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"Supervisory Control and Data Acquisition Analysis for Wind Turbine Maintenance Management"

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Supervisory Control and Data Acquisition Analysis for Wind Turbine Maintenance Management

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Abstract

Wind energy is growing to become a competitive energy source. An efficient wind turbine maintenance management is required for ensuring the reliability of the energy production and the costs reduction. Supervisory control and data acquisition system provide information about the condition of the wind turbine by signals of the different subsystems and alarm activations in case of failure or malfunction. Due to the volume and variety of the data, operators require advanced analytics to control the performance of the wind turbines and the identification and prediction of failures.

The novelty proposed in this work is based on statistical analysis for analyzing supervisory control and data acquisition data to optimize the use of the data in neural networks. The first phase is the alarm analysis, quantifying the critical alarms regarding on the number and time of activation. A filtering algorithm is developed for considering only interest periods with enough range to make the study. The second phase is based on the initial data treatment, classifying alarms and signals identifying the interest time periods. Neural network is defined and trained for evaluating the signal trends, with the aim of detecting the alarm activations cause. This information will be used in the maintenance management plan for programming maintenance tasks.

Key Words: Wind Turbine, Maintenance Plan, SCADA System, Neural Network, Wind Turbine Management.

1 Introduction

Wind energy is growing as renewable energy due to greater heights and powers of current wind turbines (WT), with new and moderns installations [1]. It is expected new installations, with more than 55 GW every year in the world until 2023 for onshore and offshore, see Figure 1~~Figure 1~~ [2]. Offshore installation is increasing its capacity with the associated technical issues in installation and maintenance, and ~~. I~~it is expected to reach 2182 TW h by 2030.

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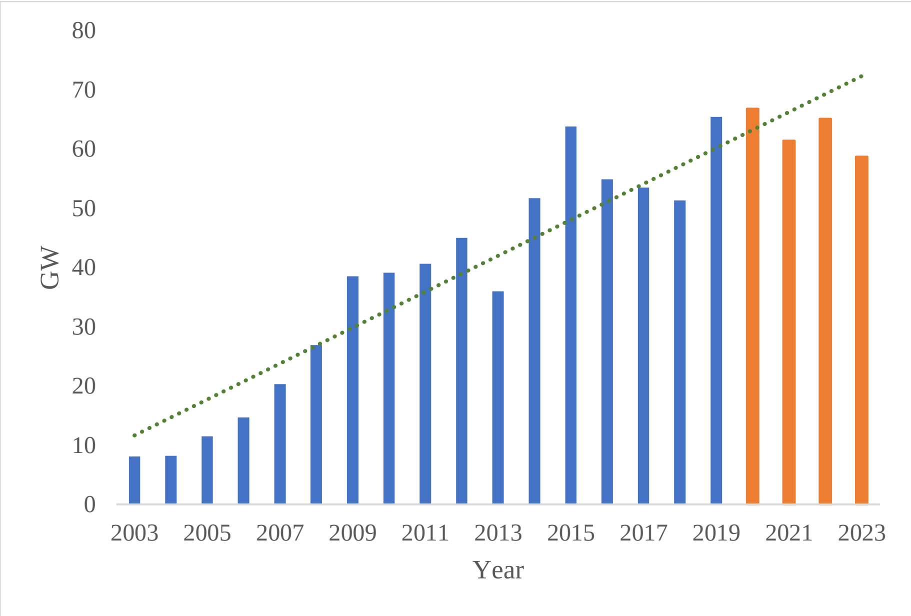

Figure 1: Wind energy capacity and projection.

The WT is composed of several subsystems, transforming wind energy into electric energy [3]. ~~The wind induces the movement into the blades, and the main shaft transmits the mechanical energy into the gearbox. The main shaft is supported by bearings and it is connected with the generator. Different subsystems are designed for supporting the normal behaviour of the WT, e.g. the meteorological unit, for controlling the pitch and brake systems.~~ Wind farms are located in areas with hard environments with proper wind conditions and, consequently, each WT may present issues related to energy losses, e.g. mechanical failures and blade icing [4,5]. The rotor blades, electrical devices, plant control system, hydraulic and sensors congregate more than 50% of total failures [6,7]. The maintenance operations have important associated costs, high risks for human resources in the WT access and the energy production losses due to downtimes [8]. The WT operation and maintenance (O&M) costs are between 10%–25% of the total costs [9]. ~~Due to the working conditions, the efficiency and security of O&M activities are reduced, and it is required novel failure prediction techniques for avoiding downtimes and increasing the reliability of the installations~~ [10]~~.~~ Novel technological solutions are needed to increase the competitiveness based on the maintenance cost reduction for ensuring the efficient positioning of this technology in the energy market [10,11]~~. The improvement in the maintenance management operations will allow to reach the competitiveness in wind power in terms of reliability, lifetime and availability~~ [12].

Current large-scale WTs require novel O&M approaches and, therefore, the role of the condition monitoring system (CMS) is fundamental for failure detection, allowing proper maintenance management and the reduction of down-times [13,14]. The monitoring techniques are based in performance monitoring, vibration (for gearbox and mechanic monitoring), acoustic emissions (this analysis provides data about waves generated by the failures) [15,16], thermal, oil and ultrasonic analysis [17], among others. ~~Several types of maintenance operations are developed for incrementing the reliability of the energy production~~ [18]. Industrial CMS provide information about the real state of the WT, being possible the identification of potential failures using different data analysis [19]. ~~The efficiency of the integrated CMS is based on the number, location and sensor types.~~

~~The methodology for fault diagnosis in WTs is divided into model or data type. The ´method analysis uses mathematical models developed with the comprehension of the physical behaviour of the WT. Monitoring established with data system is developed analysing the historical data and mathematical algorithms are applied for pattern recognition.~~ The volume and diversity type of the data provided for the CMS requires different analysis for extracting the real condition of the WT [20]. Different researches and techniques are focused in the analysis by components. Fault Tree Analysis (FTA) is a qualitative analysis for representing graphically the connections between the effect of the produced faults to the components~~. FTA is a technique performed by binary decision diagrams that allows the quantitative analysis and the identification of the critical components of each WT, identifying the critical risks with by gates~~ [21,22]. Supervisory control and data acquisition (SCADA) system integrates all the sensors and measurement systems, and the data from the WT is received and storage. The SCADA system monitors signals and alarms with a range acquisition period per minute o per ten minutes. The alarm activations display the anomalies or failures detected by the sensors although CMS may induce false alarms due to wrong analysis or non-defined failures [23]. This issue reduces the veracity of the system, being necessary novel algorithms for false alarm identification [24]. The generation of false alarms by SCADA system is a fundamental issue due to unnecessary stops, false interventions by the maintenance team and loss of productivity. Several researches are based on the detection and reduction of WTs false alarms [25] with different rules for the reset of certain number of alarms.

SCADA data are used in the control of the WT for improving the operation and the reliability of this method is probed in different researches [26], although it is required novel analysis techniques for pattern identification [27]. Due to the amount of data, intelligent algorithms and signal processing techniques are included in the analysis for early failure detection [28,29]. Machine learning algorithms are applied for data processing in order to extract valuable information. Artificial neural networks (ANNs) are computational models based on the nerve system formed by neurons in human brains. Several neurons are connected to each other with different weights and layers. The design of ANNs is determined by the connections and the transfer function between neurons, being the number of neurons a fundamental parameter in the neural network performance. ANNs are trained using specific datasets, and the network modifies the weight of each layer and the connections between neurons. ANNs are able to deal with complex problems with reduced operational response times, and it is not required the determination of the analytical function of the model for the data treatment. This algorithm works with variety of input and output information proving the suitability of the method. For these reason, the ANNs are established in several application fields, e.g. power electronics [30], photovoltaic energy [31], medicine[32] and image processing, due to its suitability and efficiency.

It is probed the effectiveness and strength of ANNs in the patter identification of failures in WT [32]. With an efficient training, it is possible to identify patterns for prediction, classification and forecasting. Zhang and Wang [33] propose a fault detection model using ANNs with SCADA data in main WT bearing system.

The novelty proposed is based on the combination of different method analysis for fault detection and diagnosis employing SCADA data. It is pretended a better ANN accuracy by means of basic statistical analysis of the data before the use of the ANN. Initial statistical analysis for selecting critical alarms for further analysis and principal component analysis (PCA) will be applied for reducing the dimensions of the data [34]. The ANN application provides valuable information for pattern identification. A real case of WT with failure is presented and analysed with the method presented, analysing the results obtained and probing the reliability of the method.

2 SCADA fault detection methodology and case study

The data analysis is a key factor for WT maintenance management. The methodology proposed in this work is based on the SCADA data signals with PCA for the identification of the causes of alarm activation for further analysis based on ANN. The signals will be filtered and evaluated with PCA with the aim of reducing de volume of the data and improving the efficiency of the ANN. The results of the ANN will be used in early detection of failures.

The first phase is the alarm filtering for identifying the critical alarms with Pareto chart and the activation information of the alarms. Initial alarm analysis is determined for detecting critical alarms for further analysis. Pareto chart is applied to identify the critical alarms. The number of activations, time of activation and difference between alarms will give the alarm for study. Once the alarm set is done, it is studied the period of interest, analysing the time between alarms and filtering the alarms with no interest in the study, e.g. alarms with reduced activation period with periods of time with no alarms. The second phase is signal analysis. Different signals are pre-selected and it is pretended to analyse the behaviour of these signals in the periods with no alarm activation. Using P-Value, it is probed the importance of several signals and the signal with no required values will be deleted from the study. The third phase is based on the identification of the interest range of the data, as it is possible to see in Figure 2~~Figure 2~~. Due to the extension period between alarms, it is necessary a synchronization between alarm and associated signals, and then a proper selection of the signal period for increasing the reliability of the analysis method. It is considered in this model that the signal data closer to the alarm activation have more relevance in the failure causing. Two different zones have been designed: the first zone is the area with no influence in the alarm activations. The second zone includes the cause of the alarm activation. Once it is defined the possible alarm activation periods in the signal data, PCA is applied. PCA analysis is a dimension reduction algorithm that allows the transformation of an amount of data into smaller groups that hold most of the source information [35]. PCA is a multivariate analysis with different linear combinations and transformations of the original dataset

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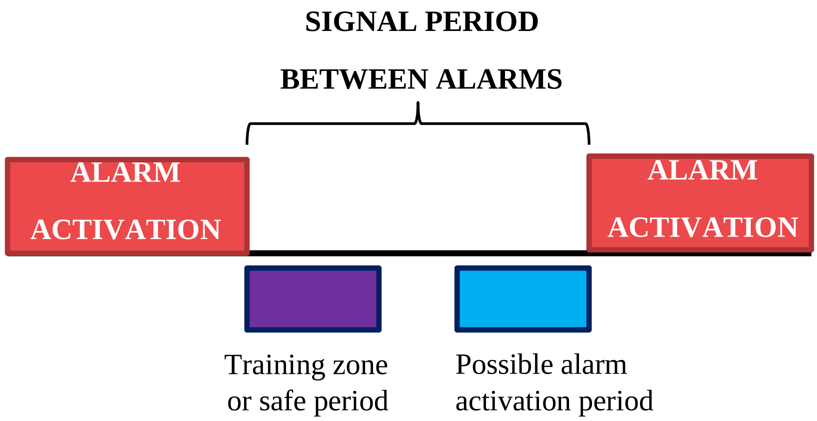

Figure 2: Interest period diagram.

A real case study is considered for testing the reliability of the methodology analysing the SCADA data extracted from a real WT. This turbine has a rated power of 2 MW and different alarms are identified in the system. Pareto chart is applied in different alarms in Figure 3~~Figure 3~~, analysing the number of activations, the period of the activated alarm, the maximum period of the alarm and the difference between alarms.

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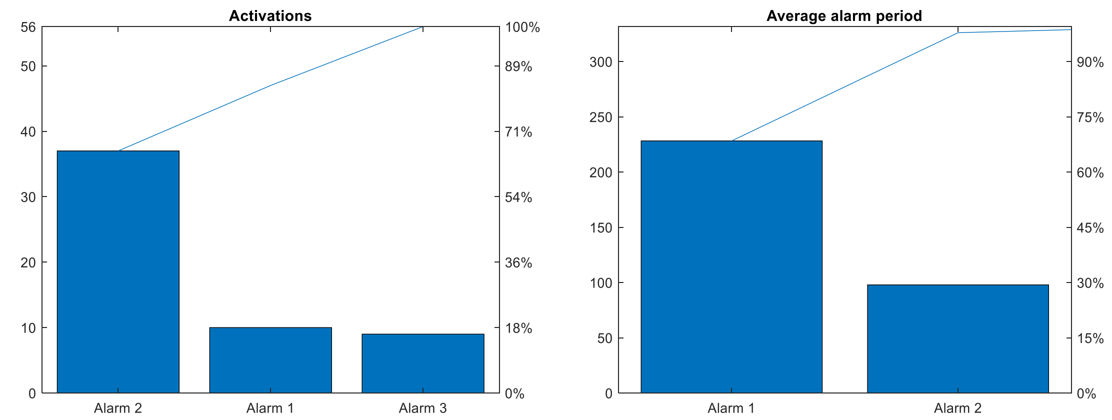
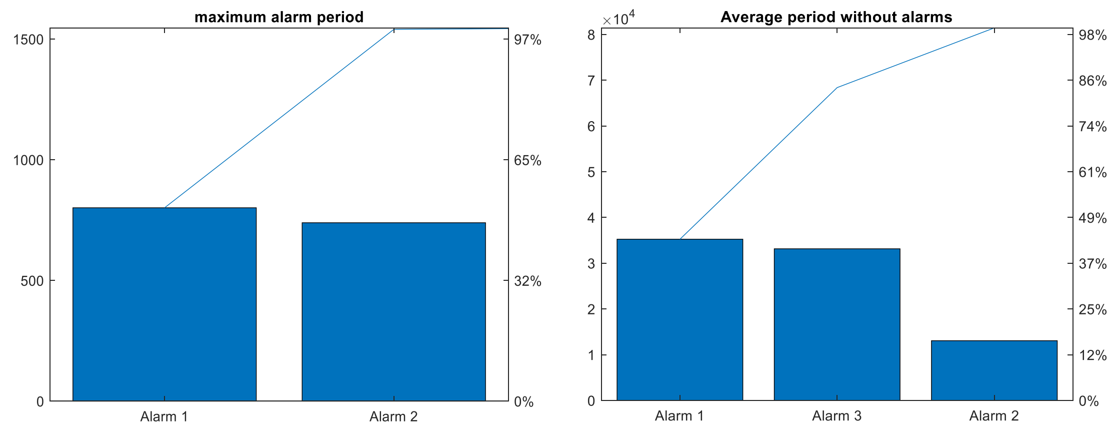


a) b)



c) d)

Figure 3: a) Alarms activation. **b)** Average alarm period. **c)** Maximum period of each alarm activation. **d)** Average period without alarms.

Alarm 2 presents an elevated number of activations in comparison with other alarms. Alarm 1 is activated less periods, but the period of each activation is higher compared to Alarm 3 and Alarm 3. Alarm 1 and Alarm 2 present similar values, although Alarm 1 shows more distance between each activation. The period between alarms is fundamental for ensuring the proper activation of the alarm, therefore, decreased periods produce reduced information about the failure. This characteristic allows a greater range of data for the study and, for this reason, Alarm 2 is studied in detail in this paper. Once the alarm is selected, the first phase of the methodology filters the alarm for the acquisition of valuable information, showed in Table 1~~Table 1~~.

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Table 1: Alarm information

Number of data	597618 (415 days)
Number of activations	10
Average period time of activation	228,2
Mean deviation	300,39
Average period between alarms	35232,2
Mean deviation	64431.38

The average period of time and average period between alarms do not provide valuable information because of there are different alarms with elevated values. Figure 4~~Figure 3~~ shows that the initial alarms have reduced separation. The most activation periods of the alarms are located in 3 and 8.

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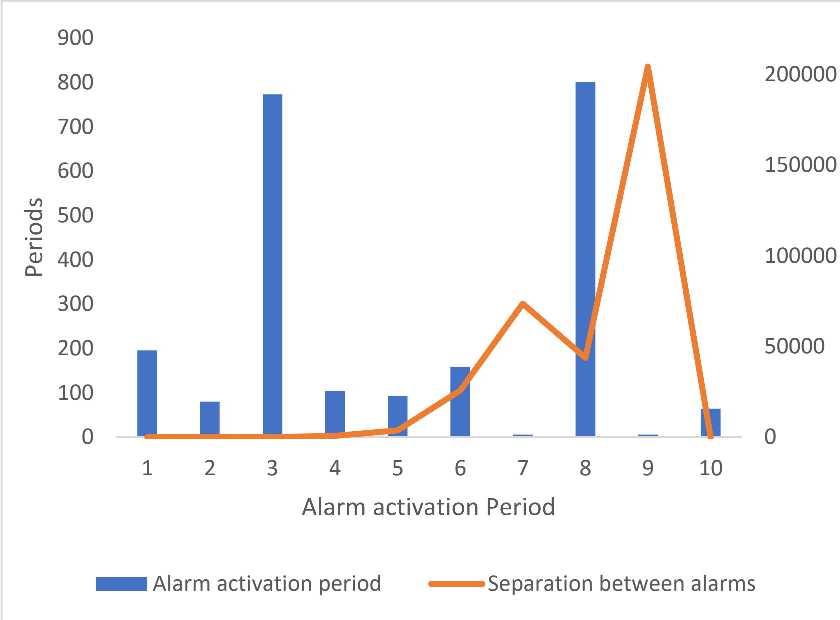

Figure 4: Alarm analysis: alarm activation period and time separation between each alarm

A minimum period between two alarm activations must be guaranteed to have a training and possible alarm activation periods. With this previous analysis, it is possible to prefilter alarms and select only the most fundamental alarms. For this particular case study, the alarm separation threshold is stablished in 700 periods due to the alarm analysis. All the alarms with less separation are considered not relevant for this study.

3 Results

A basic scenario with no statistical analysis is simulated for further comparison with the methodology proposed in this work. In this case, the data is not filtered or analysed with PCA or alarm positioning. The ANN diagram is showed in Figure 5~~Figure 6~~. For the initial case without statistical analysis, it is determined a basic ANN with ten hidden layer and the input and output distribution required for the selected data.

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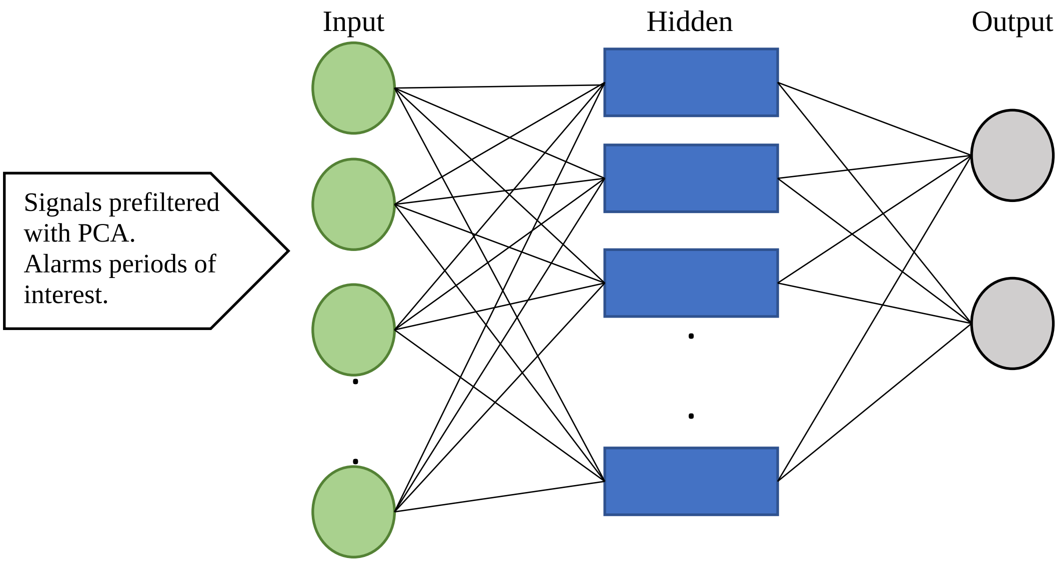

Figure 5: Neural network diagram

The performance of the ANN displayed in Figure 6~~Figure 7~~ is very low and the possibilities of finding patterns are reduced due to the reduced epoch and not stabilization of the network. The ANN is not suitable for this situation and since there are no validations or tests allowed.

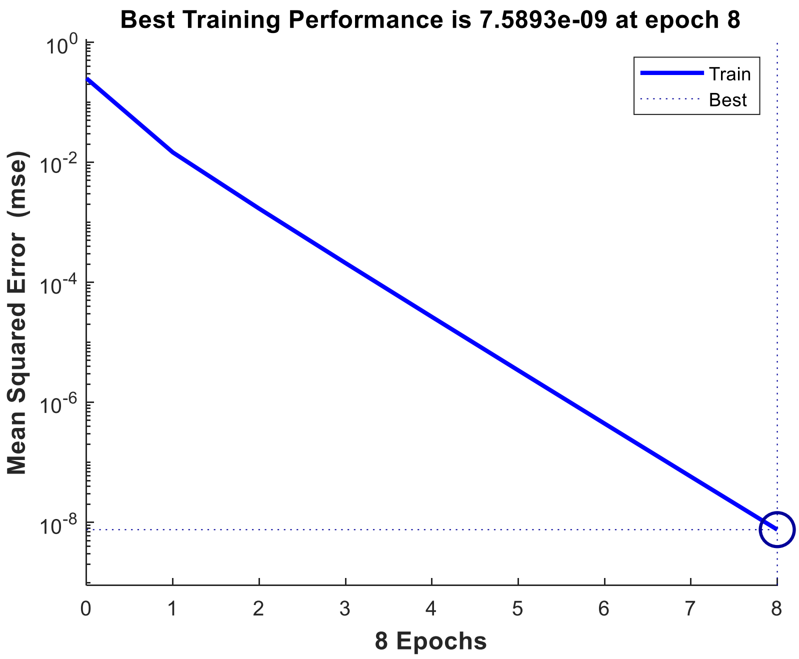

Figure 6: Performance of the neural network with no statistical analysis.

Once the basic ANN is developed, it is employed PCA to the initial dataset for improving the efficiency of the network. The application of PCA provides a valuable information about the detection of failures. For this particular case, it is proposed a dataset of signals related with the alarm. The signals provided for this study have different values and nature, and there is no information about the relevant signals or the signal with more influence in the alarm development.

For this reason, it is applied PCA, with the aim of reducing the data volume and obtain an improvement in the ANN efficiency. Figure 7~~Figure 5~~ shows that 97% of the dataset could be explained with one principal components.

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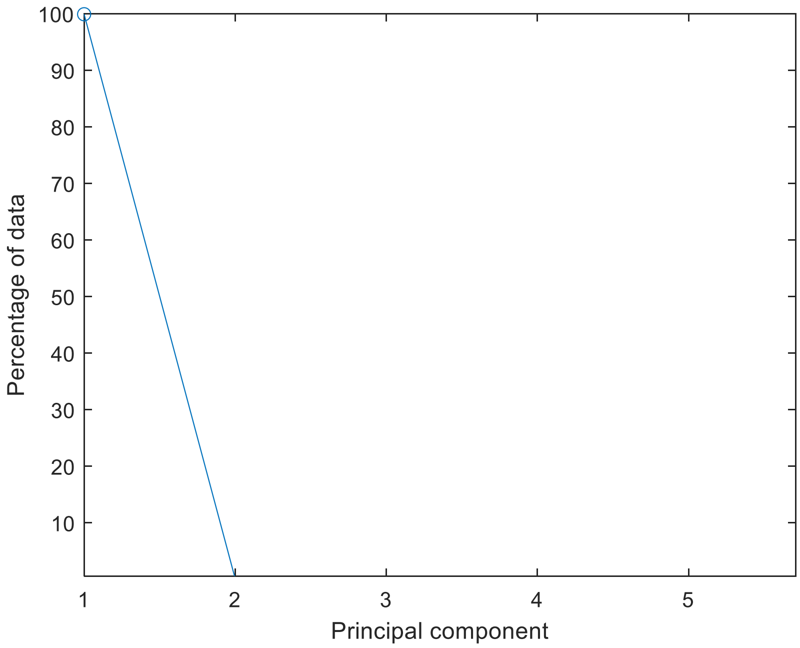

Figure 7: Percentage of the data explained with different principal component.

The initial dataset is transformed into one principal components with the aim of obtaining an efficient data selection to be used as inputs in the ANN. This new dataset will be used in the ANN design and development. Figure 8~~Figure 8~~ shows the performance of the ANN with the dataset treated by the statistical analysis.

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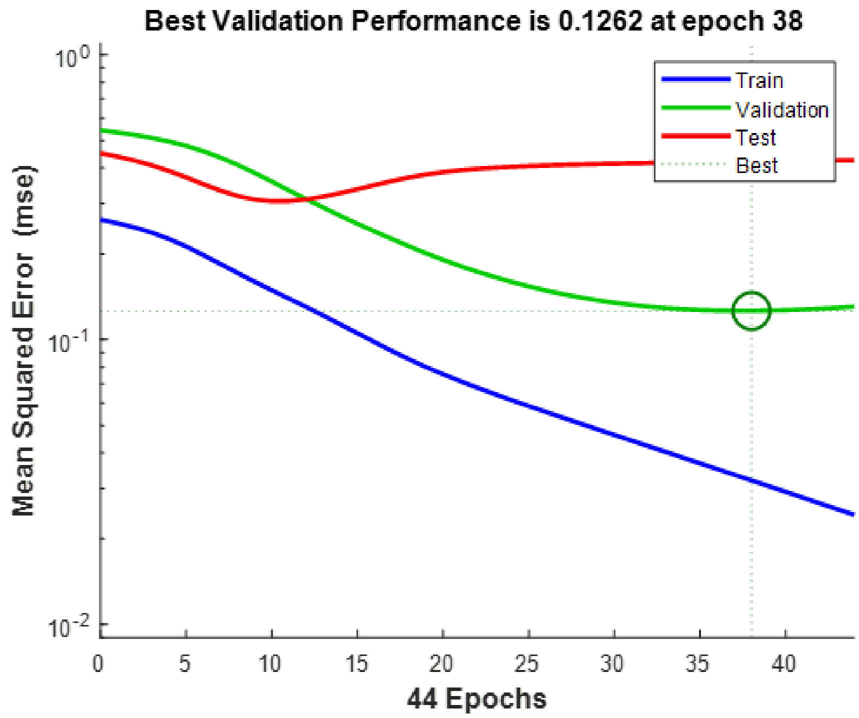

Figure 8: Performance of the neural network with no statistical analysis

Figure 8~~Figure 8~~ shows that the ANN develops a validation and test with adequate accuracy although it is required an ANN with more efficiency and reduced errors for ensuring the pattern detection.

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4 Conclusions

The data generated in the supervisory control and data acquisition requires of algorithms and methods for obtaining valuable information applicable in the operation and maintenance management. The volume and variety of the data increment the importance of advanced algorithm for data analysis. This paper presents a method combined statistical analysis and advanced algorithm for pattern recognition. The first phase is based on the alarm identification for the use of this information in the signal combination. The interest periods of the alarm are defined and identified in the dataset. The initial dataset of signals is reduced using principal component analysis. The new dataset is implanted in a basic neural network defined for this study. A real case study is applied using different alarms and signals, and ~~studing~~studying the results obtained with the data with no initial statistical analysis. The analysis between the performance of both situations validates the approach.

Acknowledges

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