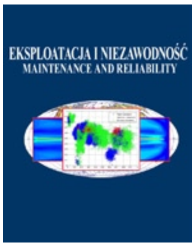

Eksploatacja i Niezawodnosc – Maintenance and Reliability

Volume 23 (2021), Issue 1

journal homepage: http://www.ein.org.pl

Article citation info:
Segovia Ramirez I, Mohammadi-Ivatloo B, García Márquez FP. Alarms management by supervisory control and data acquisition system for wind turbines. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2021; 23 (1): 110–116, http://dx.doi.org/10.17531/ein.2021.1.12.

Indexed by: Web of Science Group

Alarms management by supervisory control and data acquisition system for wind turbines

Isaac Segovia Ramirez[a], Behnam Mohammadi-Ivatloo[b,c], Fausto Pedro García Márquez[a]*

[a]Ingenium Research Group, Universidad Castilla-La Mancha, 13071 Ciudad Real, Spain
[b]Faculty of Electrical and Computer Engineering, University of Tabriz, 5166616471 Tabriz, Iran
[c]Department of Energy Technology, Aalborg University, 9220 Aalborg East, Denmark

Highlights

- We propose a new approach for signal processing, fault detection and diagnosis.
- A New approach is based on principal component analysis and artificial neural networks
- We analyse the signals and detect the alarm activation pattern.
- The dataset has been reduced by 93%
- The performance of the neural network is incremented by 1000%.

Abstract

Wind energy is one of the most relevant renewable energy. A proper wind turbine maintenance management is required to ensure continuous operation and optimized maintenance costs. Larger wind turbines are being installed and they require new monitoring systems to ensure optimization, reliability and availability. Advanced analytics are employed to analyze the data and reduce false alarms, avoiding unplanned downtimes and increasing costs. Supervisory control and data acquisition system determines the condition of the wind turbine providing large dataset with different signals and alarms. This paper presents a new approach combining statistical analysis and advanced algorithm for signal processing, fault detection and diagnosis. Principal component analysis and artificial neural networks are employed to evaluate the signals and detect the alarm activation pattern. The dataset has been reduced by 93% and the performance of the neural network is incremented by 1000% in comparison with the performance of original dataset without filtering process.

Keywords

alarm management, maintenance management, principal component analysis, SCADA, wind turbines.

1. Introduction and Objectives

The wind energy capacity in the world energy production is increasing every year, being one of the fastest growing renewable energy. This growth in recent years is due to the increasing size, increment of complexity of wind turbines (WTs) and favourable policies adopted by governments. The wind energy new installations exceeded the 60,4 GW at the end of 2019, with the United States and China as the most relevant markets [19]. The impact of COVID-19 pandemic on this growth has not been quantified yet and, therefore, it is required technical and economic advances to ensure the reliability of this technology.

WTs are complex electromechanical systems formed by a rotor that transforms the wind energy into mechanical energy and it is converted into electrical power. The blades transmit the mechanical energy through the low speed shaft to the high-speed shaft connected to the generator. The yaw system rotates the nacelle to align the blades with the direction of the wind and the gearbox regulates the speed. Different subsystems, e.g., meteorological units, refrigeration, brakes, security levels, etc., increase the complexity of the WTs [30]. The working conditions of WTs produce a variety of potential component failures with high failure rates and economic losses. Different researches reported that the gearbox, yaw and hydraulic system, electrical control and blades, concentrate the 60% of the total failures [11], being necessary the application of novel techniques or methodologies [10].

The objective of the maintenance management is to ensure an accurate behaviour of WTs, minimizing the use of human and material resources, reducing reduced costs and avoiding energy production losses due to downtimes [35]. The operation and maintenance (O&M) costs are estimated between 15-25% in onshore [27], and they are higher in offshore WTs [32]. The increment of faults reduces the availability of energy generation due to downtimes and unplanned maintenance activities [31]. New improvements in maintenance management are needed through novel conditions monitoring systems (CMS) and data analysis to ensure proper levels of reliability, availability, maintainability and safety (RAMS) [9,20].

Several data acquisition systems and CMS are installed to determine the condition of WTs. The measurement techniques are based on traditional monitoring, e.g., vibration analysis with low-frequency ranges for fault detection [36], thermal analysis for failure of electric elements, ultrasonic waves or acoustic emissions generated with energy pulses to detect blade failures [14, 16], among others. Catelani et al. [5] proposes a set of techniques combined in a single system for advance detection and the identification of the anomalies and failures in WTs, based on data processing. The results lead to inform with enough time to make the appropriate decision to maintain their WTs,

(*) Corresponding author.

E-mail addresses: I. Segovia Ramirez - isaac.segovia@uclm.es, B. Mohammadi-Ivatloo - bmohammadi@tabrizu.ac.ir, F.P. García Márquez - faustopedro.garcia@uclm.es

similar to [3]. Despite these techniques, new inspection techniques are being developed for early fault detection, e.g., noise waves analysis. Supervisory control and data acquisition (SCADA) system is widely implanted in the wind energy industry and this system collects main parameters of any WT from sensors and measurement systems.

The SCADA system provides alarm records and signal dataset, usually every ten minutes. The signals are numerical values about certain parameters, such as temperature, energy production or vibration. The alarm is defined as an operational indicator to identify different anomalies or issues that has already done in the WT. Faults in the sensors, inaccurate design of the diagnostic model or measurement uncertainty may lead to false alarms [6]. The false alarms identification is a critical issue in the wind energy market, since it is produced elevated alarm flood, unnecessary stops and maintenance interventions [28]. Several researches are focused on false alarm determination to reduce or reset the maximum alarms as possible, employing statistical analysis, deep learning, machine learning or neural networks, etc. The SCADA data volume and complexity increment the difficulty in the data analysis and the computational cost is elevated. Reliable and robust algorithms are required for false alarm detection and signal analysis. Fault tree analysis together with binary decision diagrams are employed for quantitative and qualitative analysis of these problems [13,23]. Machine learning algorithms are largely applied to evaluate the state of the WT and process a large amount of data. Artificial neural networks (ANNs) are based on the biological nerve system formed by neurons. This computational structure is formed by several layers with different weights and transfer functions for the connection between neurons. They can work with non-linear problems and the training phase defines the learning of the network [21]. ANNs have been used in several applications, highlighting pattern recognition and image processing with high accuracy [33]. ANNs are used in wind energy maintenance for forecasting and prediction, design, control optimization and fault detection and diagnosis (FDD) [18]. Gomes and Castro [15] employed the autoregressive moving average and ANNs to develop a wind energy forecasting with better results than the reference model. Li et al [22] probed that the type of ANN has an relevant influence in the analysis and different ANNs may present better capabilities in each case. Other authors have developed different researches about the false alarm identification. Adouni et al. [2] used a new ANN to increase the FDD procedure and the robustness to avoid false alarms. Bangalore et al. [4] developed filtering methods to ensure a strict training to improve the fault detection with the ANN. The advantages of the methodology are tested in different case studies. Peco et al. [7] developed a novel approach to detect false alarms in gearbox bearing with a partitioning methodology. None of these researches consider a preselection of the signals and data using statistical methods to reduce the computational cost and the accuracy results of the ANN.

This paper presents a novel approach in alarm and signal filtering to increase the accuracy in fault detection. The alarms are analyzed by Pareto chart to select the most critical, stabilizing interest periods of study. The signal dataset is reduced using principal component analysis (PCA), decreasing the amount of data an incrementing the accuracy of ANN. This approach is validated with a real case study based on different alarms and signals acquired from a WT.

The paper is divided in the following sections: Section II defines the overview and the methodology based on different phases and the information about the algorithms of the approach, a case study is proposed in Section III to test the approach; Section IV validates the results obtained with neural network and finally, Section V summarized the main findings from this research work.

2. Method

This work proposes a data filtering process in alarms and signals to increase the reliability of the ANN in fault detection due to the volume of the data and the number of alarms. Figure 1 shows flowchart of the proposed approach.

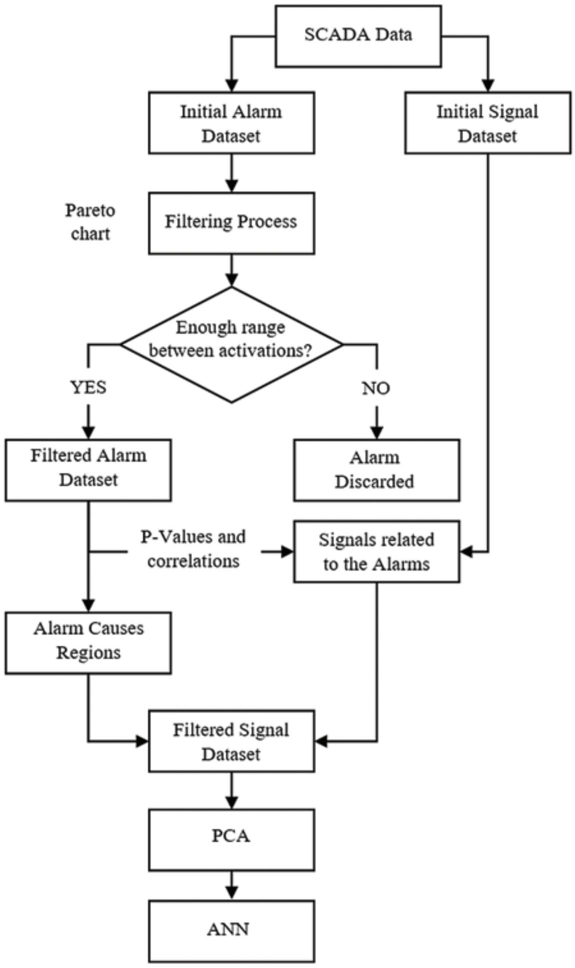

Fig. 1. Approach diagram

The SCADA data is divided into alarms and signals. The alarms are filtered analysing its main parameters. The critical alarms are identified with Pareto chart, considering its main characteristics, e.g., number of activations. Pareto chart shows the frequencies of the selected variables and, in this paper, is employed for determining the critical alarm. The user may introduce different weights regarding on the needs of the system. The main characteristics are the number of activations, time of activation and difference between alarms. For this work, the alarm must present several activations with elevated time periods with no failures in order to increase the reliability of the method. Schlechtingen and Ferreira [34] considered the alarm analysis for prediction one day before the failure. Reduced periods with less than one day between alarm activation are discarded, ensuring suitable range periods for the analysis. It is necessary to obtain the dataset of signals related to the critical alarm determined in previous phase. The signals with no correlation with the alarm increase the complexity of the operation and do not provide valuable information. Once the alarms and signals are properly determined, the regions of interest for the study are determined analysing the region with alarm deactivation. The data closer to the alarm activation is considered more relevant to the alarm since it is more probable to find data patterns that generate the activation of the alarm in that data range. A diagram of alarm and signal ranges related to the temporal scale is shown in Figure 2. The region of interest is defined in the graph as alarm causes range. The other region, registered as safe period, presents data related to the alarm activation but, in this period, the probability of alarm activations is low, being considered as training zone for the next phases.

Despite the filtering process, the signal dataset may present large volume of data. PCA has been employed in this paper to reduce this data volume. PCA is a multivariate analysis that decreases the dimen-

Fig. 2. Alarm and signal periods

sions of the initial dataset to a reduced number of uncorrelated variables or principal components [12,26]. The patterns in multivariate datasets may be extracted by PCA and the transformed space is defined by the eigenvalues and eigenvectors of the covariance matrix.

2.1. P-values

The P-value contributes with statistical measurements about the relation between signals, being possible the identification of more relevant signals [24]. The P-values are defined as the maximum probability under the null hypothesis, providing information about the combination of the data. In first place, it is necessary to calculate the distribution of the test statistic T by equation (1):

$$T = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{1}$$

being $\hat{p}$ the sample proportion; p_0 the population proportion in the null hypothesis, and; n the sample size. The P-value is defined by equation (2):

$$P - value = \text{Probability}(T \geq ts \,|\, Hypothesis\, is\, true) = cdf\,(ts) \tag{2}$$

where *ts* the observed value of *T*, and; *cdf* the cumulative distribution function of the test static.

For this work, P-values of 5% are employed to confirm that the model is suitable for this dataset, because of the common criteria in several researches is that p-value lower than 0,05 is needed [8].

2.2. Principal Component Analysis

Large datasets may have correlated variables with redundant information that increase the complexity of the data analysis. PCA is a dimensionality-reduction tool to reduce and simplify the dimensionality of large datasets, developing an orthogonal linear transformation with the original data, to obtain a maximum variance in the new dataset [25]. The initial matrix data $\mathbf{X}$ is defined with n x p dimensions, being n samples and p variables, and the objective is the obtention of a reduced dataset [17]. The principal components Y_j are new uncorrelated variables, defined by (3):

$$Y_j = a_{j1}X_1 + a_{j2}X_2 + a_{j2}X_3 + \ldots a_{jp}X_p \tag{3}$$

being a_{j1}, a_{j2},... a_{jp}., constants to develop the linear correlation. The sum of the square of these constants is usually 1. The first principal component is defined to take the greatest variance in the data set. The transformed space is given by the eigenvectors of the covariance matrix **S**, defined by equation (4):

$$\mathbf{S} = \frac{\mathbf{X}^T\mathbf{X}}{n-1} = \mathbf{U}\,\mathbf{\Lambda}\,\mathbf{U}^T \tag{4}$$

being $\mathbf{\Lambda}$ the diagonal matrix with real eigenvalues and **U** the matrix with eigenvectors in columns. The correlation between variable and principal component Y_j s given by equation 5:

$$r_{ij} = \sqrt{\frac{a_{ij}^2\, Var(Y_j)}{s_{ii}}} \tag{5}$$

being s_{ii}, the variance-covariance matrix of the original data. For this work, the PCA definition depends on the dataset filtered in previous phases of the approach.

2.3. Artificial Neural Network

The ANN is formed by large number of interconnected neurons with the capacity of process information [1]. The ANN may be classified regarding on the presentation of the information, the topology of the network, the relation between input and out and the training method (unsupervised and supervised). In Figure 3, it is observed the two types of ANN employed in this work. Figure 3 shows a multilayer perceptron (MLP) structure of ANN architecture, with the neurons organized in different layers.

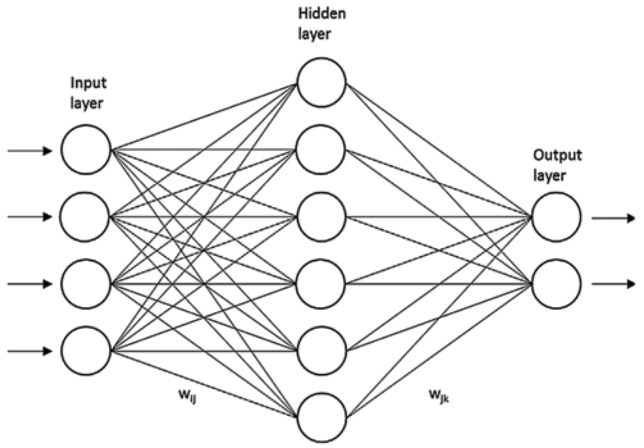

Fig. 3. ANN structure [29]

ANN requires large datasets and training process to design the interconnection weights. The connections between neurons are determined with number reference or weight. Equation (6) determines the output h_i of neuron i:

$$h_i = \sigma\left(\sum_{j=1}^{N} W_{ij}x_j + T_i^{hidden}\right) \tag{6}$$

being $\sigma()$ the transfer function; N the number of input neurons; W_{ij} the weights; x_j inputs to the input neurons, and; T_i^{hidden} the threshold of the hidden neurons.

This paper considers a MLP ANN since the objective of this work is the definition of the approach. The simulations show that the best configuration is an ANN network architecture with 100 hidden layers. The inputs are variables, regarding on the filtering phase developed in previous phase. The validation and test phase of the ANN is developed dividing the dataset into 65% for the training, 20% for validation and 15% for testing. The adjustment of the network is obtained with the training phase.

3. Case study and results

A real database from the OPTIMUS European Project has been employed [60]. The database is composed of a set of parameter measurements and an alarm report. The SCADA generates an alarm when a set of variables reach a certain threshold. The SCADA system shows a sampling rate of 10 minutes.

The SCADA system also provides a detailed alarm report. This information will be employed for validating the model proposed. The collected data are:

- Date of the alarms.
- Code of the alarm (confidential).
- Cause or description of the alarm.
- The state of the alarm (activation or deactivation).
- The severity.
- Required tasks.

A real case study with SCADA data from one WT for 400 days and a data frequency of one minute, is employed to validate the approach. The WT presents more than 100 alarms with different activation periods. The initial signal dataset is composed by 96 signals analysing different parameters of the WT, e.g., temperature, electric performance, among others. Each signal is acquired per minute presenting more than 500000 data, and it must be related to the critical alarm with the aim of predict failures with accuracy. Due to non-disclosure agreements with the operators, the location of the wind farm and the alarm nomenclature are omitted. The alarm selection criterion has been established by the plant operator according to the needs.

Figure 4 shows the Pareto chart, considering the number of activations, the period of the activated alarm, the maximum period of the alarm and the difference between alarms without filtering process, being the red line the accumulated data in each case.

Table 1. Alarm codification.

Alarm	Alarm definition
Alarm A	Brake alarm
Alarm GB	Regulation of the pump motor
Alarm GEFL	Out-of-bounds winding
Alarm GM	CW motor alarm
Alarm GP	WT yaw mechanism alarm
Alarm GCD	Degradation alarm
Alarm GPL	Limitation of the cosine of (φ)
Alarm GPLP	Active power limitation
Alarm GRCT	Voltage drop of the grid
Alarm RFT	Voltage failure of the grid
Alarm HBP	Low pressure hydraulic group
Alarm RDT	Failure in the thermal ventilators of the gearbox
Alarm RMV	Slow operation of the ventilator
Alarm RBPS	Low pitch value at the WT stop

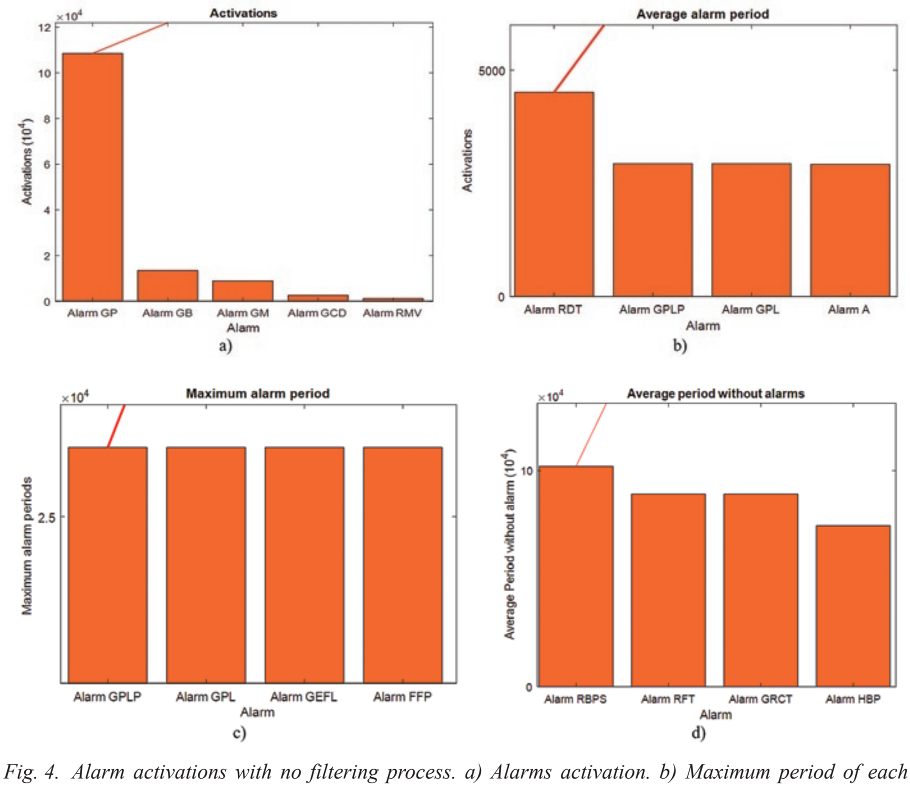

Fig. 4. Alarm activations with no filtering process. a) Alarms activation. b) Maximum period of each alarm activation. c) Average alarm period. d) Average period without alarms

Table 1 shows the alarm codification following the alarm log defined in the wind farm. Several alarms present elevated activations, but this information does not provide value to the analysis. It is required a further filtering phase to ensure proper ranges and avoid alarms with several correlated activations with inadequate data for the analysis.

The range of interest is defined in previous section in one day before the alarm activation. The alarms that do not comply with these requirements are discarded. Operators may provide different guidelines to determine the critical alarm. For this case study, the critical alarm is determined following the internal criterion of the plant operators and it is related with the overspeed of the WT. This alarm is activated in several periods but only 22 ranges between alarms achieve the condition of at least one day between activations (other case is considered as false alarm). This process ensures the reduction of the data volume, the computational cost and increasing the accuracy of the ANN. Figure 5 shows the separation between alarms and the activation between periods.

The signals related to the critical alarm are set by the P-values and correlations, obtaining thermal signals in the 71% of the cases and the rest are vibration signals. PCA is applied on this new dataset employing the data analysis showed in Figure 2 to reduce the data volume and select fundamental periods of time. Figure 6 shows that 99% of the original dataset can be defined with two principal components, being the red line the accumulated data.

PCA modifies the initial dataset to obtain a new dataset with the same patterns, and the reconstruction error of PCA must be determined to analyze the importance of the selected variables. Figure 7 shows the unexplained variance depending on the number of components defined in the PCA process. In this case, it is confirmed that two components are suitable to reduce the uncertainty in the variance and define a new suitable dataset.

The original dataset has been reduced by 93%, from 96 signals to a new PCA dataset. The ANN will be trained and designed using this new dataset, with the same capabilities and patterns.

4. Validation

The validation of the filtering process is essential for methodology acceptance. It is proposed a comparison between the scenario with no statistical analysis and the filtering method proposed in this work to validate this method. It is designed a MLP neural network with ten hidden layers and its performance is analysed with both datasets.

Figure 8 compares the performance of both ANNs, with filtering and data treatment, and with the original dataset. The cross-entropy quantifies the error between the defined outputs and the desired outputs in the training data. Minimizing cross-entropy leads to better networks The ANN performance with the original dataset is showed in Figure 8.a) and in this case, the network employs more epochs in the stabilization, producing elevated errors and reducing the possibilities of finding reliable patterns. Figure 8.b) shows a better performance

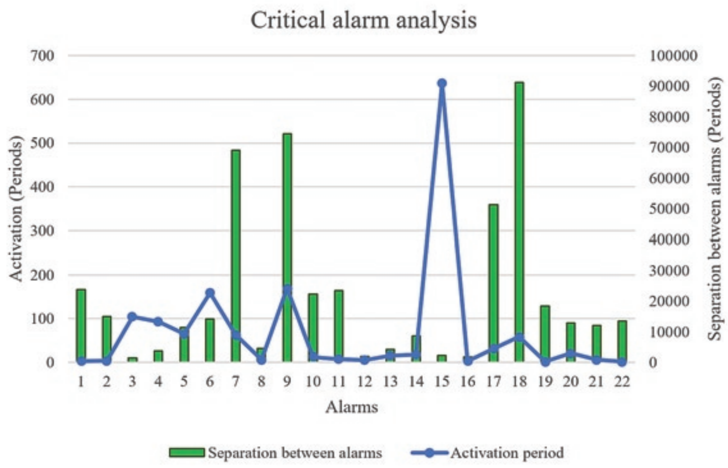

Fig. 5. Critical alarm analysis with filtered ranges

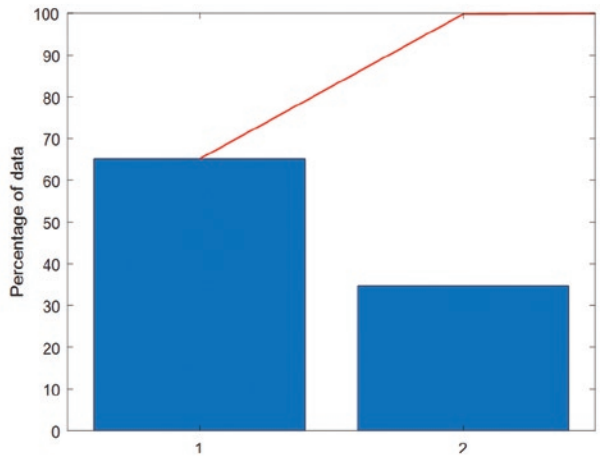

Fig. 6. Percentage of the data explained with different principal components

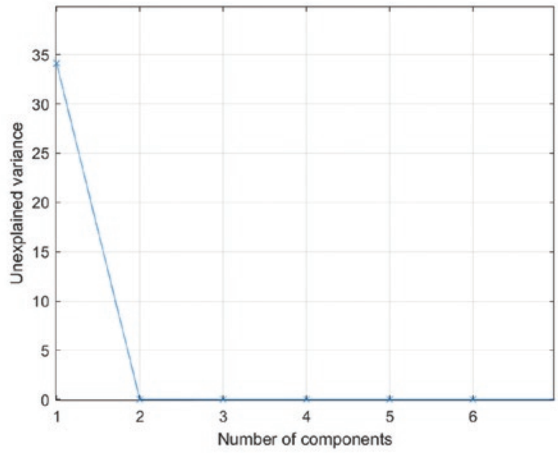

Fig. 7. Unexplained variance regarding on the number of components

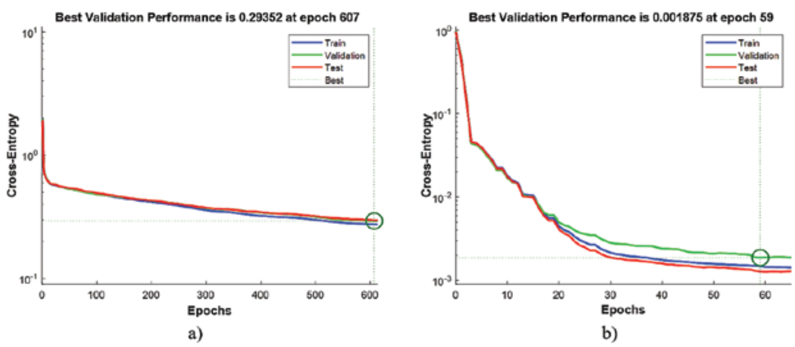

Fig. 8. a) Performance of the neural network with original dataset. b) Performance of the MLP neural network with PCA.

of the ANN, with reduced number of epochs and cross-entropy. The stabilization of this network is developed with less epochs due to an optimized and reduced dataset. The methodology proposed in this work increments the ANN performance by 1000% due to an efficient data filtering and selection.

The confusion matrix for the MLP with the filtering and data treatment process is showed in Figure 9. The number of positive cases properly identified by the algorithm is high. The overall accuracy of the ANN with the filtered dataset is about 94%, proving a high capacity to classify the periods before the activation of an alarm. It is concluded that the 6% of the alarms studied were activated without evidence of real damage in the WT, according to the signals acquired with the SCADA system.

5. Conclusions

The volume and type of data acquired by supervisory control and data acquisition system implies the need of robust and accuracy methods and algorithms to analyse the data. This paper presents a novel approach that filter the alarms and signals with the aim of increasing the accuracy of neural networks employed for signal processing. The initial phase is focused on the identification of the critical alarm by means of statistical analysis and Pareto chart. The signal dataset is filtered, analysed regarding with the critical alarm and reduced with principal component analysis to employ reliable and filtered data in the neural network. It is presented a real case study formed by a new dataset with thermal and vibration dataset, being electric signals filtered. The 93.5% of the cases are accurately classified, validating the methodology proposed for this paper.

Fig. 9. Confusion matrix for the MLP ANN developed with the approach

Acknowledgments

The work reported herewith has been financially by the Dirección General de Universidades, Investigación e Innovación of Castilla-La Mancha, under Research Grant ProSeaWind project (Ref.: SBPLY/19/180501/000102) and the Spanish Ministerio de Economía y Competitividad, under Research Grant (DPI2015-67264-P).

References

1. Abiodun OI, Jantan A, Omolara AE, Dada KV, Mohamed NA, Arshad H. State-of-the-art in artificial neural network applications: A survey. Heliyon 2018; 4: e00938, https://doi.org/10.1016/j.heliyon.2018.e00938.
2. Adouni A, Chariag D, Diallo D, Ben Hamed M, Sbita L. FDI based on artificial neural network for low-voltage-ride-through in dfig-based wind turbine. ISA Transactions 2016; 64: 353-364, https://doi.org/10.1016/j.isatra.2016.05.009.
3. Alcaide-Moreno BA, Fuerte-Esquivel CR, Glavic M, Van Cutsem T. Electric power network state tracking from multirate measurements. IEEE Transactions on Instrumentation and Measurement 2017; 67: 33-44, https://doi.org/10.1109/TIM.2017.2754838.
4. Bangalore P, Letzgus S, Karlsson D, Patriksson M. An artificial neural network-based condition monitoring method for wind turbines with application to the monitoring of the gearbox. Wind Energy 2017; 20: 1421-1438, https://doi.org/10.1002/we.2102.
5. Catelani M, Ciani L, Galar D, Patrizi G. Optimizing maintenance policies for a yaw system using reliability centered maintenance and data-driven condition monitoring. IEEE Transactions on Instrumentation and Measurement 2020, https://doi.org/10.1109/TIM.2020.2968160.
6. Chacón AMP, Márquez FPG. False alarms management by data science. Data Science and Digital Businesse 2019: 301-316, https://doi.org/10.1007/978-3-319-95651-0_15.
7. Chacón AMP, Ramírez IS, Márquez FPG. False alarms analysis of wind turbine bearing system. Sustainability 2020; 12: 7867, https://doi.org/10.3390/su12197867.
8. Feise R.J. Do multiple outcome measures require p-value adjustment? BMC Medical Research Methodology 2002; 2: 8, https://doi.org/10.1186/1471-2288-2-8.
9. Galar D, Gustafson A, Tormos Martínez BV, Berges L. Maintenance decision making based on different types of data fusion. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2012; 14: 135-144.
10. Gao J-X, An Z-W, Ma Q, Bai X-Z. Residual strength assessment of wind turbine rotor blade composites under combined effects of natural aging and fatigue loads. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2020; 22: 601-609, https://doi.org/10.17531/ein.2020.4.3.
11. García Márquez F, Pliego Marugán A, Pinar Pérez J, Hillmansen S, Papaelias M. Optimal dynamic analysis of electrical/electronic components in wind turbines. Energies 2017; 10: 1111, https://doi.org/10.3390/en10081111.
12. García Márquez FP, García-Pardo IP. Principal component analysis applied to filtered signals for maintenance management. Quality and Reliability Engineering International 2010; 26: 523-527, https://doi.org/10.1002/qre.1067.
13. García Márquez FP, Segovia Ramírez I, Mohammadi-Ivatloo B, Marugán AP. Reliability dynamic analysis by fault trees and binary decision diagrams. Information MDPI 2020; 11: 324, https://doi.org/10.3390/info11060324.
14. Glowacz A. Diagnostics of direct current machine based on analysis of acoustic signals with the use of symlet wavelet transform and modified classifier based on words. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2014; 16: 554.
15. Gomes P, Castro R. Wind speed and wind power forecasting using statistical models: Autoregressive moving average (ARMA) and artificial neural networks (ANN). International Journal of Sustainable Energy Development 2012; 1, https://doi.org/10.20533/ijsed.2046.3707.2012.0007.
16. Gómez Muñoz CQ, García Márquez FP. A new fault location approach for acoustic emission techniques in wind turbines. Energies 2016; 9: 40, https://doi.org/10.3390/en9010040.
17. Holland S.M. Principal components analysis (pca). Department of Geology, University of Georgia, Athens, GA 2008: 30602-32501.
18. Iqbal R, Maniak T, Doctor F, Karyotis C. Fault detection and isolation in industrial processes using deep learning approaches. IEEE Transactions on Industrial Informatics 2019; 15: 3077-3084, https://doi.org/10.1109/TII.2019.2902274.
19. Joyce Lee F.Z. Global wind report 2019 (global wind energy council); https://gwec.net/global-wind-report-2019/, 2020.
20. Kabiri M, Amjady N. A new hybrid state estimation considering different accuracy levels of pmu and scada measurements. IEEE Transactions on Instrumentation and Measurement 2018; 68: 3078-3089, https://doi.org/10.1109/TIM.2018.2872446.
21. Kalogirou SA. Artificial neural networks in renewable energy systems applications: A review. Renewable and Sustainable Energy Reviews 2001; 5: 373-401, https://doi.org/10.1016/S1364-0321(01)00006-5.
22. Li G, Shi J, Zhou J. Bayesian adaptive combination of short-term wind speed forecasts from neural network models. Renewable Energy 2011; 36: 352-359, https://doi.org/10.1016/j.renene.2010.06.049.
23. Li Y-F, Huang H-Z, Liu Y, Li H. A new fault tree analysis method: Fuzzy dynamic fault tree analysis. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2012; 14.
24. Ludbrook J. Statistical techniques for comparing measurers and methods of measurement: A critical review. Clinical and Experimental Pharmacology and Physiology 2002; 29: 527-536, https://doi.org/10.1046/j.1440-1681.2002.03686.x.
25. Marquez FG. An approach to remote condition monitoring systems management. IET International Conference on Railway Condition Monitoring 2006: 156 - 160, https://doi.org/10.1049/ic:20060061.
26. Márquez FPG. A new method for maintenance management employing principal component analysis. Structural Durability & Health Monitoring 2010; 6: 89-99.
27. Márquez FPG, Karyotakis A, Papaelias M. Renewable energies: Business Outlook 2050. Springer: 2018.
28. Marugán AP, Márquez FPG, Papaelias M. In Multivariable analysis for advanced analytics of wind turbine management, Proceedings of the Tenth International Conference on Management Science and Engineering Management, 2017; Springer: 319-328, https://doi.org/10.1007/978-981-10-1837-4_28.
29. Marugán AP, Márquez FPG, Perez JMP, Ruiz-Hernández D. A survey of artificial neural network in wind energy systems. Applied Energy 2018; 228: 1822-1836, https://doi.org/10.1016/j.apenergy.2018.07.084.
30. Pérez JMP, Márquez FPG, Tobias A, Papaelias M. Wind turbine reliability analysis. Renewable and Sustainable Energy Reviews 2013; 23: 463-472, https://doi.org/10.1016/j.rser.2013.03.018.

31. Pliego Marugán A, Garcia Marquez FP, Lev B. Optimal decision-making via binary decision diagrams for investments under a risky environment. International Journal of Production Research 2017; 55: 5271-5286, https://doi.org/10.1080/00207543.2017.1308570.
32. Rademakers L, Braam H, Zaaijer M, Van Bussel G. In Assessment and optimisation of operation and maintenance of offshore wind turbines, Proc. EWEC, 2003.
33. Saufi SR, Ahmad ZAB, Leong MS, Lim MH. Gearbox fault diagnosis using a deep learning model with limited data sample. IEEE Transactions on Industrial Informatics 2020; 16: 6263-6271, https://doi.org/10.1109/TII.2020.2967822.
34. Schlechtingen M, Ferreira Santos I. Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection. Mechanical Systems and Signal Processing 2011; 25: 1849-1875, https://doi.org/10.1016/j.ymssp.2010.12.007.
35. Walford CA. Wind turbine reliability: Understanding and minimizing wind turbine operation and maintenance costs; Sandia National Laboratories 2006, https://doi.org/10.2172/882048.
36. Zuber N, Bajrić R. Gearbox faults feature selection and severity classification using machine learning. Eksploatacja i Niezawodnosc -Maintenance and Reliability 2020; 22: 748-756, https://doi.org/10.17531/ein.2020.4.19.