DOI:10.1186/s41601-023-00328-4.

[3] Khan M M S, Giraldo J, Parvania M. Real-time cyber attack localization in distribution systems using digital twin reference model[J]. Ieee transactions on power delivery, 2023, 38(5): 3238–3249. DOI:10.1109/TPWRD.2023.3296312.

[4] Mani D, Harispuru C, Wetterstrand N, Bonetti A, Thota S C R. Revolutionizing power system protection: closed-loop testing with digital twin technology[C]//IET Conference Proceedings CP916. Stevenage, UK: The Institution of Engineering and Technology, 2025, 2025(5): 36–40. DOI:10.1049/icp.2025.1043.

[5] Najar A, Kazemi Karegar H, Esmaeilbeigi S. Multi-agent protection scheme for microgrid using deep learning[J]. IET Renewable Power Generation, 2024, 18(4): 663–678. DOI:10.1049/rpg2.12929.

[6] Sultana A, Bardalai A, Sarma K K. Salp swarm-artificial neural network based cyber-attack detection in smart grid[J]. Neural Processing Letters, 2022, 54(4): 2861–2883. DOI:10.1007/s11063-022-10743-7.

[7] Mashal I. Smart grid reliability evaluation and assessment[J]. Kybernetes, 2023, 52(9): 3261–3291. DOI:10.1108/K-12-2020-0910.

[8] Li F, Zhuyuan L. A summary of relay protection-based simulation for Dynamic Performance and Reliability Assessment[J]. International Journal for Applied Information Management, 2023, 3(1): 11–23. DOI:10.47738/ijaim.v3i1.46.

[9] Hu Q, Han R, Quan X, Wu Z, Tang C, Li W. Grid-forming inverter enabled virtual power plants with inertia support capability[J]. IEEE Transactions on Smart Grid, 2022, 13(5): 4134–4143. DOI:10.1109/TSG.2022.3141414.

[10] Li Y, Yu C, Shahidehpour M, Yang T, Zeng Z, Chai T. Deep reinforcement learning for smart grid operations: Algorithms, applications, and prospects[J]. Proceedings of the IEEE, 2023, 111(9): 1055–1096. DOI:10.1109/JPROC.2023.3303358.

[11] Noman M, Ullah I, Khan M A, Qazi A, Farooq W, Saqr A, Elsheikh A. Analysis of overcurrent protective relaying as minimum adopted fault

protection for small-scale hydropower plants[J]. International Journal of Environmental Science and Technology, 2024, 21(4): 4457–4470. DOI:10.1007/s13762-023-05284-y.

[12] Ataee-Kachoee A H, Hashemi-Dezaki H, Ketabi A. Optimal adaptive protection of smart grids using high-set relays and smart selection of relay tripping characteristics considering different network configurations and operation modes[J]. IET generation, transmission & distribution, 2022, 16(24): 5084–5116. DOI:10.1049/gtd2.12659.

[13] Shittu M A, Shittu H A, Adeleke O J, Adeleke O J. Digital Twin Modeling for Real Time Monitoring and Fault Detection in Smart Substations[J]. International Journal of Industrial Engineering, 2023, 14(2): 25–44. DOI:10.34218/IJIERD_14_02_003.

[14] Grasmair M, Haltmeier M, Scherzer O. Sparse regularization with lq penalty term[J]. Inverse Problems, 2008, 24(5): 055020. DOI:10.1088/0266-5611/24/5/055020.

[15] Tiwari R, Singh R K, Choudhary N K. Coordination of dual setting overcurrent relays in microgrid with optimally determined relay characteristics for dual operating modes[J]. Protection and Control of Modern Power Systems, 2022, 7(1): 1–18. DOI:10.1186/s41601-022-00226-1.

[16] Ashraf S, Evkay I, Selamogullari U S, Baysal M, Hasan O. Performance analysis of the dual-setting directional overcurrent relays-based protection considering the impact of curve types and fault location[J]. Electric Power Components and Systems, 2023, 51(7): 706–723. DOI:10.1080/15325008.2023.2182840.

[17] Srivastava A, Liu C C, Stefanov A, Basumallik S, Hussain M M, Somda B. Digital twins serving cybersecurity: More than a model: Cybersecurity as a future benefit of digital twins 2[J]. IEEE Power and Energy Magazine, 2024, 22(1): 61–71. DOI:10.1109/MPE.2023.3325196.

[18] Arraño-Vargas F, Konstantinou G. Modular design and real-time simulators toward power system digital twins implementation[J]. IEEE Transactions on Industrial Informatics, 2022, 19(1): 52–61. DOI:10.1109/TII.2022.3178713.

[19] Vikram Raju G, Srikanth N V. Single fuzzy inference based fault detection and classification protection scheme for different types of short circuit faults on double circuit transmission lines[J]. International Journal of Modelling and Simulation, 2025, 45(1): 218–236. DOI:10.1080/02286203.2023.2193912.

[20] Önder M, Dogan M U, Polat K. Classification of smart grid stability prediction using cascade machine learning methods and the internet

of things in smart grid[J]. Neural Computing and Applications, 2023, 35(24): 17851–17869. DOI:10.1007/s00521-023-08605-x.
[21] Mendoza M A T, Segundo-Ramírez J, Gurrola A E, Visairo-Cruz N, Guitierrez C A N, Torres U. Digital twin adaptive remedial action scheme for preventing voltage collapse[J]. IEEE Journal of Emerging and Selected Topics in Industrial Electronics, 2024, 6(2): 523–535. DOI:10.1109/JESTIE.2024.3465429.

Biographies

Zhong-liang Xie (April 1990–), male, graduated from the School of Electrical Engineering and Automation at Guizhou University with a Bachelor's degree in Electrical Engineering and Automation. After graduation, I worked as an engineer at Guangzhou Dongke Electric Co., Ltd. My current research direction is engaged in electrical automation and computer application work.

Huang Tian-xiong, born in April 1990, male, graduated from the School of Hydroelectric and Digital Engineering at Huazhong University of

Science and Technology with a Bachelor's degree in Water Resources and Hydropower. After graduation, I worked as an engineer at the Wudongde Hydroelectric Power Plant of China Yangtze Power Co., Ltd. My current research direction is engaged in the automation and intelligence of hydropower.