UNLOCKING SUBSTATION VALUE:

TURNING INFRASTRUCTURE INTO DATA-RICH STRATEGIC ASSETS

Turning Infrastructure into Data-Rich Strategic Assets

GE VERNOVA

CONTENTS

ABSTRACT

Substation monitoring technologies enable continuous performance tracking and diagnostics of an aging electricity grid that is experiencing rapidly rising demand for reliable power. This white paper examines the technologies used to collect and analyze data to provide actionable insights into critical assets such as transformers, circuit breakers, and switchgear. It addresses key challenges and discusses the shift toward integrated digital solutions using AI and edge computing for fault prediction, early intervention, and root-cause analysis. At the heart is data fusion, which standardizes and correlates diverse sources to unlock predictive analytics. Utility professionals will find a practical roadmap toward more autonomous, reliable, and sustainable substations.

INTRODUCTION

Substations serve as essential centers in electrical grids, transforming, distributing, and controlling power to ensure a reliable energy supply. Growing grid complexity, declining reliability indicators, siloed visibility and decision-making, and unclear data governance have emerged as critical pain points at the substation level.

Substation monitoring involves deploying sensors, intelligent devices, and advanced analytics to continuously collect and analyze live data from key physical assets, including transformers, circuit breakers, gas-insulated switchgear, battery banks, disconnectors, and capacitor banks, typically found in utility substations. The collected data include time-series measurements (such as voltage, current, and temperature), event logs, thermal images, and diagnostic indicators, such as dissolved gas analysis (DGA) and partial discharge (PD). These monitoring systems use edge-based processing to deliver actionable insights, shifting responses from reactive to proactive interventions that extend asset life and enhance grid stability.

This paper identifies current customer challenges in substation operations and highlights data fusion as the key enabler for data-driven intelligence. It also presents a practical framework for converging, enhancing, and simplifying substation monitoring.

Figure 1. *The challenges utilities face when acquiring robust operational data and integrating it into their decision-making.*

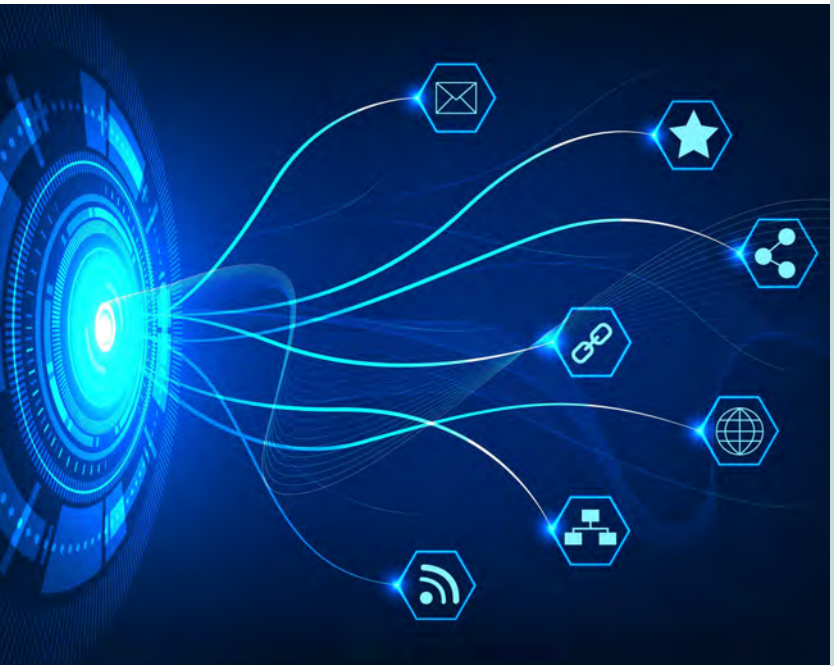
KEY UTILITY CHALLENGES

Substation operators, engineers, and maintenance planners at transmission and distribution utilities encounter numerous challenges that hinder effective asset management and grid reliability. The difficulties utilities face in enhancing their data collection and integration are diverse and extensive **(Figure 1)**. These problems are compounded by traditional operations and maintenance practices that rely on periodic manual inspections and reactive measures.

Many operational problems arise from organizational and structural barriers within utilities, such as data silos and fragmented systems. Data silos often align with departmental divisions such as protection and control engineering, SCADA operations, information technology (IT), cybersecurity, and asset management, each maintaining separate repositories and workflows. Regulatory restrictions and security policies further limit data sharing, with operational technology networks isolated from IT systems to reduce cyber risks. Bandwidth and storage limits at substations worsen this separation, as transmitting all raw sensor data to central locations is impractical, forcing utilities to rely on periodic polls or compressed data that reduce resolution and timeliness. Consequently, high-fidelity data—such as relay oscillography, fault records, or process bus streams—remains confined in isolated systems, blocking the potential for comprehensive analytics and proactive decision-making.

Further, data from sensors, monitoring devices, and intelligent electronic devices (IEDs) are often fragmented and stored separately across different vendors, formats, and platforms, making it difficult to get a complete view of substation performance. For example, measurements from DGA, PD detectors, thermal imaging, protection relays, and digital fault recorders are typically kept isolated, requiring time-consuming, error-prone, and hard-to-scale manual cross-referencing. This fragmentation often causes false alarms and misconfigurations.

Data heterogeneity is another issue in data fusion. Sensors and devices generate information in different formats, resolutions, sampling rates, and protocols, making it more difficult to standardize and align inputs for analysis. For example, time-series data from electrical measurements may differ in detail from thermal images or event logs, requiring advanced normalization techniques that many utilities lack.



Latency and synchronization issues further impede effective data fusion. Timing mismatches between sources—such as delays in sensor readings or asynchronous event capture—can cause inaccurate correlations, especially when milliseconds are crucial for fault detection. Data quality and missing information pose additional challenges, including sensor drift, communication failures, incomplete records, and varying resolutions that create noise or gaps in datasets. A related concern is computational scalability, as substations produce large amounts of data that must be processed without overloading edge computing resources.

Finally, cybersecurity and privacy concerns are essential, as integrating sensitive infrastructure data across systems must adhere to strict standards while also protecting against vulnerabilities caused by the integration.

Data fusion is essential for all these data-related challenges and is crucial to unlocking the full potential of substation monitoring. It involves combining and correlating multi-modal data from different sources to generate actionable insights. These challenges are not just technical; they have important implications for decision-making. Without addressing these issues, utilities cannot fully leverage AI for pattern recognition, failure prediction, or insights, leading to continued reactive maintenance and increased risk. Solving these problems requires integrated solutions that focus on data synchronization and analytics, as discussed next.

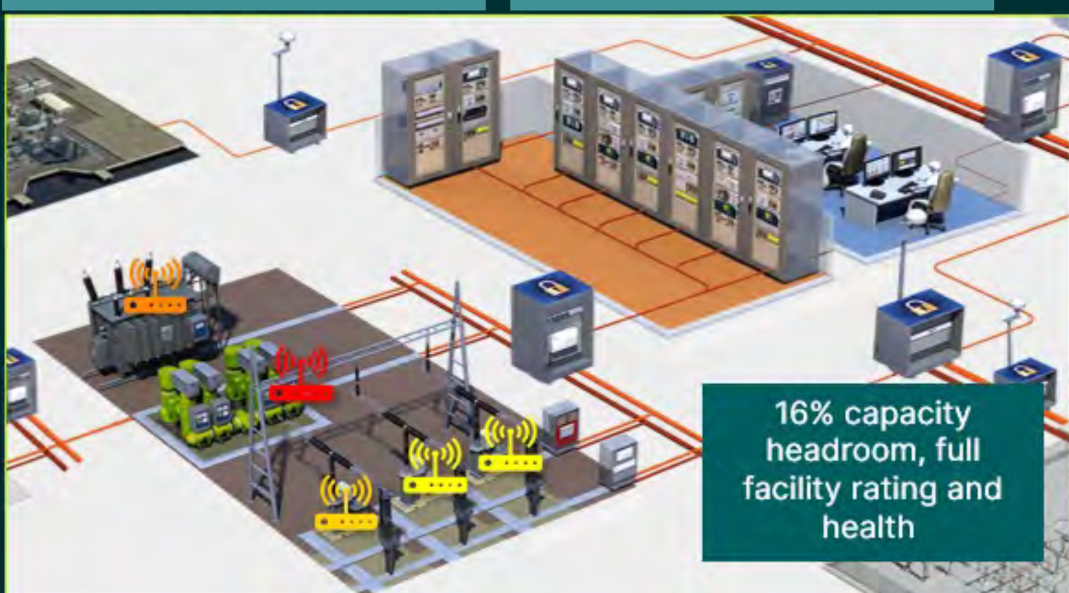
TRANSFORMING SUBSTATION MONITORING

Utilities must fundamentally update substation monitoring to solve the operational challenges mentioned earlier. This change requires a shift in mindset from traditional, reactive methods to advanced, proactive systems that leverage data collection and analysis. By integrating multiple sources and applying AI and ML, utilities can track performance and provide prescriptive diagnostics—detecting issues early and suggesting actions—ultimately improving asset performance and reliability **(Figure 2).**

DETECT | DIAGNOSE | DIRECT

Data & analytics that direct your next investment to the highest risk, highest impact issue

Right-size the solution to your challenges for different personas and the underlying technology



Sample Asset Legend:

- Repair now (RCA complete)
- Overloaded by 120% for 4 hours
- 36% BIL degradation
- Weak but stable

Figure 2. *The future of substation monitoring relies on actionable intelligence.*

Visible | **Predictable** | **Actionable**

The following sections describe the transition process.

Integrating Data Gathering

Current substation monitoring practices often rely on manual, isolated data collection, limiting the ability to obtain comprehensive insights. The prevailing asset management approach is characterized by time-based or event-driven maintenance schedules, periodic health assessments conducted every 1 to 2 years through manual, offline testing, reactive fault detection that only occurs after a failure or trip, fragmented data access across multiple disconnected systems, and decision-making driven by experts. These methods create inefficiencies because data from various sensors and devices remains separate, preventing a comprehensive view of asset performance **(Figure 3)**.

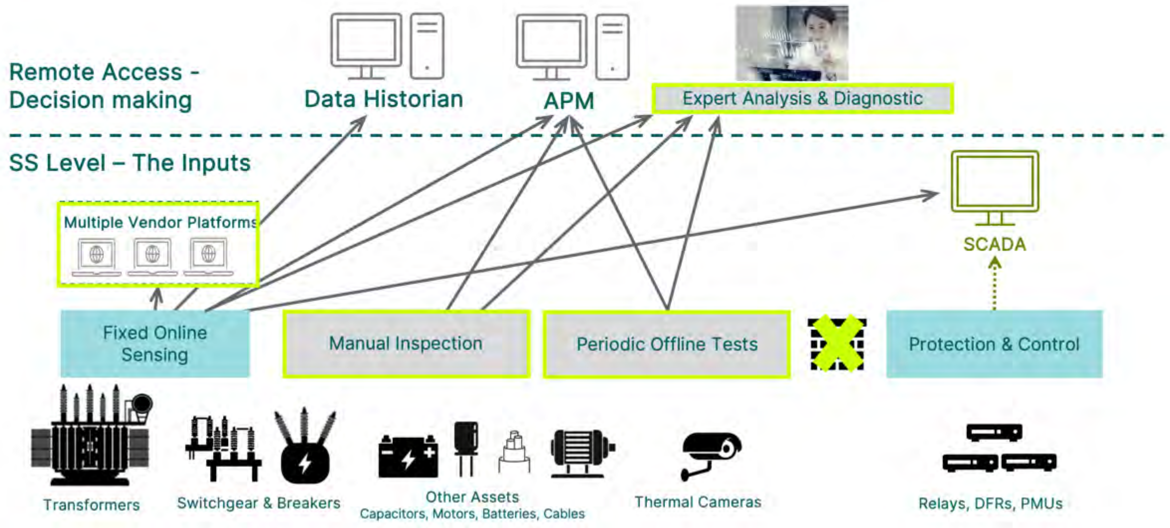


Figure 3. *Operations and maintenance decisions are currently inefficient and fragmented.*

In contrast, a digitalized model that focuses on continuous data monitoring can enable proactive interventions. This process includes ongoing health assessments, early warnings for potential issues, harmonized and reliable data integration, and data-driven decisions that lessen reliance on human expertise alone. To illustrate this shift, consider the following comparative framework **(Table 1).**

Furthermore, this integration model enables detailed utilization analysis, such as tracking breaker switching cycles and transformer load factors in real time, enabling prescriptive diagnostics to suggest capacity improvements and prevent under- or over-utilization.

This transformation depends on integrating digital tools that gather data from strategic assets into unified platforms. By improving data collection, utilities can remove blind spots, simplify workflows, and make better decisions based on current operational status and usage metrics. This digital approach allows for precise tracking of asset use, such as continuous load balancing in transformers or breaker operation cycles, giving operators diagnostics to optimize performance and prevent failures caused by overuse.

Table 1. Overview of Current and Future Asset Management Strategies in Substation Monitoring

Aspect	Current State	Future State
Maintenance	Time-based or event-driven	Prescriptive
Health Assessment	Every 1-2 years (manual, offline testing)	Continuous and real-time
Fault Detection	Reactive - After failure/trip	Proactive - Early warning
Data Access	Fragmented across multiple systems	Holistic, harmonized & more reliable
Decision Making	Expert driven	Data driven

Advancing Fault Prediction

Building on the integrated data foundation, this transformational process introduces advanced capabilities for fault prediction, early intervention, and root cause analysis. This evolution goes beyond basic monitoring to include predictive and prescriptive analytics. Key elements of the process include:

1. Early anomaly detection to catch subtle deviations before they escalate
2. Pattern recognition to identify recurring issues
3. Forecasting of asset degradation trajectories
4. Root cause analysis to pinpoint underlying failure mechanisms
5. Actionable recommendations to guide interventions

This development enables utilities to shift from condition-based maintenance to truly predictive approaches, allowing them to detect potential faults days or weeks earlier. For example, analyzing multimodal data—such as electrical signatures, thermal profiles, and mechanical vibrations—helps identify precursors, such as rising gas levels in transformers caused by overloads, enabling timely load reductions to prevent trips. These capabilities rely on standardized, synchronized data streams that form the foundation for AI algorithms to generate prescriptive insights, such as prioritized maintenance actions or operational adjustments.

Overcoming Data Fusion Challenges

The success of this transformation greatly relies on addressing data fusion challenges. As discussed earlier, the primary barriers include data heterogeneity, latency and synchronization issues, data quality problems, scalability, and cybersecurity concerns. By addressing these issues, utilities can unlock AI-driven correlations, extract meaningful insights, and deliver not only predictive failure warnings but also prescriptive analytics, including root-cause identification and recommended actions.

Leveraging Edge-Based Techniques

Edge-based AI methods implemented directly at the substation level support these advancements. These approaches process local sensor data in real time, offering low-latency insights without depending on centralized systems. Key strategies include:

- **Recurrent Neural Networks (RNNs)** are used for time-series forecasting and anomaly detection, such as predicting transformer temperatures from historical loads or identifying abnormal DGA ratios that indicate early faults.
- **Convolutional Neural Networks (CNNs)** for pattern recognition and classification, enabling the analysis of PD pulse patterns or infrared thermographic images to detect heat signatures indicating loose connections.
- **Hybrid CNN-RNN models** for spatiotemporal learning, capturing evolving dynamics in signals like PD waveforms that combine persistent and transient components.
- **Statistical and clustering methods**, such as k-means, for unsupervised anomaly detection in resource-constrained environments, grouping normal patterns across inputs, such as voltage sags or harmonic distortions.

These techniques operate independently at the edge for immediate diagnostics while sending insights back to fleet-wide models for improvement, ensuring consistent performance within power system safety limits. This edge-focused approach directly aids in fault prediction and prescriptive diagnostics by providing high-quality insights into asset operational status and use.

KEY USE CASES FOR SUBSTATION MONITORING

Substation monitoring offers practical solutions that use data collection for continuous performance tracking and prescriptive diagnostics.

The following subsections describe five main use cases, highlighting their functions, customer benefits, and contributions to enhancing safety, reliability, efficiency, and scalable automation.

USE CASE 1: Early Fault Detection and Outage Prevention

This use case emphasizes the ability to identify issues early before they lead to disruptions. By continuously analyzing sensor data, systems can detect abnormal operating conditions, insulation degradation, thermal hotspots, and signs of mechanical wear in components. Technologies such as DGA, PD detection, and thermography are vital for identifying failure indicators, enabling early interventions to prevent unexpected outages. By collecting real-time data, this method supports prescriptive diagnostics by suggesting immediate actions, such as load adjustments, thereby improving reliability and safety while reducing downtime and related costs **(Table 2)**.

Table 2. *Sub-Use Cases for Early Fault Detection and Outage Prevention*

Use Case	Customer Outcome	Technology Examples
Detect abnormal operating conditions	Prevent unplanned outages by alerting teams before protection relay trips	Multi-sensor anomaly detection
Identify insulation degradation or thermal hot spots	Schedule corrective actions prior to failure	DGA, PD, thermography
Detect signs of mechanical wear in circuit breakers or on-load tap changers	Avoid operational failures and reduce manual inspections	Vibration analysis, signature modeling

USE CASE 2: Root Cause Analysis and Event Interpretation

Effective root cause analysis transforms event data into diagnostic insights, helping teams quickly understand and resolve issues. This use case involves:

- Connecting data from multiple sensors to identify fault sources
- Categorizing event types
- Reconstructing event sequences
- Modeling the spread of failures
- Analyzing historical trends
- Assigning confidence scores to anomalies

These capabilities reduce investigation time after events and ensure solutions target the root causes rather than just the symptoms. By linking live data to prescriptive outcomes—such as data-driven recommendations—this use case enhances efficiency, reduces the risk of cascading failures, and supports scalable autonomy in asset management **(Table 3)**.

Table 3. Sub-Use Cases for Root Cause Analysis and Event Interpretation

Use Case	Customer Outcome
Correlate event data across multiple sensors	Pinpoint the actual fault driver
Fault-type classification to label the event	Apply the right remedy
Sequence-of-events reconstruction	Understand failure progression and reduce time on post-event analysis
Failure propagation modeling	Detect and forecast cascading effects on nearby assets
Historical trend-based insights	Stop emerging failure modes
Anomaly confidence score	Prioritize investigation efforts

USE CASE 3: Maintenance Prioritization and Planning

Transitioning from reactive to predictive maintenance requires tools that can forecast asset health and optimize resource allocation. By analyzing data on operational conditions—such as voltage fluctuations, temperature trends, and usage rates—these models provide specific recommendations that connect maintenance efforts to actual asset stress, improving overall substation performance.

This use case uses predictive degradation models to anticipate failures, especially for assets showing multiple symptoms, and provides estimates for upcoming maintenance costs, including labor, materials, and downtime. It supports a shift to condition-based and predictive maintenance strategies, helping prioritize critical assets and enhance budgeting accuracy **(Table 4)**.

Table 4. Sub-Use Cases for Maintenance Prioritization and Planning

Use Case	Customer Outcome
Predictive asset health degradation model	Move from condition-based to predictive maintenance
Prioritize assets with multi-symptom degradation	Focus on the most critical assets
Maintenance-cost forecasting to aggregate upcoming work into budgeted estimates	Improve budgeting accuracy

USE CASE 4: Avoidance of False Positives

Nuisance alarms can undermine the effectiveness of the monitoring system, leading to operator mistrust and resource waste. This use case addresses this by implementing multi-sensor agreement for confirmation, notifications based on abnormal conditions rather than static values, adaptive thresholds that account for seasonal changes, ambient conditions, or load profiles, historical pattern learning to distinguish genuine alerts from benign states, flagging sensor faults or degradation, and cross-validating readings across assets. This approach improves efficiency using prescriptive filtering based on real-time data, reducing false alerts and supporting safer, more reliable operations while decreasing operator fatigue **(Table 5)**.

Table 5. Strategies for Avoiding False Positives in Substation Monitoring

Use Case	Customer Outcome
Multi-sensor agreement or confirmation	Increase operator trust and reduce nuisance alarms
Notifications based on abnormal operating conditions, not static values	Avoid human errors in setting alarm levels and save configuration time
Adaptive thresholds for seasonal changes, ambience, or load profile	Maintain sensitivity without noise
Historical pattern learning to distinguish genuine event precursors from known acceptable conditions	Reduce nuisance alarms, improve alarm quality, and lower operator stress
Flag sensor faults or degradation	Avoid decisions based on bad data
Cross-validate sensor readings across assets	Improve reliability without needing perfect sensors

USE CASE 5: Operational Decision Support

Empowering operators with contextual guidance enhances response times and decision confidence. This use case offers confidence scores based on data quality and fusion, failure response and action guidance, and weather-related alerts that include forecasts. These components enable dynamic recommendations that lessen environmental impacts and accelerate interventions. Examples of applications include scenarios where high fault current combined with gas spikes, or on-load tap changer operations, produce a high confidence score (e.g., 0.9) for an internal fault, prompting load reduction. Conversely, weak correlations (e.g., score 0.35) lead to logging without alerts (Table 6).

In summary, these use cases demonstrate how substation monitoring yields insights that enable prescriptive diagnostics, creating a proactive ecosystem that prioritizes safety, enhances efficiency, and adapts to changing demands. Building on these use cases, the enabling role of data fusion becomes evident, as discussed in the next section.

Table 6. Sub-Use Cases for Operational Decision Support

Use Case	Customer Outcome
Provide operators with a confidence score	Empower action without needing subject matter expert consultation
Failure response and action guidance	Accelerate response and increase confidence
Weather operation alerts, including forecasts	Mitigate storm and heat-stress impacts

DATA FUSION IS THE CATALYST

Data fusion is essential for enhancing substation monitoring by integrating various data sources to produce valuable insights, as noted earlier. By addressing the challenges of multi-modal data, this process enables AI to connect data, generate insights, predict failures, and provide prescriptive analytics. Without effective data fusion, the full potential of performance monitoring and diagnostics cannot be realized, as raw sensor and device data cannot be translated into clear, decision-ready outputs.

Positioning Data Fusion as the Priority

At the core of substation monitoring lies the challenge of data fusion. This process involves integrating various data streams—such as time-series measurements, thermal images, partial discharge patterns, event logs, and structured diagnostics—into a single, time-aligned format that is easy to analyze.

Overcoming these challenges enables the use of advanced analytics, which in turn reveals hidden patterns and supports predictive and prescriptive insights. Solutions focus on non-invasive, easy-to-implement technologies that can be used across multiple assets, including thermal and visual cameras for detecting heat anomalies and surface phenomena, acoustic sensors for identifying partial discharges or mechanical faults in components like tap changers and breakers, and ultraviolet cameras for capturing transient events such as sparks or arcs. These tools, suitable for both fixed setups and mobile platforms like drones or vehicles, enable periodic or event-driven data collection, thereby increasing the quantity and quality of input data.

Adopting a System-Wide Perspective

Effective data fusion goes beyond individual assets to deliver a complete, system-wide overview. This approach combines data from fixed sensors embedded in equipment, mobile sensors used for on-demand assessments, grid operational data, event logs from smart electronic devices, and weather or environmental inputs. By integrating these sources, virtual sensors—software-based indicators that infer asset conditions without needing additional hardware—can be created to provide comprehensive insights.

For instance, combining electrical signatures with thermal profiles and environmental data enables the detection of overload-induced stress on transformers, enabling prescriptive actions such as load redistribution to improve utilization and extend operational life. This integrated view shifts monitoring from individual asset checks to substation-level insights, promoting proactive measures that prevent cascading failures and improve overall performance.

Levels of Data Fusion

Data fusion operates through a layered system to systematically process and refine information. At the data level, raw inputs from various sources and types—such as DGA trends, loading profiles, temperatures, PD phase-resolved patterns, oscillography files, and event records—are combined and normalized. The feature level extracts and merges relevant attributes from processed data, linking them across assets, network conditions, and environmental factors to identify multi-domain trends.

Finally, the decision level combines insights from various streams to produce high-confidence outputs, such as aggregated health assessments from electrical, thermal, and chemical indicators. The supporting architecture includes:

- **Sensors and intelligent electronic devices at the base layer**
- **Data collection and processing layers for initial handling and alignment**
- **Fusion layers for advanced correlation**
- **Decision layers that provide recommendations**
- **Backed by strong cybersecurity measures to protect data integrity and access**

This architecture addresses key operational challenges, such as decision-making in isolated teams that require expertise from multiple disciplines, varied data characteristics that need normalization and alignment, and event correlation across assets and environmental conditions. Using AI-powered techniques, it enables continuous detection of abnormal patterns, predicts failures based on cross-domain trends, confirms alarms to reduce false positives, and provides comprehensive root-cause analysis.

Data Fusion Algorithms at the Substation Level

At the substation level, AI algorithms improve data fusion by enabling pattern recognition, failure prediction, alarm validation, and root cause analysis. These algorithms process fused data to detect anomalies from noise, forecast degradation using correlated signals, and confirm alerts through multi-sensor agreement. For example, they combine inputs to identify insulation failures or arcing events and provide actionable recommendations, such as maintenance scheduling or operational adjustments. Deployed at the edge, these algorithms provide low-latency responses, meeting the deterministic needs of power systems and supporting a feedback loop that enhances models over time.

In summary, data fusion acts as a crucial enabler, turning scattered data into a powerful tool for continuous performance monitoring and prescriptive diagnostics. By addressing its challenges and harnessing its architecture, utilities can build a resilient, sustainable substation ecosystem that meets the demands of modern grids.

CORE PRINCIPLES: CONVERGE, ENHANCE, SIMPLIFY

The primary goal of substation monitoring is to provide a practical, reliable, and easy-to-implement solution. This is accomplished by following three core principles—Converge, Enhance, and Simplify—that collectively enable continuous performance monitoring and prescriptive diagnostics through seamless data collection and intelligent analysis. These principles address the complexities of modern substations, ensuring utilities have full visibility into the status of assets and usage while minimizing operational workload.

Converge

Converge means combining multiple monitoring functions, data sources, and systems into one unified platform. Instead of using separate devices and interfaces for different assets, this solution integrates electrical, thermal, chemical, and mechanical data streams into a single system. This unified view eliminates the need for multiple vendor tools and dashboards, enabling operators and engineers to see a comprehensive picture of substation health from a single interface. Convergence directly supports continuous monitoring by enabling the collection of sensor data, event logs, and environmental data, thereby facilitating accurate prescriptive diagnostics, such as fault prediction and root-cause analysis.

Enhance

Enhance focuses on improving the monitoring system's capabilities through advanced analytics, improved data accuracy, and AI-driven insights. This includes adding predictive maintenance models, ML algorithms for anomaly detection, and higher-precision sensors that detect subtle signs of failures. Enhanced functionality enables earlier fault detection, more accurate root cause analysis, and dynamic recommendations that guide operational decisions—such as load adjustments or maintenance scheduling—before issues become serious. By continuously updating these insights with live data, the system offers prescriptive guidance that extends asset life, reduces unexpected outages, and bolsters overall grid resiliency and sustainability. This also aids regulatory compliance by generating auditable records of asset performance and contributes to sustainability objectives by reducing energy waste and minimizing environmental impact from failures.

Simplify

Simplification aims to reduce complexity across deployment, operation, and maintenance. This is accomplished through intuitive user interfaces, automated configuration steps, streamlined hardware setup, and minimized training needs. Simplified systems use fewer components, support non-invasive upgrades, and automate routine tasks such as alarm filtering and report creation. The result is faster adoption, lower maintenance costs, and less operator stress, allowing teams to focus on high-value activities instead of managing multiple tools. Simplification makes prescriptive diagnostics and continuous monitoring accessible even to non-expert users, making advanced features practical for everyday use.

When used together, these principles enable quicker, more intelligent decisions at the substation level by providing operators with clear, prioritized insights from harmonized continuous data.

Embracing Converge, Enhance, and Simplify supports the vision of transforming substations from passive assets into intelligent, autonomous systems that continuously ensure power availability with minimal human intervention. This framework lays the groundwork for future self-healing capabilities while maintaining appropriate human oversight. It also redefines the visibility of substations by improving reliability, efficiency and earlier detection of asset wear.

Example Scenario 1: Auto reclosing operation

TODAY	FUTURE STATE
Trip and reclose alarm	Fault, protection, breaker, transformer aligned and correlated automatically
Was this really a temporary fault?	Clear outcome: successful vs. failed reclosure
Manual reconstruction of event	Context visible to O&M teams
Truck roll "just in case"	Immediate confidence in system state
Repeated stress on asset goes unnoticed	Asset health tracked across operations & early warning of repeated faults

Example Scenario 2: Peak demand due to a heat wave

TODAY	FUTURE STATE
Nameplate & SCADA measurement	Real-time load, oil temperature, cooling system status, moisture, gases correlated automatically
Generic Alarm: Transformer overload 110%	Clear outcome: Carry overload for 4 hours safely, continue to monitor
Conservative operation (lost capacity) or blind risk	Informed decision
	Asset health tracked across operations & early warning of repeated faults

CONCLUSION

Substation monitoring provides a robust framework for ongoing performance tracking and prescriptive diagnostics by leveraging real-time data collection and analysis. It effectively addresses common customer challenges—such as data silos, limited visibility, inefficient diagnostics, and high maintenance costs—through a comprehensive approach that combines digital data gathering, fault prediction, early intervention, and edge-based AI to provide proactive insights.

Data fusion tackles heterogeneity, latency, and quality issues, enabling comprehensive analytics and predictive capabilities at the substation level. These methods provide insights into strategic assets such as transformers and switchgear, offering continuous visibility, confidence scores, and customized recommendations. This improves safety, reduces risks, extends asset lifespan, reduces inefficiencies, and supports scalable automation.

Utilities are encouraged to implement integrated solutions that focus on convergence, enhancement, and simplification. This approach will create resilient, efficient substations capable of supporting the demands of a growing energy ecosystem, ensuring continuous power supply and sustainable operations.

Learn More

Explore these concepts through **GE Vernova Grid Solutions** resources to inform your grid modernization strategies or **contact our experts for further insights.**

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