Enhancing Grid Resilience with Grid Visualisation (Grid-V)

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ABSTRACT

The increasing frequency of extreme weather events in recent years poses significant challenges to power grid operations by causing physical interference and potential damage to infrastructure, which may lead to power incidents. To address this emergent challenge and ensure the safe operation of the grid, CLP Power Hong Kong Limited (CLP Power) has developed an advanced, centralised asset and worksite activity management system known as Grid Visualisation (Grid-V). Grid-V integrates various monitoring and management systems and leverages artificial intelligence (AI) technology. It provides real-time monitoring of the condition of critical assets, such as transmission overhead line circuits, power substations, and ongoing worksite activities. The AI component of Grid-V can detect disturbances impacting these critical assets, such as hill fires, smoke, or flying objects, and alert operational staff to take prompt action. Furthermore, the AI feature enables the detection of physical security intrusions, thereby enhancing the physical security protection of power substations. The deployment of Grid-V has significantly enhanced grid resilience by proactively identifying and mitigating risks, supported by the continuous monitoring from multiple sources and AI-assisted analytic functions.

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1. Introduction

In recent years, the frequency and severity of extreme weather events worldwide have significantly increased, raising public concerns. These events, such as hurricanes and storms, pose significant challenges to power grid operations for power utilities worldwide (Lv et al., 2023). Severe storms with strong winds can lead to a potential risk of transmission tower collapse, causing power outages (Poudyal et al., 2023). Heavy rainfall and flooding can submerge critical components like electrical substations, resulting in prolonged service disruptions (Bahrami et al., 2021). Therefore, it is necessary for utilities to enhance the network reliability and resilience.

Remote monitoring of critical assets and their surrounding environment is considered an effective support to enhance network reliability and resilience (Yang, 2023). However, the network contains a large number of assets, such as substations, transmission lines and switchgears. It is impractical to assign operational staff to continuously monitor every concerned asset. Recent advancements in artificial intelligence (AI), specifically machine learning (ML), deep learning (DL), and computer vision, provide a transformative opportunity to simultaneously process vast amounts of data (Regev et al., 2022). Thus, AI is introduced into the monitoring system to achieve cost-effective and efficient data analysis of the monitored data and facilitate the operator's management of the network (Alqudah and Obradovic, 2023).

For example, in the case of inspecting transmission overhead lines, traditional inspections would require inspectors to carry out routine patrols. In contrast, with the AI-assisted fixed monitoring system, operators can view the real-time situation remotely and receive warning signals timely. Operators can take relevant actions based on the analysis to secure the network, such as scheduling ad hoc maintenance tasks or assigning the repair team to attend the required location more effectively.

Taking a step further, CLP Power integrates existing remote monitoring and information systems into one single platform called Grid Visualisation (Grid-V). With AI-supported smart analysis, this platform allows operators to have a comprehensive view of the entire power grid. It provides easy access to live video feeds and delivers smartly analysed results from all integrated systems. This integration enhances operators' ability to monitor and make informed decisions about the power grid, thereby further bolstering network reliability and resilience. This paper systematically presents Grid-V's technological architecture, evaluates its effectiveness, and discusses future enhancements, contributing valuable knowledge for industry-wide implementation of AI-driven grid resilience solutions.

2. Technique for AI in Grid-V

AI technology is employed for processing the data to achieve rapid and effective assessments of the monitored assets. In the exploration of AI applications for enhanced supervision, Grid-V integrates two primary processing architectures: edge processing and centralised processing.

2.1. Data Processing Mechanisms

The accuracy and responsiveness of Grid-V's AI applications rely on robust data processing mechanisms. Initially, data collected by various monitoring devices such as surveillance cameras, drones, and environmental sensors undergo pre-processing. This includes noise reduction, data normalisation, and format standardisation, ensuring data quality and consistency for accurate AI inference.

AI data processing within Grid-V operates under two principal AI data processing architectures: edge processing and centralised processing. In edge processing, lightweight AI models embedded within local devices conduct immediate data analysis, significantly reducing latency and bandwidth requirements. Conversely, centralised processing involves aggregating data in a centralised server in a data centre, enabling comprehensive analysis using more complex, computationally intensive AI models. This dual-architecture approach allows Grid-V to leverage the strengths of both localised and centralised data processing, adapting dynamically to operational demands and optimising computational efficiency, latency bandwidth usage, and decision-making efficacy.

2.2. Edge Processing

Edge processing involves the installation of AI modules directly at the data collection points, such as cameras and sensors, enabling real-time analysis of data at the edge of the network. Upon receiving monitored data from surveillance cameras or drones, the monitoring system can directly assess the integrity and status of the monitored assets. This localised processing significantly enhances the system's responsiveness and efficiency in detecting and responding to potential risks.

The edge processing architecture is shown in Figure 1, where the monitored data is processed using a Video Analytics (VA) box, and the metadata, such as warning signals or reports, is transmitted to the cloud. This facilitates operators' swift and informed decision making.

Additionally, the edge AI modules utilise lightweight convolutional neural network (CNN) models optimised for fast inference, typically achieving a detection accuracy of around 85-90% in practical deployments. Bandwidth requirements for this architecture are minimal, typically less than 1 Mbps per video stream, due to localised data processing.

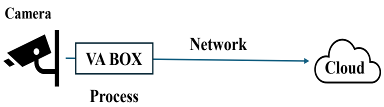

Figure 1. The edge-processing architecture.

This architectural framework offers three main benefits.

1) Reduced Latency: By processing data locally at the edge, the system can provide immediate alerts and responses, crucial for time-sensitive incidents. This minimisation of processing time enhances the system's ability to timely identify and mitigate potential risks.

2) Bandwidth Efficiency: Edge processing ensures that only relevant and pre-processed data is transmitted to central servers. This selective data transmission optimises bandwidth usage, reducing network congestion and the operational costs associated with excessive data transfer.

3) Enhanced Privacy and Security: The ability to process sensitive data locally at the edge minimises the exposure of critical information during transmission. This approach strengthens data privacy measures and reduces vulnerabilities to potential cyber threats, safeguarding the integrity of the monitored assets.

By leveraging edge processing within the monitoring system, organisations can effectively enhance their asset management, respond promptly to potential risks, and optimise operational efficiency through streamlined data processing and analytics.

2.3. Centralised Processing

Centralised processing systems consolidate data from diverse sources into a powerful central cloud server for comprehensive analysis, as depicted in Figure 2. In centralised processing, deep learning models such as Residual Neural Network (ResNet) and YOLO (You Only Look Once) are commonly employed for data analysis, correlation, and anomaly detection tasks, which typically achieve accuracy rates of above 80%. Bandwidth requirements for centralised architectures vary according to the number of data streams but generally range from 5 to 10 Mbps per video stream, depending on the data volume and complexity.

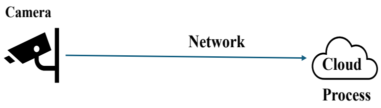

Figure 2. The centralised processing architecture.

This conventional approach offers four notable advantages:

1) Comprehensive Analysis: Centralised systems leverage substantial computational resources, facilitating intricate data analysis across vast datasets. The centralised nature of data aggregation enables in-depth examination and correlation of information from various sources, enhancing the system's analytical capabilities.

2) Scalability: Centralised systems exhibit scalability by accommodating an expanding array of devices and data sources. This flexibility allows for the seamless integration

of new data streams and devices into the existing infrastructure without necessitating extensive modifications, thereby supporting the system's growth and adaptability over time.

3) Resource Optimisation: Centralised processing systems can optimise resource allocation by pooling computational power and storage capacities within a centralised server environment. This centralised resource management enhances efficiency and streamlines data processing tasks, contributing to improved system performance and operational effectiveness.

4) Consolidated Management: Centralised systems offer centralised data management and control, simplifying the monitoring and maintenance of the overall system. This centralisation oversight facilitates uniformity in data handling and system operations, promoting cohesive management practices and ensuring consistency in data analysis procedures.

By utilising centralised processing systems, organisations can harness the benefits of robust computational capabilities, scalability, resource optimisation, and consolidated management, thereby enhancing their analytical proficiency and operational efficiency in handling diverse and voluminous datasets.

3. AI applications in enhancing Grid Resilience

There are three main applications of AI in Grid-V designed to enhance grid resilience. Firstly, AI technology is employed to detect environmental disturbances affecting critical assets within the transmission network, including transmission overhead lines and towers. Secondly, Grid-V detects intrusions into power substations to ensure physical security. Thirdly, AI technology facilitates real-time monitoring of worksite activities to improve work safety and compliance. The subsequent subsections provide detailed descriptions of these applications.

3.1. Anomaly Detection of the Transmission Network

The utilisation of AI-powered video analytics plays a vital role in monitoring assets within the transmission network, providing enhanced surveillance capabilities and efficient risk detection. The system is specifically programmed to identify and respond promptly to various potential risks, including hill fire and smoke detection, third-party interference detection, and overhead line structural integrity inspection.

1) Hill Fire and Smoke Detection.

In the event of hill fires, the AI-powered system employs trained convolutional neural network models to detect smoke and flames. Captured images are analysed using CNN-based models to detect hill fire or smoke, achieving approximately 70% accuracy during real-world deployments. Upon detection, immediate alerts are automatically triggered to grid operators. Figure 3 illustrates a typical scenario where a hill fire is successfully identified by the Grid V system. This real-time information allows for swift and coordinated responses, enabling the rapid deployment of emergency response teams and the implementation of targeted mitigation strategies, significantly reducing potential impacts to critical transmission infrastructure.

Figure 3. The detection of hill fire.

2) Third-party Interference Detection.

The AI system utilises advanced object detection algorithms, such as YOLO, specifically trained to identify third-party equipment like construction cranes or flying objects in proximity to overhead transmission lines. These models achieve greater than 85% accuracy in operational environments. By continuously analysing video feeds for suspicious behaviour patterns, the system promptly triggers alerts which enable timely action by emergency response teams. This proactive approach significantly mitigates the potential risk posed by third-party interference to the overhead transmission line network.

3) Overhead Line Structural Integrity Inspection.

To monitor the structural integrity of overhead line components, AI-based image classification models such as EfficientNet are employed, achieving accuracy rates of over 80%. Autonomous drones equipped with high-resolution cameras systematically navigate predetermined routes with visual line of sight, capturing detailed images at specified inspection points, as illustrated in Figure 4. Subsequently, the AI system performs rapid evaluations of the captured images, identifying structural anomalies or damaged components. For instance, Figure 5 demonstrates the AI detection of a damaged insulator on a transmission tower (Li et al., 2023). This innovative methodology significantly enhances the inspection efficiency, reduces labour costs, and ensures timely maintenance interventions.

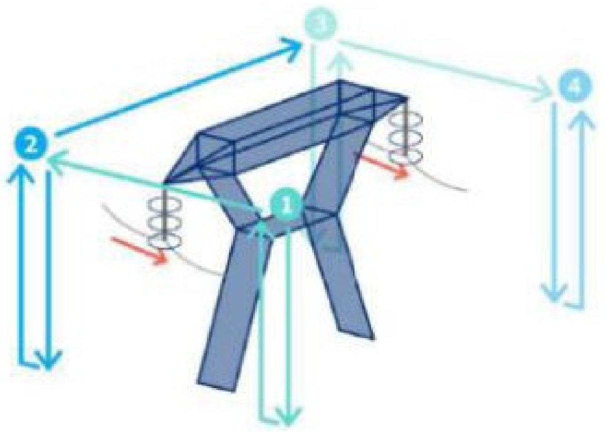

Figure 4. The predetermined routes of drones for the detection of overhead line components.

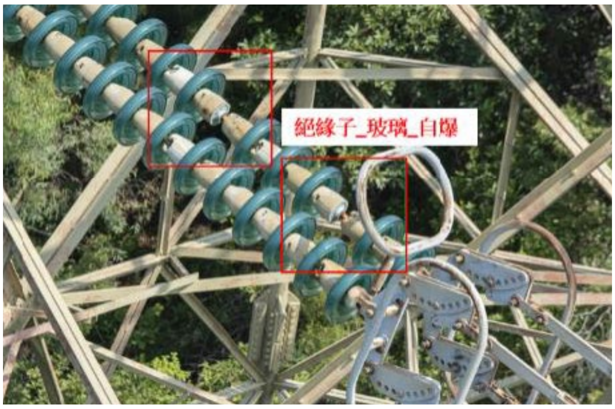

Figure 5. Damaged insulators detected using AI technology.

3.2. Substation Security through AI-based Intrusion Detection

Substations are critical nodes within power grids, requiring robust physical security. AI-driven video analytics systems implement sophisticated security measures such as motion guard and fence guard detection functions. Deep learning models, including Region Proposal Networks (RPNs), object detection networks, and YOLO, effectively differentiate between authorised personnel, wild animals, and unauthorised intruders, as illustrated in Figure 6. When an intrusion is detected, immediate alarms are sent to security personnel, enabling a swift response and the enhancing of substation security, substantially reducing the risks associated with unauthorised access, vandalism, and sabotage.

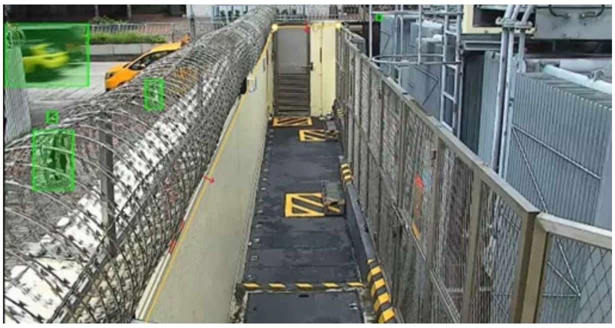

Figure 6. Security's fence guard intrusion alarm for power substations.

3.3. Worksite Activity Monitoring

AI technology in Grid-V is also utilised to enforce the safety of worksite activities. The system proactively identifies unsafe behaviours or non-compliance acts, immediately notifying relevant project-in-charge personnel through automated alerts. This real-time monitoring capability significantly enhances workplace safety and compliance adherence.

Two specific tests have been conducted to validate the AI's efficiency at worksites:

1) Detection of Personal Protective Equipment (PPE) Compliance

A site test was conducted to monitor and detect PPE compliance at construction worksites. AI-powered video analytics successfully identified instances of compliance and non-compliance, allowing supervisors to take immediate corrective actions. The test concluded that advanced AI technology provided comprehensive and accurate detection of PPE usage, enabling proactive reminders and ensuring a safer work environment.

2) Worksite Fire Detection

Another AI system test involved the detection of fire hazards within a worksite. The AI system demonstrated effective real-time detection of fire incidents, promptly alerting site supervisors and emergency response teams. Figure 7 illustrates a successful detection scenario during the trial. Both PPE compliance and worksite fire detection tests achieved accuracy rates exceeding 85%, underscoring the reliability and effectiveness of AI-driven monitoring systems in enhancing worksite safety standards.

Figure 7. Successful detection of fire at a worksite during the trial.

4. Expansion and future directions

As Grid-V continues to evolve, future developments will focus on enhancing AI capabilities through advanced machine learning techniques, such as federated learning, reinforcement learning, and explainable AI (XAI), which will improve transparency, decision-making interpretability, and adaptive learning capabilities. These enhancements aim to further improve predictive analytics, anomaly detection accuracy, and adaptive responses to potential risks. Additionally, integration with emerging communication technologies such as 5G and IoT will enable more extensive real-time data capture and faster data processing capabilities. This integration will significantly bolster grid resilience and reliability, particularly against increasingly adverse and unpredictable weather conditions.

Through continued innovation and strategic technology integration, CLP Power aims to position Grid-V as a critical asset management system in modern grid management, ensuring enhanced grid reliability, security, and operational excellence for the future power grid.

5. Conclusion and way forward

The deployment of Grid-V leverages advanced AI technology to enhance the supervision of assets and workforce safety, which largely increases the working efficiency.

Grid-V has substantially elevated the resilience and operational efficiency of the power grid. Through its sophisticated real-time monitoring and AI capabilities, Grid-V has shown its capability in reducing downtime, optimising resource allocation, and enhancing the safety of worksite activities. CLP Power is committed to operational excellence and application of innovative technologies, which enable a more agile and responsive power network, ensuring a reliable power supply service. In the future, the AI capabilities of Grid-V will be further enhanced to bolster grid resilience and reliability, particularly against extreme weather events.

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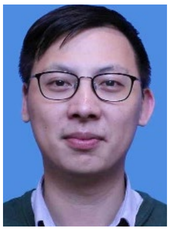
Notes on contributors

Mr Jason SC Au currently serves as Lead Engineer, providing strategic and technical oversight for Grid-V operations and enhancement initiatives. He spearheads the development and implementation of artificial intelligence algorithms aligned with CLP's business objectives and operational requirements. With extensive expertise in power systems, his experience spans the entire electricity supply chain, encompassing generation, transmission, and distribution networks. His comprehensive background includes managing engineering projects across transmission plants, cable systems, and overhead line infrastructure in both Hong Kong and Shenzhen. His expertise covers the complete project lifecycle, from initial design and construction through to commissioning, operations, and maintenance.

Mr Jeff KW Sun is currently the Manager - Security Systems of Security Branch of Technical Services Department, CLP Power Hong Kong Limited and is the core member of Video Analytics Tribe in CLP. The electronic security systems at various locations of CLP are under his management including the daily systems projects, operations and maintenance. He possesses in-depth experience in CCTV surveillance system and intelligent video analytics that it enables to strengthening the security protection of the assets of the company.

Mr Alvin CK Lit is currently the Principal Manager of Smartgrid Development at CLP Power Hong Kong Limited overseeing innovation and technology initiatives and smart grid development projects within power system business. Since joining the power industry in 2011, he has held diverse engineering roles in power system protection, corporate logistics and transport management and resources programming. He has played a key role in advancing smart grid initiatives, such as Gird Visualization (i.e., “Grid-V”) and Low Voltage Smart Grid. He received his Bachelor’s Degree and Master’s Degree in Electrical Engineering from The Hong Kong Polytechnic University.



Mr Mike KW Ng is currently the Principal Manager - Smartgrid Technology & Innovation at CLP Power, with extensive experience in protection systems, digital systems, construction, and smart grid applications. Key contributor in advancing smart grid initiatives, including the Intelligent Transmission Substation and Low Voltage Smart Grid projects.

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