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Fault Detection in Power Systems with Synchronized Phasor Measurements and Machine Learning

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Abstract: This paper proposes a solution for fault detection in power systems using machine learning algorithms, namely Random Forest and Support Vector Machines. A Phasor Measurment Unit (PMU) network is emulated in the IEEE 39-Bus New England Power System, and several fault types are simulated, including three-phase to ground, two-phase, two-phase to ground and single-phase to ground as well as line and load contingencies. The magnitude and phase of voltage and current, alongside with frequency, are measured from each PMU, and used as input to the machine learning models. Two scenarios were contemplated in this work, the first with a network of 14 PMUs, and the second with half that number, in order to verify the robustness of the aforementioned methods in relation to the number of PMUs present in the system. A Feature Importance analysis is also made, via Permutation Feature Importance, indicating which features contributed the most to the classification task at hand. Both algorithms reached a performance of around 93% accuracy and 0.94 F_1-Score and the feature analysis method seems to be suitable for systemic visibility analysis. Future works are also discussed in this paper, briefly elaborating on the possibilities and immediate impacts of the addition of a feature engineering stage in this problem and on the application of the used algorithms on problems such as fault identification and location.

Keywords: Support Vector Machine, Random Forest, Fault Detection, Phasor Measurment Units, Feature Importance

1. INTRODUCTION

Electrical faults can happen anywhere and anytime throughout the electric grid, impacting the power system as a whole and hindering the delivery of electricity to customers (Ajenikoko and Sangotola, 2014). In order to increase a system's sustainability and reliability, it's necessary to capture the real-time dynamics with high enough resolution to detect dynamic events such as faults. The synchronous phasor measurement unit (PMU) technology comes as a solution to this problem, monitoring the voltages, currents and frequencies of distinct buses with sufficient sampling rates to do so (Phadke, 1993). The measurements are made synchronously, even if the buses are geographically distant from each other, composing the so-called Wide Area Measurement Systems (WAMS). With a WAMS, the overall visibility, reliability and control of a power system can be improved (Phadke et al., 2016).

However, PMUs generate a large quantity of data in a short time span, rendering real-time observation by human operators unfeasible. Thus, the application of some kind of computational technique prior to the presentation of the data to the operator becomes necessary. The type of technique may change accordingly to one's goal. Jiang et al. (2012) propose a method for fault detection and location method based on the injected fault current and the estimated fault distance. Das et al. (2017) tackled this task with a different approach, using only the voltage measurements and the system's admittance matrix.

A strong trend of artificial intelligence techniques for fault detection and location has been noted in recent years, since they are more easily adaptable and more robust to transmission line parameters and fault type. Out of them, Artificial Neural Networks (ANN) and Support Vector Machines (SVMs) are the most used, and achieve good performance when coupled with a feature extraction procedure (Chen et al., 2016; Rivas and Abrão, 2020). Zhang et al. (2011) used pattern recognition and linear discrimination to detect and locate faults, and extract interpretative decision rules based on voltage and current measurements. Gopakumar et al. (2015) used SVMs for the same tasks, classifying the Equivalent Voltage Phasor Angle, estimated using Clark and Park Transform followed by the Fourier Transform. Barreto et al. (2021) studied the removal of a feature extraction step and applying an ANN directly to PMU measurements, being able to successively detect faults and identify their types in the IEEE 39-Bus New England Power System.

This paper serves as a continuation of the research conducted by Barreto et al. (2021). Here, machine learning algorithms, such as SVMs and Random Forests will be used for fault detection, instead of ANNs in the aforementioned work. An additional Feature Importance analysis is made

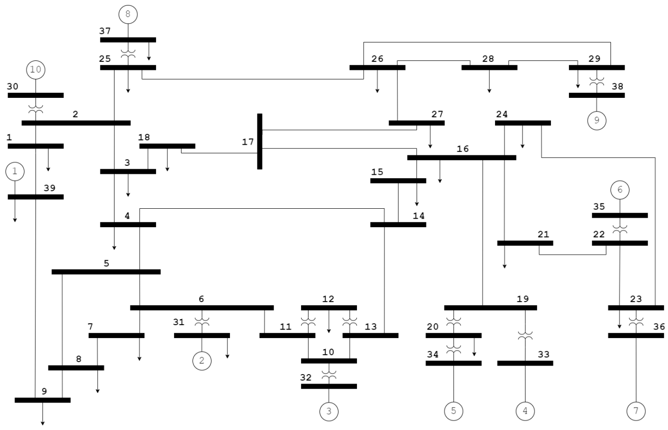

Figure 1. New England Power System Diagram

with Permutation Feature Importance, to determine which were the most important electrical quantities or the most critical buses for the classification. These analyses will be made for two scenarios: The first with 14 PMUs installed in the aforementioned power system, and then only seven, in order to verify the robustness of these techniques in relation to the number of PMUs present in a system.

This paper is organized as follows: Section 2 presents details about the power system used in this work, the IEEE-39 Bus New England Power System, how the PMU networks were emulated in it, and the structure of the resulting dataset. In section 3 encompasses all machine learning techniques, the algorithms, evaluation metrics, and feature importance assessment methods. Section 4 details how these techniques were applied and the obtained results, and finally section 5 presents a conclusion and perspectives for future works.

2. IEEE 39-BUS NEW ENGLAND POWER SYSTEM

The New England Power System, operated by the ISO New England company, encompasses six states in the New England area of the United States of America, providing energy for about 15 million inhabitants, including a major metropolis in Boston. When operating under normal conditions, the system presents 39 buses, 10 generators and 46 transmission lines, with a total consumption of around 6,3 MW. The system's diagram can be seen in figure 1. Ever since its adoption as a standard IEEE system, a wide range of studies were made in order to better characterize its dynamic behaviour, some of which can be found in Hiskens (2013) and Law (2007).

2.1 PMU Network Emulation

The PMU-based WAMS for the New England Power System (NEPS) is emulated and the PMU placement was decided after a line contingency study, identifying the most sensible buses of each area.Therefore, these, alongside generator buses (whose monitoring is essential for the operation of the system and the reaction to faults and outages) were selected as monitored buses, as described in Barreto et al. (2021). In the first scenario, emulations were made with PMUs at buses 4, 8, 16, 28, 31 to 39, totalling 14 PMUs. Afterwards, this number is halved by reducing the number of generators monitored, limiting the monitoring to buses 4, 8, 16, 28, 31, 33, and 39. The first 4 buses have large loads allocated their immediate surroundings, are located in different areas and/or interconnect said areas.

Each PMU continuosly measures both magnitude and phase of voltage and current, as well as frequency of the bus the unit is installed to. Measurement noise is modelled after a Gaussian distribution with zero mean and signal-to-noise ration of 45 dB, as characterized in Brown et al. (2016), rendering the simulations more truthful to a real application. Proceeding to the simulations themselves, seven distinct situations were contemplated: Short-circuits events (3ϕ, 2ϕ, 2ϕ—G and ϕ—G), load contingency, line contingency, and no dynamic events (normal operation), in all 39 buses and transmission lines. Each simulation runs for a duration of eight seconds, with a sampling rate of 60 Samples/s, totaling 480 samples per simulation. Each sample contains every variable measured by the aforementioned PMUs. These were later downsampled by a factor of 12, resulting in a sampling rate of 5 Samples/s and 96 samples/simulation to reduce computational effort while maintaining the main characteristics of system's dynamics.

2.2 Dataset Structure

PMU emulations were made based on the IEEE NEPS one-line diagram. The data is organized in such way that a given column represents one of the five variables measured by the PMUs, and each line corresponds to one sample of one simulation. Since the scope of this work implies binary classifications identifying whether the system is operating under normal condition (index 0) or under anomalies (index 1), a single Operation Index column was added after all the variable columns. Table 1 illustrates the overall structure of the data set. For each PMU present in the simulation, the five displayed columns will be repeated, meaning that in the first scenario, the data set has 70 variable columns, while the second has only half, 35 variables, all of them being normalized between 0 and 1 column-wise. Since all faults were present in the same dataset, this normalization does not result in the loss of information on the severity of the fault. After normalization, the samples are also randomized - meaning that not necessarily two consecutive samples come from the same simulation and/or are ordered. These variables will be used as inputs for the machine learning algorithms, while the operation index serves as the labels for each sample.

Table 1. Dataset structure

Bus Voltage Magnitude	Bus Voltage Angle	Bus Current Magnitude	Bus Current Angle	Frequency	Operation Index
96 Samples/Simulation Columns are repeated for each PMU					0 - Normal Operation 1 - Anomalous Operation

3. MACHINE LEARNING TECHNIQUES

This sections describes the two machine learning algorithms used in this paper, Random Forest and Support Vector Machines, and how their parameters were tuned. Information concerning the evaluation metrics and the Feature Permutation Importance is also provided.

3.1 Random Forest

The Random Forest algorithm consists of multiple decision trees, in order to reduce the variance when in comparison to an individual tree. Normally, a Decision Tree would perform successive binary partitions on the data set D of size N, based on an impurity criteria, for instance the Gini Index, until a certain stop criteria is reached, be it a pure node, a node containing only samples of a certain class, or when the number of samples on the node is less than a threshold defined by the user Hastie et al. (2009).

The bagging technique generates, from the data set D, n subsets D_i, by randomly selecting samples of the original data set with replacement, ensuring that each subset D_i is different from each other. For each subset, a decision tree will be grown, and in each, and in each node of this tree, a reduced number of m features are randomly chosen out of the available M will be used. For classification problem, the chosen number of features at each decision split of each tree is usually $m = \sqrt{M}$. The Random Forest is an aggregation of the n Decision Trees generated on the available subsets, and it's prediction is based on a plurality vote of all of them Breiman (2001).

Due to the replacement of samples during the bagging process, it's estimated that around one third of the total samples are not viewed during the training process (Breiman, 2001). These are the so-called Out-Of-Bag (OOB) samples, and are a common subset used to assess the performance of the Random Forest model, specially for hyperparameter selection. This was the selected approach for the choice of the number of decision trees n. Classification error (1 - Accuracy), was measured for Random Forest models containing one to 250 trees. The number of trees n is chosen when there increasing n does not decrease the OOB classification error. For this reason, an number of $n = 100$ was chosen.

3.2 Support Vector Machines

Support Vector Machines uses hyperplanes decision boundaries to linearly separate samples belonging to different classes. The optimal separating hyperplane is found on the max distance of the two closest points of different classes, the support vectors, the ones that define the position of the separator (Cortes and Vapnik, 1995). However, perfect linearly separable data is very hardly found. In this situation, the input samples are mapped to a sufficiently higher dimension until they become linearly separable. Although this seems computationally expensive, it is possible to represent the transformed feature vectors involving the input features with inner products, represented by a kernel function K.

In this work, the parametrization of the SVM was limited to the choice of the kernel function K, since it's the parameter with the most effect on the resulting model's performance. The choice was made based on the accuracy and F_1-Score of each kernel function, with 70% of the data set and the remaining 30% used for testing. For higher complexity functions to be chosen, they must provide have a non-negligible impact on the metrics, since they also increase the computational burden and overall likely-hood of an over-fitted model. Seven different functions were tested: Linear, Gaussian, and Polynomials with degree two to six.

Table 2 shows the results for each of these functions. In the 14 PMUs case, a significant drop in performance is noted for the sixth degree polynomial, indicating that the model is over-fitted at this point. The fifth degree polynomial performed better than the fourth degree, but the increase in accuracy is under 0.2%. The same happens with the F_1-Score Because of this, the fourth degree polynomial was chosen as the kernel function for this case. A similar behaviour is observed for the 7 PMU scenario, where the increase of performance is negligible after the fourth degree polynomial, of under 0.2% accuracy. For the same reason as the previous case, the fourth degree polynomial is chosen.

Table 2. SVM performance with different kernel functions

		14 PMU		7 PMU	
		Accuracy (%)	F1-Score	Accuracy (%)	F1-Score
Linear		89.44	0.9223	89.95	0.9279
Gaussian		89.96	0.9269	90.00	0.9326
Polynomial	Degree 2	90.81	0.9358	90.76	0.9364
	Degree 3	91.59	0.9425	91.27	0.9406
	Degree 4	92.08	0.9458	91.85	0.9446
	Degree 5	92.24	0.9464	91.93	0.9472
	Degree 6	71.89	0.7821	92.03	0.9494

3.3 Evaluation Metrics

Most of the most common evaluation metrics of machine learning algorithms can be extracted via the confusion matrix, a way to visually inspect the performance of a model, where each row represents the instances in an actual class while each column represents the instances in a predicted classes. An example of a confusion matrix can be seen in figure 2.

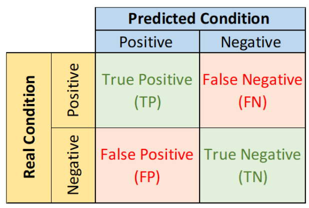

Figure 2. Example of a generic confusion matrix

Accuracy, F_1-Score, Precision, and Recall were the chosen metrics, and can all be extracted of the confusion matrix. Accuracy (ACC) is a ratio between correctly predicted observations, both true positives (TP) and true negatives (TN), to the total observations. This metric however does not fully grasp the underlying performance of a model, specially in the case of unbalanced data, or when the classifier's predictions favors one class over the other. In this case, one should also analyse precision (P), the ratio of correctly predicted observations, to the total positive predicted observations, true and false positives, recall (R), the ratio of correctly predicted observations to all of predictions of a certain class, true positives and false negatives. F_1-Score, their harmonic mean, can also be calculated as shown in equation 1.

$$F_1 = \frac{2 \cdot P \cdot R}{P + R} \quad (1)$$

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Values of F_1-Score closer to 1 indicate a good balance of class prediction, meaning that no class is favored by the model's prediction.

3.4 Permutation Feature Importance

Analysing feature importance is important if one is interested on gather more insights from the available data, specially which features are more or less discriminant or the ones that contributed the most to the solution of the problem at hand. One technique to do so is the Permutation Feature Importance, as proposed by Breiman (2001), that can be used on any fitted estimator. By randomly shuffling one of the estimators while maintaining the others and the target variable, breaking the relation between the feature and the target, one can measure the decrease of performance of a model. This procedure is repeated for each estimators, and the ones that decrease the most the performance of the model are said to be the most important for this problem.

In this paper, the selected score is accuracy. The original accuracy of the model ACC_{orig} is calculated, and for the shuffling of each feature j, the accuracy ACC_{permj} is calculated. The FI value assigned to the feature j will be:

$$FI_j = ACC_{orig} - ACC_{permj} \tag{2}$$

In the case of bagged classifiers, such as Random Forests, this metric is calculated for each individual predictor. The FI estimate in this case will be computed with respect to equation 3:

$$FI_j = \frac{\overline{d_j}}{\sigma_j} \tag{3}$$

where $\overline{d_l}$ is the mean of the FI values over all classifiers, and σ_j the standard deviation. It's important to note however that this method does not reflect to the intrinsic predictive value of a feature by itself but how important this feature is for a particular model, since it carries all possible bias the model has.

4. APPLICATION AND RESULTS

Having defined the hyperparameters of the algorithms, the evaluation metrics and the feature importance assessment methods, it is possible to train and validate the models on the IEEE 39-bus emulated WAMS dataset.

4.1 K-Fold Cross Validation

In order to assure generalization and to validate the robustness of the algorithms in regards to the training data, K-Fold Cross Validation is used. The dataset is randomly divided into K different subsets, and $K-1$ will be used for the training of the model, and the remaining one for validation. This is then repeated until every subset is used for validation, where the chosen metrics will be computed. For this work, the chosen number of folds is $K = 10$. This procedure is made on both datasets, the one resulting from the 14 PMUs scenario and the one with seven.

4.2 Performance Evaluation

Model's performance are displayed here in the form of a table, containing two columns, each corresponding to a simulated dataset. The lines corresponds to the chosen metrics, and results are presented in the form of *mean* ± *std*, the mean and standard deviation over the 10 folds respectively.

Feature Importance is analysed via graphs, containing the FI estimates on the y-axis and their corresponding features on the x-axis. For the sake of good visibility, only the 20 most important features for each model and for each scenario is shown.

Table 3 and 4 show the evaluation metrics for the random forest and the SVM models respectively. Both these algorithms yielded satisfactory results, of accuracy over 90% and F_1-Scores of above 0.94, in both simulated datasets. Random Forest performed slightly better, reaching around 93% accuracy, 0.95 F_1-Scores and 0,91 recall, all of them with non significant standard deviation.

Table 3. Performance of the Random Forest Models

	10-Fold Cross Validation	
	14 PMU	7 PMU
Accuracy	92.98 ± .68	92.91 ± 0.2
F1-Score	0.953 ± 0.005	0.953 ± 0.002
Precision	0.999 ± 0.0006	0.999 ± 0.0006
Recall	0.911 ± 0.008	0.911 ± 0.004

Table 4. Performance of the SVM models

	10-Fold Cross Validation	
	14 PMU	7 PMU
Accuracy	92.0 ± 0.69	91.72 ± 0.31
F1-Score	0.943 ± 0.003	0.94 ± 0.007
Precision	1 ± 0	1 ± 0
Recall	0.893 ± 0.006	0.894 ± 0.004

It's also interesting to note that both models have very high precision scores, the SVM having exactly 1, and the Random Forest near that value. This means that likelihood of false positives, a situation where the models predict a fault while the system is operating under normal conditions, is extremely low. The SVM model specifically never predicted a fault while under normal operation.

Evaluation scores did not drop significantly in the second scenario, even though the system had only half the number of PMUs. In fact, lower levels of standard deviation were observed, indicating that these methods are not only have a degree of robustness in regards to the number of PMUs present in a power system, but also that less PMUs may reduce the overall bias of the training data used. One reason as to why recall levels are not higher, is the fact that some simulated faults present post-fault data that are very similar to normal operation levels.

4.3 Feature Importance Analysis

Figures 3 to 6 show the FI estimates, calculated with equation 2 for the SVM models and equation 3 for the Random Forest ones. Features here are represent by two letters and a number: C corresponds to current, V to voltage, M to magnitude, A to Amplitude and the number to the bus on which this variable was measured. For instance, feature CM16 corresponds to the current magnitude variable measured in bus 16.

As seen in figure 3 out of the 20 most important features, for the Random Forest, in the dataset with 14 PMUs, only seven of them were from generator buses. The remaining ones are distributed between buses with large loads allocated to them, with the most present one being the bus 28.

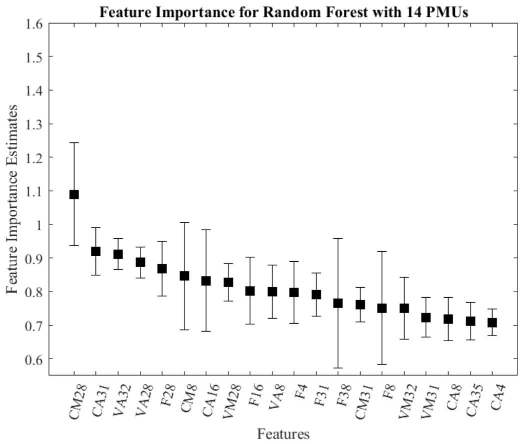

Figure 3. FI Estimates for Random Forest with 7 PMUs

A similar event is observed in figure 4, in the dataset containing only 7 PMUs, where only features from generator buses were not ranked amongst the most important feature. Out of these, three belonged to bus 31, the ground bus. By viewing the remaining 15, the most important features belonged to buses 8, 16, and 4, in that order, indicating that these buses were crucial for the correct predictions made by the model.

Here, the features presented an wider range of mean FI values, ranging from 0.6 to 1.5, in contrast with the previous scenario where the FI values ranged from 0.7 to 1.1, showing that no feature severely outweighed others in the importance criteria. Moving to the SVM models,

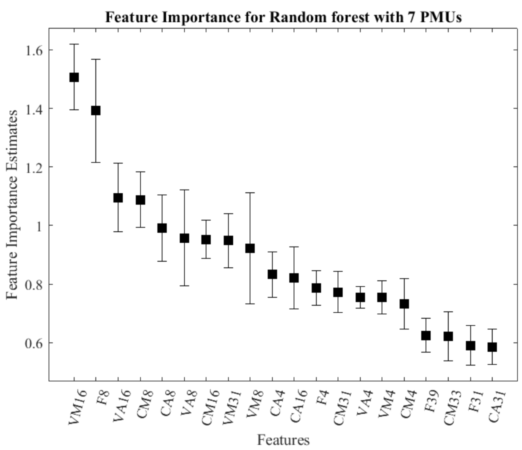

Figure 4. FI Estimates for Random Forest with 14 PMUs

in the first data set of 14 PMUs, shown in figure 5, most of the important features belonged to generators buses, more specific, buses 31,32,35, and 38. Similarly to the Random Forest model for this data set, the range of FI values is low, going from 0.04 to 0.08. Note that, since the FI estimates from bagged and non bagged classifiers are calculated differently, their numerical values should be compared directly.

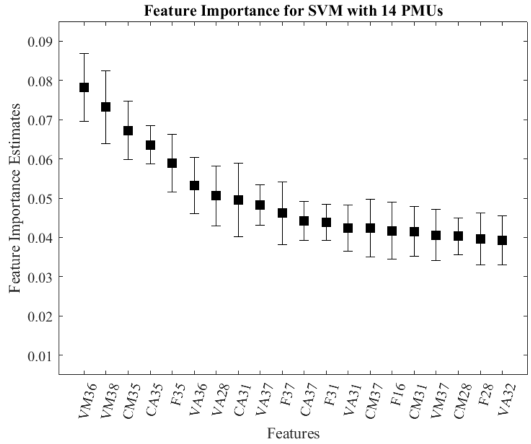

Figure 5. FI Estimates SVM with 14 PMUs

Upon viewing figure 6, it is clear that there are 15 features significantly more important to the classification, having FI values about four times greater than the remaining ones. All of them belong to only four buses, 8, 16, 31, and 33. Four out of the five most import features belong to bus 31, the ground bus. Bus 16 was the second most important feature in this case.

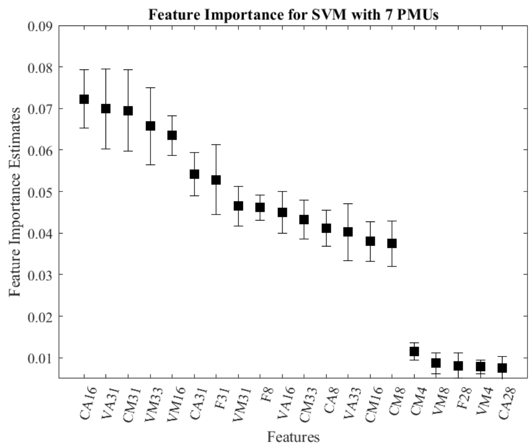

Figure 6. FI Estimates SVM with 7 PMUs

The proposed feature importance analysis method seems more suited to extract the most critical buses for the classification at hand, and not determining a specific electrical magnitude. Frequency estimations however, were the magnitude that appeared the least in the top 20 most important features in every scenario, likely due to the that the faults contemplated in the emulations have a higher impact on voltage and current.

Overall, the bus that contributed the most for fault detection in this paper was bus 31, the ground bus. Measures from buses 8 and 16 were the most important for both machine learning models when the system had only 7 PMUs. The first one, had the largest load allocated to it,

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and the second interconnects the three geographical areas of the system. This indicates that this method may be suited for a system visibility or sensibility analysis.

5. CONCLUSION

In this paper, a new method of fault detection in power systems using Random Forest and Support Vector Machines is proposed. Electrical faults emulated on the IEEE 39-Bus New England Power System previously found in Barreto et al. (2021) was used, without the need of pre-fault data. Two scenarios were contemplated in this work, the first with 14 PMUs and the second with only seven, and the magnitude and angle from both voltage and current, as well as the estimated frequency, were measured from each of them. Both machine learning algorithms presented satisfactory results, reaching 93% of global accuracy and a F1-Score of 0.95, for both scenarios, indicating that these techniques are robust to decreasing the number of PMUs present in the system. This methods have an extremely low likelihood of presenting false alarms to the operator, with SVM never having incorrectly predicted a normal situation as an anomalous one.

A feature importance analysis is also proposed, using the Permutation Feature Importance method, determining the most important PMU measurement, and from which bus it was extracted, for the detection of a given fault. This analysis provides useful information on which buses were more affected by a certain fault, regardless of the nature of the fault, indicating that this method may be suitable for systemic visibility or analysis, or even PMU placement.

The methods here presented go along the financial constraints of PMU network installation, since they work with a reduced number of PMUs. They can also be used in real time operation, and can serve of great help to system operators, presenting them with a fast diagnosis of the state of the system and possibly aiding them to react faster to faults.

Future developments in this area can consist of adding a feature engineering stage, considering the temporal nature of the data at hand. This could render the prediction time slower, but could also increase performance scores. One could also consider applying these algorithms for fault type detection, or even fault localization, even tough the proposed PMU network is not implemented on every bus and line of the power system.

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