A Robust and Explainable Data-Driven Anomaly Detection Approach For Power Electronics

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Abstract—Timely and accurate detection of anomalies in power electronics is becoming increasingly critical for maintaining complex production systems. Robust and explainable strategies help decrease system downtime and preempt or mitigate infrastructure cyberattacks. This work begins by explaining the types of uncertainty present in current datasets and machine learning algorithm outputs. Three techniques for combating these uncertainties are then introduced and analyzed. We further present two anomaly detection and classification approaches, namely the Matrix Profile algorithm and anomaly transformer, which are applied in the context of a power electronic converter dataset. Specifically, the Matrix Profile algorithm is shown to be well suited as a generalizable approach for detecting real-time anomalies in streaming time-series data. The STUMPY python library implementation of the iterative Matrix Profile is used for the creation of the detector. A series of custom filters is created and added to the detector to tune its sensitivity, recall, and detection accuracy. Our numerical results show that, with simple parameter tuning, the detector provides high accuracy and performance in a variety of fault scenarios.

Index Terms—Industrial Internet of Things, anomaly detection, fault classification, cyber-physical system, visualization

I. INTRODUCTION

Recent advances in power electronics have increased renewable energy generation, which positively contributes to global decarbonization goals. Converters are among the key power electronic components that play an important role in enabling an increase in renewable energy sources and storage units. Photovoltaic power plants, wind farms, and electric vehicles utilize these converters so improving them is critical to increasing operational reliability. For instance, power converters are prone to different classes of faults, including issues in physical components, faulty operation in the electrical grid and cyberattacks from external agents.

Anomaly detection strategies are thus required to enhance security and reliability, and enable a widespread penetration of converters in the grid [1]. Most of the anomaly detection methods in the literature rely on classic strategies like switching pattern and voltage observation [2], [3] or frequency analysis of output voltages [4]. Despite the effectiveness of these approaches, they are quite application dependent, focused mainly on the modulation techniques.

Improvements in computational techniques and machine learning models are now opening the opportunity for anomaly detection in converters, with the advantage of generalization and no interdependence on specific parameters across the models. In [5], a fault detection method based on deep neural networks using a sparse auto encoder obtained promising results. In [6], a methodology based on wavelet packet decomposition is used to obtain energy values of the voltage signals which are then input into a 4-layer deep belief network to perform fault diagnosis. A long short-term memory network for the creation of the detector. A series of custom filters is created and added to the detector to tune its sensitivity, recall, and detection accuracy. Our numerical results show that, with simple parameter tuning, the detector provides high accuracy and performance in a variety of fault scenarios.

In this paper, we propose a general framework for anomaly detection, considering different types of uncertainty and anomaly in cyber-physical systems [16], which allows for testing several machine learning approaches. To illustrate the efficacy of the proposed robust and explainable framework, we consider a simple example of the controllability of a 2-level,
3 phase grid-tied voltage source converter (VSC). As shown in Fig. 1, the control structure has been implemented in the dq0 frame. Since this architecture involves forming the grid at its output, we use VSG control philosophy [17] to obtain the frequency and phase angle information. As the grid-tied VSC operates with different active and reactive power reference points given by $i_{drcf}$ and $i_{qrcf}$ respectively, the corresponding data has been obtained from the control platform to train an ensemble regression based learning model to imitate the control response. Our numerical results illustrate the efficacy of the proposed solution.

The remainder of the paper is divided as follows. Section II presents an overview of explainability in machine learning. Section III introduces different classes of anomaly detection approaches. Section IV presents the numerical results for the adopted power grid model. Section V concludes the paper.

II. ALGORITHM EXPLAINABILITY

Certain high-risk use cases for machine learning algorithms demand a high level of explainability and confidence in the algorithm outputs for decision-making. In many cases, an algorithm makes a classification decision, but there is no clear explanation as to why. In the field of power electronics, understanding why a data-driven controller is making a decision is critical to incorporating it into real world power distribution scenarios.

A. Types of Uncertainty

Determining sources of uncertainty in a model or system is essential. In the following, we differentiate between two basic types of uncertainty.

Epistemic uncertainty results from inadequate training data. In this case, the training data is not sufficient to provide enough or accurate data to the model. This can result from imbalanced or insufficient training information. Increasing the amount of training data or decreasing class imbalance can help reduce this type of uncertainty.

Aleatoric uncertainty arises from probabilistic errors in sampling that follow a specific probability distribution. This type of uncertainty is independent of the amount of data collected and therefore cannot be corrected with additional training data. If a signal has noise inline with a given probability distribution, having more data on that signal does not change the noise probability distribution. This type of uncertainty references the distribution of random errors in the data and not the data distribution itself.

As an example, suppose there is a continuous audio recording at a train station. There are three announcements each hour that disrupt the recording, but their occurrence in the hour is unknown. Having more data (hours), does not change the amount of announcements that occur. In the systems’ domain, a malfunctioning sensor or bad connection can generate aleatoric uncertainty in the form of noise that cannot be fixed by more measurements or more data.

B. Combating Model Uncertainty

With deep learning algorithms, it is important to know the confidence level of the model output. Authors in [18] explain that adding simple adversarial data (e.g., similar to adding small noise to a photo) makes an image recognition algorithm incorrectly classify an animal as a completely unrelated one. This is further concerning since adversarial data does not need to be tailored to a specific algorithm. The transferability of this type of adversarial data allows its application against many black-box algorithms to achieve an unintended or potentially malicious result.

To solve this problem, authors in [19] propose using conditional entropy to determine how each input is related to each output. The generated plots are then compared to the physical insights of the system. In the process, adversarial data that falls outside the plot is identified and removed, and the model is retrained. This technique is helpful for identifying and removing adversarial data that falls outside the range of accepted values. Unfortunately, it does not identify data overloading in a specific portion of the graph, which would create an incorrect classification.

1) Bayesian Dropout: Bayesian techniques can be used to create a probability distribution over the weights of each neuron to determine a level of prediction uncertainty. The work in [20] introduces a standard Bayesian neural network implementation with back-propagation that can determine these probability distributions. Authors in [21] explain that retraining a large number of models on a variety of datasets is computationally expensive and time-consuming. A dropout technique can instead be used to approximate the Bayesian representation with improved computational efficiency. This technique avoids over-fitting by randomly sampling and dropping network nodes across many different training iterations. Performing Bayesian dropout while training and testing the algorithm enables the computation of variance to determine the uncertainty level of the outputs. This allows researchers to determine if an algorithm is providing a best-guess answer with high levels of uncertainty for specific values; in turn, this can signal the need for human intervention or review before making decisions based on the algorithm output.

2) Shapley Additive Explanations (SHAP): Using reverse-engineering, the output of a machine learning algorithm can
be analyzed and explained. Authors in [22] introduce SHapley Additive exPlanations (SHAP) to interpret and explain the why behind machine learning algorithm results. Machine learning models usually output the likelihood of a certain prediction given a set of inputs. SHAP explains why a model makes a classification decision, in terms of how important each of the input features is for a given decision. To determine this, SHAP analyzes every possible combination of input weights to determine how significantly each input contributes to the overall output.

3) Rule-based Explanations: In the data mining literature, there exists a large body of research focusing on extracting association rules from data. Starting with the development of algorithms for the extraction of qualitative association rules [23], [24] of the type bread → milk, various algorithms were proposed over the years for extracting mixed and quantitative association rules that hold over a dataset [25]–[27].

Several EU-funded projects (FIREMAN, QU4LITY, AI4PublicPolicy) recently demonstrated that having all the rules that apply on a given dataset available can be very useful in explaining a third-party classifier/regressor’s decision. Given a new data instance, together with the decision of the classifier, a single scan over the database of all rules that hold on the dataset can select the best-fit rule that explains the decision; a best-fit rule is one whose antecedent preconditions are satisfied by the new instance’s feature values, and the rule’s consequent target value matches optimally the decision made by the third-party classifier (constrains the target value as tightly as possible to an interval that contains the classifier decision value). In case of multiple rules satisfying the tightness criterion, the rule with the highest confidence and then support can break the ties; alternatively, all rules optimally supporting the decision can be presented to the user seeking explanations for the decision of a black-box classifier.

In the context of the AI4PublicPolicy project\(^1\) research in explainable AI, a REST web-service is developed, explaining the decisions of a deep neural network predicting the number of available parking slots in the Municipality of Athens. This was performed by first extracting all rules of the form \(I_1 \in [l_1, h_1] \land \ldots \land I_k \in [l_k, h_k] \rightarrow T \geq v\) as well as all rules of the form \(I_1 \in [l_1, h_1] \land \ldots \land I_k \in [l_k, h_k] \rightarrow T \leq v\) that hold with sufficiently high minimum support and confidence thresholds on the dataset, using the QARMA algorithm [26].

Then, when a new HTTP POST request arrives on our web-service end point, we perform a single in-memory scan of the rule sets above and we return the best ones.

C. Anomaly Taxonomy

The term ‘outlier’ or ‘anomaly’ can have a variety of meanings depending on the context. In order to select appropriate techniques for outlier detection, it is essential to create a taxonomy for various outlier types. Fig. 2 illustrates the difference between the two types of outliers described below.

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\(^1\)https://www.ai4publicpolicy.eu
This outlier type classifies abrupt faults in a system and constitutes an important outlier type for this study.

2) **Seasonal:** Seasonal outliers are classified by an increased or decrease pattern frequency during a specific time period. Identifying seasonal outliers is important in understanding specific phenomena, e.g., a spike in web traffic related to a major holiday. Another example is an increased demand in residential electrical demand because of a large televised sporting event.

3) **Trend:** Trend outliers are classified by a sub-sequence of the dataset that modifies the underlying distribution of the data. Trend outliers are present in certain faults in the Power Electronic Converter (PEC) dataset under study.

### III. Detection Approaches

#### A. Matrix Profile

The Matrix Profile algorithm computes the distances between neighboring points in a dataset. It exhibits a variety of advantages, including speed and generalizability to a variety of problem domains. Authors in [30] explain that in the algorithm, the results for each point or sub-sequence are stored in a vector and the combination of all the sub-sequences forms the overall matrix. The conventional algorithm utilizes the Euclidean method to determine point-wise distance; other distance calculations can also be utilized. Z-normalization technique is traditionally used to scale the data; however, normalization can be modified or omitted depending on the specific dataset requirements.

Using a fixed \( m \) sized window, the algorithm computes the nearest-neighbor distances compared to the entire data stream. To select an appropriate window size \( m \), it is important to consider the granularity of the studied anomalies. A large windows size would detect and identify significant disturbances, like sensor failure, whereas a small window size would identify more localized disturbances, like a voltage sag, in a signal.

The results of the computation of the nearest-neighbor distances and the index of the closest neighbors are stored in order of closeness in a new index. In particular, the algorithm steps are outlined as follows [31]:

1. For each point in the window \( m \), compute the distance to the nearest neighbor against the entire data set.
2. Exclude identical or nearly identical matches to prevent inaccuracy.
3. Update the distance matrix with the new closest neighbor distance.
4. Set the position matrix with the index position of the new closest neighbor.

Using the Matrix Profile technique, it is easy to extract information, like motifs or repeated patterns, from the dataset. More importantly, discords which represent anomalies can be discovered from a data stream.

#### B. Deep Learning

Recent emergence of transformer deep learning methods based on attention [32] reveal promising results not only in the field of natural language processing [33], but also in the processing of the tabular [34] and time-series [35] data. Transformers were shown to be able to outperform the Gradient Boosting Decision Tree (GBDT) methods and ResNet-like architectures [36], [37]. In this work, we focus on providing complementary results to the Matrix Profile algorithm, by applying transformers for unsupervised anomaly detection [38]. An anomaly-attention mechanism is used to compute the association discrepancy to distinguish between normal and abnormal (anomalous) data points. Adjusted implementation code of the authors\(^2\) and related datasets can be found on the FIREMAN project GitHub pages\(^3\).

### IV. Applications in Power Electronics

Transitioning from conventional power systems to power electronics-dominated grids (PEDG) has increased demand for grid-forming converters (GFM) to facilitate operational reliability. GFMs have made significant progress in recent years to expedite stability under different grid conditions, but their operation during faults or large signal disturbances still remains a challenge. Authors in [39] note that GFMs handle a significantly smaller percentage of over-current (usually only 20%) compared to synchronous generators (SGs) which can handle seven times their nominal current. This makes fault detection for GFMs critical to maintain synchronization with the grid. Since the network infrastructure of power systems keeps expanding, it is important to identify these faults accurately under varying grid parameter uncertainties.

This study examines four faults in the PEC dataset: line-to-line (LL) fault, three-phase sensor fault, single-phase voltage sag and three-phase grid fault. It is worth noting that the location of these faults can be determined from Fig. 1.

\(^2\)https://github.com/5uperpalo/Anomaly-Transformer\_FIREMAN

\(^3\)https://github.com/5uperpalo/FIREMAN\_project/
promptly. Interestingly, the detector performed well when cop-
detect anomalies quickly so that remedial action can be taken
dataset. For the power grid use cases, it is important to
detect all four faults with zero false positives in the PEC
advisable. In our case, the detector was able to successfully
detection and false positive rates in a traditional way is not
detecting the start.
the ending of an anomaly sometimes takes more time than
false positives (i.e., 0% error rate). It is noted that detecting
and end of each anomaly (i.e., 100% detection rate) with no
that the detector was able to accurately determine the start
and accurately for all fault types presented. Fig. 6 shows
found in Section II. The detector is shown to behave robustly
description of the characteristics of these fault types can be
values during each fault type examined in this experiment. A
(a) Line-to-Line (LL) fault
(b) Three-phase sensor fault
(c) Single-phase voltage sag  
(d) Three-phase grid fault
Fig. 5: PEC dataset fault detection using Matrix Profile algorithm.

Fig. 6: PEC ground truth comparison [Normal: green, Anomaly: red].

The frequency \([f_c]\) of the system throughout various fault
conditions is used for detection. Each fault has significantly
different characteristics and magnitude. The faults explained
in this section are illustrated in Fig. 4.

A. Matrix Profile

Fig. 5 depicts a zoomed in window of the matrix profile
values during each fault type examined in this experiment. A
description of the characteristics of these fault types can be
found in Section II. The detector is shown to behave robustly
and accurately for all fault types presented. Fig. 6 shows that
the detector was able to accurately determine the start
and end of each anomaly (i.e., 100% detection rate) with no
false positives (i.e., 0% error rate). It is noted that detecting
the ending of an anomaly sometimes takes more time than
detecting the start.

By nature, anomalies are rare, therefore interpreting the
detection and false positive rates in a traditional way is not
advisable. In our case, the detector was able to successfully
detect all four faults with zero false positives in the PEC
dataset. For the power grid use cases, it is important to
detect anomalies quickly so that remedial action can be taken
promptly. Interestingly, the detector performed well when cop-

B. Anomaly-Transformer

In Table I, we provide the detection performance summary
per fault type using the anomaly-transformer in the PEC
dataset. For model evaluation, we used full datasets per fault
consisting of 13 features, including the frequency \([f_c]\) used by
the Matrix Profile algorithm. Training and testing parameter
values are included in the provided GitHub repositories. From
the results, we can observe that in the default configuration,
the model was able to identify all anomalies. We also note
that additional tuning is needed to decrease the number of
false positives in the case of three-phase grid fault. The Matrix
Profile is shown to outperform the model in our use case, but
further testing with multi-feature anomalies and faults would
be needed to confirm this observation.

| Fault                        | Accuracy | Precision | Recall | F-score |
|------------------------------|----------|-----------|--------|---------|
| LL fault                     | 0.990    | 0.860     | 1.000  | 0.925   |
| Single-phase voltage sag     | 0.998    | 0.998     | 1.000  | 0.999   |
| Three-phase grid fault       | 0.985    | 0.630     | 1.000  | 0.773   |
| Three-phase sensor fault     | 0.997    | 0.996     | 1.000  | 0.998   |

TABLE I: Anomaly-transformer per fault performance report.

V. CONCLUSIONS

Real-time detection and classification has significant impli-
cations in grid cyber-security and reliability. Attacks against
the power grid are becoming more sophisticated, and it is
essential to discern whether the system is under attack or
experiencing a fault condition. Furthermore, it is important
to know whether a fault is occurring so that automated
or manual corrective actions can be performed, to protect
system components and ensure maximum system reliability
and uptime. In this paper, we have presented different methods
for anomaly detection while proposing an effective approach to
identify faults in the operation of power electronic converters
in PEDGs.

As future work, we plan to extend the proposed approach to
a real-time dynamic detector. There is currently a MATLAB
power grid control and monitoring interface for a real system,
and in order to integrate with it, a module for MATLAB must
be created. This would involve creating an implementation
of the Matrix Profile algorithm in MATLAB, and utilizing it
in tandem with the control system. With this setup, it would
be possible to test the real-time detection capabilities of the
algorithm. Once implemented, it would be possible to couple it
with a classification algorithm to attempt to determine the type
of fault. If a fault was determined, the appropriate corrective actions could be performed depending on the classification.

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