Maintenance 4.0 of Wind Turbine

Ahmed Hammami, Fathi Djemal, Atef Hmida, Fakher Chaari, and Mohamed Haddar

Abstract Energy production through Wind turbine installations is increasing fast. In fact, wind turbines become bigger in size and power, what incurs that a simple unit defect causes huge energy losses. They are running in severe conditions of speed and load due to the variation of the wind speed. In addition, Wind turbines are subject to the environmental conditions such as wind shear, turbulence, gusts, rain, snow, sand and sea for offshore wind turbines. For this, their diagnoses and their follow-up is a priority to avoid the stops of production. In, developing techniques for prognostic and remaining useful life estimation is a very urgent necessity in wind turbine maintenance. Maintenance 4.0 is smart maintenance which refers to the last industrial revolution "Industry 4.0": It proposes strategies to meet these expectations by implementing advanced monitoring techniques through highly developed instruments and real-time signal processing techniques and by building models based on algorithm that will ensure a self- improvement and optimize the failure prediction. In this paper, a process of the predictive maintenance 4.0 is proposed and applied to a wind turbine in order to optimize operating costs and improve the energy efficiency of this system. In fact, dynamic, thermal and material information which are extracted from sensors are combined and characterized in the real time for a global process monitoring.

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1 Introduction

The wind turbines are frequently built as wind farm. They can have several faults that can cause failures with different levels of severity (Ziane 2017). Since their maintenance work is very hard task, many researchers focused on wind turbine in order to understand its dynamic behavior (Srikanth and Sekhar 2016; Tounsi et al. 2016), to improve their reliability (Musial et al. 2007) and efficiency, to develop their maintenance, to reduce their operating costs and to improve their running life. In fact, Marquez et al. (2012) achieved a state of the art of the strategies of maintenance and they presented the different used methods and techniques in the condition monitoring and signal processing of wind turbines. In addition, Marquez et al. (2016) used a quantitative method called Fault Tree Analysis (FTA) to identify the critical components of wind turbines. This method is computed through the Binary Decision Diagram (BDD) in order to reduce the computational costs. They applied the FTA method on four groups of elements of wind turbine: the tower, the blade system, the electrical components and the power drive train which is very sensitive to the variable speed and load running conditions (Hammami et al. 2015a). So, it is essential to identify the modal properties (Hammami et al. 2015b; Mbarek et al. 2018; Hmida et al. 2019) of the drive train especially in the non stationary conditions (Mbarek et al. 2019). The drive train can present inevitable defects and its diagnostic is not evident since the wind turbine is running in non-stationary conditions (Zhang et al. 2012; Dempsey and Sheng 2013; Sawalhi et al. 2014 Yang et al. 2016; Hammami et al. 2019). Wind turbine drive train is the most critical and expensive group of components of wind turbine (Leite et al. 2018) and it is also sensitive to the implementation conditions such as the offshore floating plate form (Viadero et al. 2014). Recently, many researchers focused on the prognostic and performance degradation of rotary machinery systems (Lee et al. 2014; Fourati et al. 2017; Derbel et al. 2019) and specially the drive train of wind turbines: Pan et al. (2019) used an approach the empirical Mode Decomposition called CEEMDAN and the Kernal Principal Component Analysis in order to evaluate the performance degradation of WT gearbox and to predict the Remaining Use Life which is computed through the Extreme Learning Machine.

Research on wind turbine blade is also very attractive. Not only design, exploring and performance of blade system receive an increasing amount of attention (Hayat et al. 2019; Hua et al. 2019; Ansari et al. 2019), but also many studies on fatigue and failure of blades are carried out (Jensen et al. 2006; van Leeuwen et al. 2002; Griffin and Zuteck 2001): Mishnaevsky (2019) summarized the repairing techniques of wind turbine blade and developed new ideas for maintenance blades.

According to the cited research studies, wind turbine is a very complex system and it needs an intelligent maintenance. For this purpose, we call on maintenance

4.0 which refers to the last industrial revolution "Industry 4.0". In this paper, the maintenance 4.0 is defined in Sect. 2 where the implementation approach is described. In Sect. 3, maintenance 4.0 approach is applied on the case of wind turbine.

2 Definition of Maintenance 4.0

Maintenance 4.0 refers to the last industrial revolution "Industry 4.0" where smart companies, which operate through lean manufacturing strategies and which enable humans and robots to communicate more easily, are equipped with the smart machines and tools in order to take advantage of better decisions and self-development.

2.1 *Maintenance Evolution*

The predictive maintenance is always evolving. Four levels of predictive maintenance can be found (Fig. 1).

It has been years since we applied the first level of predictive maintenance by carrying out the visual inspection in the daily rounds.

In the second level, instrumentation and advanced techniques such as thermography, vibration analyses are used and we can make the comparison with the old measurements.

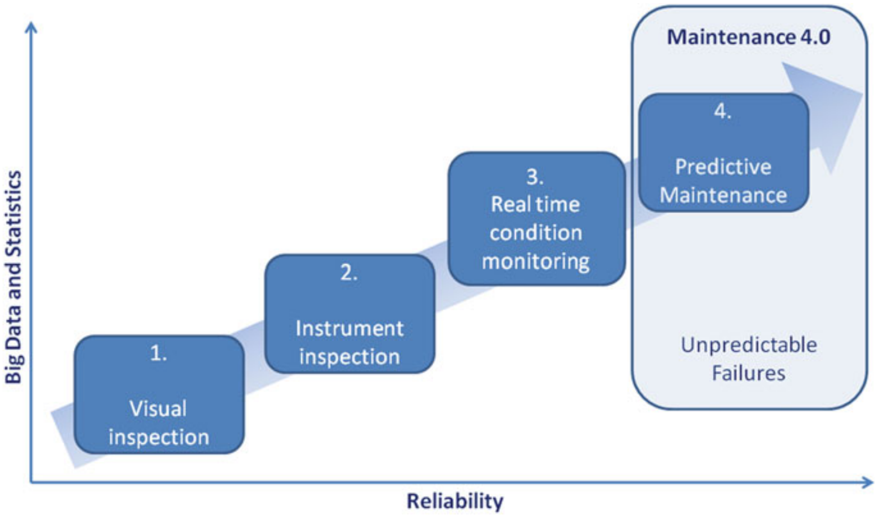


Fig. 1 Predictive maintenance evolution (Haarman et al 2017)

In the 3rd level, the measurements are permanent. So, we have finer means in monitoring the state of the machine and its degradation.

The 4th level corresponds to the maintenance 4.0, it is the proactive or predictive maintenance where we will work with the big data and the more sophisticated analysis techniques of the statistics type and the Learning machines. So, we will build models based on algorithm that will ensure a self-improvement.

2.2 Predictive Maintenance 4.0

The predictive maintenance 4.0 can be defined by the ability to predict potential failures or failures of an installation and describe the preventive actions of corrections using data analysis techniques. These data are of several orders and of several sources such as the technical state of the installations, operating machine condition, the evolution of the environment of the installation (dust, temperature, humidity …).

The maintenance history can also be used using Computerized Maintenance Management System software (maintenance tasks and preventive maintenance). We can use big data especially when it comes to installations that are similar (for example wind turbine farm) where can compare and increase the volume of data. And more than we have to give more than the algorithms will be optimized.

2.3 Implementation Approach of Maintenance 4.0

The implementation of this approach is proposed by Haarman et al. (2017) and it is shown in Fig. 2.

Maintenance 4.0 requires seven steps: the first and the second steps which are *Asset value ranking and feasibility study* and *Asset selection* can be done together and at the same time. Maintenance 4.0 approach is based on the creation of value. So, it is necessary to understand the functioning of machine and the parts of installation more penalizing and not necessarily those which have the most information. Reliability study is carried out on third step "*Reliability modeling*" and the fourth step "*Algorithm design*" through the proposal of a mathematical model and the creation of a corresponding algorithm. Then, tests are carried out on the fifth step "*Real time performance monitoring*", the saved data are integrated into the model to refine and link with the preventive ranges on the sixth step "*Failure prediction*" and seventh step "*Preventive task prescription*".

To do this, we need a whole series of data. So, we need to make our selection of conventional indicators. Some data is structured in the CMMS and some that are not structured.

It is important to optimize regularly the algorithm through Machine Learning and to have links with what we know and what we observe in order to predict the default and prescribe actions before suffering the effects of failure.

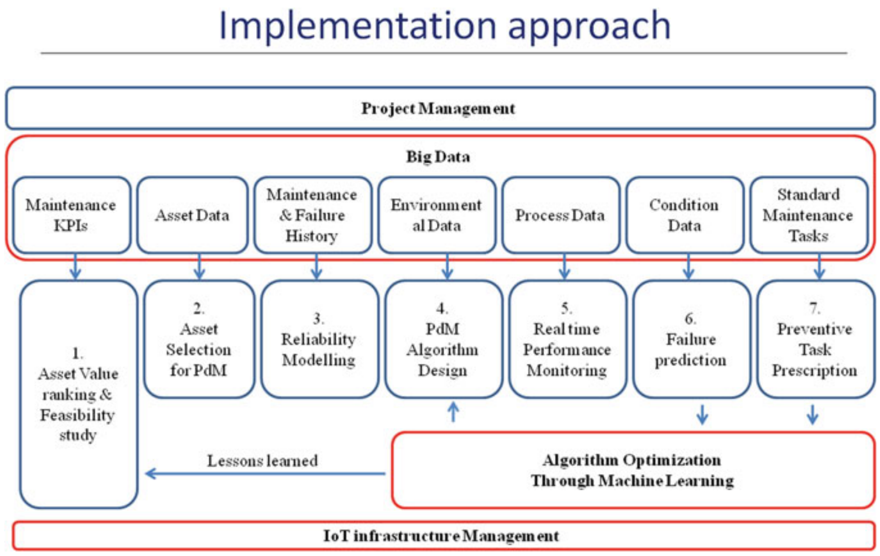


Fig. 2 Implementation approach of maintenance 4.0 (Haarman et al. 2017)

So, we have to manage this approach in order to arrive on the one hand to set up infrastructure IOT (Internet Of Things) and on the other hand up date of organization.

3 Case Study: Maintenance 4.0 of Wind Turbine

The case of wind turbines is selected to illustrate the implementation approach of maintenance 4.0 since they are building as wind farm and their maintenance is hard.

3.1 Identification of Critical Components of Wind Turbine

The first two steps of maintenance 4.0 which are *Asset value ranking and feasibility study* and *Asset selection* are applied in this subsection.

In fact, the wind turbine can be divided into four groups of components: the foundation and tower, blades system, electrical components and the power train including shafts, bearings and gearbox.

The Fault Tree Analysis can be applied on each group in order to identify the critical components (Marquez et al. 2016).

3.2 Instrumentation and Condition Monitoring of Wind Turbine

Instrumentation of wind turbine is preparing to the fifth step of maintenance 4.0 "*Real time performance monitoring*". Many techniques of condition monitoring can be used in the case of wind turbines. Vibration analysis is the most used techniques especially for rotating components. In fact, monitoring of gearbox and bearings through this technique is very common. In addition, vibration analysis can be adapted to the monitoring of rotor, blades and tower. Nerveless, these components can be protecting against the high stress through the strain measurement. The control of generator can be performed like other electrical equipment through voltage and current analysis (Feki et al. 2012, 2013). We can found other techniques of condition monitoring such as acoustic emission, radiographic inspection and thermography of blades, oil analysis of gearbox. Since the condition monitoring should be performing and in real time, it is better to use the vibration analysis for the gearbox, bearings and the tower, the stator current analysis for the generator and the strain measurement for the blades (Schröder et al. 2005). To carry out test, accelerometers are mounted on the bearing, gearbox and the tower; strain gauges are mounted on the blades and current sensors are mounted to measure the stator current (Fig. 3).

3.3 Prognostic and Health Management of Wind Turbine

This subsection covers four steps which are on the one hand the third and the fourth steps "*Reliability modeling*" and "*Algorithm design*" and on the other hand the sixth and the seventh steps "*Failure prediction*" and "*Preventive task prescription*".

In fact, steps "*Reliability modeling*" and "*Algorithm design*" are carried out together. As an example, Pan et al. (2019) applied these two steps on vibratory signals of wind turbine gearbox to predict its Remaining Use Life (RUL). They performed a highly accelerated life test and they employed the Extreme Learning Machine (ELM) and fruit Fly Of Algorithm (FOA) which is proposed by Ye et al. (2015). This algorithm is applied after de-noising the vibratory signals and extracting the health indicator through an approach of Empirical Mode Decomposition (EMD) called Complete Ensemble EMD with Adaptive Noise (CEEMDAN) and Kernel Principal Component Analysis (KPCA). In fact, the evolution of the health indicator as shown in Fig. 4 can be divided into three time-periods: run in, stable and wear.

The comparison between the real RUL and the predicted RUL at the wear period (Fig. 5) proves the supremacy of the used algorithm.

In addition, this algorithm allows the seventh step "*Failure prediction*" because they (Pan et al. 2019) predict debris damage happened to the low-speed stage bearing, the ring gear and the oil filter.

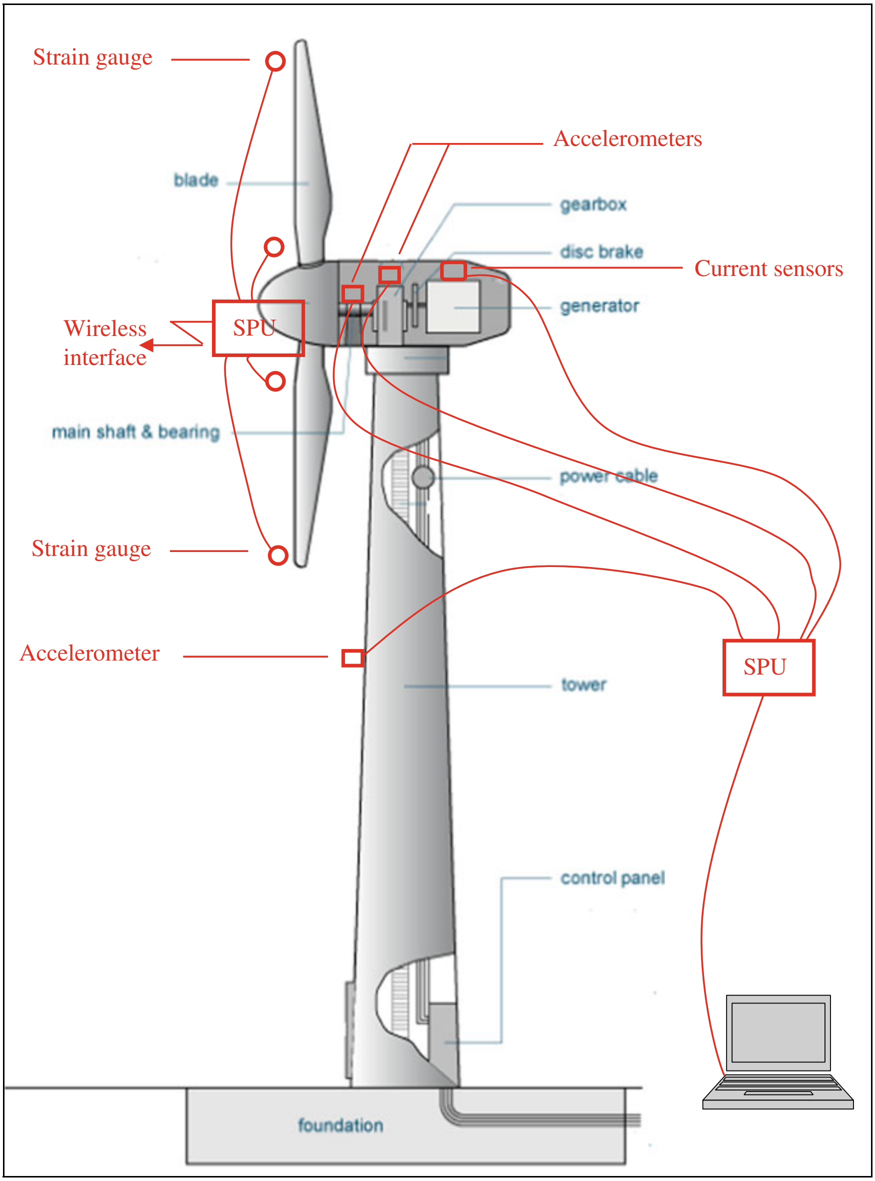


Fig. 3 Instrumentation of wind turbine

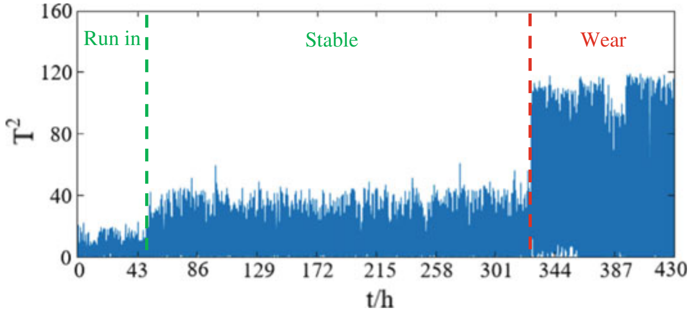
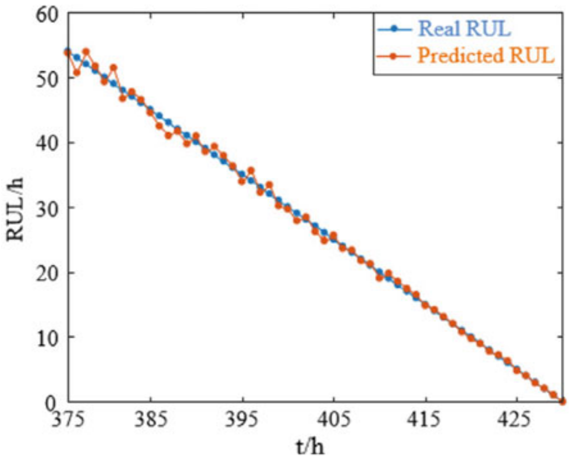


Fig. 4 Health indicator (Pan et al. 2019)

Fig. 5 RUL prediction model based on FOA-ELM algorithm (Pan et al. 2019)



4 Conclusion

Maintenance 4.0 is a smart maintenance and it can be applied on wind farm where wind turbines are comparable installations and they are running in the same conditions. So, Big data can be used to predict failure by applying Learning Machine Algorithm to predict failure. Extreme learning machine (ELM) optimized by fruit fly of algorithm (FOA) is an effective algorithm for RUL prediction.

To carry out this, strain gauges, current sensors and accelerometers should be mounted respectively on the blades, alternator and rotating components (gearbox, bearing and tower). The measurements should be in real time and the extracted signals are processed to be used by a learning machine for failure prediction.

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