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Artificial intelligence applied to explore the causes of transmission line faults.

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SUMMARY

One of the significant challenges to guarantee a good availability of the transmission systems corresponds to the diagnosis time of the causes of transmission line faults since having a correct and fast diagnosis allows an essential reduction of the time in the restoration of transmission lines. In order to carry out an automated diagnosis that allows fast decision-making in real-time operation, a solution has been proposed in this paper by implementing a methodology based on the incorporation of AI(Artificial Intelligence) trained from oscillographic records (COMTRADE files) from the original faults in transmission circuits operated by ISA INTERCOLOMBIA power utility.

KEYWORDS

Machine Learning - Fault Disturbances - Fault Resistance – Oscillograph - Digital Fault Recorder - Transmission Line Restoration.

1. INTRODUCTION

One of the relevant challenges to guarantee the reliability of the power transmission systems involves the needed time of diagnosis for transmission lines fault causes; hence, having a correct and fast diagnosis represents a significant reduction of the time related to restoration of transmission lines.

The worldwide research is mainly related to fault location and classification fault type (single-phase to ground, two-phase, two-phase to ground, and three-phase). On the other hand, the researches [1], [2], and [3] describe the application of an ANN algorithm for training, testing, and evaluation based on a multilayer perceptron feed-forward neural network with a back-propagation algorithm. In [4], the authors propose a method that exploits the temporal sequence of the power system's operational data and develops a model employing Long Short-Term Memory (LSTM) units working directly on the operational data instead of features. Paper [5] shows the literature relevant to the implementation of intelligent unmanned aerial vehicle (UAV) approaches for fault detection and classification. In conclusion, most of the researches discuss the fault location and fault type but does not consider the causes of transmission line failure.

Depending on the fault causes, those faults can cause permanent outages of the transmission lines. For instance, cases that require the displacement of maintenance personnel. When this kind of failure happens, the real-time time operators with the support of post-operational analysts, work quickly to find the cause of failure. The resources mentioned before should be managed fast and efficiently for a successful restoration of any affected asset.

The diagnosis required for finding the failure origin involves a detailed and complex analytical process. The main source of information is the oscillograph records (principally COMTRADE files) since they have the electrical variables involved in the studied phenomena and the representative sample rate.

There are several causes for transmission line faults that might lead to a permanent outage; however, this work focuses on two frequent fault causes which are fire under the transmission line and close-up with vegetation.

These two causes are considered critical due to the likelihood of occurrence in the Colombian power system as in other tropical countries; additionally, the difficulty of discrimination between these two causes when evaluating a ground fault.

Preventive maintenance by local inspection may reduce the likelihood of vegetation close-up with transmission lines; however, in some cases, the maintenance labor is not an easy task due to the social risk, owner borders, and inaccessible geographic areas.

On the other hand, fires under the transmission line are due to natural phenomena such as high temperatures at certain times of the year, malicious acts, or agricultural activities in the surrounding areas of the transmission lines. If these faults are not handled promptly, they can lead to more than one transmission line being affected, increasing the risk of unattended demand, as well as the integrity of people, animals, crops, and homes.

Therefore, there is a clear need to develop expert systems based on artificial intelligence to diagnose transmission lines failure, which is very beneficial for the operation in real-time, allowing more time to manage the resources required.

This paper presents an automatic diagnosis method allowing fast decision-making to the real-time operators of the power system, implementing a methodology based on the incorporation of AI (Artificial Intelligence) built and trained by oscillographic records from real disturbance fault from ISA INTERCOLOMBIA utility.

2. METHODOLOGY

The proposed methodology consists of three fundamental steps to implement the diagnosis of transmission lines fault using AI.

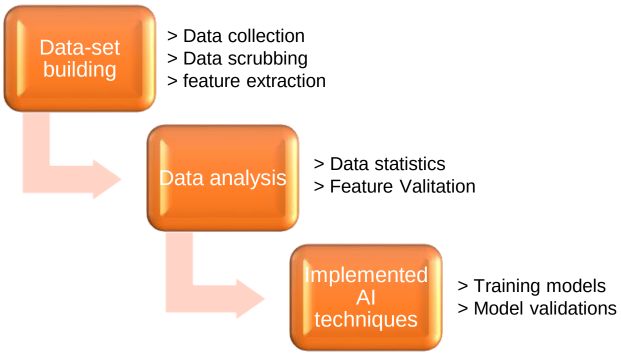


Figure 1 – Methodology for AI implementation

2.1. Data-set Building

The information available for the analysis comprises 70 cases of faults in transmission circuits. These cases are composed by the oscillographic as the primary information since those contain the electrical variables directly involved in the fault phenomenon; however, single-phase faults caused by burning and close-up with vegetation present similarities in these variables, which makes the classification between them difficult.

Reduction of the dimensionality of variables corresponds to the first step for the extraction of characteristics, for which, given the currents and voltages coming from the DFR (Digital Fault Recorders) at each end of the circuit, we can calculate the fault resistance in time $RF(t)$ resulting in a single signal [6].

$$RF(t) = \frac{VF(t)}{I2R(t) + I2S(t)} \qquad (1)$$

Where $VF(t)$ refers to the phasor voltage in the fault, $I2R(t)$ and $I2S(t)$ represent the negative sequence of fault current in both transmission line terminals.

In Figure 2 it is shown the fault resistance calculation in the time (green curve) for a close-up with vegetation fault. Note that this signal presents some noise distortion due to the phasor calculation at the fundamental frequency and measurement error generated from CT(current transformer), PT(Potential Transformers), DFR, among others; therefore, we developed a low-pass filter used to cut those frequencies above 45 Hz, which allowed to smooth the resistance fault calculation in the time (blue curve).

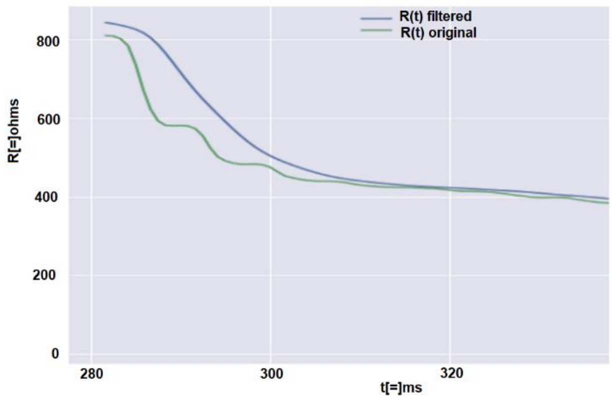


Figure 2 – Fault resistance calculation.

Due to the physical phenomenon related to the fault resistance that always starts at a maximum value and tends to decrease in time, we used this phenomenon to create the data set from the descriptive statistics. In addition, we complement it with an algorithm for defining the length of the fragment time duration of the signal; for this propose, we used the difference between the first and second derivative of the resistance over time so that the recorded signal ends when this difference is less than 10% of the maximum magnitude of the first derivative.

With the creation of the cutout fragment, it was possible to eliminate the bias due to the arbitrary duration of each record, which mainly depends on the time of the operation time of protections and circuit breaker opening time. Hence, the data-set contains percentiles between 25 and 90, mean of resistance, time t1 (time between the percentiles 75 to 25 percentile), time t2 (time between the percentiles 90 to 50), and minimum value of the first derivative of the resistance.

As an illustration, Figure 3 shows the resistance calculation for a failure caused by close-up with vegetation under the transmission line; from this cut fragment in the time domain, we obtain the features (percentiles P25, P50, P75, and P90) represented by dashed lines in the graph above; in the graph below, is present the first and second derivative in which is obtained the minimum first derivative min_df/dt. Figure 4 shows the data statistics from the features resulting from the previous step in Figure 3.

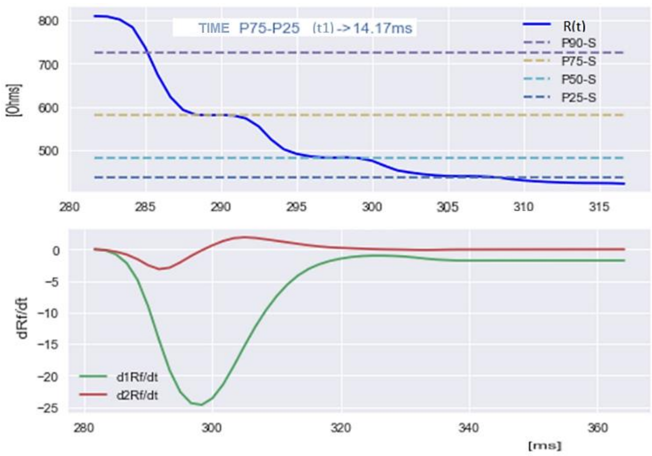


Figure 3 – Resistance calculation from a close-up with vegetation fault

2.2. Data Analysis

The data analysis aims to identify the most appropriate model to represent the sample data distribution. The analytical graphs and statistics allow us to explore the distribution, identifying characteristics such as outliers, discontinuities, concentrations of values, and data distribution. This analysis can be performed on all cases together or separately by groups. In the latter, the graphs and statistics make it possible to identify whether the data come from one or several populations, considering the variable that determines the groups as a differentiating factor of the populations. It also makes it possible to check, using graphical techniques and non-parametric tests, whether the data comes from a normal distribution or not.

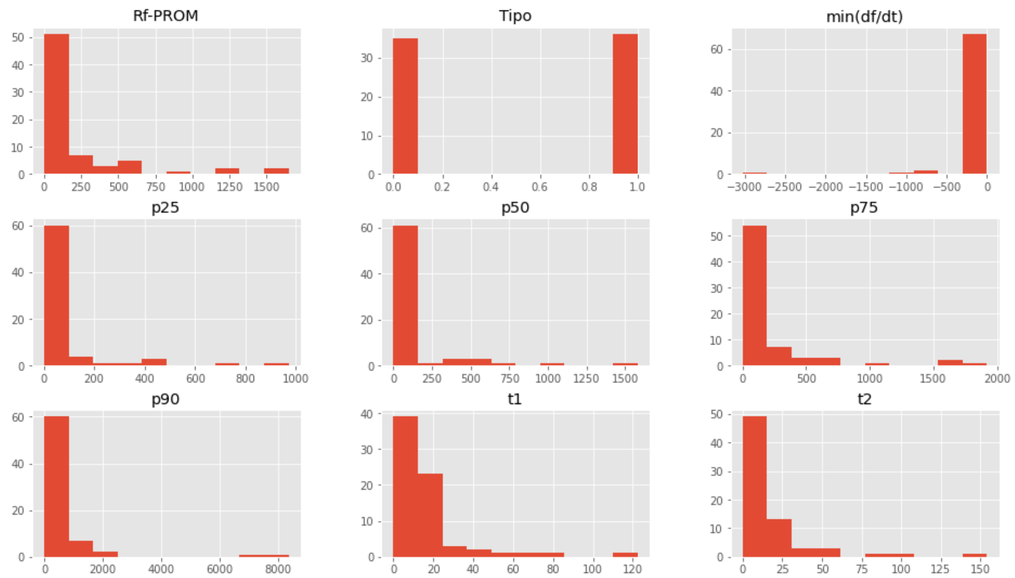
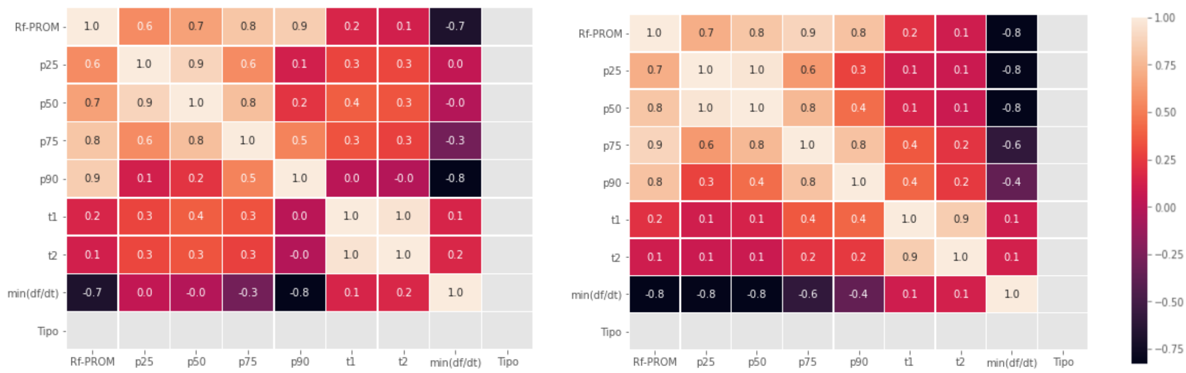


Figure 4 – Histogram plot from features of a close-up with vegetation fault.

Scatter Plots are used to create a graphical representation of 2 or 3 dimensions (the third dimension is represented by the size of the point), taking into account the following elements: the eventual belonging of an observation to a group, the eventual overlapping of some points of the plot, the eventual presence of data labels, the crossing of several X (abscissa) and Y (ordinate) variables.

Figure 5 – Scatter plot for fire under transmission line (red dots) and close-up with vegetation (blue dots).

The variables were correlated for the close-up vegetation and fire under the transmission line, showing that the 25th to 90th percentiles show low correlations, which concludes that they are good features.



Close-up with vegetation Fire under transmission line

Figure 6 – Correlation plot for fire under transmission line and close-up with vegetation causes.

3. RESULT

Prior to AI training, a strategy was defined for data-set selection using a method known as subset selection. This method is used to find the best features that can solve the problem better, creating different data-set from the original one. In our case, four data-set was created, the first from the Lasso-type linear regressor, the second by heuristic selection (by eliminating the least correlated features), the third by the PCA(Principal component analysis), and the fourth using the origina

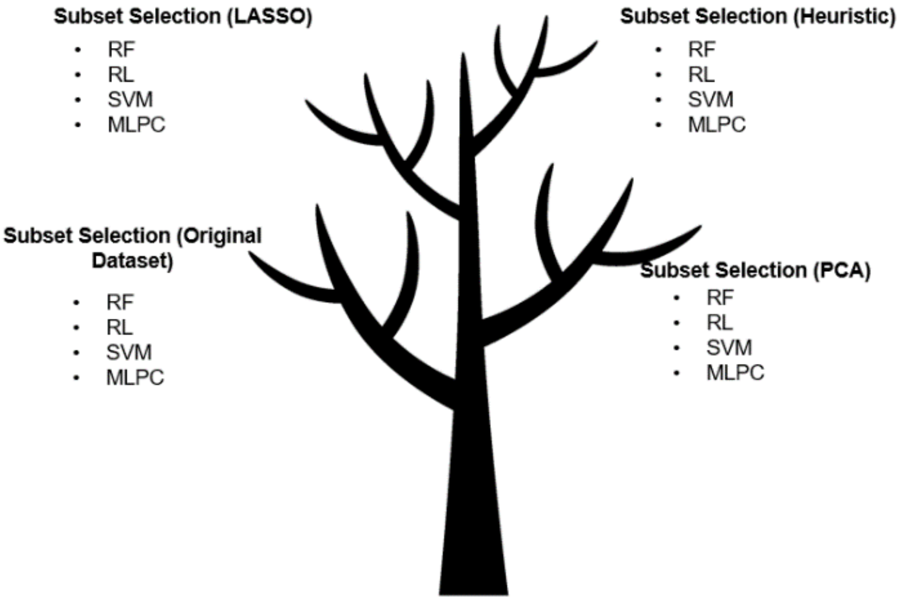


Figure 7 – Training methodology for AI.

From the four types of data sets obtained in the previous step, training of the different AI techniques was performed; as a result, Figure *8* shows that the best accuracy was obtained for the SVM techniques with linear kernel trained with the data set generated from the extraction method with PCA.

The training is performed to each data-set built in the previous step; additionally, each data-set is divided into two different training-set and validation-set with 80% and 20 % of the data, respectively. Finally, several machine learning methods are used and applied to each training-set (RF-Random Forest, RL-Linear Regression, SVM-Support Vector Machine, and MLP-Multy Layer Perceptron Classifier).

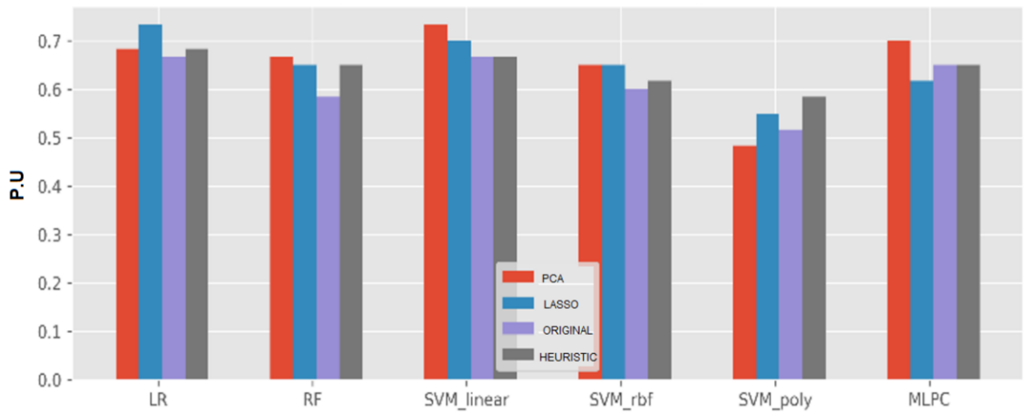


Figure 8 – Accuracy of the trained models.

On the other hand, Figure 9 shows that the technique that presented the lowest standard deviation was MLPC trained with the data set obtained from the PCA extraction. It should be noted that this metric is related to the generalization of the model, so when crossing the information in Graph 9 and Graph 10, it is concluded that the best choice would be MLPC since its accuracy is good and its standard deviation is the best.

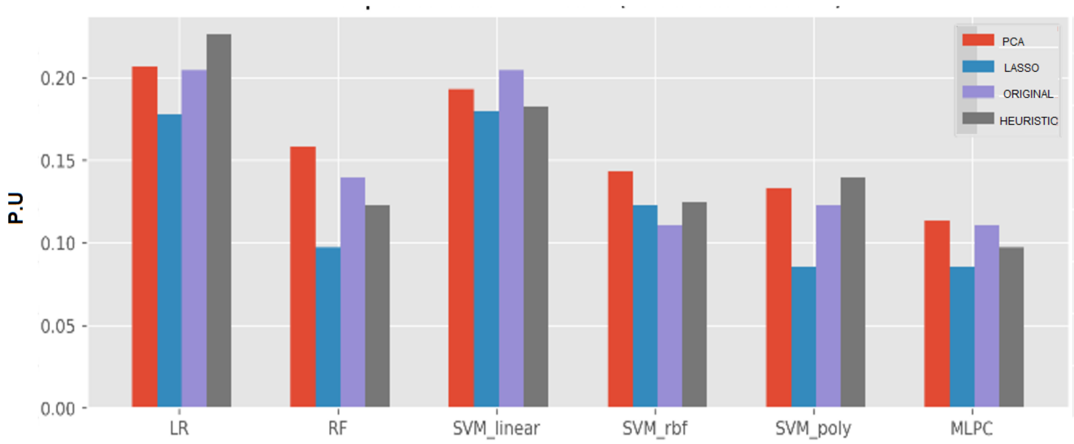


Figure 9 – Standard deviation of the trained models.

4. CONCLUSIONS

This research contributes to the strategic objectives 2030 of the ISA group, related to the digital transformation, generating value by achieving efficiencies in the operation and maintenance of the company's assets by being an input for the timely identification in the diagnosis of failure causes, resulting in the reduction of unavailability and OPEX.

A methodology based on AI was successfully implemented as a test prototype using information from the oscillographic records to diagnose the types of faults caused by approaching vegetation or burning under the transmission lines.

Different supervised AI techniques (RL, RF, SVM, MLPC) were implemented; selection techniques (lasso and heuristic), feature extraction techniques (PCA), and complete set were also tested, where the method was selected for accuracy and simplicity was MLPC.

During the training, the need to expand the data-set with future faults was observed because currently, there are no more records reported for the types of faults proposed.

The next step involves other causes of transmission line faults. For example, distinguish between several low impedance causes like insulator faults and atmospheric discharge faults; furthermore, increase the data-set with information regarding meteorological variables like atmospheric discharge density and other information from the operation.

Although the model does not predict the future, a fast diagnosis of fault causes helps the operators to make quick decisions to ensure the safe operation of the power system. For instance, if several transmission lines share the same area and there is a fire under those transmission lines, that may cause multiple outages and high operative costs if no action is taken. But instead of this the model helps to make a quick decision, then the operator can redistribute generation resources through this area, avoiding the secondary effects.

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