Machine Learning-based Predictive Maintenance for Renewable Energy: The Case of Power Plants in Morocco

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1. Context

The production of energy currently accounts for 40% of global Greenhouse Gas (GhG) emissions, and the consequences of global warming are already being felt: extreme and severe weather, melting ice, wildlife extinction, and higher sea level. In order to keep the rise in global temperatures below 2°C (Paris Agreement), the share of renewables must reach 65% of the worlds primary energy supply by 2050, up from 15% today. Thus, energy sector is placed at the heart of climate change mitigation and adaptation efforts (1; 2). During the last decade, renewable technologies have seen considerable advances, and solar and wind energy have had dramatic growth trajectories. This is manifested by the large deployment of renewables. At the end of 2018, the global cumulative renewable installed capacity is 2.5 TW with an annual growth rate of 8% (1). The cost of energy continues its decline, accelerated by technological progress, and this trend is projected to continue. In fact, the weighted Levelized Cost of Energy (LCOE) of solar photovoltaic at utility-scale has reached USD 50 per MWh in 2017, down from USD 180 per MWh in 2009 (3). Arguably, renewables represent the most economical solution for new capacity in a growing number of countries and regions. Despite this success, there is still some way to go to ensure better penetration of renewables into an energy market mostly based on fossil fuels. To this end, it is important to continue on the path of cost reduction whether in capital (Capex) or operating (Opex) expenditures.

In this project, the focus will be on the reduction of the overall electricity cost by the reduction of operating expenditures, including maintenance costs. We propose a predictive maintenance (PdM) framework for multi-component systems in renewables power plants based on machine learning (ML) and optimization approaches. This project would benefit from a real database acquired from the Moroccan Agency Of Sustainable Energy (MASEN) that own and operate several wind, solar and hydro power plants spread over Moroccan territory. Morocco has launched an ambitious energy strategy since 2009 that aims to ensure the energy security of the country, diversify the source of energy and preserve the environment. Ultimately, Morocco has set the target of 52% of renewables by 2030 with a large capital investment of USD 30 billion (4). To this end, Morocco will install 10 GW allocated as follows: 45% for solar, 42% for wind and 13% for hydro, avoiding the emission of approximately 21 millions tonnes of CO_2. Through the commitment of many actors, in particular in Research and Development, Morocco intends to become a regional leader and a model to follow in its climate change efforts. MASEN is investing in several strategies to reduce the cost of renewables, including the cost of operations and maintenance. Our project will provide a ML predictive maintenance framework to support these efforts.

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2. Predictive maintenance process

PdM aims to predict when system failure might occur, and to prevent the occurrence of failure by performing maintenance. It allows the maintenance frequency to be as low as possible to prevent unplanned corrective maintenance, without incurring costs associated with doing too much systematic preventive maintenance (5; 6). Experts agree PdM could reduce maintenance cost by 10% to 40% (7). It also improves the availability, the reliability, and the security of critical components.

System structures become more and more complex with a large number of components and very complex interactions between them. Wind turbines are a good example of complex systems. They are composed of several critical components such as the blades, the pitch, the gearbox and the generator and they present impressive characteristics such as the hub height, rotor diameter or rated power. They normally run on a 24/7 schedule, are geographically distributed and operating under arduous conditions. Each unexpected failure can lead to a drop in availability and huge financial losses. Therefore, they are ideal candidates for savings through PdM.

According to International Standard ISO 13381- 1 (5), PdM process can be divided into three different steps, namely: (i) Diagnostics, (ii) Prognostics and (iii) Decision Making. Diagnostics involves fault detection, isolation (which component is failed), failure mode identification (what is the cause of failure) and degradation level assessment (quantification of failure severity). The prognostics task consists of determining the Remaining Useful Life (RUL). The RUL is the lead-time to failure and a good RUL prediction accuracy is critically important since it has impacts on the planning of maintenance activities, spare parts logistic and operational performance. Decision making is a process resulting in the selection of right maintenance actions among several alternatives. The maintenance decision maker must evaluate the each action based on the diagnostics or prognostics results and he should be able to estimate the outcomes of each alternative (8; 6; 9).

3. ML predictive maintenance framework for multi-components system

We believe ML can provide a large improvement to all steps of PdM process: (i) ML failure detection models, (ii) ML failure identification models, (iii) ML system components prioritisation models, (iv) ML RUL prediction models and (v) Maintenance policy optimization models. Several ML algorithms have been applied in PdM: Vector Support Machines (10) Decision Trees (11) Random forest (12). More recently, the emergence of deep learning algorithms has given rise to new applications in PdM (13; 14; 15; 16; 17).

Our PdM model for multi-components system, based on ML and optimization, consist of four key steps: (i) Data Acquisition and Processing (ii) Failure Detection (iii) RUL Prediction and (iv) Maintenance Policy optimization.

1. **Data Acquisition and Processing.** Data are collected through a set of sensors using various technologies (e.g: vibration, oil analysis, sound, thermography and tribology). A particular attention will be paid to the preparation, processing and analysis of the data for a better understanding of the multi-component system and to eliminate errors that might affect the interpretation of degradation phenomena.

2. **Failure Detection.** The first level of detection is to distinguish between two classes: failure and no-failure. Based on the assessment of any deviation between normal and abnormal behavior, one can also evaluate the severity of the failure. This step allows isolating and identifying the component that stopped functioning (from effects to causes).

3. **RUL Prediction.** This step aims to predict the RUL (from causes to effects). RUL prediction models have drawn great attention over the last decades and they can be categorized into four main groups (18; 5): (i) Knowledge-based models (ii) Life expectancy models (iii) Data-based models and (iv) Physical models. However, the use of these models in predictive maintenance decision process for multi-component systems is still an under investigated area but also an open challenge. In our framework, RUL prediction represents an even more advanced step. The consideration of predicting RUL problem as a time-series prediction and the availability of large-scale datasets is a strong incentive to seek deep learning algorithms in general and LSTM in particular. Impressive progress has been made in a variety of application of LSTM in RUL prediction (13).

4. **Maintenance Policy Optimization.** Based on the RUL prediction of each system component, one can evaluate locally the outcome of the maintenance at component level (generally in terms of cost and availability). In real life, systems (such as wind turbines) are composed of several critical components. So the aim of our model is to propose an optimal and a global PdM policy at the system level by considering the existence of numerous dependant components.

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