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Artificial Neural Network Solution for Anomalous Operation Detection in Power Systems

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Abstract: This paper presents an anomalous operation detection system for power systems using the artificial neural network approach while discussing its advantages and disadvantages. The initial data for the proposed technique is a set of simulated post-fault bus voltages and currents obtained in a sampling rate so as to emulate a phasor measurement unit network. Several types of faults are dealt with, such as three-phase to ground, two-phase, two-phase to ground and single-phase to the ground as well as line and load contingencies. All fault and steady-state simulations were performed on MATLAB using Graham Rogers' Power System Toolbox. The artificial neural network was designed on MATLAB, using an architecture proper for pattern recognition with supervised learning and obtaining high accuracy predictions within a short amount of time. The test system used in all simulations is the IEEE 39-Bus New England Power System, which presents 10 generation units, 21 loads and three distinct areas alongside transient and sub transient models, with phasor measurement units in 14 buses. Future works are discussed, showing the possibilities for feature engineering in this type of problem, fault type detection and fault location in operation using analogous dataset and neural network structures.

Resumo: Este artigo apresenta um sistema de detecção de operação anômala para sistemas de potência utilizando-se da abordagem das redes neurais artificiais com uma discussão das suas vantagens e desvantagens. Os dados iniciais para a técnica proposta consistem em um conjunto de tensões e correntes de barra pós-falta obtido visando emular uma rede de unidades de medição fasorial. Diversos tipos de faltas são contemplados, tais quais as trifásicas, bifásicas, bifásicas-terra e monofásicas-terra bem como contingências de linha e de carga. Todas as simulações foram realizadas no MATLAB usando-se da Power System Toolbox desenvolvida por Graham Rogers. A rede neural artificial foi desenvolvida no MATLAB, utilizando-se de uma arquitetura apropriada para um problema de reconhecimento de padrões com aprendizado supervisionado e obtendo-se predições de alta precisão dentro de um pequeno intervalo de tempo. O sistema utilizado em todas as simulações é o IEEE 39-Bus New England Power System, que possui 10 unidades geradoras, 21 cargas e 3 áreas distintas, contando com modelos de regimes transitório e subtransitório e 14 unidades de medição fasorial. Futuros trabalhos são discutidos, mostrando as possibilidades para *feature engineering* neste tipo de problema, detecção de tipo de falta e de localização de falta utilizando estruturas análogas de conjunto de dados e rede neural.

Keywords: Artificial neural networks; Power system simulation; Power system faults; Fault detection; Phasor measurement units.

Palavras-chaves: Redes Neurais Artificiais; Simulação de sistemas de potência; Faltas nos sistemas de potência; Detecção de faltas; Unidades de medição fasorial.

1. INTRODUCTION

Nowadays, stable, sustainable, reliable and continuous electricity must be provided to all sorts of consumers throughout the world without fail. Therefore, preventing and allocating resources to remedy voltage collapses and power oscillations – all of which are direct consequences of system faults – becomes one of the most important and arduous tasks power transmission and distribution system operators face in their daily commute (Ajenikoko and Sangotola, 2014; Liang, Wallace and Nguyen, 2017). As such, a method that detects anomalous behaviors throughout the electrical grid would be of great help in assuring reliable and safe operation and would shorten the duration of outages on the customer's side (Sanad Ahmed *et al.*, 2017).

Since all sorts of faults can happen anywhere, anytime throughout the electric grid and a fault on a given bus impact every other bus of the system to some extent, the need for constant, broad and synchronous bus voltages and currents monitoring arises. As a solution to this problem, the sophisticated digital technology of synchronous phasor measurement units (PMUs) was introduced in the industry in the early years of the last decade and has been further improved ever since, substantially impacting the energy quality in power systems. This technology allows operators to synchronously monitor the voltages and currents on a given bus with sampling rates far exceeding those of previous technologies, enabling engineers to analyze dynamic events on the grid (Nuqui, 2001).

However, the number of samples PMUs can provide over a short time span makes real-time observation of instant anomalies too much of a task for human operators. Thus, the application of computational techniques that present a fair amount of reasoning and inference – intelligence – becomes of high interest in regard to the solution of such a problem. Given the structure of the data provided by the PMUs, one of the most convenient techniques available is the artificial neural network (ANN) with supervised learning, using data on previous faults for its training. To a degree of certainty, the ANN can provide a diagnosis on whether the system is being normally operated or not, what types of fault are occurring and in which buses – thus helping the system operator fulfill his tasks in a shorter amount of time and improving the reliability of the power supply.

2. IEEE 39-BUS NEW ENGLAND POWER SYSTEM

The New England power system encompasses all six states in the New England area of the United States of America and supplies major metropolis Boston, Massachusetts. It is currently operated by the ISO New England company and was better documented and structured after the Northeast Blackout of 1965 (Babula and Planning, 2017).

2.1 Steady-state characteristics

When normally operating, the New England power system presents 39 buses, 10 generators, 46 transmission lines and 3 areas totaling a consumption of roughly 6.3 MW out of total generation capacity of 7.367 MW. A power flow simulation for this system was run using Graham Rogers' Power System Toolbox (PST) for MATLAB (Chow and Cheung, 1992). More data on the system is available in Table 1. Its diagram is available in Fig. 1.

Table 1. New England Power System data

Parameter	Data
Generation (Used)	6.298 GW
Generation (Total)	7.367 GW
Maximum Voltage Magnitude	1.064 pu @ bus 36
Maximum Voltage Angle	4.47 deg @ bus 36
Minimum Voltage Magnitude	0.982 pu @ bus 31
Minimum Voltage Angle	-14.54 deg @ bus 39

2.2 Transient and sub transient characteristics

In regards to the system's dynamic behavior, there are models and parameters for the generators' positive, negative and zero sequences as well for controllers such as power system stabilizers (PSS), automatic voltage regulators (AVR) and governors – all of which are taken in consideration during PST's fault simulation and can be found in (Hiskens, 2013) and (Law, 2007). Furthermore, in this paper, anomalous operation is defined as a situation where bus voltage, current and power levels differ from those measured in normal operation, regardless of the cause.

2.3 PMU network emulation

Each fault simulation has an output of 5 seconds worth of samples. The PMU sampling rate chosen in this paper is 10 samples per cycle – meaning there are 500 samples per simulation for every variable.

Furthermore, in a regular simulation, PST outputs all voltages and all currents entering and leaving every single bus in the system. However, in real life, there aren't PMUs in all buses of the grid, as their measurements are rarely – but sometimes – uncertain due to possible firmware, hardware and software malfunction as well as possible communication system interferences, making system operators use state estimators in order the validate the current state of the systems (Oladeji and Adu, 2018).

Thus, in this paper, all data asides the currents and voltages in buses 4, 8, 16, 28 and 30 – 39 is disregarded. As such, the aforementioned buses are the ones in which PMUs are located. The first 4 buses (4, 8, 16, 28) all have large loads allocated in them and are, in most part, located in different areas from one another or are physically close to area inter-ties. The last 10 are all generator buses, whose measurements and constant monitoring are key to the system's well-being and proper running and, ultimately, are the fastest way to indicate power surges.

Such an arrangement provides for a sufficient overview of the system's current state without the need of having PMUs installed in all buses – implying a lower installation and maintenance cost for power companies.

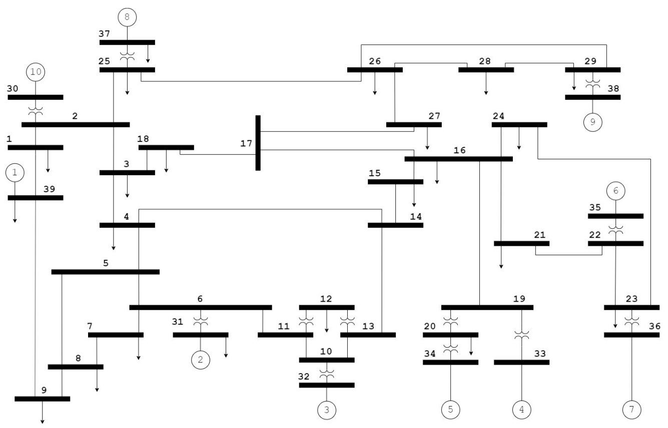

Fig. 1 New England Power System electric diagram.

3. ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks can be described as a set of elementary neurons that are usually connected in biologically inspired architectures and organized in several layers (Ayyagari, 2011). There are N_i neurons in a network in each of the i_n layers and the inputs to these neurons are connected to the outputs of the previous layer's neurons.

Each of these neurons has an assigned weight, which is tailored through the training process – thus, making the ANN learn to produce a response based on the inputs given by adjusting the node weights. Hence, we need a set of data referred to as the training data set, which is used in the network's training processes.

The input layer is fed with the excitation signals – all the parameters established in the dataset and the samples – and the output layer returns the ANN's judgment concerning the task at hand. Namely, the output is a non-linear function of the sum of all neuron's outputs. There may be several "hidden" intermediate layers each with a possibly distinct number of neurons whose meanings and node weights are not easily (nor commonly) understood by humans.

A common structure for a generic ANN is depicted in Fig. 2.

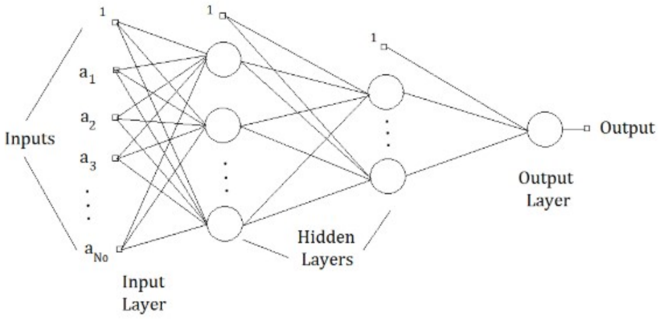

Fig. 2 A generic three-layer architecture of a feedforward ANN.

3.1 Dataset obtainment and structure

As mentioned in the previous section, all data used in this paper is the PST fault simulation results. The simulated faults were 3ϕ, 2ϕ, 2ϕ – G, ϕ – G alongside with line and load contingencies in all 39 buses and 46 transmission lines of the IEEE 39 bus New England power system. Thus, 280 distinct fault, line and load contingency simulations and a normal operation power flow simulation were performed. A binary system operation condition index was added to each simulation, indicating whether the system is operating normally or if there is any sort of anomaly in it.

The dataset is structured so that the columns represent the PMU buses and the lines are the samples of every simulation. Since the samples were all ordered in timestamp and the number of simulations, a MATLAB script was coded in order to process all samples into the aforementioned arrangement of 14 PMUs and randomize the order of the lines in the .mat file. All bus voltages and currents were normalized to values between 0 and 1.

A more cohesive understanding of the dataset's structure can be reached by observing Table 2.

Table 2. Dataset format example

Bus Voltage Magnitude	**Bus Voltage Angle**	**Bus Current Magnitude**	**Bus Current Angle**	**Operation State Index**
500 samples per simulation, each sample in a line indicating its timestamp				0 – Normal Operation 1 – Anomalous Operation

3.2 Artificial Neural Network design

The learning process selected for the ANN architecture is supervised learning, which shows good results when the task involves pattern recognition (Ayyagari, 2011). Thus, there must be an input dataset – containing information on bus voltages and currents – and an output dataset – containing information on whether that sample represents a normal or anomalous operation. Such a process is depicted in Fig. 3.

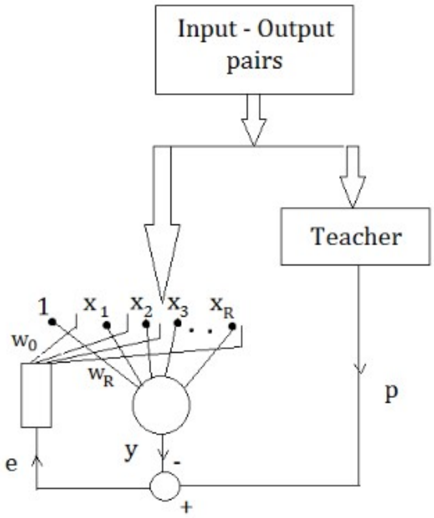

Fig. 3 Supervised learning for artificial neural networks.

In pursuance of the best evaluation of a machine learning model's performance, one can make use of the accuracy, precision, recall and F1 Score metrics – all of which make use of the number of true and false positives and negatives yielded at the end of any training method. (Haque, Rahman and Siddik, 2019). Other metrics such as negative predictive value and true negative rate can also be analyzed.

Accuracy is a metric used to ascertain the quality of the predictions of an ANN, regardless if they're positive or negative. Precision, in its stead, is used to measure the quality of an ANN's predictions based only on what it claims to be positive. Recall, on the other hand, is used to measure such quality in respect to the mistakes commited by the predictor.

F1 Score, being the weighted average of precision and recall, has a range between 0 and 1 and conveys the balance between the both of them.

F1 Score is widely accepted as a more realistic measure of a predictor's quality when compared to accuracy alone, since a good balance between precision and recall means that the F1 Score tends to 1 and the classifier has a high degree of generalization.

Through an empirical procedure, an ANN was designed to have an input layer with 56 entries (14 PMU bus voltages and currents magnitudes and angles), a hidden layer with 12 neurons and a sigmoid transfer function and an output layer with 2 neurons and a SoftMax transfer function, as seen in Fig. 4.

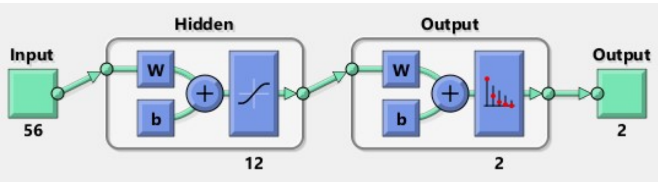

Fig. 4 Designed feedforward ANN diagram.

In order to better validate the robustness of this model and assure net generalization, a 10-fold cross validation was applied. This ensures all samples inside the dataset were used at least once in a testing process – thus, being more robust to biases that may come from the selection of a particular set of data and ultimately preventing overfitting.

In regards to the neural network's neuron weights for all layers and its biases, the Scaled Conjugate Gradient method was used for the traning process with Cross-Entropy as a performance measure (loss function). Out of all samples, 70% were used for training, 15% for the validation process and 15% for the testing process.

In order to lessen the effects of random initialization in regards to the neurons' weights and biases, the training-validation-testing process was repeated a total of 50 times. The network that presented the lowest Cross-Entropy (CE) value was chosen for application.

The usage of genetic algorithms envisioning the optimization of the number of hidden layers and its respective neurons is a fairly common practice in all fields of knowledge concerning artificial intelligence (Yang, Zhao and Chen, 2017). However, in this paper, such an approach was not considered because of the binary nature of the problem and its samples.

4. APPLICATION AND RESULTS

The 10-fold cross validation for the proposed model yielded means of 0.905 accuracy, 0.640 precision and 1.0 recall in regards to the normal operation class and 0.78 F1 Score – thus, validating the robustness of the ANN structure presented on Fig. 4.

Upon the training, validation and testing processes' end described in section 3.2, the best CE value found equaled 0.0851. Therefore, the model instance associated with this value was chosen for application. Furthermore, its performance can be evaluated. The training took 432 iterations (epochs) in order to reach an acceptable margin of Cross-Entropy in a time span of 28 seconds.

The validated performance plot of the proposed neural network is depicted in Fig. 5., in which it can be graphically seen that the ANN achieved a desired low CE value by the end of the process.

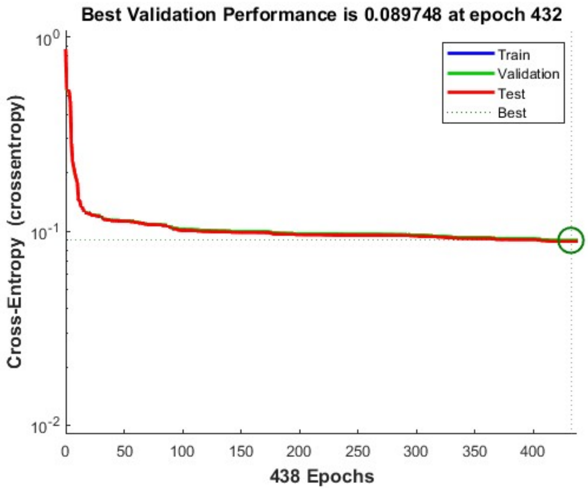

Fig. 5 Validation performance plot for the ANN proposed in this paper.

One of the most common means of visualizing the performance of an ANN is by plotting the confusion matrices for all phases of the network's learning process. All of them are depicted in Figs. 6 - 9.

The diagonal cells in green indicate the number of cases that have been classified correctly – true positives and negatives – by the neural network and the off-diagonal cells that are in red indicate the number of cases that have been wrongly classified – false positives and negatives – by the ANN.

Once again, the usage of accuracy alongside precision, recall and F1 Score is substantial to ascertain an acceptable functioning of the designed network.

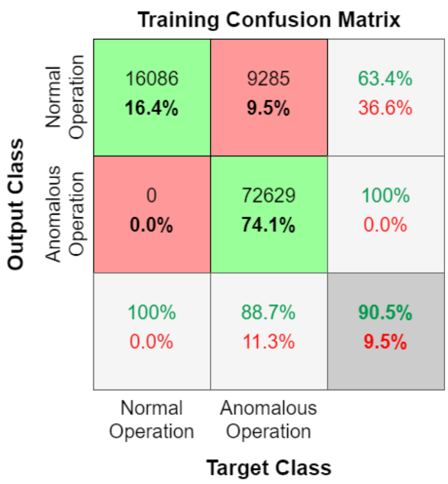

Fig. 6 Training confusion matrix of the proposed ANN.

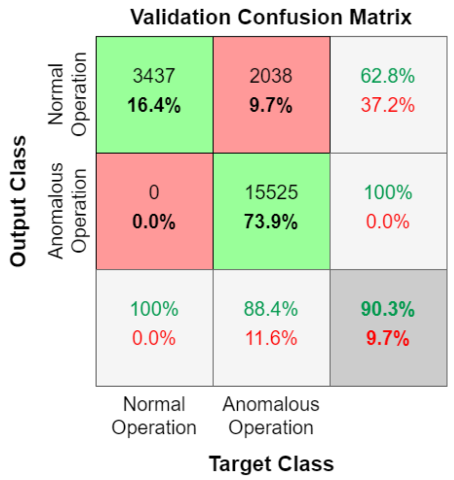

Fig. 7 Validation confusion matrix of the proposed ANN.

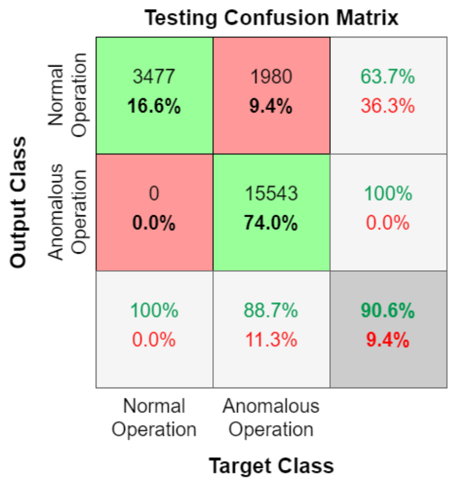

Fig. 8 Test confusion matrix of the proposed ANN.

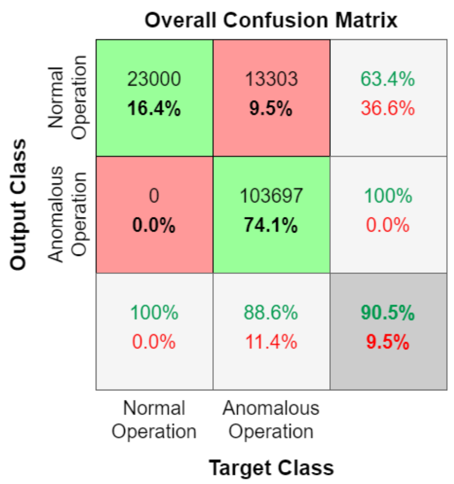

Fig. 9 Overall confusion matrix for the proposed ANN.

By inspecting the overall confusion matrix (Fig. 9), it can be seen that the neural network achieved an accuracy of 0.905 with 0.634 precision and 1.0 recall in regards to the normal operation class, yielding a 0.776 F1 Score. The negative predictive value (NPV) equals 1 and the true negative rate (TNR) equals 0.886.

5. CONCLUSIONS

In this paper, an artificial neural network that can detect how the power system is being operated is presented without the need of pre-fault data. The network depends on post-fault data that formulates a pattern recognition problem in regard to the operation state.

The presented ANN can infer correctly on whether a system is in normal or anomalous operation in 90.5% of the time. It can correctly indentify normal operation in 100% of all cases, being correct 63.4% of the time. On the other hand, it correctly identifies anomalous operation 88.6% of all cases, being correct 100% of the time.

One of the reasons as to why precision levels regarding normal operation prediction aren't higher is the fact that some simulated faults present post-fault data that are very similar to normal operation levels. Another reason is that the first ten samples of each fault simulation are what one might consider "normal operation".

In order to assess this problem, considering the temporal nature of PMU data, future developments of this work can involve feature engineering in order to further improve the presentation of the data to the proposed model – thus, yielding the best possible prediction results.

However, the presented metrics are sufficiently high to consider the designed network as a solution to the proposed problem.

Furthermore, this paper can also be considered as a study of how ANNs can work together with the PMU technology in order to further develop power systems around the world and better supply all clients – from industrial to residential – contemplated by power companies.

In an analogous fashion, with the proper changes to the dataset structure for the desired outputs in the learning process, one can use ANN – or any other optimization or intelligent computational technique, as a matter of fact – in order to do a fault type detection system.

Further developments in this area of work can also lead to artificial intelligence or an algorithm that not only detects the type of fault happening in a system but that also locates where the fault is taking place through a PMU network that doesn't encompass every single bus and line in the power system.

Therefore, system operators would be able to rapidly detect what type of fault or contingency is or might happen and where so as to have an assisted judgment and assessment on the situation in regards to what preventive or remedial measures can be taken in order to evade or solve any sorts of problems that might affect the consumers.

This paper's work, however, can also assist system operators by automating alarms to be triggered whenever the system enters in anomalous operation – thus speeding and easing the problem solution as a whole as well.

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