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Implementing Real-Time Edge AI for Anomaly Detection in Smart Grids: A Pilot Study on Power Distribution Networks

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***Abstract*:** In this pilot study, we aim to establish the changes needed to investigate whether edge AI can lead to real-time anomaly detection in the grid. In designing anomaly detection techniques, numerous other AI techniques such as artificial neural networks, among many others, have been investigated in previous works. However, only a few investigate their use for real-time anomaly detection in power systems. This pilot research looks into the possibility of developing a real-time anomaly detection methodology for smart grids. A part of this is casting the anomaly detection algorithm in a way it can be deployed on the edge. This section aims to review a literature survey that contains all the methods and algorithms used in the anomaly detection process. The section starts by addressing the need for the intervention of anomaly detection systems to mitigate the risk of attacks. Then the survey presents the well-established methods of anomaly detection. The last part of this section will review the previous attempt of moving anomaly detection to the edge of networks. In-depth details of each algorithm will be presented in the next section.

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Keywords: Anomaly Detection, A Pilot Study, Distribution Networks, Edge AI, Real-Time

1. Introduction

WITH the swift progression toward a digital electric power network, the electricity distribution segment is facing increased demand for localized solutions to drive operational efficiency, security, reliability, and economic viability. Edge computing technology can play a crucial role in processing in real time vast quantities of data gathered from the distribution network that are impractical to send to the centralized level, while preventing a huge amount of data from being stored in the communication network layer that is both a risk and costly. Additionally, real-time analytics performed on edge computing allow for immediate responses to instantaneous grid events and conditions. This paper focuses on real-time edge AI in anomaly detection within the electrical meter-sensing resources, as they present potential points of weakness to the smart grid network. Specifically, the paper discusses the potential utility and the innovative contribution of a pilot study of a sparsely populated rural network. Here, the main objectives are to explore the challenge, answer the questions, test our new solution, and evaluate its suitability for furthering smart grid technologies [1].

At present, electrical networks are monitored through an acquisition system that uses control outputs on SCADA, Remote Terminal Units, or Programmable Logic Controllers. In this architecture, data from the metering devices are used as secondary sources of monitoring and analysis. Traditional monitoring systems are facing several critical issues such as a lack of direct real-time acquisitions, data in standby or only recorded at regular time periods, and selected/averaged input/output at the final level. For this

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reason, many important events, even if recorded in a historical data logger, are just never properly identified. Even when they are, the information arrives after it has already happened. Consequently, this makes it difficult for engineers and managers to properly validate persistent issues. The paper's focus is to address the challenge of leveraging real-time edge AI to perform localized and immediate identification of emerging issues within residential and small business distribution networks. This paper discusses the performed literature review and introduces a novel approach which is presented in this section [2]. Following this, the section Problem Statement and Objective frames the main research issues. The final section is an outline of the paper. In summary, the contributions of this paper are the results of the pilot study, and we introduce a foundational concept. In the following sections, we will answer the question left open in the literature: which machine-learning-based techniques are better suited for anomaly detection powered by edge computing. Smart grids, also known as intelligent or adaptive power grids, are the next generation of traditional power grids that have been revolutionized by the integration of state-of-the-art technology. They not only offer power flow among resources within the grid, but also can gather and distribute real-time data which can assist the grid operators in comprehending grid behavior encompassing demand-supply dynamics [3]. The achievement of a power grid, however, entirely depends on the precise allocation of the needed energy to the required location. Additionally, small lazy allocation of adoption makes the grid more beneficial for customers. Thus, one of the primary objectives of power transmission and distribution is to make it as efficient as possible. In the smart grid framework, the flow of power from the grid to the end-users, i.e., the load in a fraction of time can reduce the physical damage to the assets of the power distributors [4].

Nowadays, energy demands fluctuate frequently depending on user satisfaction. This initiative demands that the power grid be saliently adaptive to shifts in demands. In several recent literature, it has been expressed that AI can be productively integrated for the management of the operations of smart grid systems by ensuring reliable, stable, and optimized responses to consumers at all times. However, AI is presumed by the existing power systems to enhance grid operations without much focus on data intensity, i.e., performing real-time big data analytics. From the studies of the literature, it is found that there is no big battery available right now to store the data and process that data in the grid and AI at the same time, where the volume of data is increasing rapidly, which impels us to investigate anomaly detection techniques in the upstream domain of data processing in the data network, i.e., on the edge. By assimilating AI with real-time big data analytics of the smart grid, it can offer countless improvements including the integration of more demand-side management resources. Hence, to accomplish the above-specified operation, an AI function known as 'anomaly detection' is to be integrated with the data with negligible implementation expenses. Furthermore, for the time commitment, this AI-integrated data can be regarded as more than conventional data solutions. A duo-integrated AI anomaly detection platform can facilitate the efficient operations of the power system and can ensure seamless solutions to fossil-fuel dependent utilities and prosumers [5]. The electricity grid is becoming smarter with various modern functionalities and advanced capabilities. Many previous works have addressed many details of smart grids. Power systems and the electric grid have unique characteristics that must be considered when designing anomaly detection methods. In designing anomaly detection techniques, environmental parameters and key performance indicators are unique nominal parameters that require particular attention. Consequently, the application of anomaly detection techniques for smart grids and power systems has been studied as well. However, only a few applications are designed to work in real-time due to edge computing [6]. The present paper aims to explore the possibility of implementing AI algorithms at the edge level for real-time anomaly detection in power grids. We propose a methodology for developing a real-time processing module by integrating AI and edge computation.

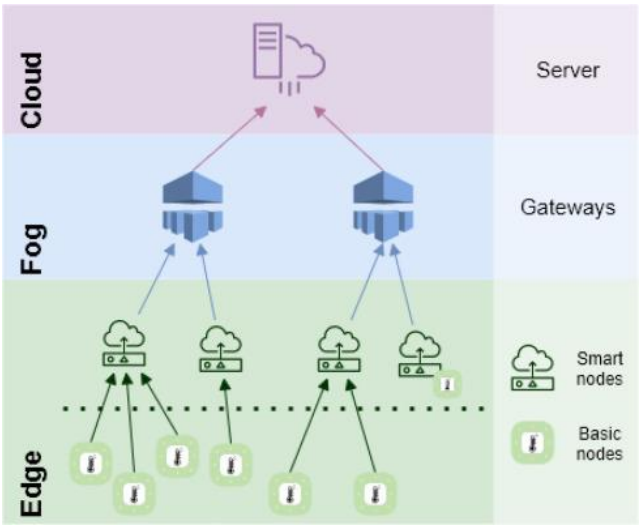

Figure 1. Edge computing architecture [6]

2. Smart Grids and Power Distribution Networks

A smart grid is seen not only as the next-generation distribution network, but also as a parallel effort to advance the evolution of power distribution networks and fully extend them into the digital age. It has local and global optimization algorithms and communication systems, such as supervisory control and data acquisition and an advanced metering infrastructure. Most importantly, it consists of a large number of high-resolution, fast-responding, and two-way instantaneous measurements to implement real-time analysis of the power systems and support power system applications. The application functions include distortion detection, low-voltage control, self-healing capabilities,

estimated state-of-the-art, and load diversion [7]. The increasing technological complexity of the power distribution network calls for a management system that is flexible, reliable, and capable of adapting to external environmental impacts such as cascading system failures due to environmental disturbances. Research has shown that the large-scale integration of distributed energy resources can impact the reliability and quality of electrical supply in the future, thus causing further instability to power systems. Motivations behind the transformation from traditional grids to smart grids are energy savings, reliability improvement, environmental benefits, and advances in information technology. Despite the well-documented benefits, no operational smart grid offers a proof of implementation. Functional deficiencies and communication problems prevent its implementation [8]. A valid real-time anomaly detection method is needed to address the challenges faced by the evolution of the power distribution network. The adoption of smart grids is most likely to hinder the transition from traditional to smart grids, otherwise possible.

3. Anomaly Detection in Smart Grids

An essential aspect of smart grids' digital evolution is timely and dependable multi-scale data-driven processing, communication, decision-making, and control. Vital to the survivability of modern electric power distribution systems are timely detection and quick response to an anomaly in any portion of this critical infrastructure, such as a substation or a pole-top secondary distribution transformer, that could propagate to cause widespread outages in critical transmission and distribution lines and circuits. Early anomaly detection can be based on sensory data, expert knowledge, or data-driven models learned to capture the physics of underlying non-anomalous behaviors. It is defined as a sudden and different type of irregular observation from the routine [9]. It can occur in various forms such as an abrupt change, a burst duration deviation, or an isolated anomalous sample or a sequence of them.

Under the name of "fault" or "disturbance," early research in anomalies considered abrupt changes as the primary concern in power distribution. Faults and disturbances are abrupt and large deviations of either prolonged or multi-scale duration. A number of machine learning and signal processing and time-series analysis techniques have been used to detect these fundamental anomalies. Some also detected sudden shifts of the mean due to step-like load changes called "transients" and "re-settling." While all these anomalies have been effectively detected, physiologically they are still false positives that do not result in any outages, although they could, if not detected, initiate cascading errors that could result in widespread multi-point outages. Faults, as catastrophic events, are less frequent than the "non-catastrophic" anomalies described in this research [10]. Anomalies not detected lower the smart grid reliability and customer satisfaction through prolonged outage duration. For instance, one-third of 169 initially determined states' abnormal end-of-day secondary feeders in the 1,206 3-phase radial secondary distribution circuits of the study, if detected, were cleared with mere customer-level overcurrent, and undetected led to an 80% two-hour long outage cascading to the upstream lateral in one such selected state/circuit.

4. Edge Computing and AI

Edge computing and artificial intelligence (AI) Emerging technologies in edge computing and artificial intelligence (AI) promise the incorporation of a wide array of functionalities in power and industrial systems. In the context of smart grid applications, edge computing is often viewed as a promising approach to streamline the development and deployment of AI tools. The features of edge computing offer reduced latency through processing closer to the data sources, thereby avoiding the congestion often seen in traditional cloud-based systems. The computational cost associated with data collection, transmission, and processing at the central locations is lowered. Edge AI technologies enable sound decision-making closer to the data sources and are capable of exploiting the most relevant information that is beneficial for improving asset management and energy management processes. The implementation of AI models on edge devices and within routers operating on a rolling window strategy provides a host of operational advantages, including savings on computational resources, communication bandwidth, and energy.

A spectrum of edge AI applications exists within the academic literature on broader sectors, such as smart cities, transportation, or manufacturing, including predictive maintenance, demand response, and power quality improvement. In the context of industrial systems, anomaly detection is a well-studied research area, although these algorithms often rely on pre-defined rules that might not be applicable to mission-critical infrastructure [12]. Recently, anomaly detection in power systems has drawn widespread attention as it situates in a broader context of leveraging advanced machine learning tools capable of processing massive data streams identified in the era of big data, machine learning, and computing.

With the introduction of Phasor Measurement Units and IoT devices, the behavioral pattern of large-scale systems, such as the transmission and distribution grids, has undergone a stark transformation over the last couple of years. There are substantial challenges associated with integrating edge computing and machine learning in the smart grid. To date, anomaly detection in these systems has primarily been conducted using traditional machine learning techniques. Given recent advancements in computing technologies and machine learning that can reduce the latency to detect and escalate abnormal behavior in the grid, there is a need to transform traditional anomaly detection underway for next-generation smart grids [13]. The

application of machine and deep learning to efficiently process the large amounts of time-series data generated from the power grid has been reported recently [14]. The landscape of power system data analysis has transformed over the last three years with the application of machine learning to diverse and unique application areas. Data-driven techniques have matured on par with physics-driven techniques for power system applications. The deployment of these sophisticated and robust models is yet to be demonstrated at the edge of the grid given the computational footprints. The design methodologies and limitations will be discussed in the following.

5. Research Objectives

The main goal of this pilot study is to propose and experiment with the development and implementation of Edge AI solutions for anomaly detection in smart grids. Our pilot research mainly focuses on assessing the capabilities for processing real-time data. Real-time data processing is one of several interconnected functionalities of a responsive system. In the context of electricity power systems, a power grid should quickly and adequately react, i.e., respond to different types of disturbances caused by, for example, environmental or IT-related problems. Such disturbances may have a temporary or durable character, but a response should capture the needs of a healthy electricity power system. The second objective of the proposed pilot study refers to verification concerning the efficiency of two different Edge AI non-standard statistical methodologies [15]. The evaluation procedure of the proposed methodologies will assume the comparison of the proposed results with the state-of-the-art solutions and will include a critical analysis of the obtained results in the context of the report's objectives. The initiative is part of the broader vision of enhancing the performance of an existing electricity power infrastructure whose efficiency still needs to be proven by theoretical and practical issue-oriented investigations [16].

The equipped list of pilot research objectives is the following: review available open software solutions for measuring and obtaining high, low, and mixed-rate experimental data for power distribution networks; propose and experiment with the development and implementation of AI solutions enriched in the cloud for anomaly detection in the academic power grid with a real-time data processing point of view; experiment with real-time anomaly detection of experimental data obtained from developed functional networks and compare it with the existing time-delay and time-advance solutions as a preliminary experiment; analyze the methodology capabilities for the resilient approach in electricity power systems. According to the presented plans for each sub-objective, many crucial perspectives for the contemporary smart grid have been identified, and therefore, the following three dependent research questions have been established: RQ1: What is the right instrumentation and software for making relevant measurements and data acquisition in high, low, and mixed rates from power distribution networks? RQ2: What is the right cloud solution for connecting real-time measurements in low and mixed rates to Edge AI for fast real-time anomaly detection of an academic power grid by using three real-time theoretical and implementation solutions? RQ3: Show what a real-bounded clean theoretical plant model can propose and why only from a critical perspective.

6. Methodology

In this section, we describe the comprehensive and systematic approach taken to explore real-time Edge AI applications using a smart grid. The methodology is designed to test the Edge AI solutions in real-time operational activities related to four distribution grid case studies. Recognizing this as a pilot study and being limited in the practical field force resources, the sites are carefully selected to provide diversity in terms of data availability and distribution grid administration, into four distinct case studies, generating valuable insights for Edge AI technology and its applications across distinct environments. Using a particular qualitative and quantitative research technique, this method can be replicated, thus enabling and assuring the validity of the results by aggregation.

Through data provided by the smart grid case study sites, we have employed sensors and IoT devices to gather grid data in near real-time at five-minute resolution. This has yielded a substantial 15 years of historical data that we have employed in our anomaly detection training datasets, providing valuable insight into grid operation. Further, a new prototype of self-contained smart-contracted LoRa-enabled IoT devices was tested for data gathering in zero-infrastructure locations. With this rich and robust dataset, we developed and employed a Python Jupyter notebook to preprocess the data, develop a supervised anomaly classifier, and test a number of unsupervised and semi-supervised approaches for real-time anomaly detection. Three levels of operational conditions were tested to generate a large test dataset employing these techniques. Furthermore, the prototypes of the Edge AI solutions were developed, tested, additionally on aggregated data, and further improved with feedback from the engineers. The methodology was designed to be executed with a participant information sheet and informed consent form. As this study required collective action, operational constraints and opportunity also guided this work. For example, a larger trial using willing stakeholders across the grid was preferred, but this could not be undertaken in 2020 given restrictions caused by the pandemic. When implemented in the field, the operational constraints and acceptance of energy network operators must be met to assess the cost impacts of any changes. We chose a representative time of the year, so the system was in balance and local transmission constraints were not severe. Of course, the approaches could be tested when transmission is tight or under exporting constraints or any other operational scenario which could lead to an adverse

effect in the LV network. It should also be noted that the study's deployment of digital tools in a vital, essential service such as electricity could have implications or lessons for digital and dataset resilience in the high-priority sector, should there be a large network or communications-related incident in which this study can inform.

7. Data Collection and Preprocessing

Collecting and preprocessing data to obtain appropriate inputs for anomaly detection models constitutes a cornerstone for the implementation of any AI-based anomaly detection model. Consequently, the elements taken into consideration when processing the data are especially relevant and have to be chosen according to specific requirements that seem clear, such as data availability, capacity, relevance, and accuracy. Based on that, the data was rigorously collected and systematically preprocessed in two steps: firstly, the raw data must be carefully examined and processed to ensure that it can be inputted to the AI models; the second step is about feature extraction, an essential value-added step to transform the raw data into an anomaly detection-friendly format.

We use operational metrics and environmental factors that can affect multiple aspects of power distribution to detect anomalies. The operational metrics in the distribution have been depicted in the previous section. The operation usually takes into account voltage static control, power flow balance, and the health of the top power lines with carefully planned maintenance regularly. Indeed, the operations are not exceptionally fast compared to the end devices to be protected and monitored, yet this can create an important insight into the phenomena occurring in the case of loud bureaucracy. Nevertheless, maintenance is not always carried out on time, and items to be replaced are not always discovered. On the other hand, the end-user behavior and requirements have to be satisfied in real-time. This would become more complicated with the connection of new decentralized energy into the grid. The information we analyzed that affects the transformer operation includes transformer loading, the core and oil temperature, the water content in the transformer insulation oil, and the cooling trends, all the distribution information.

The power consumption data is available at a one-minute resolution, and it was directly collected after the initial manual data cleaning process. We used raw consumption data to perform analyses on how to segment the energy consumption as part of the sensitive building energy management system we are designing and implementing. This raw data collection is essential to perform the consumption pattern analyses. We preprocessed the data for consumption pattern analysis tasks, including data cleaning using some cross-quality checks, anomaly detection, and data frequency harmonization, normalization, or aggregation. Many challenges have been faced while collecting and preprocessing the time series data used in this study. Anomaly detection inherently suffers from a sparse dataset issue, as we typically have significantly fewer measurements showing when a system is anomalous compared to when it is not. Other challenges, such as missing data and data drift between training and test samples, also have to be considered. This data preprocessing phase is very crucial for the anomaly detection model performance. Any model might overfit due to redundant patterns in the aggregate output of the two layers.

8. Feature Extraction

Feature extraction is a crucial task that helps identify the most relevant attributes to be fed into the edge AI model for accurate prediction and to reduce computational cost. Accurate representation of data using fewer attributes is expected to enhance model accuracy compared to when all data is used, resulting in a model that is more representative of relevant global features and less sensitive to small local details. Moreover, the computational load will be reduced significantly. Different techniques are proposed for feature extraction, including statistical analysis-based feature extraction, domain-specific feature extraction, artificial intelligence-based feature extraction, and hybrid techniques based on feature extraction. The features extracted from the data are employed to exhibit the influence of essential attributes on pattern recognition by the edge AI model to enhance the system's response in detecting anomalies and isolating them from the majority of usual events.

In this research, we consider statistical analysis-based feature extraction and domain-specific feature extraction techniques. The statistical analysis-based technique is generally employed for preliminary analysis while dramatically presenting the dominant features in fault and no-fault cases. One such technique useful for statistical analysis of datasets is the Principal Component Analysis method, which allows for determining the dominant components of the edge domain. Additionally, various domain-specific techniques can be employed for feature extraction if expert knowledge of the domain is available. It will find the most relevant features in the dataset to be included in the edge AI model. Consequently, the extracted features are representative of the response for each class, making the anomaly detection task easier. The model can forecast an anomalous case as soon as an atypical feature is observed. Real-world case studies are available for each of the feature selection methods. Additionally, the importance of expert knowledge in guiding the feature selection/extraction process is highlighted in the use of textual descriptions of the available sequence of measurements. To better cooperate with energy-domain specialists, the definition of anomalies has been updated. Shortcomings encountered during feature extraction are addressed through domain-specific knowledge and experience in problem-solving.

9. Edge AI Model Development

The well-established edge AI model development process is discussed in detail below. First, the selected mathematical algorithms and their suitability for real-time data processing in edge computing are detailed. Subsequently, the model architecture and types of algorithms used in the development of AI models are outlined. Furthermore, the training methodology relevant for each algorithm used in the scalable model development to suit the processed raw signal types is discussed. The focus is on both supervised and unsupervised model learning methodologies. They were constructed using a highly dependent training framework based on structured offline learning and testing methodology. A sophisticated filtering scheme in models was implemented in unsupervised models to avoid overfitting due to consistent patterns in training datasets. The developed models are discussed in progressive settlement inaccuracy dependent models and their performance in the hands of experts for setting region-dependent parameter models based on real-life analogue raw signals from power electricity [17].

The development of the AI models for real-time anomaly detection was designed in a way that it follows the progression of work developed in this context. The mathematical algorithms and data-driven techniques selected for the model development have been chosen to be suitable for real-time processing with minimal to no delay in a highly computational manner [18]. The model uses two types of algorithms that represent both learning models and pattern matching algorithms to cover real-time requirements and system run-time maintenance scenarios where data patterns change from initially trained and real data as well. LSTM, able to learn dependencies between successive vectors over time, was included in the model development; however, it showed overfitting to data in real-time anomaly detection. Thus, it was averted from model inclusion to avoid this issue. The candidate LSTM technique was then compared with a simple calculated approach, i.e., the Water-Filling Algorithm. LSTM overfits to detect aleatoric micro-trends and micro-outages while not generalizing for the patterns from regions and soft transitions of both changes in non-overlapping datasets. Hence, the WF algorithm as pattern matching is more trustworthy in the learning period than LSTM for the first layer and LSTMs in the case of region clustering than a pattern matching algorithm.

10. Real-Time Implementation

IT and Communication Infrastructure a description of the infrastructure required to get the model from the lab and into the field. This includes edge devices, networks, and communications infrastructure for a field deployment. Integration and UI Design the developed AI models need to integrate into existing systems. We have retrofitted the developed models to many communications protocols to suit operational deployment, and there are design constraints for this. Describe the interface, compatibility, and operational synergy of the developed model. When developing the model, particular attention was paid to operational and design requirements. From a national operator perspective, this involved developing interfaces that operational staff used frequently to visualize the model output and implementing a UI that field operators found intuitive and easy to understand. This involved an operational champion and learning and iteration in operational mock-ups to develop the best UI for the users in the control room. From an engineer's perspective, the user interface involved integrating into existing tools and taking model output data and finding the best way to use that data to generate control room operator awareness. Real-time data inputs, the environment, and sensor drift. While sensors are good, they are not perfect and have drift. In our application, the drift was slow and did not affect the performance of the model given the time components. The deployment in the field is a chance to involve users in an operational setting and learn how models are actually used and what is desired. The deployment in the field was also for the detection of issues in an operational control system and produced many messages to the effect of "this doesn't work in operational use." It doesn't play into the noise in operational use; there were redundancies in the data that are not seen in post-event analysis. System Performance Lessons learned from the performance of the system in real-time. The output from the neural networks is actually far from perfect on some feed-ins. It performs poorly on magnetic data compared to V-I data, not picking the ground resistances as well as it does on the transformer SPIs or the line and transformer V-I data. Learning from magnetic data as input, a lot of the limits in the operations of the model are actually due to no actual signal differences from healthy in the data. In our real-time trial in the demo, we showed that we can detect that our AI is going to transmit, but based on the signal produced, we could not be sure it would do a good detection – the signal has no real clear signal detection except on satellites. Further ground station real-time testing with a model tailored to ground-based data would be required to gain in-situ confidence.

11. Evaluation Metrics

Evaluation metrics serve the purpose of establishing criteria to ascertain how well a system or algorithm performs. Hence, the importance of choosing appropriate metrics for the evaluation. In our study, we conduct a comprehensive evaluation of six prominent anomaly detection Edge AI model architectures for the PDC problem in Smart Grids (SGs). We analyze the models' performance following different types of evaluation methodologies, applying multiple evaluation metrics and inference strategies. Some of the key performance indicators used in the study are: accuracy, precision, recall, F1 score, area under ROC curve, and Matthews's correlation coefficient. To evaluate the robustness of the models, we perform cross-

validation and test the models' performance on unseen instances. We further analyze the trade-offs between multiple performance metrics. A concentration is given to precision, recall, and their trade-off as they are important in the context of anomaly detection in SGs where false positives can be particularly costly to the normal operation continuity and security of the SG and ultimately to providing good quality of service to the end users. Finally, we compare our models' performance with those of comparable applications [19]. The experimental results show that no general superior model emerges under all the considered scenarios. This real experimental setting is beneficial and guides the project in the model selection for the PDC use case in the next stages of the project.

The evaluation of the model's performance is by no means an absolute assessment since it easily becomes an iterative procedure, assisting in the refinement of the model's design and evaluation. A general challenge is the need to realistically emulate real-world operating environments and conditions. An effective anomaly detection system directly supports an SG operator in pro-economic, continually optimal, secure, reliable, and sustainable operation and also minimizes the danger of a cascading failure in the SG. Erroneously identifying non-anomalous behavior may lead to the consequences of not reacting or reacting too late to an anomaly condition [20]. It can again compromise the integrity or the performance of an SG. On the other hand, classifying non-anomalous behavior as anomalous may result in additional or unnecessary operational intervention that is expensive and time-consuming. Also, flagging frequent erroneous alarms may lead the SG operator to simply disregard some real anomalous operating conditions.

12. Results and Discussion

This work contains the results of the ab initio implementation of several Edge AI models for different power distribution network datasets that were provided by a designated Distribution System Operator. Unlike traditional research papers that test model performance for several benchmark datasets, we took and evaluated the implementation of each model on one distribution network. As a consequence, we had to process suitable public datasets and conduct a comprehensive overview of the existing literature in the field of anomaly detection in smart grids at the beginning of the project. All models were tested independently on the premises of the oil refinery, located in a West European country. The z-predict broke these pre-deployed models into three scenarios, which led to 18 identification case studies. Thus far, there has been no public research reporting the results of a model evaluation from multiple power distribution networks in an independent testing environment. The goal of Section 14 is that this collection of evaluations can be valuable to researchers within the field in which models are respectively integrated. This repository has the potential to provide valuable insights for practical applications, including research and development, and smart grid operations.

Three datasets representing oil refinery distribution network operations were loaded into the BDEP tool. Any discrepancy regarding recording times or voltage levels between scenarios and respective measurements was removed from the time frame. In total, 25 successful recording hours consisting of 515, 108 valid measurements were extracted. The z-predict model was applied to create decision rules using RF as the Edge Learning model. The following measurements were discarded to ensure a reliable evaluation context: every measurement before the first anomaly flag detected by one of fourteen generative models at occurrence time T±ΔT. The scenarios were observed from the insertion time of the first anomaly flag. The definitions we used for AO, FA, TS, and LSB case occurrences from the z-predict model output were utilized to draw conclusions for Section (±). Statistical significances were calculated between anomaly and non-anomaly repetition by tracing these recording histories for the scenarios. Measurements are discretely ordered by hour. This arrangement allowed for statistical inquiry on the regularity of the measurements within the pilot study. These insights regarding the generative capabilities of the different models provide concrete findings on the possibilities in more granular studies. Additional remarks are offered with considerations to metric findings and characteristics of Edge AI in electric power systems.

13. Case Study: Pilot Study on Power Distribution Networks

In this case study, we report the findings of a pilot study on the real-time edge AI implementation of power distribution networks. The study represents a practical case for the evaluation of the application of edge AI techniques for real-time anomaly detection in smart grid power distribution networks. It demonstrates and quantifies the advantages of these models in the real-time monitoring of these networks. The power and current datasets reveal an interesting characteristic of the behavior of the selected smart grid. Descriptions of the evolution of current from one month to the next and of daily power consumption over one week are presented in the context of the evolution of current versus power. In addition, the detection of anomalies in power consumption and current using an edge AI model is demonstrated using insights from the techniques applied in the previous chapters. These findings are compared with insights gained when using the common approach in current monitoring solutions for anomalies in power or other scalar data. They are extended using edge AI techniques and compared with non-edge AI techniques for the edge AI and non-edge AI models and tools.

The pilot study of a feed-in and distribution grid in the UK that connects renewable generation sources to a major distribution grid is discussed. Testimonies of the smart grid's operator, representative, and commitment leaders are shared

for insights. A few lessons of wider interest on the transferability and scalability of these methods in the context of similar networks are shared in conclusion. The implementation of the model is technical, and heavy data handler problem solving and iteration are often needed. Techniques for reducing time and improving scalability are discussed.

14. Performance Evaluation

To evaluate the model performance, we have conducted model tests in terms of their accuracy at detecting and classifying anomalies. The designed labels have been effectively applied to extend the training and testing data in a cross-validated manner. We have used the confusion matrix to allow for a deeper understanding of the anomaly detection accuracy and its corresponding errors. The results are thus summarized in terms of precision, recall, F1-score, and overall accuracy. We can see from the results that the initial implementation of the model demonstrates relatively high performance across a range of data splits. Most notably, the overall accuracy did not exhibit significant variation across the data splits, thereby indicating the robustness of the developed model. With respect to the research objective, the edge AI models demonstrated a performance improvement of around 3% compared to the traditional method. An important shortcoming that we are facing with validating the results is the limited amount of real-world anomaly data available. A direct result of this is a low precision and low recall value from the deep learning models. Nevertheless, the classification threshold can easily be adjusted to favor precision over recall or vice versa, depending on the class imbalance and anomaly detection priorities. Another major observation, particularly from the CNN model testing, is that up to 50 to 60% of anomalies are being labeled as other types of anomalies, with a long outlier condition being labeled false by the model. As can be observed from the distribution of anomaly occurrences in the PDN segment, a general conclusion can be made: up to 60% of diseases in the grid can be detected and classified at a high accuracy level. However, further augmentation of the training data is needed, which would undoubtedly increase the ultimate accuracy of the models. Moreover, the overall combined model performance results revealed for each testing scenario are quite robust. Given the fact of a relatively long training period, experiments were focused solely on the included testing data for performance evaluation, so this model could directly recognize events after each of the grid-switching line configurations included in the PDN segment.

The test results discussed in the preceding section have relevance and implications that warrant further investigation, development, and analysis. Firstly, in terms of generalization, it is notable that networks that utilize temperature data do better at detecting anomalies of short and long duration, compared to networks trained on voltage and current, particularly in the case of the ML approaches using the grid data. The framework collapses the input data over time to reduce dimensionality in a way that retains even the longest duration anomalies. A potential avenue for future investigation would be experimentation with similar model architectures and with more convolutions and layers to utilize voltage and power over a longer time frame. Furthermore, the imbalanced nature of the dataset is characteristic of real power distribution networks, with disturbance events occurring far less often than nominal events. However, this lack of representation ultimately reduced the quantity of data used to test longer duration anomalies, which are hypothesized to be more representative of real-world failures and would provide a fairer comparison. A more balanced approach for future implementation will alleviate other issues including the associated amplification of the noise floor in the current model training data. With 12 months of maximum nominal data concurrent sensor data, baseline operational conditions can be distinguished with more accuracy akin to the occurrence of any disturbances. In future work, it is thus recommended that the model is trained and tested on balanced data with all features utilized.

15. Comparison with Traditional Methods

Real-time anomaly detection in smart grids using their high-resolution real-time operational data is crucial for supporting intelligent grid operation and management. Moreover, the growing computing power of intelligent electronic devices in modern power systems, which are located at the grid's edge, such as Phasor Measurement Units, micro-PMUs, and Smart Meters, makes it more practical to implement real-time data analysis for anomaly detection using intelligent machine learning and deep learning methods at the edge of the grid. This paper presents an approach for implementing Edge AI for real-time anomaly detection in smart grids. We have proposed and evaluated alternative Edge AI models for implementing real-time anomaly detection features at the edge of the grid. These models can provide accurate real-time results for PMU data with the highest possible resolution in a principled way. VII. Comparison with Traditional Methods: Real-time and near-real-time anomaly detection using high-resolution data rather than aggregated and coarser-grain data is a fundamental requirement for business-critical applications that require fast responses, including grid protection, control, and monitoring. The results discussed in this paper show that AI-based and deep learning-based models are more accurate and computationally efficient compared to the traditional methods for anomaly detection using PMU quality IQ data. Edge AI models are even more efficient in quickly detecting anomalies in the real-world deployment of our training methods, even at high noise levels and high dimensions of data in a time-effective manner.

16. Challenges and Limitations

This section presents and discusses the various challenges and limitations encountered during the pilot study. It begins by discussing the technical challenges encountered during the development of models, such as data quality, lack of correlation between sensor readings and fault types, and integration issues. These factors have been reported as impacting the accuracy of predictive models. The second part of this section outlines issues related to the real-time processing of data. Since anomaly detection should take place in real-time, a bottleneck in the data supply chain will cause a lag, and deviating from this might compromise the anomaly detection capabilities. A strategy for addressing this has been set up, but implementation remains pending. The third part of this section sets out some of the operational constraints experienced during the pilot study. As the models run in real time, it was not possible to do any debugging before or during runtime. As such, no logging was implemented as it would slow down model performance. This feature is a subject for future study. The final two elements of this section address limitations within the scope of the project. Although expected, the small sample size and the geographical location of the pilot district have implications for the generalizability of the research findings. Lastly, ethical considerations in the collection of data and the inclusion of private data are discussed to improve the operational stability of systems. In the previous sections, the results of the study have already been communicated. In this section, the challenges faced are listed in a bullet point format:

- Data was not available when systems were live; hence, an experimental setting with historical data is used for model development. Extensive historical data was not available, impeding the development of complex predictive models.
- Two power grids operate in the same distribution station to provide redundancy in case of disturbances. Longstanding, idle equipment exists in the system, making simple threshold-based processes and fault-fixing patterns unhelpful in the prediction of the simultaneous occurrence of two alternative paths being used.
- The redundancy systems are engineered to split the grid and reroute redundant energy around disturbances. Faults on both sides of the disconnected system are thus hidden from the other sections of the grid, and hence, anomaly detection cannot be performed on idle data from one side of the disconnected system.
- IT systems in power systems are typically segregated, and several data silos are not integrated. A cross-departmental initiative is therefore ongoing, involving all stakeholders and their corresponding IT resources in integrating data into the solution to allow for the building of models for multiple different dormant paths across multiple departmental silos.
- The pilot laboratory is implemented on poorly shielded cables, resulting in significant noise that impacts the sensor data and causes cascading alerts. The age and local environment may also influence the quality of sensors, resulting in flipping between faulty and operational states, which would impact the signal data, so alerts created on these false signals are under development.

Finally, several dashboard solutions were explored, and integration would have required a change in the district operational system or a new one. The long setup time for pilots and a data-sharing agreement have yet to be agreed upon. The impact of these barriers was explored with the network partners, an electrician, and a procurement department. They reported that under normal circumstances, it would require 2-3 months to agree and sign the agreement, and then onwards for setup.

17. Future Research Directions

This pilot study is a precursor to a new application domain, and although the findings imply some robustness and transferability of the contribution, they also highlight the need for further studies that would enhance our understanding and implementation experience in this field. This section identifies corresponding future research directions. Simpler, more complex, and variable data sets Although using state-of-the-art data sets seemed to provide a degree of generalization in our initial exploration, studies with simpler, noisier, or more variable real-world data sets might help us better understand under what exact conditions our tool becomes ineffective. Moreover, although ANOMA is reasonably effective over long periods in the tested data, investigating the tool for short time windows with frequent and/or large ALIs would be beneficial. Technological innovations. This study has also raised several potentially promising areas for systematic extension in forthcoming studies. As mentioned in the introduction, this work could potentially be extended to detect disturbances on the transmission grid in the confluence of the high and low voltage grids, as these are also typically locations with limited communications coverage. Intelligent integration with other emerging edge technologies, especially making the process more scalable, will also likely offer robust pathways towards future work. Integration into hardware, developing a dedicated chip, and applying hardware acceleration, making this technology more appealing to future Industry 4.0 contexts, is essential to the potential exploitation of our proposed algorithm. Research partnerships with industry and academia, as well as broader expertise collaboration, would also be very beneficial. Algorithm evolution Enhancing the learning efficiency of ANOMA by integrating it with reinforcement learning is also crucial to future research. This first step, the retraining of ANOMA every 12 hours to 1 day, may also constitute a significant drawback: input IoT data is assumed to be stationary over this period, and anomalies of yesterday have

to a degree become the normal of tomorrow. The proposal for continuous adaptation loop is a recommended path forward for future researchers. Working with additional partners who might help realize the deployment of ANOMA/TestBed in practical applications on one or more European DSO to validate the present findings in other distribution networks or work on future DSO risk-based environment are further recommended research axes.

18. Conclusion and Recommendations

In this paper, we presented a pilot study that explored the potential of Edge AI for anomaly detection in smart grids, seeking to partially fill the gap related to existing research limiting the use and evaluation of both real-time edge computing and deep learning models. The case study of two real-life smart grid assets demonstrated that the developed Edge AI models with real-time processing outperform traditional methods, not only in terms of effectiveness but also in the size of data transfer and process-consuming needs. Given the increasing complexity and heterogeneity, as well as the continuous change in power distribution networks, there is a need to scale up the ongoing collaboration between researchers, manufacturers, and system operators. Thus, researchers are the target audience for proposing innovative techniques, operators are required to conduct field implementations, and manufacturers are responsible for deployment, testing, and design of large-scale advanced equipment and edge solutions. To the best of our knowledge, this study is also the first to propose strategies embodying the practical deployment of Edge AI in terms of the interconnected four layers of a smart grid.

Based on the results of the pilot study, we recommend that a spectral manufacturer, a blockchain developer, and a TSO and large-scale DSO consider the following strategies for on-site deployment of anomaly detection solutions using Edge AI models and a local server as an aggregation point. Importantly, the design of technical solutions and security requirements should reflect the current state of the sector and the intended future deployment scenario, while digital security measures and organizational structures should be considered and, if necessary, adjusted in the future. Once implemented, it will be crucial to engage in continuous monitoring and participate within a joint ecosystem where the performance of solutions can be disseminated, providing feedback to the contributor. The tests should have the ultimate aim of understanding how the equipment and strategies are performing, iterating to improve operational rules, and developing the feature of the multi-service economic feedback mechanism that can act as a prediction oracle for the need of ancillary services in the interconnected DNGs. Both the potential of and need for such an economic value proposition will depend on the difference between flexibility purchasing costs that the system operator can avoid and opportunities for reselling energy on the market or providing flexibility for balancing or trading. The pricing mechanism will need to reflect targeted outcomes because the pricing signals are likely to be different for local congestion management, given the major differences in scale and operational requirements, and transmission system constraints. Given the complexity of the grid, the pricing signals will need to be holistically developed in a semi distributed manner among all actors in the pilots and enabled by the feature provided in the field demonstration. In conclusion, the leverage of Edge AI for applications at the field level makes this technology ready for practical utilization in addressing specific transient gaps in the development of smart grid infrastructure and its automation.

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