APPLICATION OF A DYNAMIC PROGNOSTIC MAINTENANCE POLICY TO OFFSHORE WIND TURBINES

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Many industries identify condition monitoring as a major opportunity to reduce maintenance costs and increase equipment availability. This is also the case for the fast emerging offshore wind turbine technology. However, when considering offshore wind turbine farms, implementation of condition monitoring also introduces a significant capital investment cost. Moreover, condition monitoring systems (CMS) are not infallible: they could potentially miss out on important failures or generate costly false alarms. This makes that the added value of condition monitoring should be assessed rigorously before implementation. Several publications on optimization of condition-based maintenance for wind turbines already appeared in literature (Besnard and Bertling, 2010; Garcia et al., 2006; Nielsen and Sørensen, 2011; Nilsson and Bertling, 2007). The objective of this paper is to quantify the added value of a prognostic maintenance policy for an offshore wind turbine farm. The prognostic maintenance policy makes use of predictive information, more specifically the remaining useful life of different components of the wind turbine. The remaining useful life estimation is based on measurements of several relevant features (e.g. vibrations), based on the evolution of these features through time a prediction of the remaining useful life of the considered component can be made. Compared to traditional condition-based maintenance policies more information, a prediction of remaining useful life into the future, is available to schedule and optimize maintenance actions. The use of a prognostic maintenance policy is an entire new approach to maintenance scheduling and optimization for offshore wind turbines. An entire wind farm is studied rather than only one wind turbine, which is another major contribution of this paper, in order to introduce the importance of dependencies between the separate wind turbines in the farm. Furthermore, the ability of the prognostic maintenance policy to react to these different dependencies (i.e. economic, structural and stochastic dependence) is quantified.

An extensive FMEA study, based on real-life collected data, is conducted in order to determine the most important failure modes of a wind turbine. This study points out that the failures of three major components (i.e. gearbox, generator and blades) are responsible for more than 80% of the total maintenance cost. These three failure modes are retained as an input for the investigated maintenance policies. The prognostic maintenance policy consists of three major parts: degradation modeling, prognosis of remaining useful life and dynamic maintenance grouping. The degradation process of all components is modeled by a gamma process, as this has been used extensively to model stochastic deterioration for optimizing maintenance (van Noortwijk, 2009). Based on this degradation process a prediction of remaining useful life of different components is made. This remaining useful life is used as an input to a dynamic maintenance activities grouping policy (Wildeman et al., 1997). Grouping of maintenance activities can be beneficial due to the existing component and system dependencies. Five major phases are distinguished in this policy, namely: decomposition, penalty function calculation, tentative planning, grouping maintenance activities and rolling-horizon step. An optimal schedule and grouping of maintenance actions is
found, based on the remaining useful life prediction and the developed dynamic maintenance grouping policy, by minimizing the long-term average cost per unit time. This optimal grouping structure is updated each time new information about the component states and remaining useful life becomes available. The optimal prognostic maintenance policy considers the dependencies between all different wind turbines in the wind farm. In order to quantify the added value and performance of the newly developed prognostic maintenance policy, a comparison is made with five other maintenance policies, which are corrective maintenance, block-based preventive maintenance, age-based preventive maintenance, offline condition-based maintenance and online condition-based maintenance. Moreover, an extensive sensitivity analysis is performed on the most important factors; these are cost parameters, number of wind turbines in the wind farm and dependencies between the components and wind turbines.
The expected results are that the developed prognostic maintenance policy will outperform the other considered maintenance policies, considering the objective of minimal long-term average cost per time unit. The major reason for this is that prognostic information is used in a dynamic maintenance scheduling algorithm, which results in optimal grouping structures of maintenance actions that take into account the dependencies (e.g. stochastic, economic and structural dependencies) between the components and wind turbines. These dependencies are definitely of crucial importance when considering an entire wind turbine farm rather than only one wind turbine. The major contribution of this paper lies in the development of a new prognostic maintenance policy for offshore wind turbine farms. As far as the authors are aware, this is the first time that prognostic information (e.g. remaining useful life of components) is taken into account to schedule maintenance operations on an offshore wind turbine farm. Furthermore, an entire wind farm is considered rather than only one wind turbine like in most of the publications available in literature, which makes it possible to quantify the effect of interdependencies between wind turbines in the same wind turbine farm.