PROACTIVE MAINTENANCE OF OFFSHORE WIND FARMS

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Abstract

For offshore wind farms, one of the biggest challenges is the preservation of operational availability. Conventional condition monitoring systems are insufficient because, in contrast to the onshore wind turbines, a service team can’t reach an impaired offshore turbine and start repair at any time. The accessibility of the turbines including underwater work depends on time slots of good weather conditions, current (e.g. tides) and equipment (e.g. type of ships). Therefore, a breakdown of a single system element in times of bad weather conditions may cause failure of energy conversion and transmission for a long time. In the present paper we propose a decision support system for proactive maintenance based on Echo State Networks ESNs [1] by means of processing of actual environmental data as well as the stress history of wind turbines considering the current and the predicted weather conditions.

Key words: proactive maintenance, condition monitoring, fault detection, offshore wind farms, artificial neuronal networks, Echo State Networks, ESNs
1. Proactive maintenance requires risk assessment
Proactive maintenance is based on a decision process which has to estimate the costs of proactive exchange of a system component versus the costs which would occur if the component would fail before the next regular visit of a maintenance team. Depending on this cost estimation, system components are replaced proactively, or not. Cost estimation has to assess
   a) the risk of failure and
   b) the accessibility of a wind farm and the resulting downtime.

2. Risk assessment based on sensor data
The environmental conditions (e.g. the effects of wind ramps) may vary substantially for wind turbines, even within the same wind farm.
The ‘stress’ history of a turbine is already represented in the sensor data recorded by supervisory control and data acquisition system (SCADA). We propose to exploit this historical data for risk assessment.
Sensors produce large amounts of data over time. Finding patterns which relate to risk of failure is a hard task, in particular if the risk should be quantified. We apply leading-edge machine learning technology to approach this challenge.

3. Condition monitoring systems (CMS) of wind turbines
The main task of condition monitoring systems, either by human-based resources or (automated) intelligent systems, is to estimate functional health of turbine components, analysing monitored data sets, recognising deviations from the characteristic behaviour of contemplated components. Most of automated CMSs are not especially developed for the monitored wind park (not to mention the target turbine), and consequently it does not consider inherent dynamisms of the turbine, as well as highly variable environmental conditions of its specific location. Thus, their characteristic behaviour is ab initio different. Consequently, estimated lifetime data of turbine components varies widely. The wear marks may be misinterpreted or potential malfunction is not correctly detected. Thus, a lot of CMSs produce an unacceptable high number of false positive estimations [2], or worst, can only detect the already given malfunction which causes a potential breakdown.
The most secure method for proper fault detection is to use vibration monitoring system adjusted to a concrete turbine. Such CSM must be able to monitor the whole of superposed frequencies of mutual influenced components. Unfortunately, some turbine component degradations are not able to be detected by using classical analysis techniques only. In many cases, to select necessary information it needs to use specific filtering which depends on many time variant parameters. Therefore, CMS should be able to adapt its information processing [3]. This is not possible in a rigid predetermined system. Nevertheless, there are several approaches to estimate the risk of failure considering multiple sensor data with artificial intelligence methods [4]. Such monitoring systems show high-level system dynamics and take advantage of dependencies between various sensor data. Based on interrelated sensor data information, they build characteristic features autonomously, with regard to the fault detection. At least, evaluation of dependencies over time between various sensor data might offer an additional benefit. The most of CMSs do not use this information, although it is known that its dynamics says a lot about the functional health of appropriate turbine components [3].

4. Methods for analysing large sensor data over time
Fraunhofer IAIS has developed a number of technologies for analysing large amounts of data. In particular, we propose Echo State Networks (ESNs) [1], a powerful technology for pattern matching on time series.
We propose to use ESNs for processing sensor data containing information about environmental stress history (e.g. wind ramps, vibrations and load cycles) to which wind turbines are exposed. From this, the reliability of components can be assessed in order to optimise maintenance efforts.

5. Echo State Networks

Echo State Networks (ESNs) is an approach to solve mathematical and engineering problems that is motivated by biological recurrent neuronal systems (RNNs): ESNs consist of number of relatively simple information processing units called artificial neurones, recurrent pathways, sparse random connectivity and local modification of synaptic weights [5].

![Figure 1. Echo State Net](image)

Their connective structure allows ESNs on the one hand, to generate a system model in such cases where there is no complete analytical model of the target system (for instance, the physical mechanisms are not completely known or they are highly non-linear and it is not computable in sufficient speed as in case of wind dynamic computation). On the other hand, because of their recurrent structure, the ESNs are able to process data over time. Such artificial RNN can learn to mimic a target system with arbitrary accuracy [6]. Information processing structure of ESNs presented in the Figure 1 consists of the input layer, the main RNN (called ESN) and the output layer.

There are many different learning mechanisms for training of RNNs. We use the learning mechanism proposed in [1]. The ESNs generate independently a target system model as a result of learning the input-output behaviour by adjusting the ESN-to-output connection weights $\omega_{o,y}$ only (Figure 1). Because of this restriction, there are no cyclic dependencies between the trained readout connections and training an ESN becomes a simple linear regression task.

Such trained ESNs are able to recognise complex patterns in input signal time series (which are similar to data set already learned) and to classify them equivalent the learned output signals. The more diverse aspects of input data are included in the training set, the better trained network describes the input-output behaviour of the target system. It is desirable to train a large number of input-output data sets, even if there are significant differences within training data sets. In such cases, ESNs learn statistical dependencies between input and output data set.

Furthermore, for purpose of more comprehensive mimic of target system we use an expert system which is formed of several ESNs called experts. Each expert is randomly connected, so each of them is potentially able to detect various features in the input data. On the one hand, this approach counteracts of undesired training overfitting effect and also increases classification capability of the overall network.

Despite systems dynamics ESNs show high stability, which distinguishes them from other recurrent systems.
6. Proposed maintenance system based on ESNs

The main task of proactive maintenance of wind farms is, based on stress history of the turbine, to estimate functional health of turbine components which should be monitored. For the stress history data, we use sensor data recorded by supervisory control and data acquisition system (SCADA) of the turbine. Indeed, there are available measured data over time for rotational speed, voltage, current, pressure and temperature available. There is a strong physical dependency between these “stress history” data and the level of wear of turbine components. It ought to be able to learn these dependencies with ESNs. With such well trained ESNs, it would be possible to estimate “Necessity for replacement” (NfR) of each turbine component based on “stress history.” Thereby, NfR represents the functional health of specific turbine components, based on measured (e.g. thermal, speed and voltage sensor data recorded by SCADA, but also vibration, tension, inertia and lubricant sensor data (new sensors required)) or empirical data. NfR ranges between 0 (not necessary to replace because of component is new) to 1 (strongly necessary to replace because of malfunction). In the practice, we suggest to use a threshold (e.g. NfR = 0.65) in excess of which system sends out a malfunction risk warning. Furthermore, NfR should consider cost estimation as well as contain precision information of its estimation.

The main idea of proposed method is to understand relations between “stress history” of the turbine and NfR data. At first, these relations are unknown, and represent a black-box with stress history input, as well as NfR output. We propose to use ESNs to learn its input-output behaviour based on stress data and the corresponding NfR, which is already known to us. ESNs leaned in this way are able to estimate NfRs based on new stress history data.

We showed analytically [7-8] that under certain conditions ESNs may be able to learn input-output behaviour of turbines within an offshore wind park. In that case the system model was built by mapping of weather conditions measured directly outside of the park to the turbine output power. For Echo State Network of 30 experts with 500 units per expert, it was possible to mimic input-output behaviour of an 80 WT offshore wind park with an accuracy given by normalized root mean square error (NRMSE) < 0.2 [7]. Thereby, wake effects within the wind park were considered.

The proposed maintenance process consists of two steps. First of all, ESNs are trained as shown in Figure2. Each training-set consists of NfR as well as the corresponding “stress history” time series. With a sufficient large training set ESNs learn time-variant dependencies between “stress history” and NfR of monitored system components.

Furthermore, accessibility of the investigated wind park shall be taken into account. Based on the weather forecast, in the next step surplus load of turbine components in the near future can be calculated. The accuracy of this estimation mainly depends on the accuracy of
the forecast. The latter will become less accurate the farther it extends into the future. Nevertheless, an estimation of NfRs for the next few days may have a high priority. This “predictive diagnostic” system represents the second step of proposed maintenance system. The latter is trained in the second step of maintenance system. The training is done in the same way as in the first step (Figure 3).

The entire trained system is able to predict the NfR of monitored system components as well as to get optimal time slots for the next visit of a maintenance team starting from the environmental condition data over time.

For the first step (Figure 2) we propose to use an Echo State Network of 10 experts 100 units per each. The second step (processing of already predicted environmental conditions regarding NfR) we recommend a higher number of experts (20 - 50) with 10-20 units (depending on weather forecast period (Figure 3)) per each.

7. Prospects

With the presented system a proactive maintenance of offshore wind farms can be implemented. For experimental evaluation, we require a large number of training sets (i.e. SCADA data). It is anticipated, that to process large training data sets, it is necessary to increase the number of units within ESNs. Furthermore, to estimate "Necessity for replacement" of numerous turbine components, maintenance system shall classify a number of various features within the stress data. Consequently, the number of experts shall be increased. Moreover, there are reasons to suppose, that there are dependencies between functional health data of various monitored components. It ought to be able to detect these dependencies using ESNs, to use these within the monitoring system.

Another extension of information processing structure of the presented system constitutes a prediction of environmental condition data (Figure 3) by using ESNs. Furthermore, it is conceivable, in addition to weather forecast data, to use further boundary conditions of condition monitoring such availability of equipment or resulting downtime to estimate the actual time slots for maintenance or replacement of impaired turbine components.
8 References