DETECTION OF WIND TURBINE BLADE DAMAGE WITH 1D CNN CLASSIFIER

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Abstract - Wind power plants are taking an active part in global electricity production. The number of wind turbines being installed is increasing every year, and the amount of energy they produce is growing as a result. As the number of wind turbines increases, so does the amount of potential damage to turbine rotor blades. This article presents an algorithm for the prediction of such damage in order to ensure the continuous operation of the device, which is followed by the continuous supply of electricity from wind turbines. The damage prediction algorithm is based on machine learning elements. By limiting the algorithm's input to a few maximum amplitudes of the fast Fourier transform, short processing times are achieved. The precision of the algorithm oscillates around 94% with 4 classes of rotor blade damage.

Keywords - Wind Turbine, Blade Damage Detection, Predictive Maintenance, Vibro diagnostics

I. INTRODUCTION

Wind turbine rotor blades are huge and complex structures that are exposed to significant loads of a changing nature. Wind turbines operate for hundreds of thousands of cycles during their lifetime. Damage to rotor blades results in a reduction in turbine power, which is becoming an increasingly serious problem. Unfortunately, even a slight reduction in turbine power results in a huge loss of electricity production on an annual basis. Field experience has determined that blades are the highest contributors to wind turbine maintenance costs [10,11]. At high wind speeds, the outer parts of the blades are damaged by collisions with sand, hail and rain. As a result of this damage, the geometry of the turbine blades changes, which reduces their aerodynamic properties.

This results in an increase in the resistance to movement and a decrease in the load carrying power of damaged wind turbine blades. Research has already been conducted on damage mitigation [1], [2]. However, before preventing damage, an easier way to keep a wind turbine running continuously is to detect blade damage and repair it as soon as possible. However, simple sensors and measurements are not sufficient to detect damage to such a huge structure as a wind turbine rotor blade.

It is hard to determine damage using simulation and a mathematical model due to the unpredictability of external factors such as weather, defective material, etc. Variable vibration characteristics of the rotor blades, which are transmitted through the rotor and gears to the turbine housing, can be used for damage detection. The variable vibration characteristics of the structure can help detect damage and even determine thetype of damage. Several methods are currently available for detecting various blade faults. Vibration, acoustic emission [12], photogrammetry [13], ultrasound [14]

II. SYSTEM FUNCTIONAL DIAGRAM

The system is built up of a laboratory bench and a fault detection algorithm embedded in a learning and processing unit.

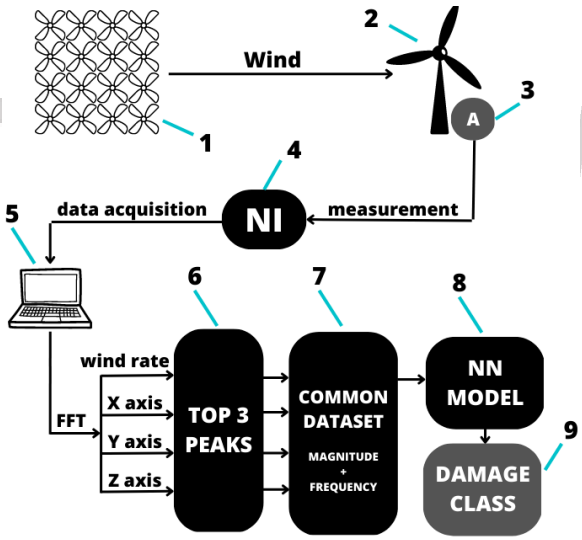


Fig. 1 System functional diagram

A. Measurement stand

The laboratory stand (Fig.1) consists of a fan array (1), a wind turbine (2), a triaxial accelerometer (3) with National Instruments equipment (4) and a PC (5). The fan array produces artificial wind blows that drives the wind turbine. The speed of the generated wind is controlled by inverters, allowing for flexible control depending on the needs of the tests. Information on wind speed is provided to the processing unit via anemometer senor mounted next to the wind generator. It is connected directly to AI measurement card. The wind turbine is equipped with a triaxial accelerometer attached to the turbine generator housing. The triaxial accelerometer takes measurements in three axes, which allows a more accurate check of the condition of the turbine rotor

blades. Sampling frequency used for all of the measurements was 20 kHz. The accelerometer sensor used in the research has linear amplitude-frequency characteristics in range from 5 Hz to 10 kHz. Such sampling frequency allowed to obtain accurate measurements in whole available frequency range. The fact that sensor is is capable to measure low frequencies is important in this case. Wind turbine blades movement is considered as low speed-low frequency. The purpose of this sensor is to measure vibrations transmitted from the rotor blades, through the rotor to the gearbox, which interacts mechanically with the generator housing. The NI accelerometer hardware delivers the collected vibration measurements to the processing unit.

B. Features extraction

The action taken to prepare the input data of the fault detection algorithm is very simple. First, the measurement signals are divided into the number of samples that corresponds to one second of measurements. Subsequently, a fast Fourier transform of the three vibration measurement signals supplied from the accelerometer and the associated wind speed information signal from the anemometer is calculated. The three largest amplitudes and their corresponding frequencies are then selected for each of these four FFT signals (6). In the end, 24 values (3 amplitude peaks, 3 frequencies for each of the 4 signals) are obtained for every one second of measurement. To these 24 values were added the type of damage to the turbine blades as a label. This is how the data describing a second of measurements was obtained. The procedure was repeated for the entire duration of measurements for each collected measurement file. This is how a common dataset (7) containing compact measurement data for different types of wind turbine blade damage was obtained. The dataset created was divided according to the 80% / 20% ratio into a training / test dataset and used for learning / validation of the model (8).

Lp.	Device
1	16x Fans withinverter T-Verter N2_Series 220V 0,75kW
2	Wind generator 500W DC12Vand Wind sensor BleBox
3	AccelerometerPCB model 604B31
4	Conditioner AVC 3000 with CompactDAQ Chassis (NI 9215)
5	Computer PC

Table I Used devices.

III. DAMAGE CLASSIFICATION

Loss of rotor blade condition for the entire wind turbine degrades the efficiency of the device making the wind turbine deliver less energy than expected. There are many types of rotor blade failures, but we only consider the most common ones.

A. Types of blade damage

The following figures show successively damaged turbine rotor blades: transverse crack (Fig, 2), longitudinacrack (Fig.3) and damage to the outer surface (Fig.4).

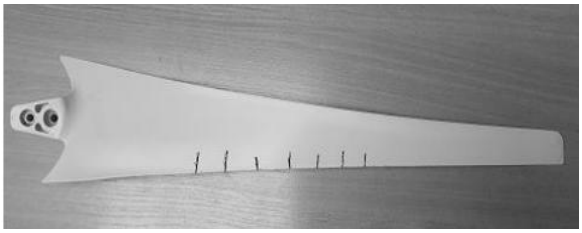


Fig. 2 Transverse crack.



Fig. 3 Longitudinal crack.



Fig. 4 Outer surface damage.

A. Measurement method

Measurements were carried out for four different settings of the frequency converter controlling the fan array corresponding to wind speeds of 5 m/s, 7 m/s, 9 m/s and 10 m/s, respectively. For each setting, the blades were assumed to be undamaged sequentially, with previously presented single damage (only one of the three blades damaged) and with all damage at once.

B. Used software

Lab View software provided by National Instruments was used for data acquisition. All measurement data was saved to .xlsx format. Subsequently, the data was imported into Google Colab and processed by a script written in Python using the Tensor Flow and NumPy modules.

IV. NEURAL NETWORK MODEL

Used 1D CNN layer-based model, the model structure consists of three convolution blocks. Each block is built from the following layers:

- CONV 1D 64x3
- BatchNormalization
- ReLU
- Dropout

The model structure (Fig.7) was originally used for time series classification and was proposed by Wang et. all [3]. However, it turned out that it also works well for classifying data after initial feature extraction. The original model was modified, however, to prevent overtraining of the network. A Dropout layer was added after each block with a value of 0.2 and after the Pooling layer with a value of 0.5.

This significantly improved the precision of the model, but increased the number of iterations needed to achieve constant precision. The end result was increased learning time for the algorithm and improved precision. The model was taught using a dynamically variable learning rate, where the validation loss value was an indicator of change.

If it remained constant for more than 1,000 epochs then the learning rate decreased by a factor of ten. An automatic learning stop was also applied based on the same value (validation loss). In this case, the threshold was 5000 epochs. The learning process of the algorithm was successful. Finally training was stopped after over 12 000 epochs. The signal feature extraction carried out significantly accelerated the process. The results of learning the neural network algorithm are shown in (Fig. 5).

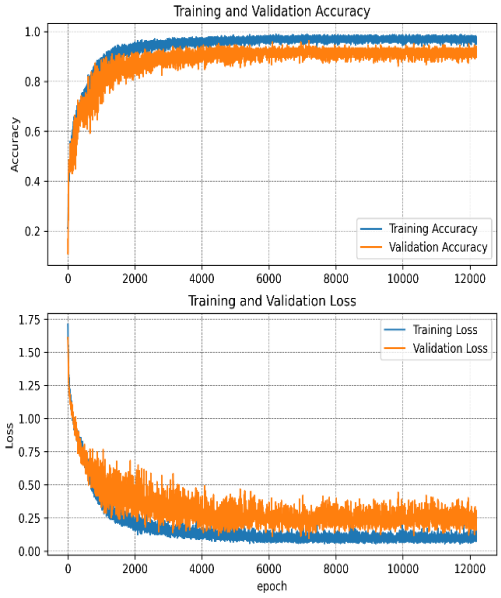


Fig. 5 Training and validation accuracy.

Validation of the algorithm was carried out using a previously prepared test data set. The confusion matrix below (Fig. 6) shows the results of the validation of the fault detection algorithm.

It allows us to trace between which classes the algorithm made errors. Based on it, we can conclude that it was mainly mistaken in the case of damage to the outer surface. It classified the damaged case as no damage eight times.

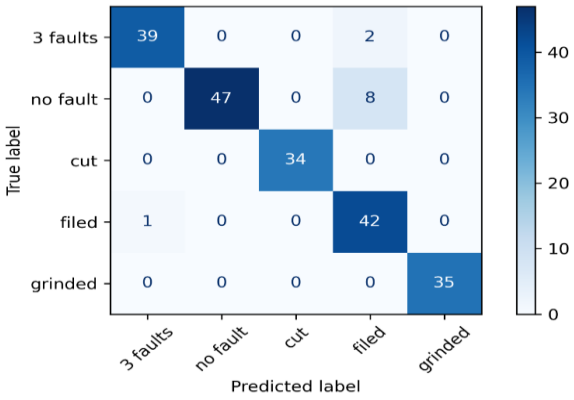


Fig. 6Validation results. (for convenience on plot there are different fault name used: cut - longitudinal crack, filed – outer surface damage, grinded - transverse crack)

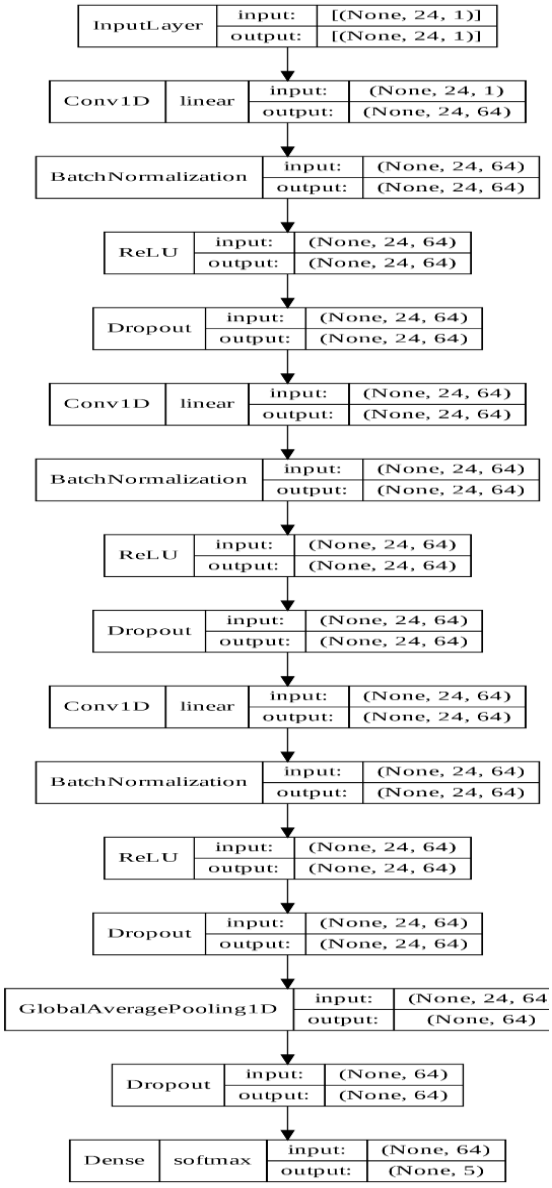


Fig. 7Neural network model.

Algorithm achieved satisfactory results during training. The metrics of the algorithm training are presented in Table II.

Test accuracy	94,7 %
Test loss	0,126
Validationaccuracy	92,8%
Validationloss	0,2292

Table II Algorithmmetrics.

The Stochastich Gradient Descent optimizer was used during learning, it is a robust and reliable choice. The dynamic learning rate varied from a value of 0.1to a value of 0.000001. The initial value of the learning rate is very large, this allows it to quickly approach the extrema of the loss function. Subsequently, decreasing the value of learning rate makes the optimizer able to quite accurately approach the mentioned extrema.

V. CONCLUSION

In this study, laboratory-scale vibration tests were conducted to test the ability of artificial neural network algorithms to classify wind turbine blade damage. Preliminary results indicate that the model based on 1D CNN layers with initial manual extraction of signal features can be used to determine the type of rotor blade damage. The accuracy of damage type typing was 94%. The vibration characteristics were studied and the three largest amplitudes of the fast Fourier transform and their corresponding frequencies were pre-extracted for each second of measurement of each signal. It was found that minimizing the input of the neural network to the listed characteristics was sufficient to train the model. Limiting the input of the network did not deteriorate the precision of the algorithm, however, it significantly accelerated the learning process. Given the results obtained, it can be concluded that the damage detection algorithm meets its objectives. Only in a couple of classifications the algorithm made a mistake in determining the absence of damage as damage to the outer surface of the rotor blade. However, a mistake in which the absence of damage was specified as damage is better than damage as absence of damage. The algorithm will be extended to provide the ability to classify not only the type of damage, but also the location of the damage and its impact on the decrease in efficiency.Varying wind speeds did not prevent accurate classification, the algorithm is resistant to changing conditions. This is a very important aspect in this case. Varying conditions are often problematic for the detection algorithms designers.The use of data from an anemometer mounted behind the turbine could also carry an improvement in the quality of the algorithm's performanceThe method of feature extraction made it possible to reduce the computational cost of the algorithm itself. It also had a positive effect on the learning time. As it turned out, the features extracted in such a way can be excellent predictors.Used non-standard network structure using one-dimensional convolutions worked perfectly in the task of classification on the basis of pre-extracted features

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