Hybrid Fault Prognosis for Excitation Capacitors of Self-Excited Induction Generator for Wind Energy Applications

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ABSTRACT

This paper presents a new fault prognosis approach applied to wind turbine system based on self-excited induction generator (SEIG) for offshore and isolated areas. This generator is very sensitive to wind speed variation and excitation source. The SEIG is excited by a capacitor bank with an appropriate value to ensure the good operating of the production system. Capacitor bank faults are usually related to chemical aging, electrical and thermal stress conditions. These abnormalities can affect one or more properties of the system, which can lead to failures or even complete breakdown of the production system. Specifically, in this paper, we propose a saturated flux model for the SEIG and develop a hybrid monitoring method that detects faults occurrence gradually and estimates the remaining useful life (RUL). Such monitoring method applies data mining techniques in order to identify and track the faults using only useful data that captures the dynamics of the degradation. Moreover, to deploy efficient maintenance schedules, RUL is estimated by exploiting wind speed (variable and max speed) information. The proposed hybrid fault prognosis method is tested under variable excitation capacitors degradation scenarios. The obtained results confirm the robustness and accuracy of the proposed method.

1. INTRODUCTION

Nowadays, the use of wind energy as a renewable energy source, has grown rapidly and has become more important as

the consciousness of global warming due to consumption of fossil energy and environmental pollution has increased (Derbal & Toubakh, 2018).

Most wind farms in the world are offshore, where wind conditions are generally better, and the issues of noise and the impact on the landscape are somewhat improved. However, the reliability of an offshore wind generator and the resources required to maintain it can make up to 30% of the overall cost of energy produced. Typically, offshore wind generators failures require greater repair resources (i.e. material cost and labor) which leads to higher cost of energy. Consequently, wind farm developers try to select wind turbines with low failure rates and those that require the least amount of maintenance resources. Because of accessibility issues, reliability of turbines becomes even more important as offshore wind energy generation increases (Carroll, McDonald and McMillan, 2016).

Self-excited induction generator is the best electromechanical converter to replace the synchronous generator in stand-alone power generators driven by sustainable energy resources such as micro-hydroelectric, biogas, wind, thermal, etc. SEIG is quite robust, relatively inexpensive and interestingly needs minimum maintenance. Using this generator in isolated and offshore wind energy system justifies the importance of supervising their normal operations (Derbal & Toubakh, 2018). Unexpected faults of wind generator based on SEIG may occur in electronic control units, electric systems, hydraulic systems, the generator, the gearbox, the rotor cage malfunctions and the stator phase imbalance. Faults can occur also in excitation capacitor, which can lead to performance degradation, unscheduled turbine shutdown, and even

damaging components of the turbine systems (Kumawat, Chourasiya, Agrawal and Paliwalia, 2015).

When a standalone induction generator is driven by a wind turbine, the residual magnetism in the rotor of the machine induces an electromotive force (EMF) in the stator windings. EMF is applied to the capacitor bank that is connected to the stator terminals causing the reactive current to flow in the stator windings. Hence, a magnetizing flux in the machine is established. The final value of the stator voltage is limited by the magnetic saturation within the machine. The voltage build process depends upon the capacitor value (Gao & Sheng, 2018). However, the performance of excitation capacitors is strongly affected by working conditions, such as current, voltage, frequency and working temperature. The degradation during a period of time will lead to a component failure which may impact the working of the production system (Derbal & Toubakh, 2018). As a result, there is a high demand to improve the operation reliability, availability, and productivity of wind turbine systems. Therefore, it is important to detect and identify potential abnormalities and faults as early as possible by (i) using real-time monitoring and fault diagnosis, (ii) predicting the remaining useful life of the components through data analysis and processing, and (iii) implementing resilient control and management system to minimize the performance degradation and economic cost and avoid dangerous situations (Bu, Huang, Huand and Shi, 2011).

In recent years, many studies have been conducted around prognosis. Prognostic methods are divided into two groups: analytical model based methods, and data driven methods. In the case of model-based prognosis, the analytical models can be developed from the system's failures (Clark, Elder, Guerry, Braitman, Trock, Schultz and Halpern, 1989) and are usually based on the physical knowledge of the system in terms of estimating possible deterioration that may occur in the future. The advantage of the model-based approach is that the number of sensed parameters can be reduced, while others can be directly determined from a model. On the other hand, the major drawbacks of the model-based approach result from the requirement of perfect physical knowledge of the system dynamics and from the scalability issue in presence of high number of discrete (Toubakh, Sayed-Mouchaweh, Benmiloud, Defoort and Djemai, 2020).

In the data-driven approach, data are collected and processed to obtain discriminative features and then learn the parameters of the prognosis model. Interestingly enough, data-driven methods can be designed to learn without prior physical knowledge of the system dynamics and to operate efficiently while handling non-linear and multi-variable problems. There exist many methods used for this aim including signal analysis (FFT, filters, etc.), graphical models (hidden Markov models, Bayesian networks), decisions trees and fuzzy rule-based systems, statistical methods (auto-regressive models, least squares and canonical variant

analysis, linear and quadratic discriminant, static and dynamic principle component analysis) as well as black-box methods based on artificial neural (self-organizing feature maps, MLP, etc.) (Emeksiz, Doğan, Mehmet and Hekim, 2017) (Toubakh & Sayed-Mouchaweh, 2016).

In this study, we focus on fault prognosis of an excitation capacitor bank of SEIG, operating in a standalone mode in offshore area. The wind system is considered as a hybrid dynamic system combining both discrete and continuous dynamics, the wind system switches between several discrete modes in response to wind speed variation. We therefore propose a new approach that models the dynamical behavior of SEIG according to wind speed in order to disaggregate the RUL estimation process by considering switching between the different control modes. To achieve this target, we start by describing the wind production system (Section 2) and modeling the capacitor bank degradation (Section 3), then we explain the proposed data-driven prognostic approach for RUL estimation (Section 4). The approach applies data mining techniques in order to identify and track the faults using only useful data that captures the dynamics of the degradation and by exploiting wind speed (variable and max speed) information. This approach contributes to improve the RUL estimation accuracy. Finally, we evaluate the developed approach for different degradation scenarios and discuss the obtained simulation results using MATLAB (Section 5) before concluding in Section 6.

2. SYSTEM DESCRIPTION

Figure 1 depicts the overall system studied here. It includes a wind turbine, an induction generator excited with a capacitor bank, converter and controller. This system is designed to feed isolated arrears with electricity based on wind energy. The DC output power can be consumed directly by DC loads or converted to AC for AC loads.
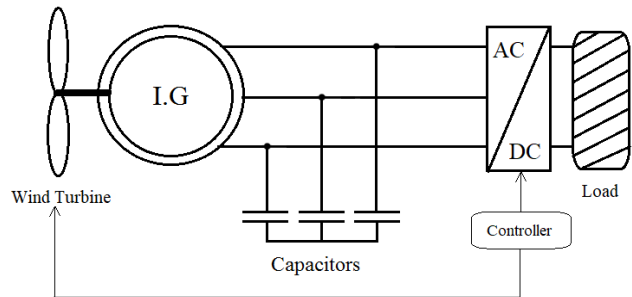
Figure 1. Structure of the wind system

The controller operates in four zones (see Figure 2), where zone 1 is the startup of the turbine; zone 2 covers power optimization; zone 3 covers a constant power production and zone 4 corresponds to the shut-down of the turbine due extreme high wind speed.
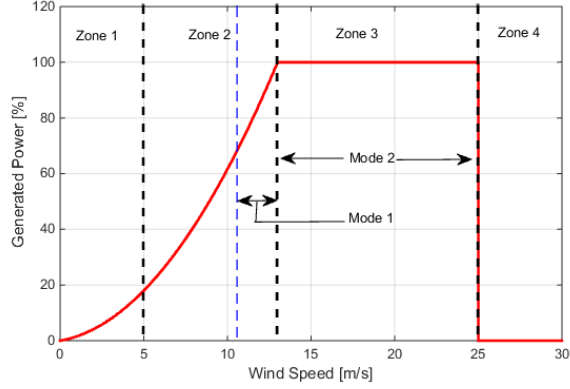
Figure 2. Generated power curve depending on wind speed.

In this study, we focus on zone 2 and zone 3 where we have two different SEIG excitation dynamics:

a) Control mode 1: in this control mode the wind generator speed is less than its nominal speed (zone 2) and the power optimal value is achieved by the controller sitting the pitch reference β = 0 and the reference torque value $\tau_{g,r}$ as follows :

$$\tau_{g,r} = K_{opt} \ \omega_r{}^2 \qquad (1)$$

where $\qquad K_{opt} = \frac{1}{2} \ \rho \ A \ R^3 \ \frac{C_{p\_max}}{\lambda_{opt}^3} \qquad (2)$

ω_r is the angular rotor speed, ρ is the air density speed (ρ =1.225 kg/m3), A is the area swept by the turbine blades, R is the radius of the blades and C_{p_max} is the maximal value of power coefficient C_p , λ_{opt} is the optimal value of the tip speed ratio λ. As a result, we have a variable excitation due to the variation of the wind speed (Odgaard, Stoustrup and Kinnaert, 2013). The capacitor bank is designed to provide reactive energy for an interval around the defined operating point. In this study the capacitor bank is designed according to the nominal operating point. The blue vertical line (Figure 2) is the limit of this interval and corresponds to the minimum capacitance required for self-excited induction generator. This value can be determined using generator parameters (Eltamaly 2002).

b) Control mode 2: in this mode, the controller sets the generator's power at its reference by controlling β, such that C_p is decreased. As a result, we have a pre-set excitation.

3. CAPACITOR DEGRADATION MODELING

Faults in a capacitor can be catastrophic as they lead to complete loss of functionality. Manifesting as gradual deterioration of the capacitor, the degradation is related to decrease in the capacitance and increase in the equivalent series resistance (ESR) over time (Derbal & Toubakh, 2018).

The performance degradation of the excitation capacitor banks often results from chemical aging. As the capacitor degenerates, the ESR rises, causing the output voltage of the SEIG's capacitor to drop and consequently the output power reduces.

Figure 3. Lumped parameter model.

A simplified electrical lumped parameter model of impedance, defined for a capacitor, is shown in Figure 3. Part of the stored capacitor energy is dissipated by the ESR. An ideal capacitor has no resistance to the current flow at its leads (Toubakh & Sayed-Mouchaweh, 2016).In order to simulate this degradation in SEIG excitation capacitor bank, the nominal value of ESR is increased gradually over time. The voltage of the capacitors is directly impacted by this gradual increase in ESR, as follows:

$$V_{cj} = \frac{1}{C} \int I_c \ dt + ESR_j \ I_c \qquad (3)$$

In this study, multiple degradation scenarios are produced in order to simulate the nominal value of ESR. Thus, ESR increases linearly in high, moderate and slow speeds. The objective of simulating different degradation speeds is to investigate the impact of different SEIG's degradation dynamics and to evaluate the performance of RUL estimation.

4. PROPOSED APPROACH

In this section, the proposed hybrid fault prognosis approach of the excitation capacitor bank of SEIG is discussed. This approach uses hybrid dynamical behaviors of the wind system according to wind speed. The goal is to achieve condition monitoring by using only the recent useful data corresponding to active control mode and improve RUL estimation process. The approach proposes to (i) process and analyze data which were collected across the capacitor bank terminals and (ii) using Auto-adaptive Dynamical Classification Algorithm AuDyC to detect degradation and finally (iii) generate a health indicator for each control mode and estimate the RUL using Auto-Regressive Recurrent Radial Based Function network (ARRRBF). The proposed approach is graphically portrayed in Figure 4.

4.1. Data Processing and Analysis

This step aims at finding the relevant features that are sensitive to the capacitor bank operating conditions using voltages and currents measured by the capacitor bank sensors as well as prior knowledge about system physics and dynamics (e.g., reference normal capacitor voltage and normal current).
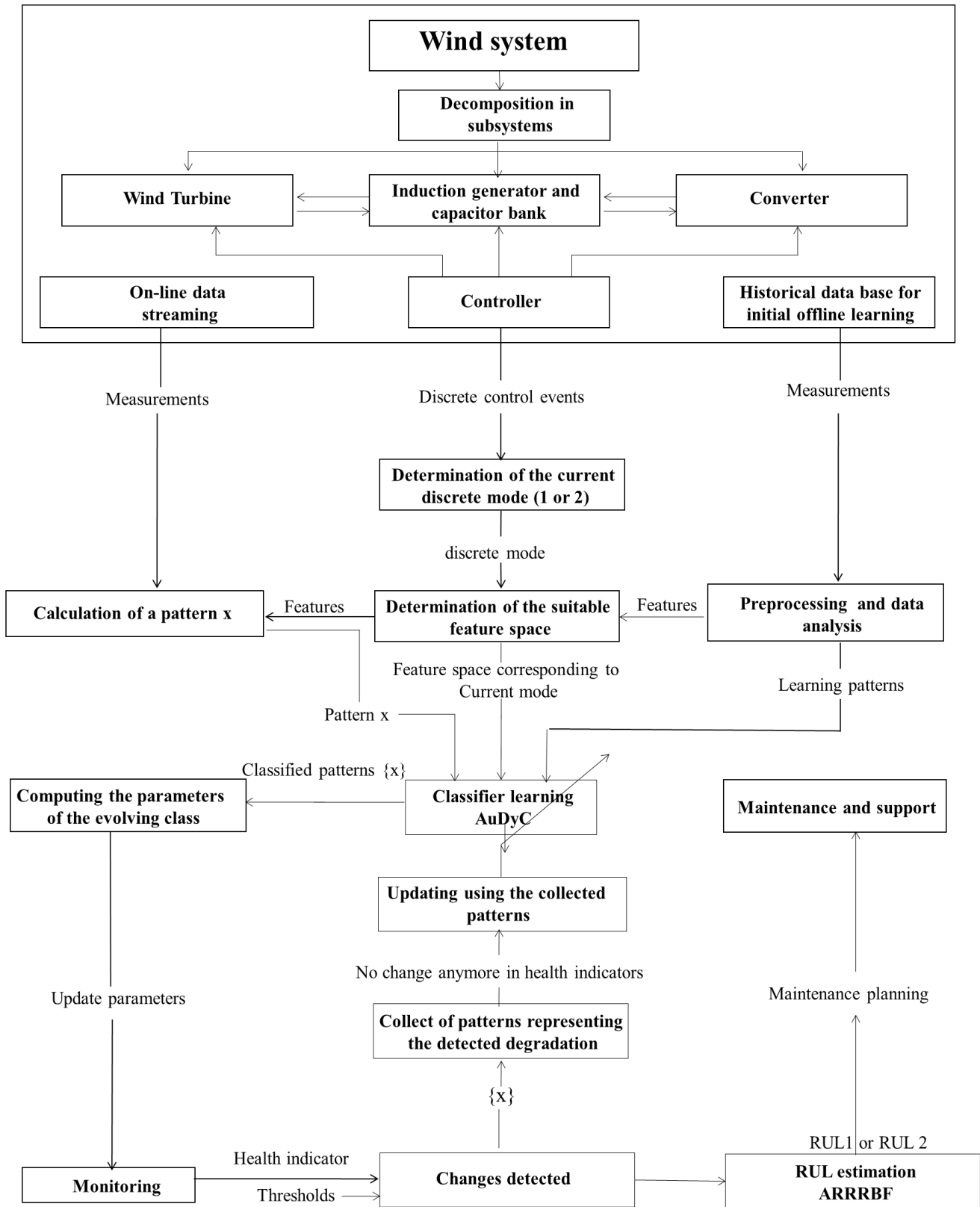
Figure 4. Steps of the proposed approach.

These features are selected depending on the operation mode in order to select only the useful data that captures the dynamics of the degradation and to detect at early stage abnormalities of the capacitor bank. To determine such abnormalities, the following residuals are computed:

$$RVs= (Vse-Vsn) \qquad (4)$$

$$RIs= (Ise-Isn) \qquad (5)$$

where Vsn, Isn are the voltage and the current values in normal conditions respectively. Likewise, Vse and Ise are the voltage and the current values in evolving conditions.

We define here faulty class as the class indicates a complete failure and non-function of the system while evolving class is the class representing the degradation from normal operation to a complete failure. In the evolving class, the system is still functional but will failing soon. In order to distinguish as much as possible the operation conditions and improve RUL estimation process, the normal and the faulty classes are split into four classes 1, 2, 3 and 4 according to SEIG dynamics, which are represented by two different modes. Class 1 is the normal class whereas class 2 represents the faulty class in control mode 1. Class 3 and class 4 represent the normal and faulty classes in control mode 2 respectively.

Each control mode is active in one zone, which can be then modeled by a finite state machine (see figure 5).
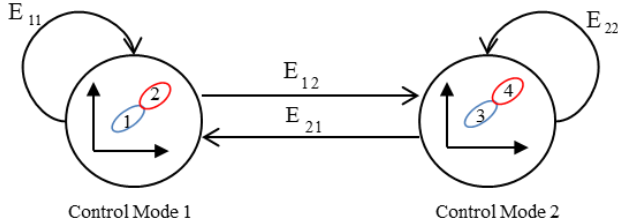
Figure 5. Control mode 1 and 2 modeled by a finite state machine (automaton)

The transition between the control modes changes the dynamics of the wind system according to wind speed. The control mode changes from one state to another, as long as wind speed is less than the predefined threshold corresponding to nominal value of ω_r, E_{11} keeps the system in mode 1. The control mode should switch form control mode 1 to control mode 2 (E_{12}) if the following event is realized:

$$E_{12}: \omega_r \geq \omega_{nom}$$

where ω_{nom} is the nominal value of ω_r. If wind speed is greater than the predefined threshold corresponding to nominal value of ω_r, then the event E_{22} will be generated. E_{22} kept the system in mode 2. The control mode should switch form control mode 2 to control mode 1 (E_{21}) if the following event is realized:

$$E_{21}: \omega_r < \omega_{nom}$$

4.2. Learning of the Control Mode Classes

The classifier aims at deciding if the present operation condition of the capacitor bank is normal. The normal and the present operation condition are represented respectively by classes in the feature space of each control mode. Therefore, the model of each control mode is designed in the form of a classifier that categorizes patterns in one of the normal classes. When the degradation occurs, the characteristics of pattern representing the present operation conditions in each discrete mode starts to change according to the one of normal classes. A degradation is detected if the difference between the evolving and normal classes characteristics is greater than a three-standard deviation for each control mode. The clustering algorithm AuDyC (standing for Auto-adaptive and Dynamical Clustering), proposed by Toubakh & Sayed-Mouchaweh (2014) is used implement the assignment task of data to the control modes. Here AuDyC builds clusters around the pre-defined classes. AuDyC calculates the initial classes parameters and continuously updates the classes by integrating the new input X and by removing the oldest one in the time window. The choice of AuDyC is justified by the ability to model data streams, since it always reflects the final distribution of the measurements in the features space and it is clustering method.

4.3. Health Indicator

Degradation of the excitation capacitor bank occurs, when the operating condition changes from healthy to a complete failure. In this study we use a health indicator based on Mahalanobis distance (6) which is used as a metric in order to measure the distance between two classes for each control mode, the initial normal class C_N and the evolving class C_e. The degradation is detected when d_{Mah} exceeds three-standard deviation of the normal class.

$$d_{Mah}(C_N, \mu_e) = \sqrt{(\mu_N - \mu_e) \Sigma_N^{-1}(\mu_N - \mu_e)^T} \qquad (6)$$

Where μ_e is the center of the evolving class C_e, μ_N is the center of the normal class C_N, and Σ_N is the covariance matrix of the normal class. We note here that the health indicator is a dissimilarity metric and consequently is unbounded.

4.4. RUL Estimation

Recall that RUL is the time to failure subtracted by its present age. RUL is obtained as soon as the health indicator trajectory of the capacitor bank reaches a pre-defined threshold. Such threshold corresponds to total system failure. RUL estimation can be seen as a prediction problem, since it depends on the behavior of the health indicator curve in the future. The choice of the prediction model depends on the degradation trend which is often nonlinear. The popular tools used in the literature for time series prediction are neural networks and

the Support Vector Machine (SVM) (Heydarzadeh, Zafarani, Akin and Nourani, 2017).

There are two main types of temporal neural networks: neural networks whose time is represented by an external mechanism, and those whose time is represented by an internal mechanism. In this study, a neural network is used to predict the progress of the health indicator, called ARRRBF (standing for Auto Regressive Recurrent Radial-Based Function network).The architecture of ARRRBF is given in Figure 6. This network has an internal representation of time with two types of memory: a dynamic memory (input layer) for considering the dynamics of the input data, and a static memory (hidden layer) for storing the prototypes. The output layer is the decision layer. ARRRBF has shown good performance compared to autoregressive prediction model applied to a similar RUL estimation problem, it has a high learning ability that makes the error between the input and output neglected, its efficient model among recurrent neural networks for time series prediction, hence the choice of this model besides its ease of integration and implementation (Djeziri, Toubakh and Ouladsine, 2013). Which justified the choice of this network to show the possibility of integrate the data of each control mode in the global approach of RUL estimation.

The output of the radial basis function is calculated as follows:

$$\Phi_i(\mu_i, \sigma_i) = \exp(-\frac{\sum_{j=1}^{m}(x^i(t) - \mu_i^j)}{\sigma_i^2}) \qquad (7)$$

μ_i and σ_i are respectively the mean and standard deviation of the radial basis function. j and m are respectively the index and total number of sigmoid functions.
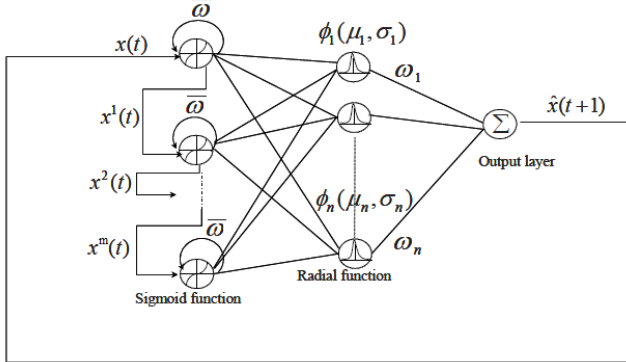
Figure 6. ARRRBF structure.

The answer of the basis function depends on the distance from the entrance x to the prototype vector μ_i such as:

$$\Phi_i(x) = \Phi(\|x - \mu_i\|, \sigma_i) \qquad (8)$$

The output of the looped neuron is governed by the following equation:

$$x^j(t) = \frac{1 - \exp(-k.(\bar{\omega}. x^j(t-1) + x^{j-1}(t)))}{1 + \exp(-k.(\bar{\omega}. x^j(t-1) + x^{j-1}(t)))} \qquad (9)$$

$\bar{\omega}$ is the weight associated with the self-connection of input neurons.

The output of the neural network is governed by the following equation:

$$\hat{x}(t + 1) = \sum_{i=1}^{n} \omega_i. \Phi_i(\mu_i, \sigma_i) \qquad (10)$$

ω_i are the weights of connections between the hidden layer, based on radial function and the output layer. i and n are respectively the index and total number of the radial basis functions.

AuDyC uses the historical data corresponding to normal operating conditions for each mode in the learning phase. Then the Mahalanobis distance is applied to detect degradation occurrence in each mode. Once the degradation is detected, the neural network predicts the health indicator evolution across the time according to wind speed. Finally, RUL is estimated depending on the present control mode.

5. EXPERIMENTAL SIMULATIONS AND DISCUSSION

The induction generator used in this study is rated: 3.5kW, 220/380V, 14/8A, 50Hz, 4 poles and a 90 μF capacitor bank connected onto the stator terminals (normal operating).

In order to test the proposed approach under different degradation dynamics, three capacitor bank degradation scenarios are generated (see Figure 7), which correspond to gradual increase of ESR at: (1) high rate evolution, (2) moderate rate evolution and (3) slow rate evolution (see Figure 7). ESR rises gradually from ESR_N (ESR value in normal condition) to ESR_F (ESR value in complete failure).
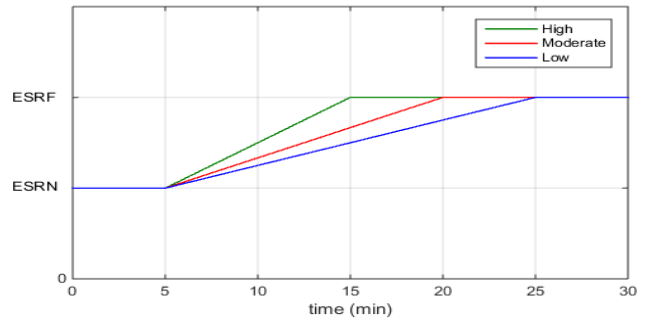

Figure 7. Capacitors bank degradation scenarios.

Our database consisted of two attributes represent the current and the voltage residuals. The ARRRBF used in this study has two hidden layers, the first hidden layer have 5 nodes of hyperbolic tangent sigmoid transfer functions while the second layers have 8 nodes of radial functions, this model have only one output corresponding to the health indicator prediction. The residuals size is 36,000 calculated by applying a slide window (window size=10, sliding step=5)

The sampling time=0.01s, the epochs number is sited to 5000 iterations and the size of training data is 25,000. The

threshold set for capacitor value equal to 75 μF. This value is empirically obtained following by studying the effect of gradual faults on capacitor banks of self-excited induction generator (Derbal, Toubakh and Hayat, 2019).
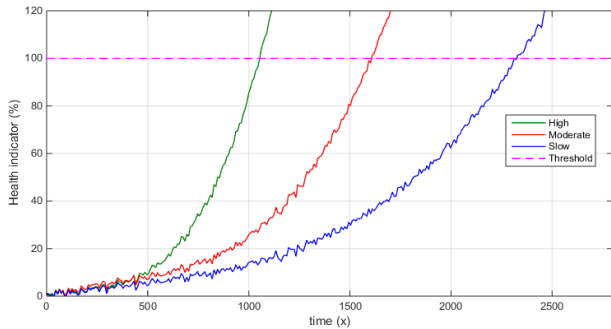
Figure 8. Health indicator progress in mode 1.

Compared to existing work not considering the change of the system dynamics according to wind speed in RUL estimation process, this study uses the wind data in order to distinguish between the control modes and also uses only the useful data corresponding to each mode to maximize the discriminating power between the normal and faulty classes. In control mode 1, the excitation current and the voltage are low making failure detection very difficult. In control mode 2, the excitation current and the voltage are high enough to detect the degradation. By doing so, we can improve the accuracy of RUL estimation.
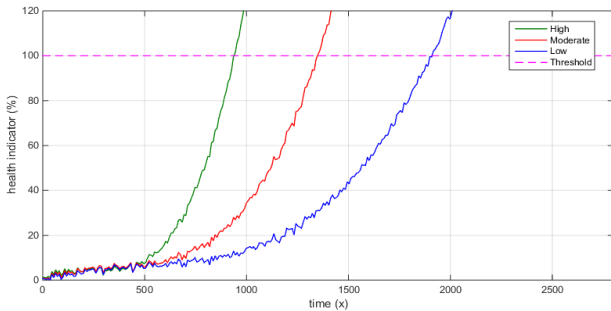
Figure 9. Health indicator progress in mode 2.

The wind speed value between control mode 1 and control mode 2 is set to 12m/s.

Table 1. Fault detection and RUL estimation.

Degradation type rate	Detection time	RUL1	RUL2
High	6.50 s	10 min 53 s	9 min 12s
Moderate	14.30 s	16 min 36 s	13 min 51s
Low	29.20 s	23 min 08 s	18 min 47 s

From Figure 8, Figure 9 and Table 1, we can say that RUL1 estimated values in control mode 1 are greater than RUL2 estimated values in control mode 2. In control mode 1 the capacitor bank operates under its nominal value, which means less stress to capacitor bank comparing to control mode 2. This explain the difference between the RUL estimated values in each control mode.

The obtained results show the importance of this hybrid approach which uses only helpful data to distinguish between the controls modes contributing to improve the RUL accuracy by disaggregating the estimation process according to the wind speed. This approach needs to be validated on real-world data.

6. CONCLUSION

In this paper, a hybrid prognosis approach of excitation capacitor of stand-alone wind power system based on SEIG is presented and discussed. This approach uses wind speed to separate the features in two control mode, then applies a classifier AuDyC to detect the degradation occurrence based on Mahalanobis distance. Finally an efficient neural network, ARRRBF, is proposed to predict RUL using the specific data of each operation mode. The obtained results show the efficiency of this hybrid method which introducing a line of investigation into how weather prediction data can be exploited to improve RUL estimation. Such investigation will be further followed-up in the future.

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