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An Intelligent Decision-Support Framework for Substation Safety Using LSTM-OOA Optimization and 3D Virtual Monitoring

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ABSTRACT

The global expansion of power infrastructure has highlighted the growing necessity for advanced safety control mechanisms that exceed the capabilities of conventional manual systems, particularly as the number of substations and their operational complexities continue to rise. This study presents an intelligent integration framework that combines a three-dimensional (3D) virtual environment with automated operation tickets to enhance substation safety and intelligent control. The system adopts a multi-source heterogeneous information fusion approach to achieve improved operational performance and enhanced reliability. Central to the architecture is a 3D visualisation platform for substations, which facilitates real-time simulation of substation operations, scheme login access, equipment status monitoring, and automated management of operation tickets. Real-time data processing and execution of decisions are achieved through the deployment of multiple smart hardware components, including multi-dimensional sensing devices, high-efficiency wearable tools, pre-aligned rods, and substation inspection robots. Substation predictive maintenance capabilities are strengthened through a forecasting model that integrates Long Short-Term Memory (LSTM) neural networks with the Orangutan Optimisation Algorithm (OOA), specifically targeting space-time data prediction of transformer oil temperatures. The Attention-LSTM model demonstrates superior short-term predictive precision, enabling early fault detection and automated diagnostics. To enhance strategic decision-making within the intelligent control system, the Analytic Hierarchy Process (AHP) is incorporated to establish prioritised action plans. Experimental validation confirms the system's ability to generate timely alerts regarding abnormal equipment conditions within substations. The proposed integrated safety control framework represents a comprehensive and practical solution for substation automation, significantly improving operational effectiveness, system reliability, safety management, and data-informed decision-making.

1. Introduction

The ongoing evolution of power grid infrastructure, paired with the rising intricacy of substation

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operations, necessitates the deployment of highly advanced safety and control frameworks. Conventional techniques currently employed in the operation and maintenance of substations are increasingly incapable of satisfying contemporary industry expectations [25]. This mismatch between capability and demand results in notable inefficiencies and heightened safety vulnerabilities across substation systems [14]. Although prevalent digital solutions concentrate on connecting physical assets via sensors, they frequently disregard essential components such as workforce safety, real-time environmental assessment, and proactive monitoring of equipment health status [28]. As the scale and technical complexity of grid maintenance expand, there emerges an urgent requirement for technologically integrated systems that can simultaneously enhance automation, operational productivity, and hazard mitigation in substations [19].

Modern substation supervision contends with the absence of a cohesive solution that can effectively address safety enforcement in tandem with predictive maintenance functionality. Many current safety mechanisms offer limited protection against exposure to hazardous high-voltage zones and adverse environmental elements [11]. Moreover, the exclusion of predictive analytics in these systems impedes the anticipation of equipment failures, leading to extended downtime, inflated operational costs, and ineffective asset upkeep [4]. To overcome these issues, this research introduces a unified system combining 3D virtual modelling with intelligent hardware and automated operation ticketing. Through virtual interfaces, operators gain real-time access to substation processes, which improves situational insight and reduces exposure to physical risk [26]. Integrated smart hardware—including body-worn sensors, spatial localisation modules, and autonomous inspection units—facilitates dynamic monitoring of personnel location, ambient conditions, and machinery status. This comprehensive technological arrangement acts to minimise accidents, refine procedural execution, and enhance overall substation operational capability [20].

Beyond intelligent automation and surveillance, present-day substations must facilitate adaptive, criteria-driven decision-making structures to manage complex conditions and uphold safety assurance. As the influx of data from sensors, fault predictions, and alert systems intensifies, it becomes increasingly critical to convert raw inputs into practical, responsive decisions. Embedding a formal decision-support approach, such as the Analytic Hierarchy Process (AHP), within the substation control framework enables prioritisation based on factors including severity of failures, equipment significance, associated repair expenditure, and safety implications. This enhances not only the ability to detect and forecast faults but also enables well-informed, transparent, and risk-sensitive decision execution for both immediate and strategic planning.

The proposed framework further incorporates an optimised Long Short-Term Memory (LSTM) model designed to advance defect prediction, maintenance scheduling, and safety monitoring. This deep learning algorithm processes a wide array of input variables—ranging from sensor feedback and equipment performance metrics to environmental indicators—to forecast equipment degradation and suggest maintenance strategies that minimise operational disruption [24]. By coupling LSTM-driven predictive intelligence with 3D virtual substation simulations, the system supports early detection of operational anomalies while reducing the likelihood of unplanned outages. Maintenance tasks, initiated via automated operation ticketing, ensure full compliance with established safety standards and lower the probability of human error. Collectively, this integrated solution reinforces worker safety, raises substation operational efficiency, and provides a resilient, intelligent response to contemporary grid infrastructure demands [10].

2. Literature Review

The rapid advancement of power infrastructure necessitates innovative strategies to enhance system management, security, and monitoring capabilities. The integration of 3D modelling, deep learning, data fusion, and optimisation algorithms has recently emerged as a promising solution to challenges related to power infrastructure development, equipment monitoring, and grid administration. A high-level combination of technologies, including Light Detection and Ranging (LiDAR), photogrammetry, neural networks, and hierarchical optimisation, contributes to improved decision-making by increasing both accuracy and operational efficiency. These techniques provide applicable approaches to modernise power systems by ensuring operational reliability, addressing integration complexities, and overcoming computational limitations. This section outlines key developments in this evolving field.

A real-time visual monitoring framework has been introduced using an octree-based structure to observe power construction environments [30]. This system integrates LiDAR and photogrammetry to generate 3D point cloud data, which is organised hierarchically via octree structures to enhance visualisation efficiency and minimise memory consumption. The approach effectively reduces processing time and improves monitoring accuracy; however, it remains vulnerable to noise sensitivity and occlusion-related tracking issues, and it requires significant computational power. Despite these limitations, the framework offers a balanced trade-off between accuracy and performance, making it suitable for overseeing large-scale construction operations. An improved 3D reconstruction technique has also been developed by enhancing Neural Radiance Fields (NeRF) for heterogeneous power equipment data processing [18]. This method leverages multi-source input from LiDAR-generated point clouds and RGB imagery to produce accurate adaptive 3D reconstructions. By improving spatial resolution and minimising surface distortion, the approach advances precision in structural modelling. It also facilitates rapid evaluation of complex equipment geometries and supports diverse data inputs. Nevertheless, the technique exhibits sensitivity to noisy data and imposes substantial computational demands, particularly in real-time operational contexts. Despite these challenges, it provides a sophisticated solution for high-precision 3D modelling of power assets.

Another proposed system involves multi-source data fusion to support joint safety management within substations [31]. This framework integrates sensor networks, smart hardware, and real-time monitoring tools to enable enhanced situational awareness, predictive diagnostics, and fault detection. Although the approach strengthens decision-making processes, it introduces complications related to data synchronisation, computational load, and infrastructure compatibility. Even with these constraints, the model contributes a structured and intelligent framework for advancing safety and control in substation environments. A further development involves a power grid monitoring and management platform that employs 3D visualisation in combination with deep learning algorithms [25]. This system constructs a digital twin of the grid infrastructure, enabling real-time visual tracking and continuous evaluation of grid components. Through deep learning integration, it supports the identification and optimisation of anomalies, maintenance schedules, and operational decisions. While the method significantly enhances fault detection and situational insight, it faces barriers related to high computational requirements, complex data handling, and limited integration with legacy systems. Nonetheless, it offers a novel and effective pathway toward modernising power grid management practices. A summary of the identified research gaps is presented in Table 1.

Existing power infrastructure monitoring systems face several technical constraints, including data synchronisation challenges, sensitivity to noise, occlusion-related errors, and limited compatibility with legacy platforms, all of which contribute to substantial computational burdens. To address these limitations, the proposed framework integrates LSTM networks with OOA. In time-series applications, LSTM demonstrates exceptional capability in capturing and retaining long-term dependencies, which is essential for identifying anomalies within dynamic operational settings.

Simultaneously, OOA is employed to optimise LSTM hyperparameters, thereby improving both computational efficiency and predictive precision. This integrated approach reduces processing demands while enabling a more resilient and adaptive monitoring solution, particularly suited for remote infrastructure oversight in power systems.

Table 1
Research Gap Validation

Author(s)	Techniques Involved	Advantages	Disadvantages
Zhang et al. [30]	Octree-Based Visual Monitoring with LiDAR & Photogrammetry	Fast Processing, Optimized Storage, Precise Monitoring	Noise Sensitivity, Occlusion Issues, High Computation
Sun et al. [18]	Multi-Objective Hierarchical Optimization for PIoT Security	Accurate Risk Assessment, Adaptive Analysis, Efficient Resource Use	High Computation, Inconsistencies in Decision-Making
Zou et al. [31]	Improved NeRF-Based 3D Reconstruction for Power Equipment	High Accuracy, Multi-Source Compatibility, Complex Structure Handling	High Computation, Noise Sensitivity, Real-Time Constraints
Wu and Hu [25]	Multi-Source Information Fusion for Substation Safety	Better Fault Detection, Situational Awareness, Predictive Maintenance	Data Sync Issues, High Computation, Legacy System Integration
Wang et al. [21]	3D Model Visualization & Deep Learning for Grid Monitoring	Real-Time Tracking, Anomaly Detection, Grid Optimization	High Computation, Complex Processing, Legacy System Challenges

3. Proposed System Model

The modern electrical system, encompassing power generation, distribution, and consumption, increasingly relies on integrated data and communication technologies to develop intelligent substations. The emergence of new elements—such as decentralised renewable energy sources, connected residential systems, electric mobility, advanced communication devices, and remote-control units—requires grid infrastructures to evolve into more complex and efficient architectures.

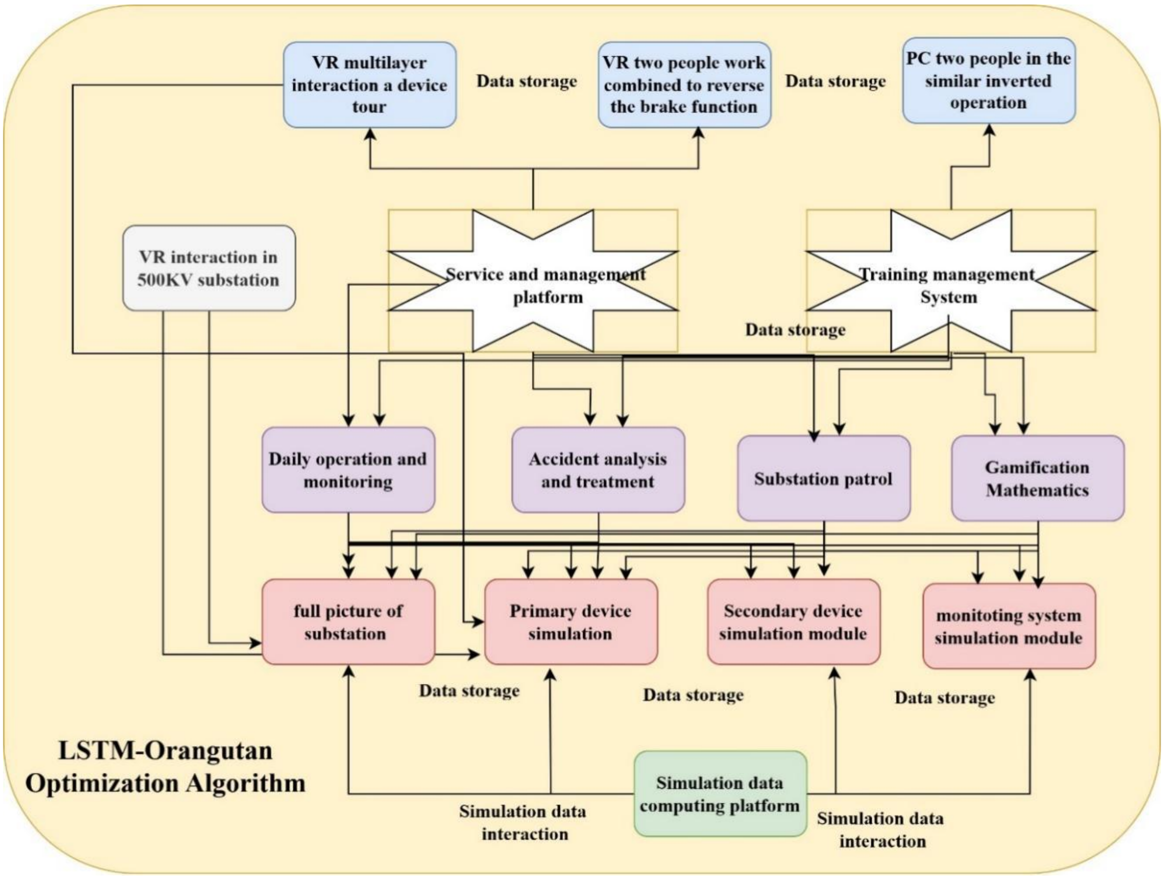

Fig.1: Proposed Architecture in 3D Virtual Environment for Substation Safety

This transformation generates a significant volume of data that energy providers must process and manage effectively. Moreover, determining the most suitable big data analytics approach from among various available techniques presents an additional challenge. With the growing number of substations worldwide, particularly in developing nations, the demands associated with daily operation and maintenance of these facilities are intensifying [5]. To address these increasing complexities, the system design enables station-level architecture to be more intuitive and controllable by allowing operators to issue commands via a tiered 3D visual interface of the substation. In response to the rising demand for intelligent, efficient, and comprehensive monitoring and control systems, this research proposes an advanced solution that incorporates wearable smart devices supported by multi-source heterogeneous data fusion. The complete architecture of the proposed system is illustrated in Figure 1.

Virtual simulation through 3D technology is employed to replicate substation layouts with high fidelity, offering a clear and comprehensive visualisation of the operational environment. This significantly enhances task efficiency, facilitates data sharing, and strengthens the capabilities and effectiveness of safety control within substation operations [25]. The research focuses on constructing a virtual 3D substation, wherein equipment models are imported at a one-to-one scale to ensure precision and close alignment with actual devices. Within the Unity development platform, these components are positioned to mirror the real-world substation layout accurately. Architectural features such as the main control room and relay room are also replicated to achieve a high level of structural and temporal consistency with the physical substation. This virtual layout forms the core upon which the simulation framework is built.

Simultaneously, data collected from multiple sensors supports real-time tracking of internal and external operational states of substation equipment. These data streams contribute to the enhancement of a dynamic simulation environment that can be visualised in real time. Based on this virtual model, a human-computer interaction and control platform is developed to support substation management activities [1]. The software interface enables users to engage with simulation-based substation functions. These functionalities include the ability to lock and store variable settings and are structured across user categories such as administrators, operators, and other managerial roles. In addition, the simulation integrates 2D animations to model routine operational procedures. The system employs work orders generated from the simulation architecture to produce step-by-step 2D animated representations of standard operational scenarios. These include primary wiring diagrams accompanied by instructional guidance and annotations. This feature helps users quickly familiarise themselves with standard workflows, reducing the potential for errors during live operations. By streamlining the interpretation and execution of work orders, the system supports smoother day-to-day substation functions and improves operational reliability [30].

3.1 The System Function

The functional design of the system integrates both manual and automated handling of procedural tasks, along with capabilities for monitoring electrical equipment and analysing standard operational tickets. By incorporating simulated accident parameters, the platform facilitates multiple emergency training scenarios, retaining historical event data to improve operators' response effectiveness based on the system's predefined architecture [13]. All operations are conducted within the parameters established by the complete manual for fault diagnosis and logical framework construction. The inspection module utilises virtual reality technology to execute procedural walkthroughs of equipment and circuit assessments for both internal and external components of the substation.

Furthermore, the system includes a weather simulation feature that displays real-time environmental data, including current time, temperature, meteorological conditions, and seasonal context, which are continuously updated and shown within the interface framework [9]. The information exchange mechanism is supported by secondary physical devices that synchronise monitoring data gathered from real hardware with the virtual simulation model. This synchronisation is securely transmitted to the simulation control platform using secure protocols and intelligent wearable technology. The system also supports collaborative operations through a dual-user reverse gate functionality, allowing two users to operate individual terminals within a shared simulation environment, thereby enhancing cooperative task execution and training efficiency.

3.2 Data Collection

When maintenance is required at a specific substation location, the pre-installed alignment rod can be either raised or lowered using a dedicated electronic positioning mechanism. By adjusting the rod's position along the relevant axis, one or more installation points can be determined. Following selection, the system transmits precise instructions to the installation computation module, directing it to execute the placement according to the identified area coordinates, thus initiating the related operational procedure. This function supports the broader objective of developing fully autonomous substation operations by providing the foundational basis for deploying a practical and effective inspection robot capable of functioning independently.

The proposed inspection robot operates under both remote switching and real-time video feedback modes. It is equipped with a high-definition visible light camera and an infrared imaging unit, enabling users to access both infrared and live video streams through a network interface. Navigation is achieved using Radio Frequency Identification (RFID) tags in combination with pre-installed magnetic guide paths [8]. Once manually activated by a remote user, the robot begins autonomous movement to inspect devices equipped with RFID tags. During the inspection process, it transmits real-time data, including visual and thermal images, allowing for the monitoring of equipment conditions such as surface temperature and operational status, along with the robot's current location. The mechanical design of the robot integrates components from both domestic and international manufacturers and adopts a wheel-driven configuration for precise angular movement control. Its four-wheel drive mechanism enables effective manoeuvring in confined or complex environments, improving inspection flexibility. Upon task completion, the robot automatically returns to its designated docking area for self-recharging, maintaining uninterrupted operational readiness [6].

3.3 Multi-Source Heterogeneous Data Fusion Analysis Technique

In this configuration, data collection for substation equipment is primarily conducted through inspection robots, wearable devices, electronically positioned full rods, and sensor modules integrated into multidimensional terminal units. Although these data originate from various hardware sources and edge-level devices, the decentralised nature of the information flow hinders the ability to obtain a comprehensive, real-time view of substation operations. Moreover, the collected data are often affected by overlapping or inconsistent signals, leading to increased complexity and time consumption in the processing phase. As a result, there is a critical requirement for a robust and efficient data fusion and anomaly detection framework [16]. To address this, the current section proposes a data integration and sharing strategy that aligns multiple substation devices to represent real-time operational states and to generate early warnings relevant to control personnel. A data fusion model based on LSTM is developed to process and analyse multi-source spatiotemporal inputs. This model performs data refinement, fault classification for high-voltage substation equipment, assessment of failure severity, and condition evaluation for large-scale machinery. Furthermore, it continuously validates changes across all monitored equipment parameters to provide timely and reliable operational insights [18].

3.4 LSTM Spatio-Temporal Data Detection Processing

Secondly, a validation method for limited substation data is proposed, combining multi-source information integration with LSTM model optimisation. This approach establishes a systematic mechanism to assess the integrity of incoming data, guided by two primary validation criteria [23]. The first criterion involves operational phase verification based on spatiotemporal parameters, specifically including checks on temperature, humidity, and arc detection. The second validation focuses on operator-related data during emergency conditions to ensure the reliability of control responses [12]. The LSTM model, known for its ability to retain both short-term and long-term dependencies, is applied within this framework. It extends the basic structure of the RNN by incorporating three gate mechanisms: input, output, and forget gates [3]. The forget gate facilitates the linkage between the current hidden state and the preceding one using an activation function. It probabilistically discards a portion of irrelevant data, thereby refining the output and enhancing the relevance of the resulting predictions, as represented in the system's computational flow.

$$F_T = \sigma(W_F.[H_{T-1}, Z_T] + B_F) \quad (1)$$

W_F is the heaviness of the hidden layer towards the gate and B_F is the bias course in this case, σ is the activation purpose. The symbol σ refers to the activation function. The parameter output generated through this process ranges between 0 and 1, which allows the system to regulate the influence of prior state information. The input gate plays a role in refining the internal cell state and typically utilises two activation functions: the sigmoid function and the hyperbolic tangent (tanh) function. In the present framework, data from the final hidden state and current input are first passed through the sigmoid function to produce an activation output constrained within the [0, 1] interval [17]. This value is used to determine the level of importance for updating cell states, where 0 indicates non-essential and 1 indicates essential information. Subsequently, the hidden state of the previous layer is combined with the current input through a processing function that generates a set of candidate parameters. The tanh function is then applied to this candidate information, and its output is multiplied with the output of the sigmoid activation to update the internal cell state [7]. The resulting information from the tanh output is deemed significant and is retained as part of the model's learning process, contributing to both short-term memory and long-term contextual interpretation.

$$I_T = \sigma(W_I.[H_{T-1}, Z_T] + B_I) \quad (2)$$

$$\hat{C}_T = tanh(W_C.[H_{T-1}, Z_T] + B_C) \quad (3)$$

The cell state of the final layer is further updated by integrating it with the output of the forget gate. If the values produced by the parameter are close to zero, it indicates that the associated data in the updated cell state should be discarded as irrelevant [27]. The remaining useful information is then combined with the input gate's output to incorporate newly generated data from the underlying neural architecture. This process results in an enhanced and refined cell state that carries forward only relevant contextual information, contributing to more accurate modelling and learning within the LSTM framework.

$$C_T = F_T.C_{T-1} + I_T.\hat{C}_T \quad (4)$$

Output Gate: Based on the latest input, the output gate determines the parameters for the next hidden state. To achieve this, the newly updated cell state is first passed through the tanh activation function, while the current input and the previous hidden state are simultaneously processed by the sigmoid function [29]. The values derived from these two functions are then multiplied to produce the data that should be retained in the hidden state. This computed hidden state represents the current output of the cell and, together with the updated cell state, is forwarded to the next time step in the sequence.

$$O_T = \sigma(W_O.[H_{T-1}, Z_T] + B_O) \tag{5}$$

$$H_T = B_O.\tanh(C_T) \tag{6}$$

The OOA supports the optimisation of weighting parameters within the LSTM architecture, enhancing model accuracy and convergence efficiency.

3.5 Orangutan Optimization Algorithm

OOA is a biologically inspired optimisation algorithm modelled on the behavioural characteristics of orangutans. In this approach, each member of the orangutan population represents a candidate solution within the optimisation problem space. These solutions are inherently diverse, as each orangutan is positioned at a distinct location within the multidimensional search space, ensuring exploration across a wide solution range [22]. This framework specifically refers to the mathematical representation of solution variables in the form of vectors.

$$Y = \begin{bmatrix} Y_1 \\ \cdots \\ Y_I \\ \cdots \\ Y_N \end{bmatrix}_{N\times M} = \begin{bmatrix} Y_{1,1} & \cdots. & Y_{1,D} & \cdots & Y_{1,M} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{I,1} & \cdots & Y_{I,D} & \cdots & Y_{I,M} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{N,1} & \cdots & Y_{N,D} & \cdots & Y_{N,M} \end{bmatrix}_{N*M} \tag{7}$$

$$Y_{I,D} = LB_D + R.(UB_D - LB_D) \tag{8}$$

The term is denoted by UB_D, by LB_D, the random number in the interval [0,1] by R, M is the number of decision parameters, $Y_{I,D}$ is the dimension in search space, and Y_I is the orangutan.

3.5.1 Stage 1: Foraging Technique

Orangutans are known to spend considerable time foraging in their natural habitats, searching for resources such as fruits and tree leaves. Within established colonies, their extensive movements and careful environmental assessment enable them to explore a wide range of locations for sustenance. When these foraging behaviours are translated into the OOA framework, the algorithm's exploration capacity is significantly enhanced, allowing it to adapt more effectively while scanning the global search space of the optimisation problem [2]. However, despite being modelled with a random search component, the algorithm remains relatively limited in its search precision and depth.

$$f_{si} = \{Y_K : F_K < F_I \; and \; K \neq I\} \tag{9}$$

That is, in this case, Y_K is the orangutan with the optimal goal function parameter F_K the objective function parameter f_{si} is the pair of potential food sources.

3.5.2 Stage 2: Nesting Skill (Exploitation Stage)

Orangutans demonstrate remarkable cognitive ability, evident not only in their foraging patterns but also in their nesting behaviours. Each day, they construct nests in trees using surrounding branches and leaves, exhibiting a purposeful strategy that reflects a form of localised optimisation. This nesting activity represents a focused search to maximise space utilisation in a controlled area. In the second phase of the OOA, this behaviour is simulated by directing the orangutan towards a nearby tree to establish a new nest location [15]. Algorithmically, this nesting strategy is modelled by determining the orangutan's updated position based on its current location, facilitating a more refined and targeted local search within the solution space.

$$Y_{I,J}^{P2} = Y_{I,J} + \left(1 - 2R_{I,J}\right).\frac{UB_J - LB_J}{T} \tag{10}$$

$$Y_J = \begin{cases} Y_{I,J}^{P2} & F_{I,J}^{P2} \leq F_I \\ Y_I & Else \end{cases} \tag{11}$$

where, T is the iteration counter of the DCA algorithm, $F_{I,J}^{P2}$, and t is the maximum number of iterations allowed by DCA algorithm. $Y_{I,J}^{P2}$ is an objective function and $P2$ is the algorithm dimension, and $Y_{I,J}^{P2}$ proposed the new location where the orangutan can exist in the second OOA phase.

3.6 AHP-Based Decision-Making for Maintenance Prioritization

To enhance the decision-making capability of the proposed intelligent substation control system, AHP is incorporated as a multi-criteria evaluation layer to support maintenance prioritisation. After conducting predictive assessments through the LSTM model optimised via OOA, the system considers several risk-based factors, including fault likelihood, equipment criticality, transformer oil temperature, component age, repair cost, and safety implications. AHP is used to assign relative weights to these criteria through pairwise comparison, generating a prioritised list of maintenance actions. This output enables operators to identify and execute the most urgent and cost-effective responses. By integrating predictive analytics with structured decision logic, the system evolves into a comprehensive decision-support platform that ensures timely, informed, and risk-aware management of substation infrastructure.

4. Performance Evaluation

The proposed intelligent integration of the 3D virtual environment with automated operation ticketing was evaluated in terms of real-time monitoring, predictive accuracy, and operational efficiency. The use of a three-dimensional interactive platform significantly enhanced workflow automation by reducing manual effort and improving fault identification capability. Real-time anomaly detection was strengthened through the integration of multi-dimensional sensors, wearable technology, and inspection robots, enabling continuous monitoring and increased detection accuracy. The system demonstrated high effectiveness in predicting transformer oil temperature fluctuations, outperforming alternative models. When benchmarked against LSTM, support vector machine (SVM), deep belief neural network (DBNN), and deep neural network (DNN), the proposed method achieved superior results by reducing loss values, minimising prediction errors, and increasing anomaly detection rates. Performance was assessed using metrics including area under the curve, accuracy, precision, recall, and F1-score. The framework enabled the generation of early warnings prior to critical failures, thereby supporting proactive maintenance strategies. Moreover, the automated operation ticket mechanism contributed to a reduction in the response time required for maintenance-related workflows. Overall, the system delivered higher predictive accuracy and classification performance compared to conventional techniques.

Fig.2: Sample Images

Figure 2 illustrates sample input and output images, while Figure 3 displays the confusion matrix.

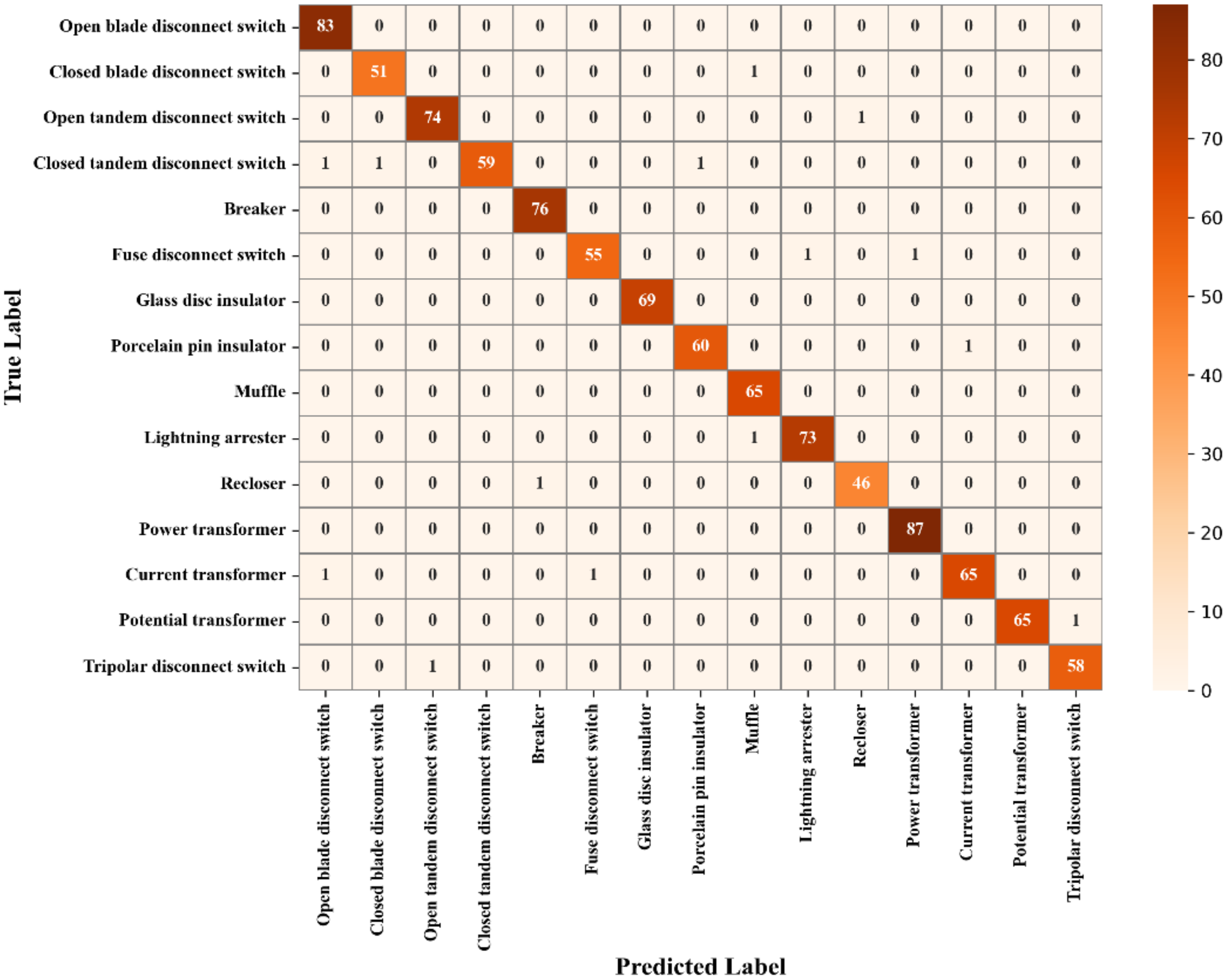

Fig.3: Validation of Confusion Matrix

Figure 4 presents a comparative analysis of the proposed model alongside LSTM, DNN, DBNN, and SVM, evaluated using four key performance metrics: accuracy, precision, recall, and F1-score. The proposed model demonstrated robust classification capability, achieving an accuracy of approximately 98.5%, precision of 98.2%, recall of 98.7%, and an F1-score of 98.4%. These results indicate high reliability and consistency in predictive performance. In contrast, the LSTM model attained slightly lower results, with an accuracy of 95.8%, precision of 94.6%, recall of 95.1%, and an F1-score of 94.8%, suggesting a minor trade-off in prediction consistency. The DNN model delivered comparable outcomes, reaching 96.2% accuracy, 95.4% precision, 96.0% recall, and an F1-score of 95.7%, though it remained marginally less effective than the proposed approach. Performance decline was more evident in the DBNN model, which recorded an accuracy of 92.4%, precision of 91.2%, recall of 90.9%, and an F1-score of 91.0%, indicating a reduced ability to manage classification errors. The SVM model exhibited the weakest results, with accuracy, precision, recall, and F1-score values of 88.1%, 86.5%, 87.0%, and 86.7%, respectively, highlighting its limited capacity to handle complex substation data. Overall, the proposed model consistently outperformed all baseline models in terms of predictive accuracy and anomaly detection, confirming its effectiveness as a reliable tool for intelligent safety control in substation environments.

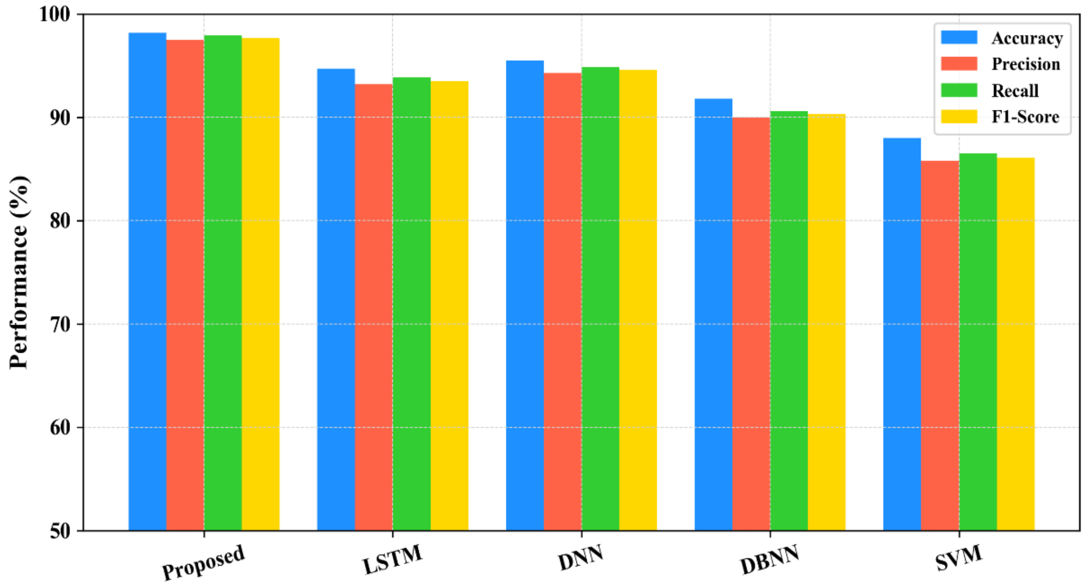

Fig.4: Performance Measures

Figure 5 presents the ROC curves for the proposed model, LSTM, DNN, DBNN, and SVM, illustrating the relationship between the false positive rate and the true positive rate across all models. The AUC values are used to assess each model's classification capability in terms of its effectiveness at distinguishing between classes. The proposed model achieves the highest performance, with an AUC of 0.99, indicating near-perfect classification accuracy. An AUC of 0.98 for LSTM also reflects strong predictive capability. The DNN model closely follows, recording an AUC of 0.96, which confirms its reliability in classification tasks, although slightly below that of the proposed approach and LSTM. In contrast, the DBNN model yields an AUC of 0.93, signifying a moderate decline in discriminative performance. The lowest AUC value of 0.91 is observed in the SVM model, indicating its reduced ability to manage complex substation data patterns effectively. Overall, the proposed model consistently surpasses conventional deep learning and machine learning approaches in terms of classification accuracy, reduced false positive rates, and enhanced robustness. These outcomes underscore its practical applicability in intelligent safety control and predictive maintenance of substation systems.

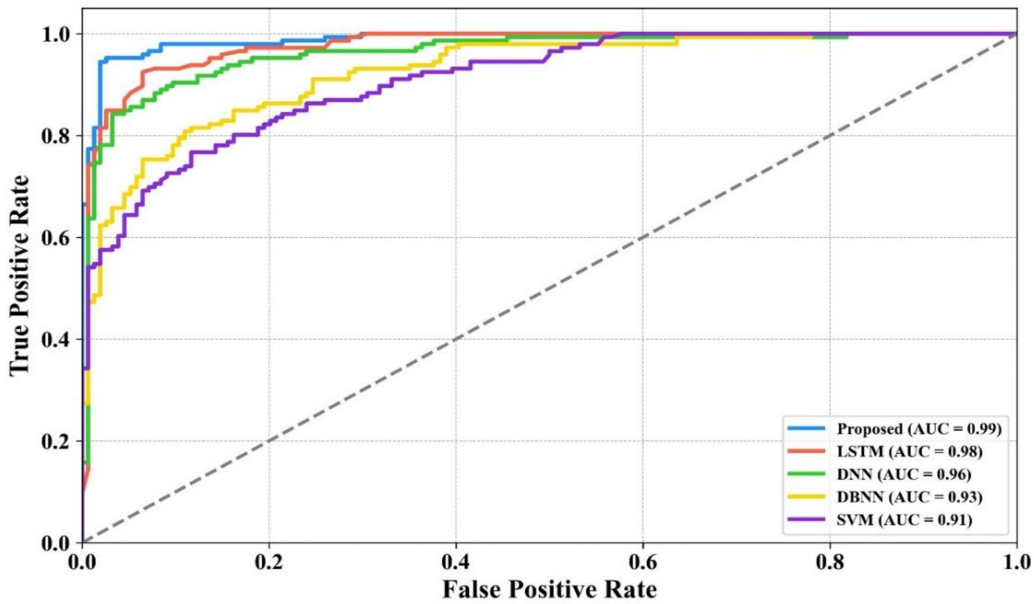

Fig.5: AUC Validation

Figure 6 presents the mean squared error (MSE) and root mean squared error (RMSE) metrics, which are employed to evaluate the prediction accuracy and error minimisation capacity of the proposed model in comparison with LSTM, DNN, DBNN, and SVM. Lower MSE and RMSE values indicate higher performance quality and more precise predictive capability.The proposed model delivers the most accurate predictions, achieving the lowest RMSE of approximately 0.15 and an MSE close to 0.02, reflecting minimal prediction errors. In contrast, the LSTM model shows a slight decline in predictive accuracy, recording an RMSE of 0.32 and an MSE of 0.08. The DNN model maintains competitive results with an RMSE near 0.28 and an MSE of 0.07, indicating reasonable predictive strength. However, both error metrics increase substantially for the DBNN model, with an RMSE of 0.40 and an MSE of 0.12, highlighting reduced prediction precision. The SVM model exhibits the weakest performance, with RMSE exceeding 0.5 and MSE reaching 0.18, signifying poor error management and diminished prediction capability. Overall, the proposed model demonstrates superior accuracy in predictive tasks, validated by its consistently lower MSE and RMSE values, reinforcing its suitability for intelligent safety control within substation environments.

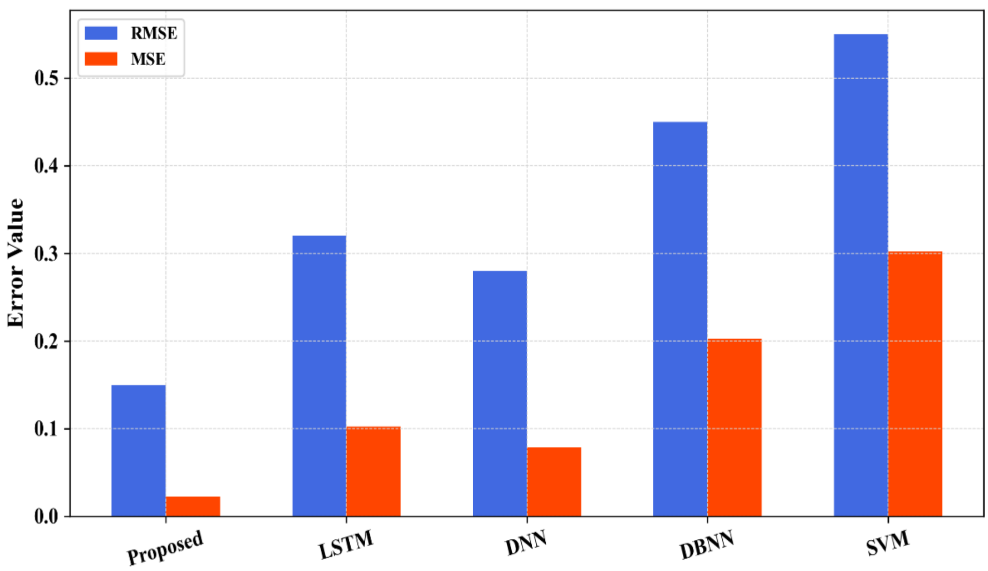

Fig.6: Error Parameter

Figure 7 presents multiple data points representing transformer oil temperature readings, each corresponding to a 15-minute interval. The temperature values in the dataset range from -15°C to 50°C and display periodic fluctuations over time. Peaks near 50°C reflect thermal loading phases, while troughs around -15°C indicate cooling periods. These cyclical patterns suggest that both environmental conditions and operational dynamics significantly influence transformer oil temperature behaviour. The observed regularity in these variations underscores the importance of continuous monitoring systems in maintaining transformer performance and ensuring stable power delivery. This dataset provides valuable input for predictive maintenance algorithms, facilitating early fault detection and supporting operational optimisation within substation environments. Figure 8 displays the training and validation loss convergence across 600 iterations. Substantial performance improvements occur during the initial 100 iterations, where loss values rapidly decline from 1.0 to significantly lower levels. Over the remaining 300 iterations, the loss stabilises near zero, indicating successful convergence. The parallel behaviour of training and validation loss curves demonstrates minimal overfitting and confirms the model's generalisation capability. The smooth decline in loss values reflects the efficiency of the optimisation process, validating both the model's reliability and predictive precision.

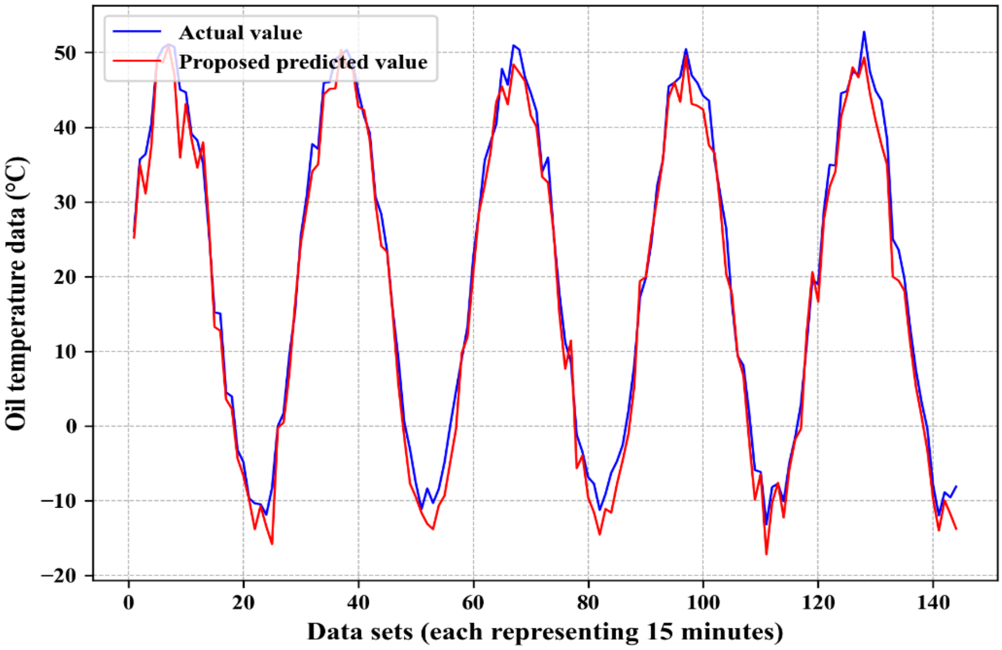

Fig.7: Oil Temperature Data

Experimental results further confirm the robustness of the proposed intelligent substation safety and control system across key performance measures. The system achieves classification metrics of 98.5% accuracy, 98.2% precision, 98.7% recall, and 98.4% F1-score, along with an AUC of 0.99 and low error values (RMSE = 0.15, MSE = 0.02), consistently outperforming traditional models such as LSTM, DNN, DBNN, and SVM. Beyond predictive accuracy, the integration of predictive outputs with intelligent ranking mechanisms enables real-time decision-making. For example, when the predicted fault probability exceeds 0.85 and the transformer oil temperature surpasses 70°C, the system recommends deploying Inspection Team A within two hours. This capability highlights the platform's ability to facilitate timely, data-informed interventions. By integrating virtual visualisation, sensor-based anomaly detection, and predictive analytics, the proposed framework enhances maintenance scheduling, reduces response latency, and mitigates operational risks. Ultimately, it evolves from a passive monitoring tool into a proactive and intelligent decision-support system that strengthens substation operational resilience, resource efficiency, and fault prevention strategies.

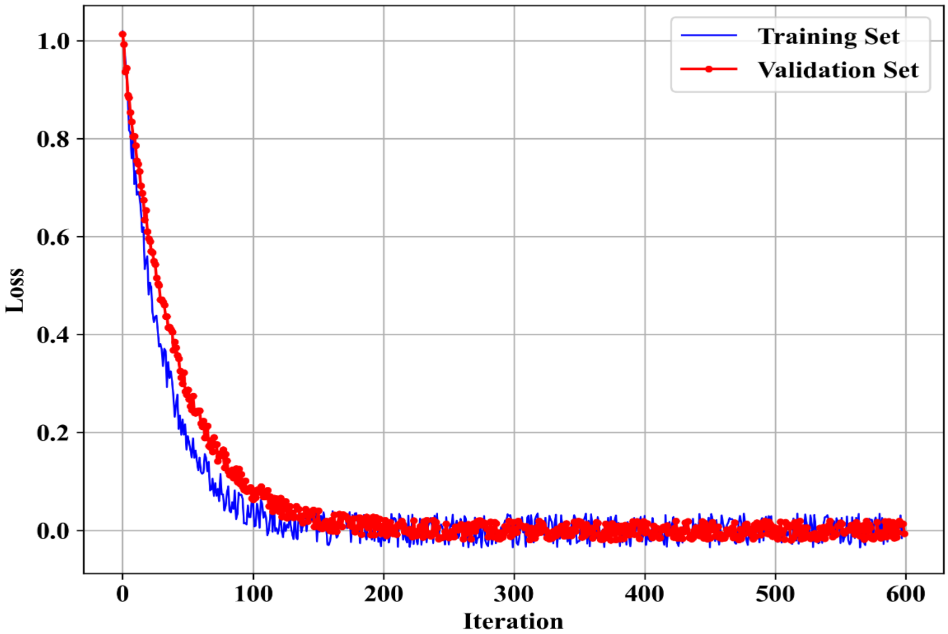

Fig.8: Validation of Loss

5. Conclusion

This study introduces an intelligent substation safety and control system by integrating automated operation ticketing with a 3D virtual environment. By leveraging multi-source heterogeneous data fusion, the system enhances real-time monitoring, operational efficiency, and predictive maintenance capabilities. The implementation of intelligent hardware—including multi-dimensional sensors, wearable technologies, and inspection robots—enables precise tracking of equipment conditions. The hybrid LSTM-OOA model demonstrated superior predictive performance, particularly in forecasting transformer oil temperatures, achieving an RMSE of 0.15 and MSE of 0.02—surpassing traditional benchmark models. The model also exhibited excellent early fault detection, with an AUC of 0.99. Analysis of the loss curves revealed stable model training, with both training and validation losses converging near zero after 200 iterations. The proposed framework successfully supports predictive maintenance while reducing operational risks and enhancing substation reliability. This research presents an effective and forward-looking approach to power infrastructure management by combining real-time monitoring with advanced forecasting techniques. Future work will explore the development of AI-driven self-healing mechanisms to enable automatic fault correction, further enhancing the system's autonomy and adaptability across various substation configurations. Efforts will also be directed toward incorporating edge computing and 5G communication technologies to facilitate real-time data processing and rapid response, thereby strengthening operational resilience.

To support structured and risk-sensitive decision-making, the system incorporates AHP as a multi-criteria evaluation tool for prioritising maintenance actions based on factors such as fault probability, equipment criticality, repair cost, and response urgency. This transforms the platform from a passive monitoring tool into a comprehensive intelligent decision-support system capable of navigating complex operational scenarios. Nevertheless, challenges remain, including reliance on precise sensor calibration and the subjectivity involved in AHP weight assignments. To address these, future enhancements will involve integrating fuzzy logic and dynamic MCDM approaches to manage uncertainty and improve decision adaptability. Collectively, these developments aim to elevate the system's resilience, intelligence, and practicality, broadening its applicability across diverse operational environments within the modern power grid landscape.

References

[1] Ayala García, A., Galván Bobadilla, I., Arroyo Figueroa, G., Pérez Ramírez, M., & Muñoz Román, J. (2016). Virtual reality training system for maintenance and operation of high-voltage overhead power lines. *Virtual Reality*, *20*(1), 27-40. https://doi.org/10.1007/s10055-015-0280-6

[2] Aydeger, A., Saputro, N., Akkaya, K., & Uluagac, S. (2019). SDN-enabled recovery for Smart Grid teleprotection applications in post-disaster scenarios. *Journal of Network and Computer Applications*, *138*, 39-50. https://doi.org/10.1016/j.jnca.2019.04.011

[3] Bavelos, A. C., Anastasiou, E., Dimitropoulos, N., Michalos, G., & Makris, S. (2025). Virtual reality-based dynamic scene recreation and robot teleoperation for hazardous environments. *Computer-Aided Civil and Infrastructure Engineering*, *40*(3), 392-408. https://doi.org/10.1111/mice.13337

[4] Dong, H., Tian, Z., Spencer, J. W., Fletcher, D., & Hajiabady, S. (2024). Bilevel optimization of sizing and control strategy of hybrid energy storage system in urban rail transit considering substation operation stability. *IEEE Transactions on Transportation Electrification*, *10*(4), 10102-10114. https://doi.org/10.1109/TTE.2024.3385821

[5] Flôr, V. B. B., Do Coutto Filho, M. B., de Souza, J. C. S., & Ochi, L. S. (2022). Strategic observation of power grids for reliable monitoring. *International Journal of Electrical Power & Energy Systems*, *138*, 107959. https://doi.org/10.1016/j.ijepes.2022.107959

[6] Frison, L., Gumbel, U., Steiger, S., Sinnesbichler, H., Ahrens, B., Lottis, D., Wecker, M., & Cadenbach, A. M. (2024). Presentation of a distributed testing infrastructure for joint experiments across multiple remote laboratories for robust development of new district heating concepts. *Smart Energy*, *15*, 100152. https://doi.org/10.1016/j.segy.2024.100152

[7] Guerra-Zubiaga, D., dos Santos, M. C., Voicu, R. C., Richards, G., Gosnell, S., & Barbosa, G. F. (2024). A digital twin approach to support a multi-task industrial robot operation using design of experiments. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *46*(8), 516. https://doi.org/10.1007/s40430-024-05114-3

[8] Huang, X., Li, L., Wang, W., Liu, L., & Li, M. (2024). Intelligent patrol inspection of low code enabled electric power communication equipment based on digital transformation. *Cluster Computing*, *27*(8), 10421-10435. https://doi.org/10.1007/s10586-024-04505-4

[9] Janagi, K., Balaji, D., Renuka, P., & Bhuvaneswari, S. (2024). Machine learning and artificial intelligence in the detection of moving objects using image processing. *Mathematical Models Using Artificial Intelligence for Surveillance Systems*, 19-49. https://doi.org/10.1002/9781394200733.ch2

[10] Kang, S., Jung, S., Lee, D., & Jang, G. (2024). Optimal control strategies for energy storage systems for HUB substation considering multiple distribution networks. *Scientific reports*, *14*(1), 20390. https://doi.org/10.1038/s41598-024-68728-6

[11] Khlebnikova, E., Pothof, I., van der Zwan, S., & Loverdou, L. (2024). On the design of 5GDHC substation control systems. *International Journal of Sustainable Energy*, *43*(1), 1-16. https://doi.org/10.1080/14786451.2024.2317141

[12] Liu, T., Zhang, B., Tan, Q., Zhou, J., Yu, S., Zhu, Q., & Bian, Y. (2024). Immersive human-machine teleoperation framework for precision agriculture: Integrating UAV-based digital mapping and virtual reality control. *Computers and Electronics in Agriculture*, *226*, 109444. https://doi.org/10.1016/j.compag.2024.109444

[13] Liu, W., Gu, Y., Zeng, Z., Qi, D., Li, D., Luo, Y., Li, Q., & Wei, S. (2024). Automated Equipment Defect Knowledge Graph Construction for Power Grid Regulation. *Electronics*, *13*(22), 4430. https://www.mdpi.com/2079-9292/13/22/4430#

[14] Lu, J., Zhou, Y., Liu, S., & Niu, Z. (2023). Safety Operation of Substation Intelligent Simulation System Based on Improved Genetic Algorithm. *Procedia Computer Science*, *228*, 701-708. https://doi.org/10.1016/j.procs.2023.11.081

[15] Moreno, E. F., Pacheco, E. E., Andaluz, V. H., & Mullo, Á. S. (2020). Multi-user expert system for operation and maintenance in energized lines. Future of Information and Communication Conference, 454-472. https://doi.org/10.1007/978-3-030-39442-4_34

[16] Paul, A., Somnath Sinha, Parveen Kumar, Shirasthi Choudhary, Krishna Samdani, & Mishra, S. (2024). *Overview of Cyber Security in Intelligent and Sustainable Manufacturing*. CRC Press. http://doi.org/10.1201/9781003405870-6

[17] Pięta, P., Jegierski, H., Babiuch, P., Jegierski, M., Płaza, M., Łukawski, G., Deniziak, S., Jasiński, A., Opałka, J., & Węgrzyn, P. (2024). Automated classification of virtual reality user motions using a motion atlas and machine learning approach. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3424930

[18] Sun, Y., Zhuang, L., Jia, T., Cheng, D., Zhao, X., & Guo, J. (2025). A risk assessment method for power internet of things information security based on multi-objective hierarchical optimisation. *IET Smart Grid*, *8*(1), e12208. https://doi.org/10.1049/stg2.12208

[19] Tang, Z., Xue, B., Ma, H., & Rad, A. (2024). Implementation of PID controller and enhanced red deer algorithm in optimal path planning of substation inspection robots. *Journal of Field Robotics*, *41*(5), 1426-1437. https://doi.org/10.1002/rob.22332

[20] Wang, C., Fu, Z., Zhang, Z., Wang, W., Chen, H., & Xu, D. (2024). Fault diagnosis of power transformer in one-key sequential control system of intelligent substation based on a transformer neural network model. *Processes*, *12*(4), 824. https://www.mdpi.com/2227-9717/12/4/824#

[21] Wang, H., Huang, Z., Zhang, X., Huang, X., wei Zhang, X., & Liu, B. (2022). Intelligent power grid monitoring and management strategy using 3D model visual computation with deep learning. *Energy Reports*, *8*, 3636-3648. https://doi.org/10.1016/j.egyr.2022.02.123

[22] Wang, J., Pan, X., Zhang, Y., Meng, Q., Qiao, Y., Wen, H., & Kou, P. (2023). An intelligent operation ticket system based on typical interval and secondary equipment anti-misoperation. Sixth International Conference on Computer Information Science and Application Technology (CISAT 2023), 1607-1614. https://doi.org/10.1117/12.3003784

[23] Wang, Y. (2024). Interactive display method of electric power business hall based on 3D technology. *Computers and Electrical Engineering*, *119*, 109490. https://doi.org/10.1016/j.compeleceng.2024.109490

[24] Wang, Y., Jin, X., Zhang, J., Zeng, C., Gao, X., Zhao, L., & Sha, S. (2024). Scheme design and energy-saving optimization of cold and heat energy supply system for substation main control building in cold area. *Applied Sciences*, *14*(4), 1562. https://www.mdpi.com/2076-3417/14/4/1562#

[25] Wu, B., & Hu, Y. (2023). Analysis of substation joint safety control system and model based on multi-source heterogeneous data fusion. *IEEE Access*, *11*, 35281-35297. https://doi.org/10.1109/ACCESS.2023.3264707

[26] Xu, Q., Liu, W., Ding, J., Tian, Z., Zhang, J., Zhang, X., & Bhatti, A. A. (2024). System-efficient Energy Regulation and Control for Reversible Substations in Urban Rail System. *IEEE Transactions on Transportation Electrification*. https://doi.org/10.1109/TTE.2024.3519336

[27] Yang, C.-W., Dubinin, V., & Vyatkin, V. (2019). Automatic generation of control flow from

requirements for distributed smart grid automation control. *IEEE Transactions on Industrial Informatics*, *16*(1), 403-413. https://doi.org/10.1109/TII.2019.2930772

[28] Yang, Q., Dong, J., Tan, M., Wang, J., Guo, D., Kang, H., & Wang, P. (2025). A novel navigation assistant method for substation inspection robot based on multisensory information fusion. *Journal of Advanced Research*. https://doi.org/10.1016/j.jare.2025.01.016

[29] Yang, Z., Ren, Y., Li, J., Li, J., Ji, X., & Zhao, L. (2023). Design of an intelligent operation and error prevention and control system for secondary voltage plate in substations based on machine vision. 3rd International Conference on Artificial Intelligence, Automation, and High-Performance Computing (AIAHPC 2023), 341-348. https://doi.org/10.1117/12.2685324

[30] Zhang, C., Zhang, L., Chen, X., Ou, L., & Xu, Y. (2024). Octree based visual monitoring method for operation process of power construction site. *Results in Engineering*, *24*, 103138. https://doi.org/10.1016/j.rineng.2024.103138

[31] Zou, Y., Pei, S., Sun, Z., Zhao, Q., Liu, H., Liu, Y., & Yang, R. (2024). A 3D reconstruction method for heterogeneous data of power equipment based on improved neural radiation fields. *IEEE Transactions on Power Delivery*, *39*(5), 2677-2692. https://doi.org/10.1109/TPWRD.2024.3421913