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Artificial intelligence-based estimation of the consumed fatigue-related lifetime for an operating wind turbine support structure

Mirjana RATKOVAC [1], Inka MUELLER [1], Rüdiger HÖFFER [1]

[1] Ruhr-Universität Bochum, Bochum, Germany

Contact e-mail: mirjana.ratkovac@rub.de

ABSTRACT: This work presents the perspectives on neural network application in fatigue lifetime estimation for a 0.5 MW wind turbine located in Dortmund, Germany. The wind turbine has been in operation since 1997, and the monitoring data was collected from 2010 to 2013 and is still being collected since 2016. Hourly fatigue damages for the whole monitored period are calculated from the displacement (strain) measurements at the tower and can be used for the remaining lifetime estimation. However, the fatigue damage that occurred during the unmonitored period can have a high influence on the accuracy of the remaining lifetime forecast. Therefore, a neural network is employed in order to estimate the fatigue damage for the unmonitored period. The calculated hourly fatigue damage is paired up with the available hourly wind data from several wind stations located in a 52 km radius and used to establish correlations (neural network training) between the wind data in the area and the strain based fatigue damage. In this way, an attempt has been made to estimate the wind induced fatigue damage. Since the hourly wind data is available for the whole operating life since 1997, the neural network is employed to estimate the hourly fatigue damages for the unmonitored period and a novel remaining lifetime estimation is given. The accuracy of the neural network is tested on a part of monitoring data, which is not used for the training and its efficiency is tested for two types of neural networks, feedforward neural network for fitting (FFNN) and Self-Organizing Map (SOM).

1 INTRODUCTION

With growing needs for clean energy sources, efficient harvesting of the wind energy implies the need to improve not only efficiency, but also safety and economic aspects of the wind energy converter systems. Many existing wind turbines are approaching or have already reached the end of their designed lifetime. This is the case with a 0.5MW wind turbine located in Dortmund, Germany, which has been in operation since 1997. Fatigue loads are the main lifetime design parameter. They are by nature cyclic loads that occur due to wind effects through wind turbine oscillation and operation, wind turbine control (pitch angle change, breaking systems and nacelle orientation) and special events. It is assumed that under normal operating conditions, the majority of the fatigue damage is related to the wind.

The state of the structure, the level of degradation and possible extension of the useful lifetime can be evaluated through application of Structural Health Monitoring (SHM) systems. Generally, the advances in SHM systems are leading to utilization of smart monitoring algorithms based on pattern recognition and machine learning, as stated in Farrar and Worden (2013). The authors came to the conclusion that statistical pattern recognition approach is the most appropriate when dealing with damage detection problems and give a summary of both supervised and unsupervised learning approach in statistical pattern recognition. The application of artificial intelligence (AI) in SHM has already been the topic of various studies, with the main idea of discovering and modeling underlying correlations between the observed features. The benefits of AI application become more obvious as the complexity of the problem increases, i.e. with increasing number of features and nonlinear dependencies among them, Figueiredo et al. (2011). In Buethe et al. (2012), a Self-Organizing Map is shown to be a good tool to differentiate between two effects in measured data, damage of a piezoelectric sensor and change of environmental or operational data, which can normally cause changes of the same order in sensor behavior. Furthermore, it was possible to use SOM to distinguish 2 different sensor faults under changing temperature conditions. In Abdeljaber and Avci (2016), a nonparametric damage detection algorithm that integrates SOM and pattern-recognition feedforward neural network is presented. SOM is used to cluster data from accelerometers for undamaged and damaged cases. Data is clustered corresponding to different damage indices, which are then used as an input for neural network and damage scenario recognition, including damage localization.

In this paper, two AI models, a feedforward neural network (FFNN) and a Self-Organizing Map (SOM) are used to estimate the wind-induced used lifetime for an operating wind turbine support structure. The hourly fatigue damage is first calculated for the available monitoring data (2010-2013 and 2016-2018) and then used for AI model development and validation. The input data for the models is the open source wind station data in the area (hourly wind speed, wind direction and temperate), which is available online on Deutscher Wetterdienst (2019) server for the whole wind turbine operation time since 1997. In this way, correlations between the wind station data and wind induced fatigue damage at the wind turbine tower are established for the monitored period, and can later be used for the fatigue assessment in the remaining years, when no monitoring data is available.

2 MONITORING SYSTEM

The studies were conducted on an operating 0.5 MW wind turbine, Airwin, where the monitoring data was collected from 2010 to 2013 as a part of a DFG-funded research project and is still being collected since 2016. The tower of the wind turbine is a steel structure, made out of three parts, each 21m long, rolled and welded in a workshop together with the top and bottom flanges for the assembling. The three tower parts are then assembled at the site, using pre-stressed bolted connections on the flanges. The schematic overview of the available monitored data is shown in Figure 1. More information can be found in Lachmann (2014).

3 FATIGUE DAMAGE FROM MONITORING DATA

The welded connections between the flange and the tower subparts are considered to be hot spots, where the damage is most likely to occur. For this reason, 3 displacement transducers (6 in total, W_1-W_6) were set above the flanges to capture strains and possible damage. The fatigue damage is calculated for all 6 displacement transducers and for the AI application in this study, the so called worst location of all measurement positions was chosen, which corresponds to dominant wind direction and in this case the position of the sensor W_3 (Figure 1 and Figure 2). Alternatively, it is also possible to superpose the measured data at the measurement locations to recalculate data for a virtual sensor in the worst location, as detailed in Höffer et al. (2017).

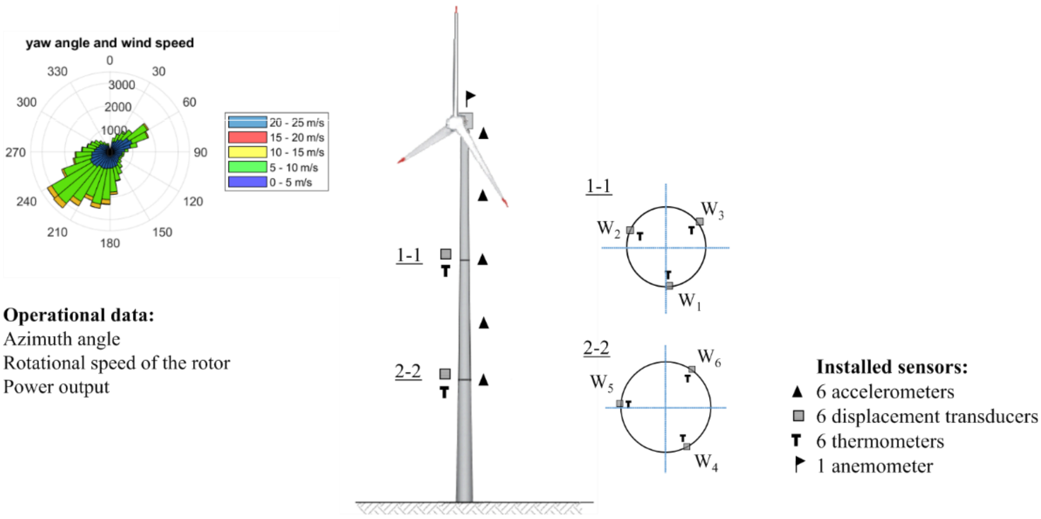


Figure 1. Installed SHM sensors and available operational data, Lachmann (2014)

3.1 *Data preprocessing*

Before applying the fatigue damage algorithm, it was necessary to address the influence of several types of sensor faults: spikes, constant values, and additionally very large amplitudes in sensor W_3 signal, which started after 2016. First, a median filter was applied to remove the spikes from the data. Then, an automatic procedure for sensor fault diagnosis, proposed by Kullaa (2013), was applied to estimate the accuracy and reliability of the acquired data. In this procedure, a sensor model is derived by estimating each sensor using the remaining sensors in the network, based on redundancy. This is done by applying the minimum mean square error (MMSE) estimation on functioning sensor network (training dataset) and then the sensor fault detection and quantification for the investigated datasets is done by means of multiple hypothesis test and generalized likelihood ratio test (GLR). The tests have shown that sensor W_3 suffers from sensor faults in a wide range of data starting from 2016 and cannot be used without previous intervention. Therefore, all data for sensor W_3 starting from 2016 was replaced with data modeled from other sensors. It has been shown that in the case that there is no or there a minor sensor fault, the modelled data corresponds to the measured data on a satisfactory level and allows the further usage of the modelled W_3 data. The applied algorithm was also capable to correct the constant values, which were detected in a small share of the measurement data, measured by sensor W_2.

After the data cleansing, strain time histories were calculated from displacement measurements by estimating the relative elongation/shortening from the initial 500mm sensor rod length. Then, the strain time histories are used for stress calculation using the Hook’s law, which assumes the linear connection between strain and stress over Young’s modulus of elasticity (here 210 GPa).

3.2 *Fatigue calculation - rain flow counting and S-N curve*

According to the wind turbine standard DNVGL-ST-0126 (2016), fatigue damage is defined as degradation of the material caused by cyclic loading. The Palmgren-Miner rule can be used for the calculation of the cumulative damage, D_c, by assuming a linear damage accumulation over time as shown in the equation (1):

$$\mathrm{D}_c = \sum_{i=1}^{\mathrm{I}} \frac{\mathrm{n}_{c,i}(\Delta\sigma)}{\mathrm{N}_{c,i}(\Delta\sigma)} \tag{1}$$

where, $n_{c,i}(\Delta\sigma)$ is the number of cycles for a stress range $\Delta\sigma$, estimated from stress time histories using the rain-flow counting algorithm, and $N_{c,i}(\Delta\sigma)$ is number of cycles until failure for stress range $\Delta\sigma$, which is interpreted from the characteristic S-N curve.

In this work, the cumulative fatigue damage is calculated for every hour of the existing data (2010-2013 and 2016-2018) using the Palmgren-Miner rule. The C_1 S-N curve (Figure 2) for double sided butt weld was chosen for the hot spot above the welded flange-tower connection according to wind turbine standards DNVGL-ST-0126 (2016) and DNVGL-RP-C203 (2016). The resulting cumulative fatigue damage for the whole monitored period is then calculated from the hourly fatigue damages and shown in Figure 3. As seen in the figure, sensor position W_3 proves to be the worst location with highest cumulative damage over the monitored years.

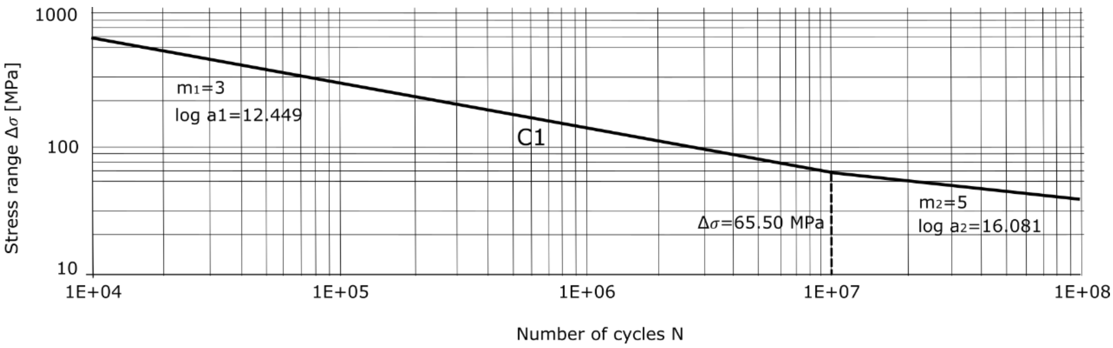


Figure 2. C1 S-N curve, DNVGL-RP-C203 (2016)

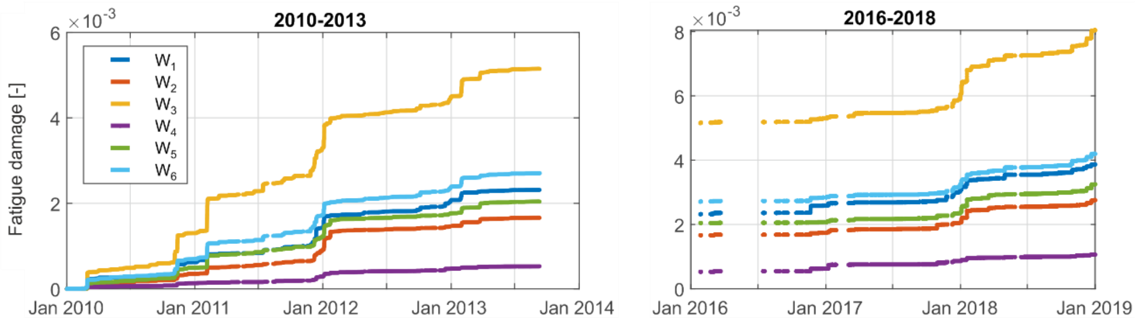
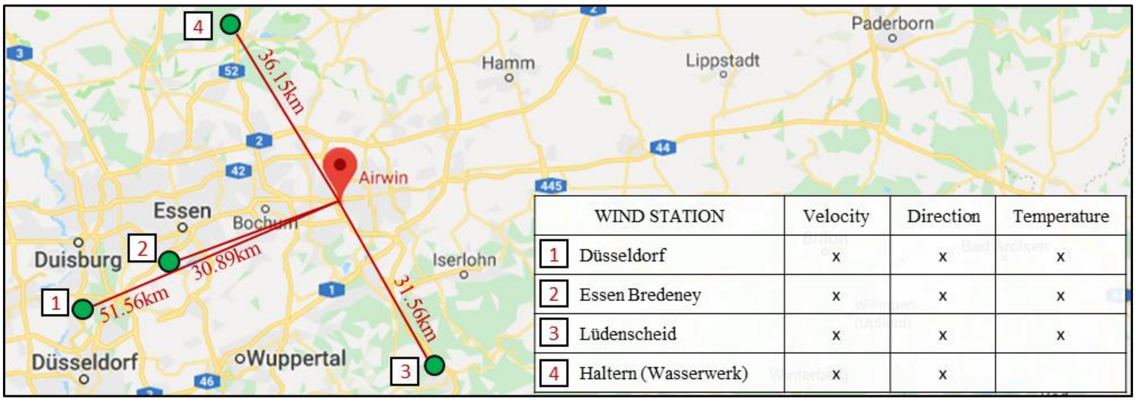


Figure 3. Cumulative fatigue damage for the existing data

4 WIND STATIONS DATA

Since the fatigue damage for periods when no monitoring data is available influences the accuracy of the consumed lifetime estimation and therefore the useful lifetime forecast, within this paper an attempt has been made to estimate the hourly fatigue damage for the whole operation period by utilizing the wind climate data in the area. For this purpose, the information on hourly wind velocity, direction and air temperature were taken from Deutscher Wetterdienst (2019). The database is open source and offers the climate information for the public use. For this study, the wind stations that are located in approx. 52km radius and offer the hourly information on wind data since 1997 were chosen. The overview and location of the wind stations in regard to the Airwin wind turbine in Dortmund is shown in Figure 4, together with the available data used in this study.

Since the distance from the available wind stations and the wind turbine is relatively large, the correlations between the data were investigated. In Figure 5, an example of hourly wind speed and wind direction during the first third of January 2010 is given. The same figure shows the correlation coefficients *c*, which are calculated between the wind data at the Airwin wind turbine and each of the wind stations for the whole monitored period. As it can be seen, the data for all measurement locations follows a similar trend. The correlation coefficients (min. 0.62 between wind direction at Düsseldorf wind station and wind direction at Airwin, max. 0.81 between wind speed at Düsseldorf wind station and wind speed at Airwin) show that it might be possible to establish a model for the wind-induced fatigue damage estimation from the wind stations data.



WIND STATION	Velocity	Direction	Temperature
1 Düsseldorf	x	x	x
2 Essen Bredeney	x	x	x
3 Lüdenscheid	x	x	x
4 Haltern (Wasserwerk)	x	x	

Figure 4. Overview of the available wind station data (1997-2018)

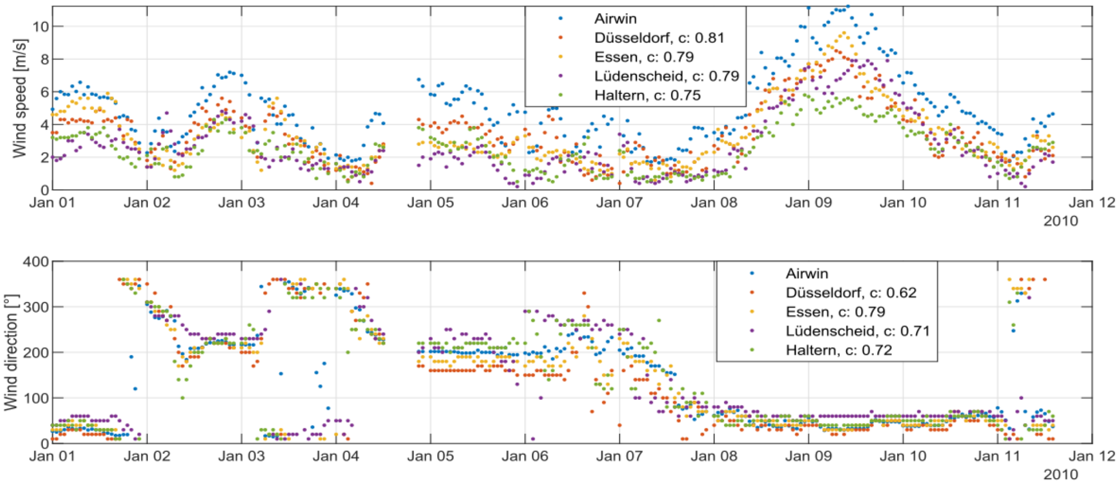


Figure 5. An example of the correlations between the wind data at Airwin and each of the wind stations

5 WIND INDUCED FATIGUE ESTIMATION BY ARTIFICIAL INTELLIGENCE

Artificial neural networks have found a wide use in various science and engineering fields. They are designed to recognize patterns in the data and can therefore be used for pattern recognition problems, such as image and sound recognition, but also time-series modelling, system identification and data clustering. Neural networks are known for their ability to discover and model highly nonlinear dependencies in the data, which can be difficult to grasp when dealing with problems that have more than 3 dimensions.

In this study, two different types of neural networks were used to create models, which are capable to determine wind induced fatigue damage at the wind turbine tower for time periods when no monitoring data is available. Both models use the data from the wind stations mentioned in the previous chapter. The main difference amongst the models is that the fitting feed-forward neural network belongs to the group of supervised learning, which means that monitored fatigue data is used for model creation, while the SOM belongs to unsupervised learning, where training the model is independent of monitoring data and based on wind station data only, while fatigue data is only used as label after training process is finished.

5.1 Multilayer feed-forward neural network for fitting problems (FFNN)

Feed-forward neural networks are the oldest types of neural network and consist of layers that are made of neurons and connected through weight functions, Hertz et al. (1991). The basic scheme is given in Figure 6, left. A fitting neural network is mapping the input data onto the output data, establishing the underlying correlations and finding the appropriate fitting. The information flows only in one direction, from input layer to the output layer and learning is done through weight modification to reduce the difference between calculated and predetermined output. Since the output data is known for the training phase, this algorithm belongs to the supervised learning.

5.2 Self-Organizing Maps (SOM)

Self-Organizing Maps (also known as Kohonen network) display high-dimensional data on a low-dimensional 2D map and are often used for the clustering of the data. They were first introduced by Teuvo Kohonen. In Kohonen (2001), the main concepts and applications of SOMs are presented. Applications in SHM can be found e.g. in Torres-Arredondo et al. (2013), Buethe et al. (2012)and Tibaduiza et al. (2013). The main difference between standard neural networks and SOM is the meaning of the weights. Here, the weight denotes the relation between the input data vector and the map unit, located in n-dimensional space, where n is the number of observed features. The map itself is the two-dimensional display as output space. The learning mechanism is not based on predefined output, but on the data itself and training is done through “moving” of the units and adjustment of the distances so that the certain units are close to certain input data samples. In this way, a map is created to fit the input data and can be seen as 2-dimensional topology of the data. SOMs belong to unsupervised learning, since there are no output labels on which the data is trained and the labels are assigned only after the training process. Figure 6, right, shows the basic scheme of a SOM.

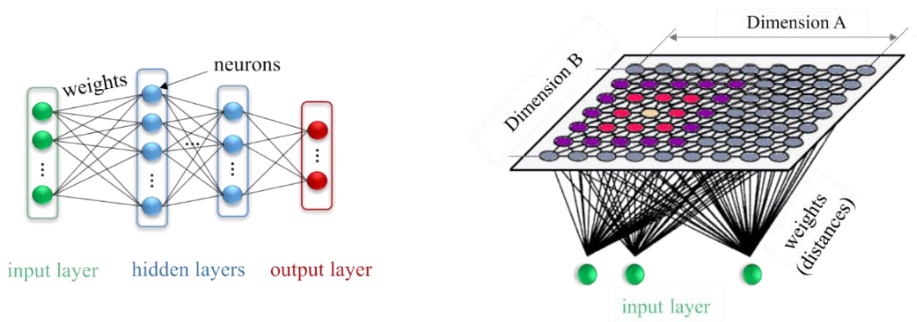


Figure 6. Basic scheme of a FFNN (left), Hertz et al. (1991) and a SOM (right), Epina & SDL (2012)

5.3 Model training and validation

Model training and validation were conducted with Deep Learning Toolbox in MATLAB by pairing up the available monitoring and wind station data. The wind station data available during the monitored time period (2010-2013, 2016-2018) is used as an input for FFNN and SOM. In this way, the input layer consists of 11 neurons (features), corresponding to wind speed, wind direction and temperature from the four wind stations in the area (temperature was not available for the wind station Haltern). In total, 45200 hours were available and half of the data distributed over the whole time period (every second hour) is used for model training and the other half (the hours in-between) is used for model validation. This was considered to be the best choice for the model training having in mind the gaps in data collection with various durations, as it can be seen in Figure 3. This way, the model will be able to estimate these gaps best. Data is first standardized to have zero mean and unit variance for the wind speed and temperature, and normalized to the main wind direction for wind direction data.

For the FFNN training, the output data is required and here it consists of 1 neuron - fatigue damage (D_c), calculated from the sensor W_3 for the corresponding hour used in input. As previously mentioned, in case of the FFNN, the learning is done through weight modification to reduce the difference between calculated and predetermined output for all 22600 hours used in the training phase. The appropriate number of hidden layers and neurons needs to be chosen for the successful network training and here, 2 hidden layers were chosen, with 7 and 3 neurons, respectively.

For the SOM training, only the wind station data is needed. The same input training dataset was used as in case of the FFNN. The initial dimension of the map is 29x31 units according to the ratio of the first and second principle component of the input data. The training is done through "moving" of the units and adjustment of the distances so that the certain units are close to the certain input data samples, following their similarities. After the training phase is finished and a map of the data is prepared, the fatigue data for each hourly training data is assigned as labels to the corresponding unit of the hourly wind data, and the mean fatigue damage of all data that belongs to the same unit is used a label.

The validation for both models is done based on the other half of the monitoring data, which is not used for the training. First, the wind station data is used as an input and the fatigue damage is estimated through FFNN and SOM. Then, the results are compared against the fatigue data calculated from the sensor W_3, which is considered to be the target ("true") value. Figure 7 shows the obtained results. On the left side the hourly fatigue damage is represented in cumulative form and on the right side an example of 200 hours is shown. As it can be seen, the cumulative estimated values are relatively close to the target values, especially for SOM, but in the closer look at the specific hours, larger differences can be observed. These differences are probably caused by influences other than wind-induced actions like influence of pitch, breaking or inspection. The models over- and underestimate the calculated fatigue damage. However, since the cumulative damage is of the main interest for the consumed lifetime estimation, the validation is considered as satisfactory.

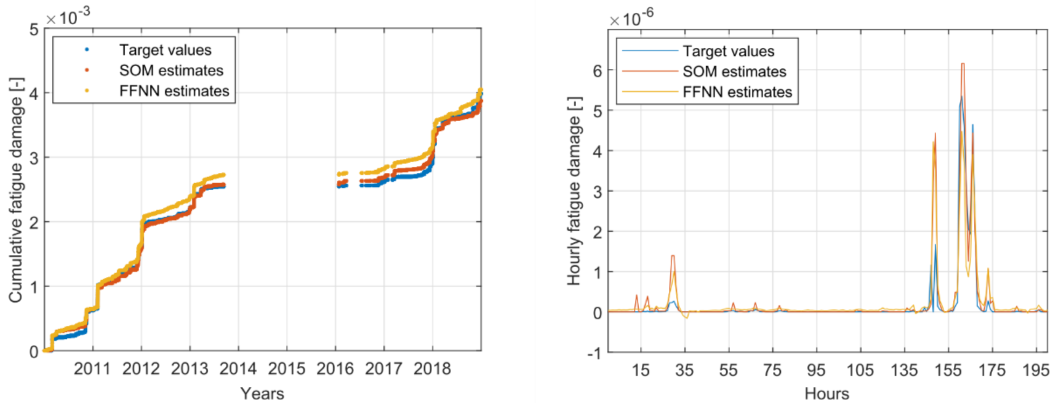


Figure 7. Validation – cumulative damage for the complete testing data (left) and 200h example (right)

6 RESULTS AND DISCUSSION

After the model training and validation, FFNN and SOM models were used to estimate the wind induced fatigue damage for the wind turbine operation between 1997 and 2018. The total number of the available hours sums up to 20.62 years. The obtained results are shown in Figure 8. It is important to note that the calculated damage is not the actual total fatigue damage, but an estimation for the wind induced component for this specific wind turbine. The remaining components due to the wind turbine control (pitch angle change, breaking systems and nacelle orientation) and special events, such as impact, fire and others were not considered in this study, since no full information was available between 1997 and 2018. Therefore, the model cannot be applied for the actual damage assessment, but only for the wind related damage estimation. However, it can be seen in the model testing phase that the majority of the fatigue damage is based on wind-dependent factors. By using data of the last years for training the models, it is assumed that the impact of wind is constant over time, which is a conservative assumption as it is known that aging leads to increased impact with increased age of the turbine.

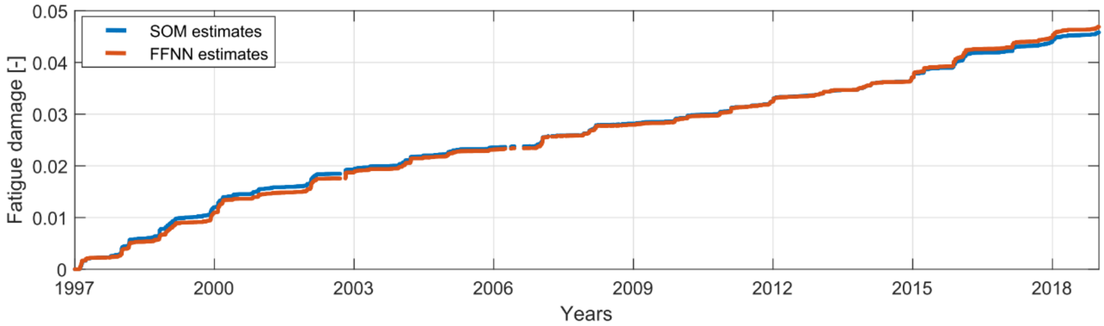


Figure 8. Cumulative wind-induced fatigue damage over 22 years of wind turbine operation

The estimated damage for the 20.62 years of operation is 0.0458 and 0.0469 for SOM and FFNN models, respectively. This gives mean yearly damage of 0.0022 and 0.0023. In a previous study for the same structure, Höffer et al. (2017), the calculated yearly damages are between 0.0022 and 0.0036 and the highest calculated yearly damage of 0.0036 is used for the lifetime estimation of 277.78 years. However, due to the lack of structural details at the time, the S-N curve given in EN 1993-1-9 (2005) is used for that study. The selected curve allows stress range of 40MPa at 2 million cycles, in comparison to the C1 curve used in this study, where 65.5 MPa for 10 million cycles is allowed. The S-N curve, selected in the present study, additionally considers the stress concentration factor and is more specific to wind turbine design.

7 CONCLUSIONS

In this paper, an estimation of wind-induced fatigue for an operating wind turbine support structure based on the artificial intelligence (AI) application is given. The wind turbine has been in operation since 1997 and therefore has reached the end of the design lifetime. Since the monitoring data is available between 2010 and 2013 and after 2016, the existing data is used for fatigue damage estimation. Afterwards, the open source data from four wind stations in the area is paired up with the calculated fatigue damage and two AI models are developed, feedforward neural network for fitting problems (FFNN) and Self-Organizing Map (SOM). The results show that both models are capable to estimate the wind-induced fatigue damage using the wind station data only, after being trained with monitoring data of the defined 0.5MW turbine from 2010 till 2018, and therefore allow estimation for missing data within this period. Estimations for the not-monitored times before 2010 and between 2013 and 2016 also show a good agreement of both AI-models.

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