Advances in Reliability, Safety and Security

ESREL 2024
Collection of Extended Abstracts

Voting-Based Condition Monitoring Using Set Of Indicators For Fleet-Wide Fault Detection In Wind Energy

Théodore Raymond[a], Sylvie Charbonnier[b], Christophe Bérenguer[b]

[a]*VALEMO, Bègles, France*
[b]*Université Grenoble Alpes, CNRS, Grenoble INP, GIPSA-Lab*

Keywords: wind energy, linear multi-variable models, condition monitoring, residual-based fault detection, intelligent variable selection, automatic model generation, industrial application

Wind energy production is a major asset in ensuring a successful energy transition. Consequently, its development has accelerated steadily over the last decade. To control the cost of producing this renewable energy, or LCOE, it is necessary to reduce maintenance costs throughout the useful life of the turbines. These costs are mainly due to the replacement of major components such as the gearbox or the generator (Bie et al., 2021; Nunes, Morais and Sardinha, 2021).

To avoid these interventions, a new maintenance strategy, using condition monitoring (or CM), has been widely studied on the literature. CM is based on the analysis of a real time representation of the health of a component. A popular CM approach is to monitor a simple residual (measured minus modeled value) that uses normal behavior model built using supervisory control and data acquisition (SCADA) to explain a key variable, representing the state of a component (Maldonado-Correa et al., 2020).

In our research work, we propose a condition monitoring strategy for wind turbine fault detection, previously presented in (Raymond et al., 2022). This CM strategy uses a set of residual indicators built from various normal behaviour models to predict a common output variable. Indeed, this multi-model approach could significantly improve detection performance, as proved in (Raymond et al., 2023).

Each model is built in an automatic way using an innovative data driven variable selection method. The models built are simple linear models, with no more than 3 variables as inputs. The use of a data driven approach enables models to be built for any component of any wind turbine, whatever its technology, without the need for expert knowledge. This point is essential for the deployment of the fault detection method to a whole wind farm fleet. Moreover, because the models are simple, they are easy for maintenance operators to interpret, which is important for the acceptance of the method by experts. Finally, the small number of variables used decrease the risk of unavailability of the associated residual.

Given an output variable and a reduced set of input variables obtained using L1 regression (Vidaurre, Bielza and Larrañaga, 2014), the model variable generation algorithm follows the forward selection process (Kumar and Minz, 2014), and iteratively compiles variable that best fits the defined criteria, calculated for the wind farm scale. An important feature of this algorithm is that it provides a set of model variables applicable to all turbines in the wind farm being used.

The model is then trained using linear least squares regression for interpretation and overfitting, and a residual indicator is constructed following the multi-turbine formula presented in (Lebranchu et al., 2019). This indicator consists of the difference between the measured and the estimated output value compared to a “farm-reference”, and is robust to seasonality and production modes, while taking into account simple models.

Finally, each residual indicator is assigned a detection threshold, tuned using a fault-free period of one year. This threshold makes it possible to decide whether an anomaly is present. This decision is called a vote.

The condition monitoring framework is shown in Figure 1 below.

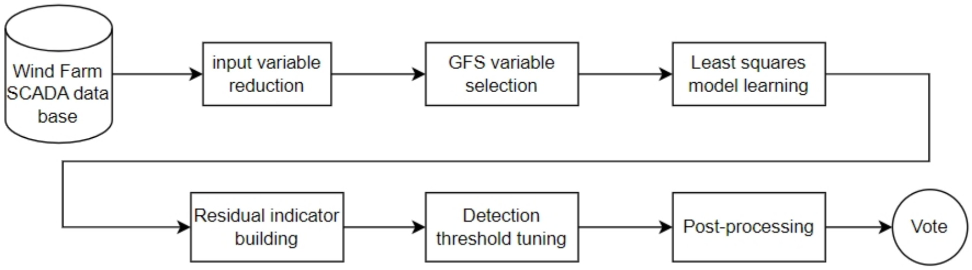

Fig. 1. Condition monitoring framework.

Several models can be built by constraining the set of potential variables the selection method can used. Two additional models are included in the set: a model composed of variables chosen according to physical knowledge, and a trivial one, computed as the deviation of the measured output variable value of the wind turbine considered with its median value at the scale of the wind farm. The binary values of this set of indicators, obtained after thresholding the residuals, are merged with a majority vote.

The assumption of our method is that these indicators provide unique and accurate residual information on the component's actual state of health, which makes the multi-model CM approach relevant for improving detection performance.

The work presented shows the detection performances obtained by the application of a complete multi-model monitoring protocol, based on the results of (Raymond et al., 2023), on a set of four real fault cases.

Detection performance using the majority vote of the associated indicators is compared with the mono-model approach proposed in (Raymond et al., 2022). The detection performance criteria used evaluate the time remaining for preventive maintenance operations before the failure and the additional costs generated by false alarms for the company in charge of maintaining the wind farm.

The results show that the use of the majority vote leads to a significant improvement in detection performance, meeting the operational specifications.

Following this study, the process has been implemented on real-time operating data on the company's data processing software.

References

Bie, Y., Liu, X., Xu, T., Zhu, Z., Li, Z. 2021. A review of the application of oil analysis in condition monitoring and life prediction of wind turbine gearboxes, Insight - Non-Destr. Test. Cond. Monit. 63(5), 289-301, May 2021, doi: 10.1784/insi.2021.63.5.289.

Nunes, A. R., Morais, H., Sardinha, A. 2021. Use of learning mechanisms to improve the condition monitoring of wind turbine generators: A review, Energies 14(21), 2021, doi: 10.3390/en14217129.

Maldonado-Correa, J., Martín-Martínez, S., Artigao, E., Gómez-Lázaro, E. 2020. Using SCADA Data for Wind Turbine Condition Monitoring: A Systematic Literature Review, Energies 13(12), Art. no. 12, janv. 2020, doi: 10.3390/en13123132.

Raymond, T., Lebranchu, A., Bérenguer, C., Charbonnier, S. Data-driven Model Generation Process for Thermal Monitoring of Wind Farm Main Components through Residual Indicators Analysis, In: Europeand Safety and Reliability Conference - ESREL 2022, Leva, M. C., Patelli, E., Podofillini, L., Wilson, S. (Ed.). In: Proc. of 32nd European Safety and Reliability Conference - ESREL 2022, vol. 32. Dublin, Ireland: Research Publishing, 2022, 1393-1400. doi: 10.3850/978-981-18-5183-4_R23-01-601-cd.

Raymond, T., Charbonnier, S., Lebranchu, A., Bérenguer, C. On the Joint Use of An Ensemble of Linear Residuals to Improve Fault Detection in Wind Turbines, In: ESREL 2023 - 33rd European Safety and Reliability Conference, Brito, M. P., Aven, T., Baraldi, P., Čepin, M., Zio, E. (Ed.). Southampton, United Kingdom: Research Publishing Services, Sept. 2023, 1784-1791. doi: 10.3850/978-981-18-8071-1_P657-cd.

Vidaurre, D., Bielza, C., Larrañaga, P. 2014. A Survey of L1 Regression, Int. Stat. Rev. 81(3), 361-387, 2013, doi: 10.1111/insr.12023.

Kumar, V., Minz, S. Feature Selection: A literature Review 4(3), 2014.

Lebranchu, A., Charbonnier, S., Bérenguer, C., Prevost, F. 2019. A combined mono- and multi-turbine approach for fault indicator synthesis and wind turbine monitoring using SCADA data. ISA Trans. 87, 272‑281.