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Improving power grid reliability using sensor-less and AI-powered fault prediction system

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Abstract: *Digital substations, characterized by their utilization of standardized communication protocols and advanced sensing devices facilitate the seamless integration of data from various network elements. This paper presents a machine learning-based fault prediction method that leverages only anomalies in voltage and current data collected from digital protection system, eliminating the need for additional sensors in the electrical network. Utilizing readily available data enables transmission and distribution system operators (T/DSOs) to proactively predict and prevent incipient faults, thus enhancing the reliability of electricity supply and minimizing customer outages. The proposed method focuses on the development of a predictive model that can integrate seamlessly into existing infrastructure, using advanced algorithms to analyze patterns and anomalies in voltage and current readings. This allows for efficient fault localization, isolation, and supply restoration processes, significantly reducing fault duration without the financial and logistical burdens of installing new monitoring equipment. Through rigorous validation and testing, our model demonstrates the potential to transform traditional reactive maintenance strategies into a proactive fault management system thus avoiding long unplanned outages.*

1. Introduction

In the quest to meet the ever-growing demands for electrical reliability, transmission and distribution system operators (T/DSOs) face an array of challenges. These range from managing the complexities of the network to ensuring minimal downtime. In an electrified society, where both the economy and day-to-day life are heavily dependent on consistent power supply, the cost of electrical faults goes beyond immediate financial losses. It affects industrial productivity, consumer convenience, and the integrity of critical infrastructure. The paper addresses this pressing issue by harnessing the power of machine learning to predict faults within the network, significantly reducing both the frequency and impact of power outages.

As electrical systems expand and become more complex, the probability and potential impact of faults increase exponentially. A fault can cause not just a temporary loss of service, but also long-term damage to the infrastructure, leading to costly repairs and extended downtime. Conventional methods of addressing these faults often involve reactive strategies that kick into action post-incident. However, the novel approach we propose pivots towards preemptive fault management. By analyzing the wealth of data from routine operations, specifically the voltage and current fluctuations recorded by protection relays, we can predict faults before they occur.

Protection relays, a staple in electrical networks, are designed to detect overloads, short circuits, and other anomalies that can lead to faults. The disturbances they record are a mine of information that, until now, has been underutilized for predictive maintenance. Our methodology capitalizes on this data to provide a detailed analysis of the network's health. The fine-grained analysis of disturbances in specific network locations can reveal patterns indicative of imminent faults using the proposed AI-powered Fault Prediction System. This allows T/DSOs to take proactive measures such as rerouting power, adjusting loads, or conducting preemptive repairs. Such interventions can mitigate the consequences of faults or, in some cases, prevent them entirely.

Our machine learning-based approach does not add to the complexity or cost of the existing infrastructure. Instead, it enhances the utility of what is already in place. By applying feature engineering to the relay data, we identify the most predictive indicators of faults. These indicators are then used to train a long short-term memory (LSTM) based deep neural network that can forecast faults up to a week in advance with high accuracy. The LSTM model is chosen for its proficiency in recognizing patterns over time, making it particularly suited for time-series data like voltage and current measurements.

This transparency is not just about detecting faults; it's about understanding them. With explainable artificial intelligence (XAI), our model provides clear reasoning behind its predictions, giving T/DSOs the ability to not only act on these predictions but also understand the underlying causes of faults. This understanding is crucial for addressing systemic issues within the network and implementing long-term improvements.

Moreover, this system's integration with the existing infrastructure is seamless. It leverages the streams of data from protection relays, thus augmenting the network's inherent intelligence. This integration negates the need for additional sensors, which often come with high costs associated with their installation, maintenance, and the need to establish high-throughput data communication channels. By intelligently utilizing existing data streams, our method provides a cost-effective, scalable, and efficient solution to one of the most significant challenges faced by T/DSOs today.

The shift from a reactive to a predictive maintenance model represents a paradigm shift in power distribution management. It promises enhanced reliability, optimized operational costs, and a significant reduction in service interruptions. This paper details each component of the predictive model, from data collection to model training and implementation. It also discusses the broader implications of this shift for the future of power distribution networks. Through this proactive approach, we envision a future where electrical faults are an anomaly, deftly anticipated and handled before they can disrupt the flow of power to society.

2. Solution Architecture

2.1 What is an anomaly?

Anomalies are small and sudden deviations in voltage and current that is captured as snapshots, and they can be signatures that precede a fault. While benign in isolation, a series of such anomalies can signify a trend leading to equipment failure or system malfunction. In Figure 1, the anomalies are compared to a bumpy road that is still drivable. This means the protection relay has not reacted to the deviations and the system is up and running.

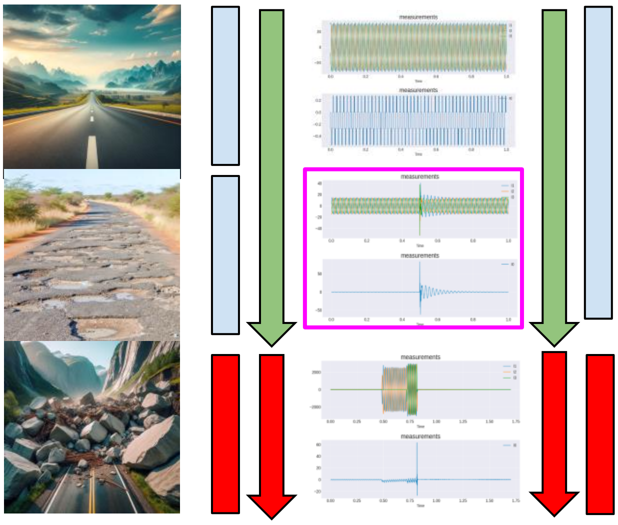


Figure 1. An anomaly, which is a transient in current and voltage together with the saturation of the transformer, is illustrated in the box and compared to the bumpy road.

2.2 How do we record anomalies?

Every relay uses a feature or a combination of features (pattern), and a rule-based classifier. A feature is typically frequency-domain transformation of time-domain measurement – current, voltage, frequency, power, impedance, harmonic content, high-frequency content, etc. A pattern is created through the combinatory logic blocks provided in numerical relays. A classifier typically has two-classes: Fault & No Fault.

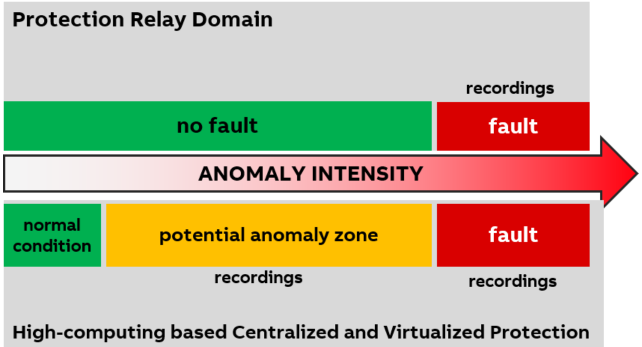


Figure 2. Comparison of traditional relay protection and advanced centralized protection, showing expanded capabilities for detecting anomalies before they become faults.

The classifier's segregation strategy involves a threshold value for individual features or a composite of threshold values for patterns. These values and combinations are established via system analytics, physics-based models, and accumulated expertise. In this context, expertise reflects the assimilation of knowledge by the human mind from historical data. However, in machine learning (ML) applications, learning occurs through algorithms crafted and honed by computer scientists. Research indicates that in scenarios employing extensive datasets, these algorithms exhibit superior data processing capabilities compared to human cognition.

2.3 Classification Types of Anomalies

Table I. IEC Standard-based Category Root Cause of anomalies

IEC standard-based category	**High level RC**	**Classification of high-level RC**	**Description**
	Faults	Sudden decreases in voltage level which may indicate a network issue.	
		High Impedance	High impedance faults that cause partial conduction.
		Low Impedance	Low impedance faults lead to a significant drop in resistance across a conductor.
		Short Circuits	Direct connection between two points of different potential leads to excessive current flow.
	Load Behavior	Variations in voltage due to changes in the load demand.	
		Motors	Issues related to electric motors that can cause dips, such as startup inrush currents.
		Other heavy loads	Issues related to other loads drawing a sudden power such as Electric Arc Furnace, or Batteries.
	Components of Transmission and distribution system	Transformers	Transformer-related faults that can lead to voltage instability.
	Others	Unknown causes are not explicitly categorized above.	
Voltage Swell	when voltage level exceeds more than certain threshold of the nominal voltage value		
Transients	Faults	Short duration over-voltage, which can be due to lightning strikes or equipment switching.	
		Intermittent EF	Intermittent ground faults that cause temporary voltage increases.
	Switching		Voltage variations due to the switching of electrical equipment.
Harmonics	Distortions in the normal waveform are generally caused by non-linear loads.		
Unbalance	Asymmetry in the three-phase voltages or currents, often due to uneven distribution of loads.		

Figure 3 to 5 illustrates examples of common anomalies that can be seen in the electric power system illustrated

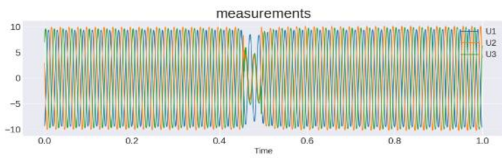
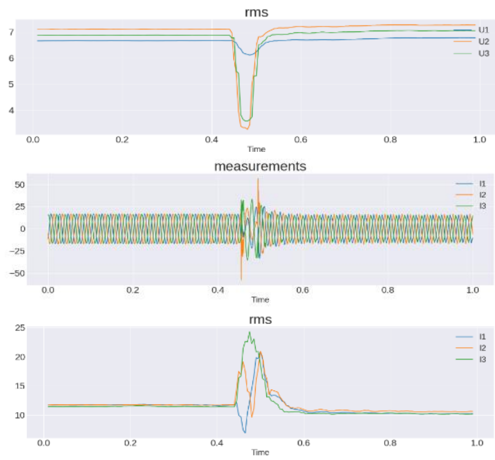


Figure 3. A voltage dip due to a short circuit occurring between phase two and three. A minor intermittent ground fault also has occurred because of this short circuit.



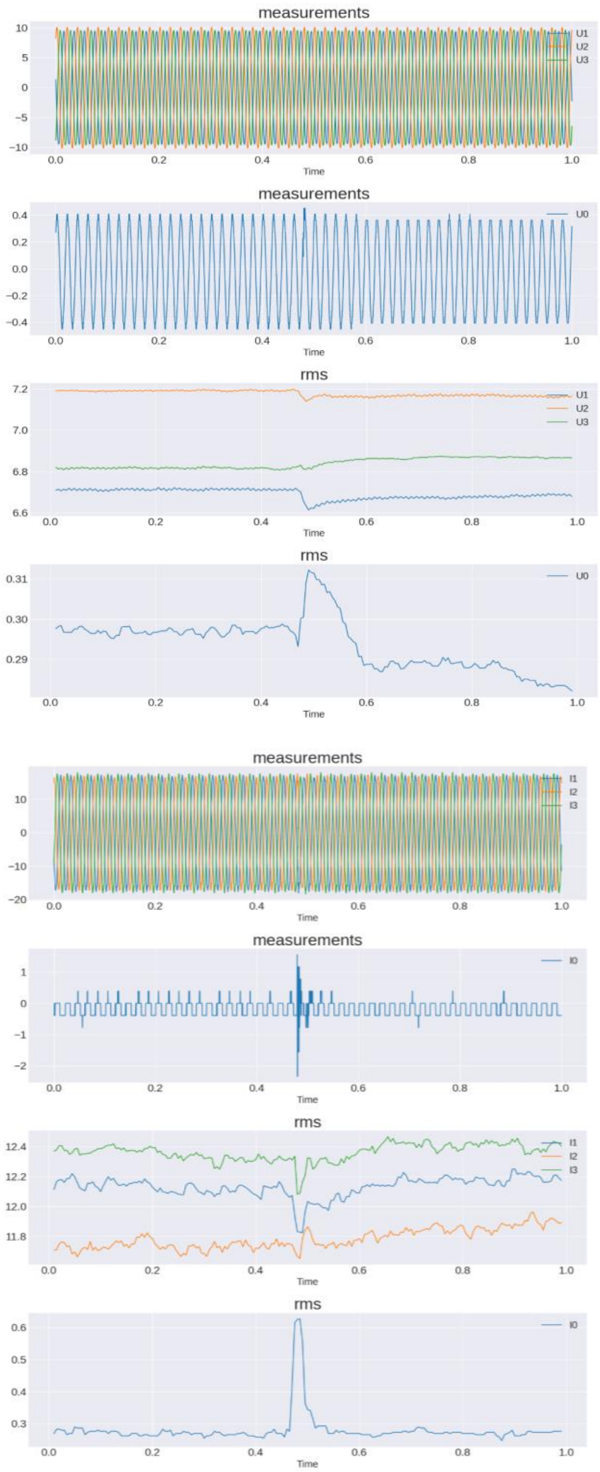


Figure 4. A transient that is categorized as an intermittent ground fault and a short spike can be seen in neutral voltage and current. The high-frequency nature of the transient has also caused saturation in the transformer.

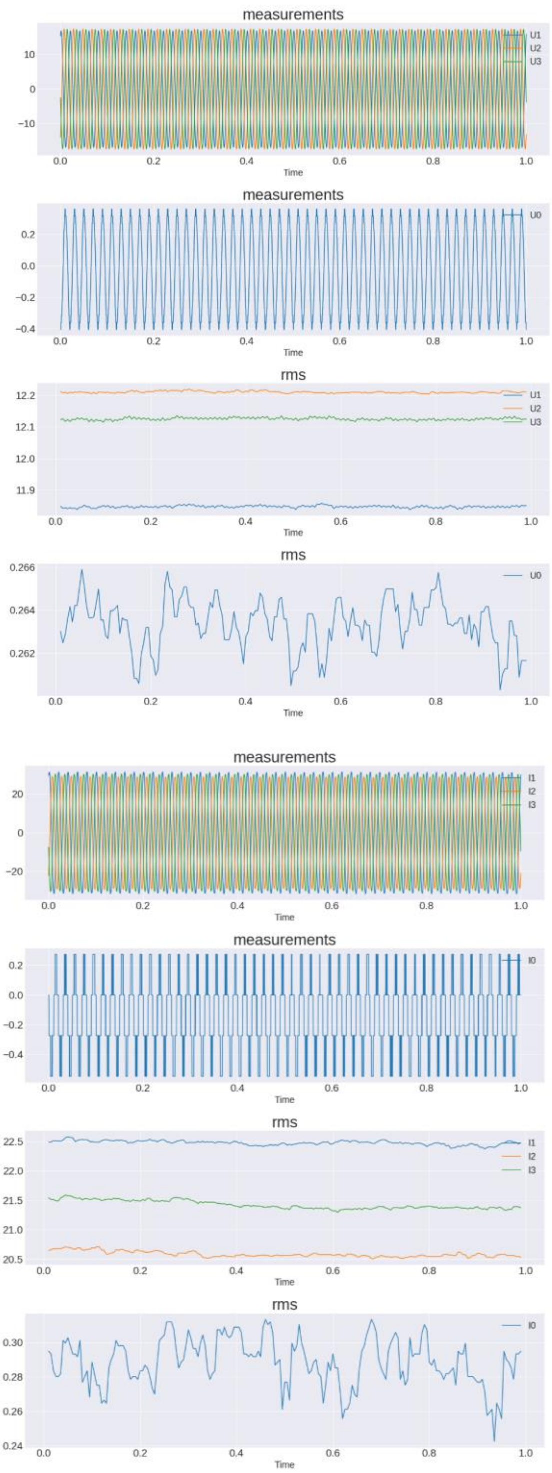


Figure 5. An example of an unbalanced anomaly that originates due to unbalanced load distribution on the low voltage side.

2.4 Smart Filtering of Anomalies with AI-Based Annotation

Within the proactive realm of the Sensor-less AI-based Fault Analysis and Prediction System, Smart Filtering emerges as a pivotal function, designed to sift through the myriad of electrical noise and identify the precursors to significant faults. This intelligent filtering is essential to the system's predictive prowess, allowing it to distinguish between commonplace fluctuations and those anomalies that herald potential failures.

Preventive Indicators: Unlike abrupt events that lead to immediate relay trips, anomalies are predictive in nature. They allow for a window of opportunity wherein preemptive measures can be taken to avert a full-scale fault.
Focal Points for AI Analysis: These minor disturbances are focal points for the system's AI analysis. Smart Filtering leverages these indicators to assess the health of the power grid and predict possible points of failure, giving operators a head start in maintenance and troubleshooting.

2.4.1 Enhanced Features of Smart Filtering

Discernment of Relevant Anomalies: The AI-driven core of the system is finely tuned to classify anomalies indicative of evolving faults. This will also help build correlations among the anomalies and create specific patterns for the evolved faults.
Intelligent Annotation: Beyond mere detection, the system automatically annotates anomalies. Each detected irregularity is analyzed and, with the aid of explainable AI, is associated with its probable root cause. This level of transparency is invaluable for operators seeking to understand the 'why' behind the 'what' of system alerts.
Context-Aware Analysis: The filtering mechanism is not static; it takes into account the operational context, considering variables such as load changes, traveling disturbances, maintenance schedules, and environmental conditions, ensuring that only pertinent anomalies are flagged.
Root Cause Attribution: By correlating anomalies with specific components and operational signatures, the system pinpoints potential root causes, thereby streamlining the troubleshooting process and aiding in faster resolution.
Continual Learning: The AI algorithms at the heart of the Smart Filtering process are self-improving. With each anomaly processed, whether relevant or not, the system refines its understanding, enhancing its predictive accuracy over time.
Operator-Centric Design: The system operates autonomously and is designed with operator insight in mind. Presenting a clear rationale for each filtered anomaly fosters a deeper comprehension and trust in the system's diagnostic capabilities.

2.4.2 Direction of Anomalies

Identification of Flow Direction: The system can determine whether anomalies are propagating downstream or upstream from the detection point. This directional insight is crucial, as it informs the maintenance teams about the possible origin of the disturbance and its path, which can significantly narrow down the search for potential faults.
Operational Impact Analysis: Understanding the direction of anomaly propagation helps assess their impact on the forgoing prediction for a specific fault. For example, downstream anomalies might affect end-users, while upstream anomalies could indicate issues closer to the generation source, bulk transmission systems, or components in substations.

2.4.3 Location of the Anomalies

Approximate Anomaly Localization: By analyzing the characteristics of the anomalies, such as their magnitude, frequency, and time of occurrence across different sections of the grid, the system can approximate the location of the potential anomaly. This allows for targeted inspections and interventions, thus reducing the time and resources spent on system-wide checks.
Geospatial Mapping: When integrated with geospatial data, the system can visually map the approximate anomaly locations, providing a clear and intuitive interface for field technicians to respond promptly and effectively.

3. Fault Prediction

What is a fault? Faults are incipient sudden deviations in voltage and current that originate from a short circuit among or between conductors and conductors to ground. This means the protection relay has reacted to the deviations and isolated the faulty area of the grid from power systems. An example of an incipient short circuit fault is shown in the figure below in the purple box, and our goal is to predict such faults weeks or days before they occur based on analyzing the anomalies.

3.2 Prediction of the Location and Root Cause of Faults

This table identifies specific fault types and their potential root causes, segmented by the location within the electrical system, such as substations, transformers, switchgear, and bays.

Substation Faults: include joint issues like cracks that can lead to insulation problems. These incorrect installations may result in connectivity issues and temperature-related faults due to excessive heat affecting substation equipment.

Transformer Faults: Listed under this are issues like bushing defects, which can cause dielectric breakdowns, core issues that may lead to magnetic imbalances, overheating problems associated with abnormal temperature rises, and tap changer faults, which can impact voltage regulation.

Switchgear Faults (SG): This includes jams, which can be due to mechanical failures or obstructions affecting the operation of the switchgear.

Faults on the Bays: These are faults identified in the distribution lines or bays, including the presence of foreign objects that can cause grounding or short circuits, irregular load behavior that can predict potential problems, and general wear and tear from long-term use that leads to degradation of insulations and components.

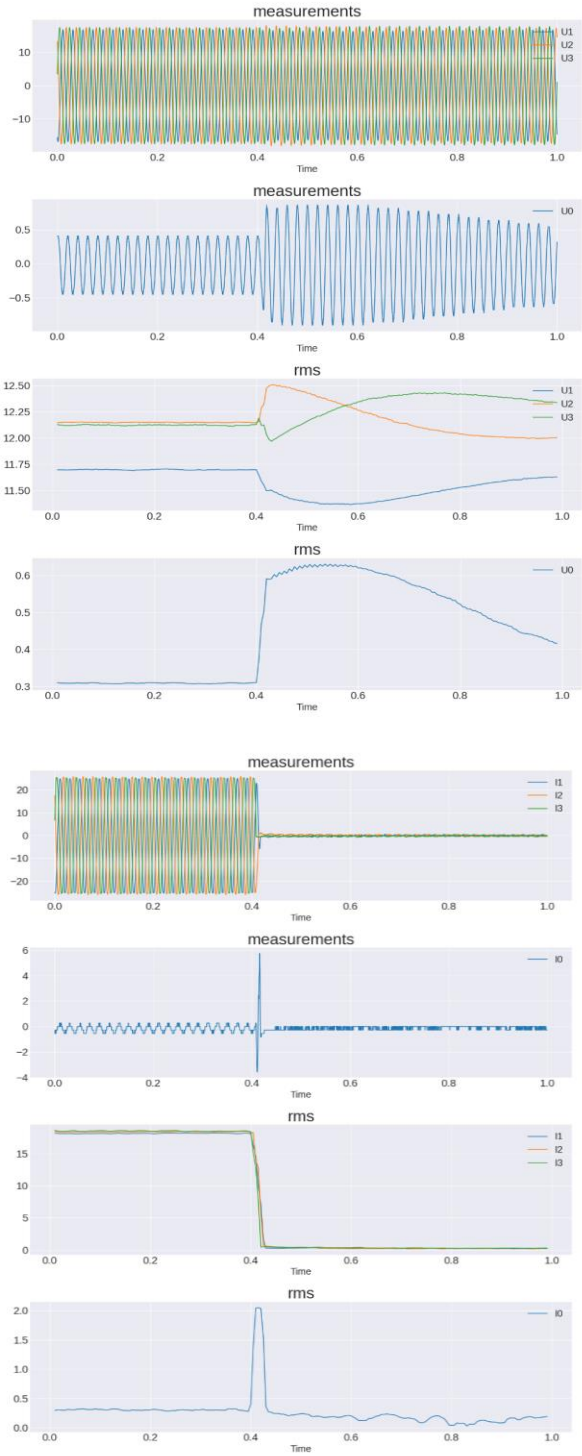


Figure 6. An example of voltage (top) and current (bottom) waveforms and RMS of an incipient fault caused by bird strikes.

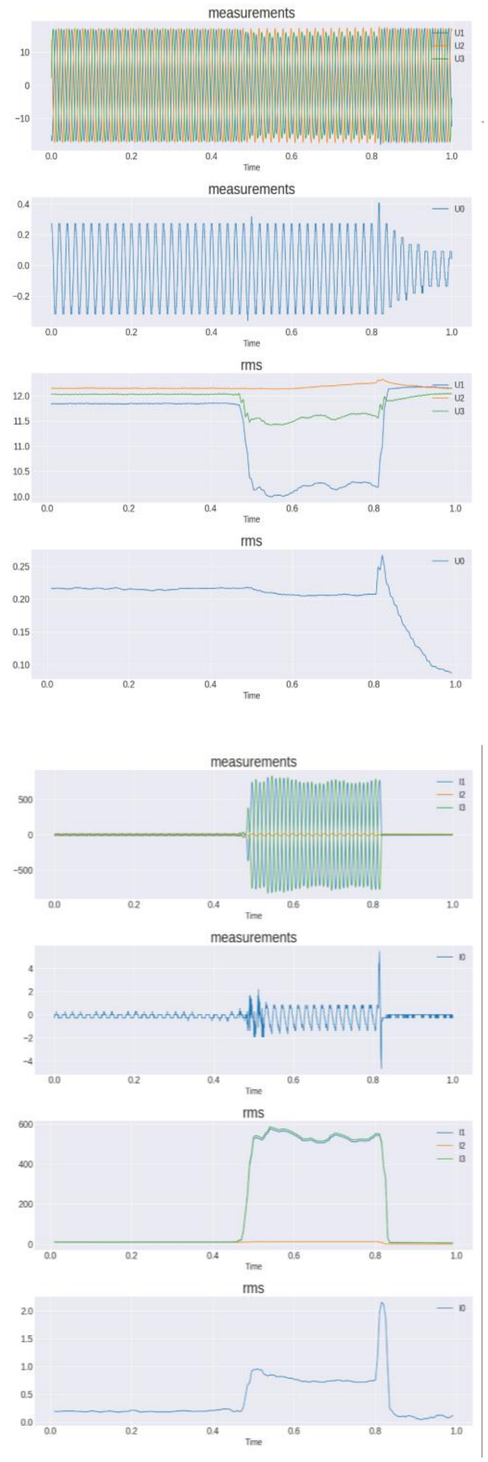


Figure 7. An example of voltage (top) and current (bottom) waveforms and RMS of an incipient high-impedance ground fault is caused by a foreign object (tree) on the line.

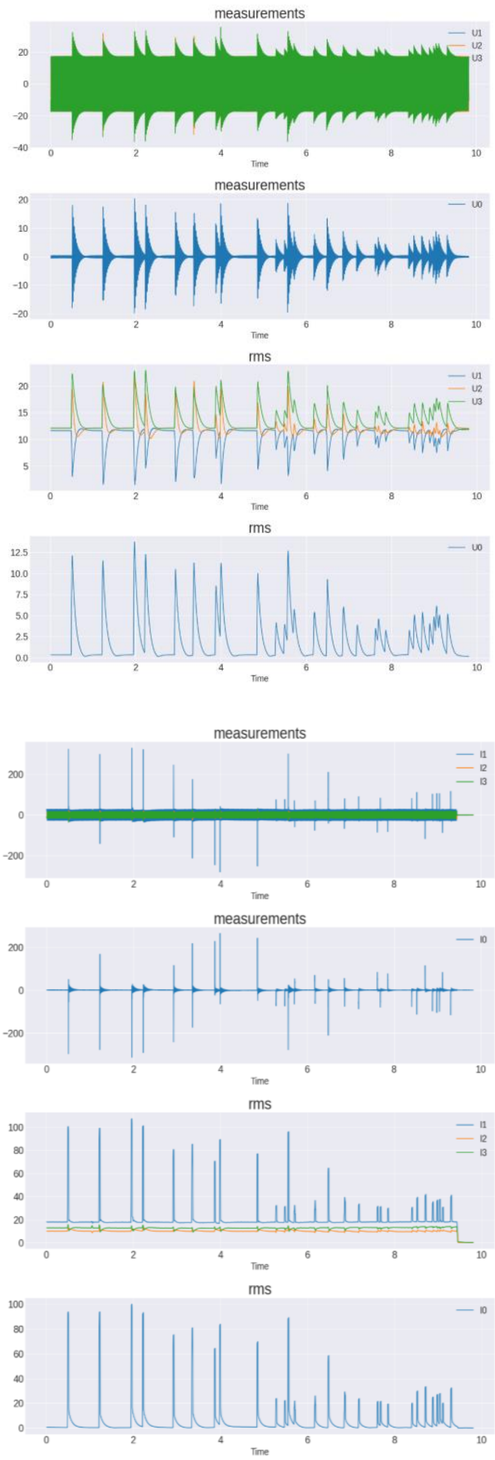


Figure 8. An example of voltage (top) and current (bottom) waveforms and RMS of incipient intermittent ground fault caused by failure of a tap changer damaged by thunder four days before.

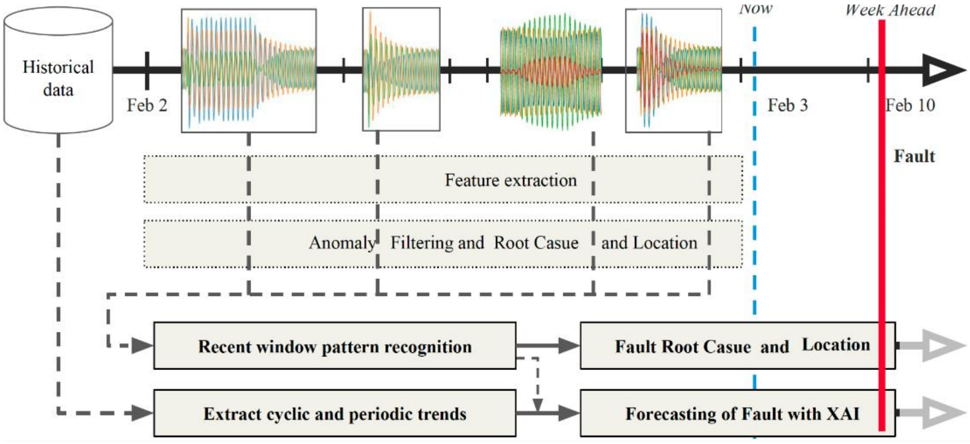


Figure 9. Overall Sketch of Anomaly filtering based on root cause and localization, as well as prediction of the faults, their location and root cause.

3.3 Advanced Fault Prediction Capabilities

The Sensor-less AI-based Fault Analysis and Prediction system brings a new dimension of foresight to substation management, harnessing the power of AI to anticipate faults before they manifest into outages or equipment damage.

Figure 9 illustrates the general overview of Anomaly Filtering by Determining Root Causes and Localization, as well as Forecasting Faults, Including Their Origins and Locations.

The main features and performance tiers of the proposed fault prediction system are summarized below.

Predictive Accuracy: The system stands out for its high predictive accuracy, with a minimum benchmark of 80%. This means the system can reliably forecast faults, allowing for:

Lower Evaluation/Factor 0.5: When accuracy is 60% or below, indicating a need for further data refinement.

Medium Evaluation/Factor 0.8: For 61 to 70% accuracy, demonstrating a solid predictive capability that can be trusted for planning maintenance.

High Evaluation/Factor 1: Achieving 70 to 80% accuracy, the system offers high reliability in its predictions, enabling more aggressive preventive measures.

Top Evaluation/Factor 2: Surpassing 80 to 95% accuracy, it provides exceptional predictive insights, allowing for strategic, data-driven asset management.

Proactive Anomaly Management:

By smartly filtering out irrelevant electrical disturbances, the system focuses on anomalies that are precursors to faults. It provides detailed annotations and explanations for each potential issue, fostering a deep understanding of underlying causes.

Comprehensive Component Monitoring:

The AI algorithms extend their predictive prowess across all substation components, from transformers and joints to individual circuit elements, ensuring a well-rounded protective measure against system failures.

Root Cause Analysis:

Utilizing a vast database of historical and real-time data, the system identifies patterns and signatures of equipment behavior, attributing anomalies to specific root causes for targeted maintenance and repair.

Direction and Location Identification

The system not only predicts faults but also determines the direction of their progression—whether downstream towards the consumers or upstream towards the generation. It also approximates the location of the fault within the substation, further aiding in swift rectification.

Implications of Prediction Accuracy:

Operational Decision-Making: The varying degrees of accuracy play a crucial role in operational decision-making, allowing utility operators to prioritize resources and responses based on the confidence level of the predictions.

Continuous Improvement: The system's AI algorithms are designed for constant learning, meaning that every fault prediction—accurate or not—feeds back into the model, perpetually enhancing its precision.

Risk Mitigation: With higher accuracy levels, the system mitigates risk by enabling preemptive actions to save substantial costs and prevent service interruptions.

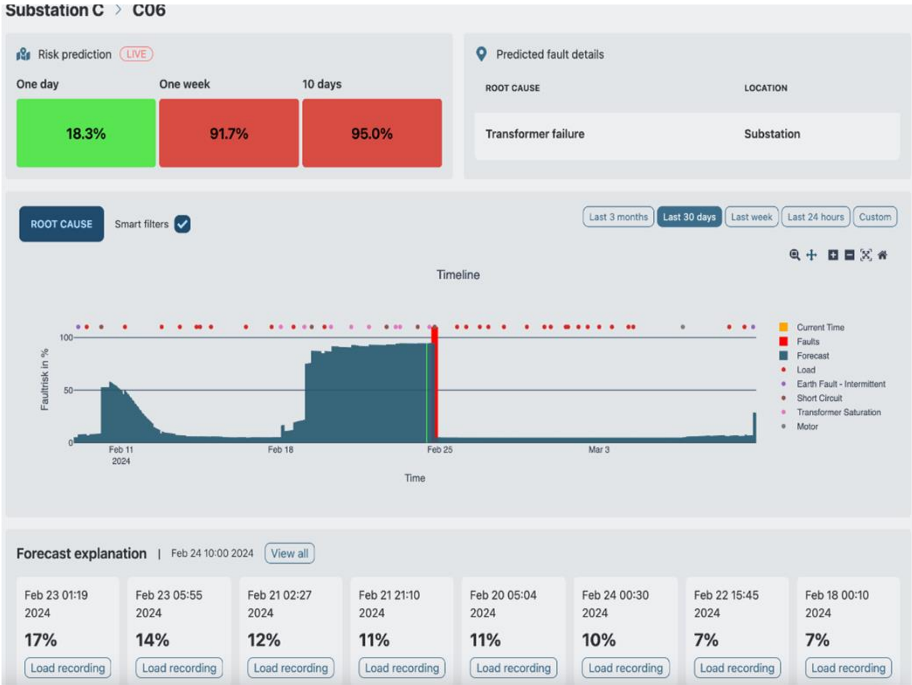


Figure 10. Illustration of a successfully predicted and localized incipient fault in the proposed system.

3.4 Necessity of XAI in Electrical Systems

Transparency: XAI provides clear insight into the AI's decision-making process. For electrical systems, engineers and system operators can understand the reasoning behind the alert when an AI tool flags a potential fault or anomaly.
Trust and Confidence: When operators understand why an AI system has made a particular prediction or classification, they are more likely to trust its reliability, leading to swifter and more confident decision-making during critical operations.
Continuous Improvement: By understanding the AI's decision-making criteria, developers can better refine and improve the AI models, leading to enhanced accuracy and reliability of the system.
Risk Mitigation: In an event where the AI's decision leads to a suboptimal outcome, XAI allows for a retrospective analysis to understand what went wrong, thereby facilitating corrective measures and risk mitigation.

3.4.1 Implementation of XAI in Fault Prediction and Anomaly Classification

Model Clarity: AI models must prioritize inherent clarity, akin to models like decision trees or linear models, where the reasoning behind decisions is transparent and readily accessible.

Significance of Influential Features: For the more nuanced models, applying techniques that spotlight the most impactful features driving a given prediction or classification is essential.

Detailed Interpretability: There should be provisions for clarifying each individual prediction, shedding light on the rationale behind the identification of specific anomalies or the anticipation of certain faults.

Comprehensive Model Understanding: XAI should offer a macroscopic view of the model's operational logic, enabling a deeper comprehension of its functioning in diverse scenarios beyond singular predictive events.

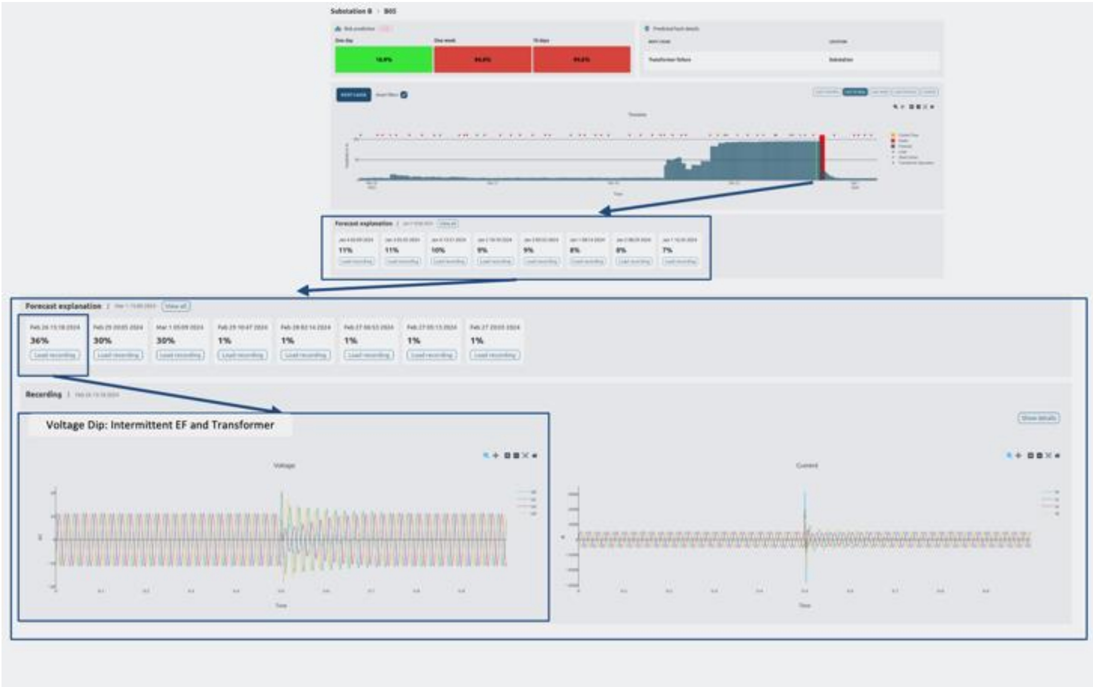


Figure 11. Example of the XAI module providing the reason for a high fault risk estimation based on 10 anomalies that are pre-indicators of evolving faults.

4. Implementation Options

The AI-powered fault prediction system offers flexible deployment options to accommodate the diverse needs of utility companies. These options ensure that utilities can implement the system in a way that best aligns with their existing infrastructure, security requirements, and operational preferences.

4.1 On-Premises Deployment

On-premises deployment is a popular choice for utilities that prioritize direct control over their data and systems. This option allows the AI-powered fault prediction system to be installed and operated within the utility's own infrastructure. It's particularly well-suited for companies operating in highly regulated environments or those with specific data sovereignty requirements.

One of the key advantages of on-premises deployment is the ability to customize the system to specific network configurations. This level of customization may be crucial for utilities with unique grid topologies or specialized equipment or operational needs.

Utilities with robust existing IT infrastructure imply in practice that on-premises deployment integrates seamlessly with their current systems. This can lead to smoother implementation and less disruption to ongoing operations. Furthermore, keeping data within the utility's own servers can simplify compliance with strict security policies and regulations.

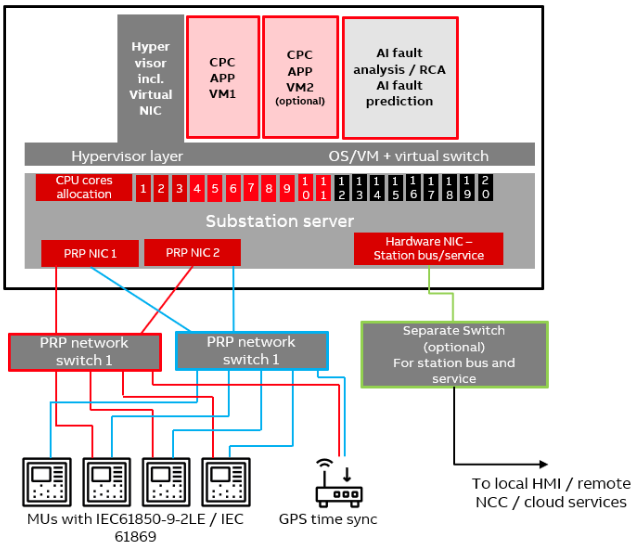


Figure 12. An example of on-premises deployment architecture.

4.2 Cloud-Based Deployment

While on-premises deployment offers certain advantages, cloud-based deployment presents its own set of benefits that may be suitable to some users. This option provides a highly scalable solution that can be accessed from anywhere, making it ideal for utilities with geographically dispersed operations or those looking to implement remote monitoring capabilities.

Cloud deployment typically requires less upfront investment in hardware infrastructure, as much of the computational heavy lifting is done off-site. This can be particularly advantageous for smaller utilities or those looking to minimize capital expenditures. Automatic updates and maintenance are often included with cloud solutions, reducing the burden on in-house IT teams.

A significant advantage of cloud-based deployment is the AI system's ability to continuously improve and stay updated. The cloud infrastructure allows the AI to learn from anonymized data across multiple utility networks globally, rapidly incorporating new insights and patterns into its predictive models. Simultaneously, the system adapts to each client's unique grid characteristics, creating a powerful combination of global knowledge and local specialization. This dual learning approach ensures that utilities benefit from the latest advancements in fault prediction while maintaining a tailored solution for their specific network. As a result, cloud-deployed systems often demonstrate faster improvement in prediction accuracy and can more quickly adapt to emerging grid challenges compared to isolated, on-premises solutions.

Regardless of the chosen deployment method, both options are designed with robust security measures to protect sensitive utility data. They can be tailored to integrate seamlessly with existing utility management systems, ensuring a smooth transition and minimal disruption to ongoing operations. Notably, most benefits of the cloud deployment option are applicable also for an on-prem deployment where connectivity for facilitating periodic updates is available.

4.3 Lessons Learned from Pilot Deployments

A recent 18-month pilot project with the Vaasa Distribution Company provided valuable insights into the real-world application of the proposed AI-based fault prediction system. This deployment has revealed significant benefits and key learnings of deploying the proposed AI-based system in practice.

The pilot deployment demonstrated potential for remarkable operational improvements. Due to the high sensitivity of the system, unplanned outages may be reduced by up to 30%, a testament to the system's ability to identify potential issues before they escalate into full-blown faults. This predictive capability enables maintenance teams to address problems proactively, often during scheduled downtime, minimizing service disruptions and enhancing overall grid reliability. The pilot project highlighted the potential for Distribution System Operators (DSOs) to lower their yearly Operations and Maintenance (O&M) costs by 15-25%, underscoring the significant economic impact of the technology.

The pilot project highlighted the crucial role of Explainable AI (XAI) in the system's success. By providing clear, interpretable reasons for its predictions, the AI fostered trust among utility operators and facilitated quicker adoption. Operators could validate the AI's insights against their expertise, leading to more confident decision-making and preventive actions. This transparency not only enhanced the system's effectiveness in preventing outages but also accelerated its acceptance among the workforce. The XAI component proved that in critical infrastructure management, the ability to understand and trust AI decisions is as important as the accuracy of those decisions.

One key learning was the importance of staff engagement and training. While the AI system provided valuable and transparent insights, the project underscored the need for a degree of training to help utility employees effectively interpret and act on these insights. This focus on human-AI collaboration proved crucial in maximizing the benefits of the technology.

These positive outcomes and lessons have been instrumental in refining the AI-based fault prediction system. As the technology continues to evolve, these real-world insights play a crucial role in shaping future iterations, ensuring that the system meets the practical needs of utility companies while maximizing the benefits of AI technology in grid management. The pilot project has set a strong foundation for wider adoption of this innovative approach to grid maintenance and reliability.

5. Conclusion

To conclude, the application of fault prediction with explainable AI (XAI), holds transformative potential for enhancing the resilience and efficiency of power transmission networks. By adeptly identifying, classifying, and predicting electrical anomalies and faults, these systems equip operators with crucial insights, enabling them to take preemptive measures. These actions are key to averting risks and ensuring a consistent electricity supply. XAI instills a level of transparency that builds confidence and reliability in the decision-making processes, bolstering the trust of stakeholders in the automated systems at play.
Furthermore, the evolution towards digital substations marks a pivotal advancement, fostering the development of adaptive, software-oriented protection and control mechanisms. Such systems, situated at the network's edge, are essential for the intelligent detection of irregularities and disturbances. When synergized with additional data streams—including geographic information, meteorological predictions, and load forecasts—these recordings become the cornerstone for sophisticated, autonomous network management systems.

In harnessing these combined technological innovations, we are paving the way for creating dynamic and resilient power transmission infrastructures. These infrastructures are designed to cope with current demands and are future-proofed to adapt to evolving energy requirements. The collaborative force of digital substations, intelligent data analytics, and XAI translates into a vision of a power transmission and distribution network that is as robust as it is agile and ready to face the challenges of tomorrow's energy landscape.

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7. Biographies

Dr. Ebrahim Balouji *holds dual Ph.D. from Chalmers University of Technology's electrical engineering department. He has developed high-sampling-rate PMU and AMUs in his PhDs according to IEC standards. He also developed AI-based applications for analyzing big data in power systems. In 2021, he received the Gunnar Engström honor reward from the ABB Foundation for his research. He is serial entrepreneur, co-founder, and CEO of Eneryield AB, which develops AI-driven software to predict the faults in power systems days and weeks ahead. In 2022, Dr. Balouji received the Outstanding Paper Award from the IEEE Transactions on Industry Applications Society.*

Dr. Karl Bäckström*, Ph.D., is a co-founder and CTO at Eneryield AB. Karl holds a Ph.D. in AI and Machine Learning Algorithms and Systems and has led several research and pilot projects with notable actors such as ABB, LKAB and DNV. Karl has received several awards for his work, including the Best Paper Honorable Mention at IPDPS 2021 and the prestigious SKAPA-prize. His work has resulted in several ventures internationally, as well as multiple patents and publications in the fields of electrical engineering, computer science, and medical technology.*

Viktor Olsson *is an engineer from Gothenburg with a background in Engineering Physics and Machine Learning from Chalmers University of Technology. He has previously worked at Volvo Cars, where he focused on self-driving car technology. For the past three years, Viktor has been with Eneryield, developing advanced machine learning methods for fault prediction.*

Fredrik Kjernald *is a dedicated Machine Learning Engineer working at Eneryield, where he has been for the past two* *years. With a background in Physics Engineering from Chalmers University of Technology and extensive experience as a consultant in the data science field, Fredrik is skilled in creating and deploying innovative machine learning solutions using Python. Passionate about problem-solving, he enjoys working in inclusive, collaborative environments and is adept at every stage of the machine learning process, from ideation to deployment.*

Petri Hovila *is currently working as a senior principal engineer in ABB Electrification, Distribution Solutions and is responsible for research programs. He has been working in various R&D positions over 25 years in protection and control domain. He has authored or co-authored several conference papers and is a co-inventor in several patent applications.*

Joe Xavier *currently serves as the Product Manager for ABB Electrification - ANSI Digital Substation and Flexitest Products with over three decades of experience in power system protection, automation, and control applications, He has authored, co-authored, and presented several technical papers on Protection, Automation, IEC 61850 applications and is an active member of IEEE PES – PSRC and PSCC committees. Additionally, Joe is a USNC designated member to IEC TC57-AG22.*