Remaining Useful Life Estimation of Hydrokinetic Turbine Blades Using Power Signal

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Objectives

In this paper, the MHK turbine RUL estimation using power signal is investigated:

- A new form of Noise-to-Signal Ratio (NSR) fault feature is defined based on the collected generator power signal to represent the degradation of MHK turbine blades and for RUL prediction.
- An adaptive neuro fuzzy inference systems (ANFIS) and 4th-order particle filter (PF) based framework is proposed to obtain the RUL in probability density function (PDF) form with respect to each time step signal, which possesses merits including nonlinear mapping and real-time state estimation.

Backgrounds

Figure 1: Southeast National Marine Renewable Energy Center at FAU

Marine hydrokinetic (MHK) energy production is becoming a welcome alternative to the use of fossil fuels for electrical power generation. However, MHK turbines usually work in harsh marine environments where corrosion and marine organisms/pollutants that become attached to moving parts can lead to the dynamic asymmetry of torque on the rotating shaft. Blade imbalances reduce overall performances, and if not detected and dealt with in a timely manner may further damage MHK turbines or even interrupt power generation.

Recently, prognostic and health management (PHM) technologies are showing promising abilities in increasing system reliability, availability, safety and reducing the maintenance cost of engineering assets. Remaining useful life (RUL) estimation is an indispensable part in PHM.

Feature Analysis

When a faulty turbine with constant load and speed, the air gap torque T_e consists of a constant component T_{eo} and an oscillatory component at fault characteristic frequency f_i and phase φ_i:

$$T_e = T_{eo} + \Sigma T_i cos(2\pi f_i t + \varphi_i) \tag{1}$$

the stator currents can be decomposed into two components: a magnetizing i_{sM} (zero when operates with a unity power factor) and a torque producing i_{sT}:

$$i_{sT} = i_{sTo} + \Sigma A_{sTi} cos(2\pi f_i t + \varphi_{Ti}) \tag{2}$$

The power of this signal over all periods is given by:

$$P = \lim_{n\to\infty} \frac{nE_1}{nT_0} = \int_{-\frac{T_0}{2}}^{\frac{T_0}{2}} |i_{sT}(t)|^2 \, dt \tag{3}$$

The amplitudes of power signal at both the fundamental frequency f and original sidebands at characteristic frequency f_i will change when an imbalanced fault occurs, along with new sidebands excited (Fig. 3). Therefore, the fluctuation of power at f and f_i can indicate the degradation of blade imbalance. To specify, define noise-to-signal ratio (NSR) as the associated characteristic feature:

$$NSR = \frac{P_{noise}}{P_{signal}} = \frac{P_{total} - P_{signal_o}}{P_{signal}} \tag{4}$$

A failure state can be defined when the NSR reaches a threshold ξ, which can be calculated as the average value of the NSRs of available imbalance fault cases:

$$\xi = \frac{1}{N} \sum_{i=1}^{N} NSR_i \tag{5}$$

RUL Prediction

The ANFIS uses the current&previous state measurements to learn the transition function, calculating the output at next time instant. The architecture utilized is a 4th order Makov model ($r = 1$, $n = 3$), with 16 fuzzy "*if-then*" learning rules based on first-order Sugeno model:

$$\begin{aligned} &IF\ (x_{t-3}\ is\ A_i^1)\ AND\ (x_{t-2}\ is\ A_i^2) \\ &\qquad AND\ (x_{t-1}\ is\ A_i^3)\ AND\ (x_t\ is\ A_i^4) \\ &THEN:\ x_{t+1}^i = w_1^i x_{t-3} + w_2^i x_{t-2} + w_3^i x_{t-1} + w_4^i x_t + w_5^i \\ &\qquad i = 1, 2, 3, ..., 16 \end{aligned} \tag{6}$$

The output x_{t+1} is the sum of all the outputs of each rule:

$$x_{t+1} = \sum_{i=1}^{16} x_{t+1}^i \tag{7}$$

Propagate A sequential Monte Carlo method PF is adopted to approximate the posterior state PDF by a set of random particles with associated weights:

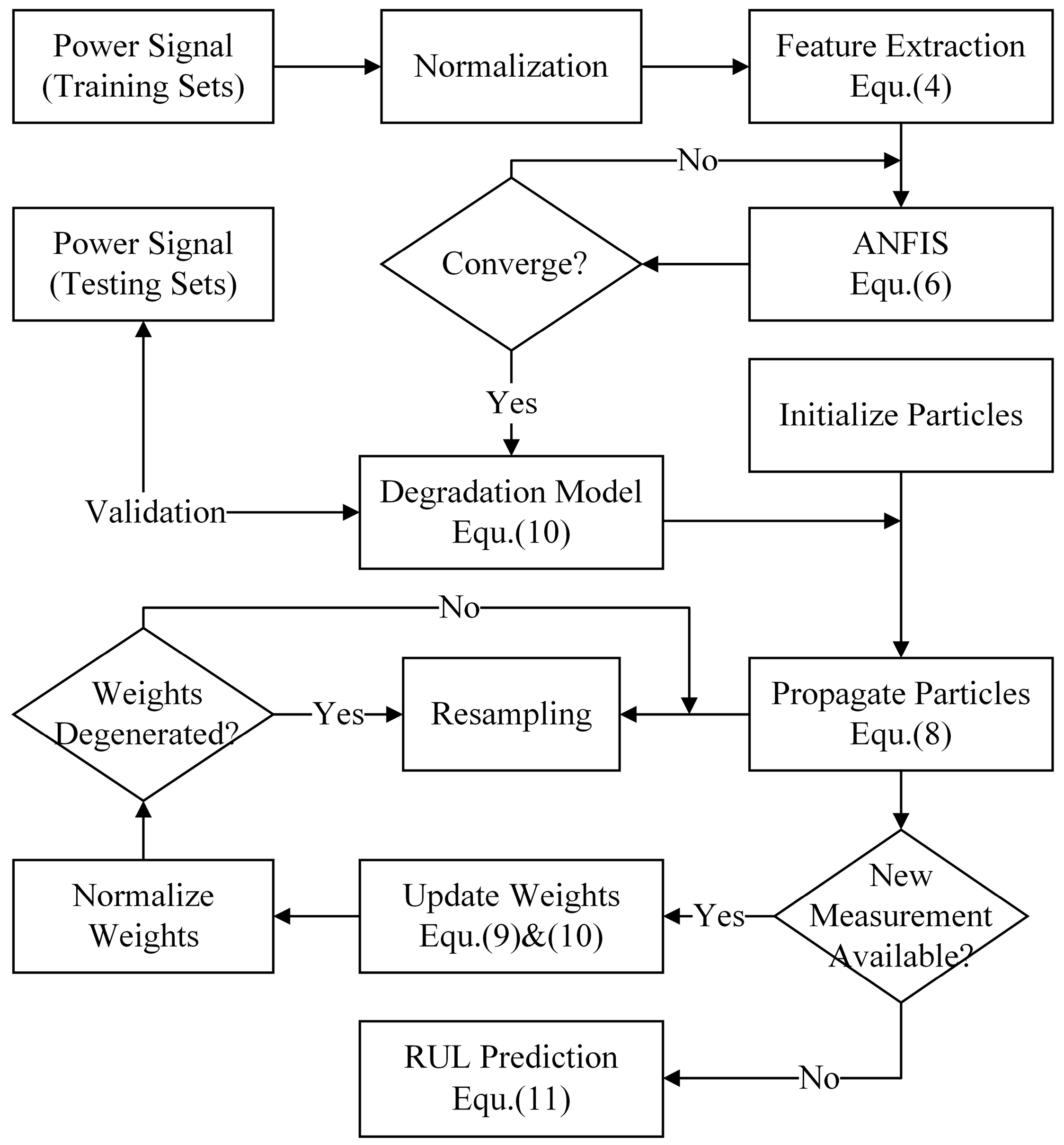

Figure 2: The proposed framework for RUL prediction

$$p(x_{k+1}|z_{1:k}) \approx \sum_{i=1}^{N} w_{k+1}^i \delta(x_{k+1} - \hat{x}_{k+1}^i) \tag{8}$$

Update The weight of each particle is updated by the importance sampling principle:

$$w_{k+1}^i \propto w_k^i p(z_{k+1}|\hat{x}_{k+1}^i) \tag{9}$$

Each particle is updated recursively with a fixed state transition function trained by the available data of the fault feature NSR as:

$$\hat{x}_{k+m}^i = f_k(\hat{x}_{k+m-1}^i, \hat{x}_{k+m-2}^i, \hat{x}_{k+m-3}^i, \hat{x}_{k+m-4}^i) + u_{k+1} \tag{10}$$

Resample Resampling is performed to eliminate the particles with lowest weights, and a set of new particles is generated by duplicating the remaining particles.

RUL Prediction When the state of the ith particle at a future time instant $k+m$ reaches a threshold, the RUL is calculated by the particle to be the time between now and that future time instant, denoted as RUL_k^i. When all the particle reach the threshold, the PDF of the RUL $p(RUL_k|z_{1:k})$ at current time instant k can be obtained by:

$$p(RUL_k|z_{1:k}) = \sum_{i=1}^{N} w_k^i \delta(RUL_k - RUL_k^i) \tag{11}$$

Result

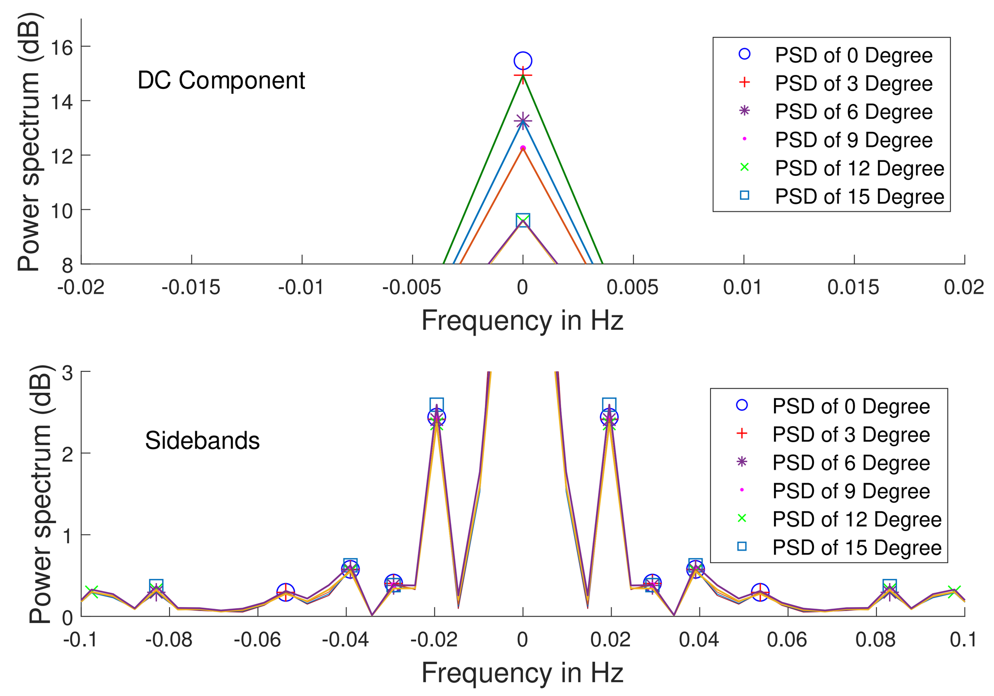

Figure 3: DC-centered PSD of the power signal

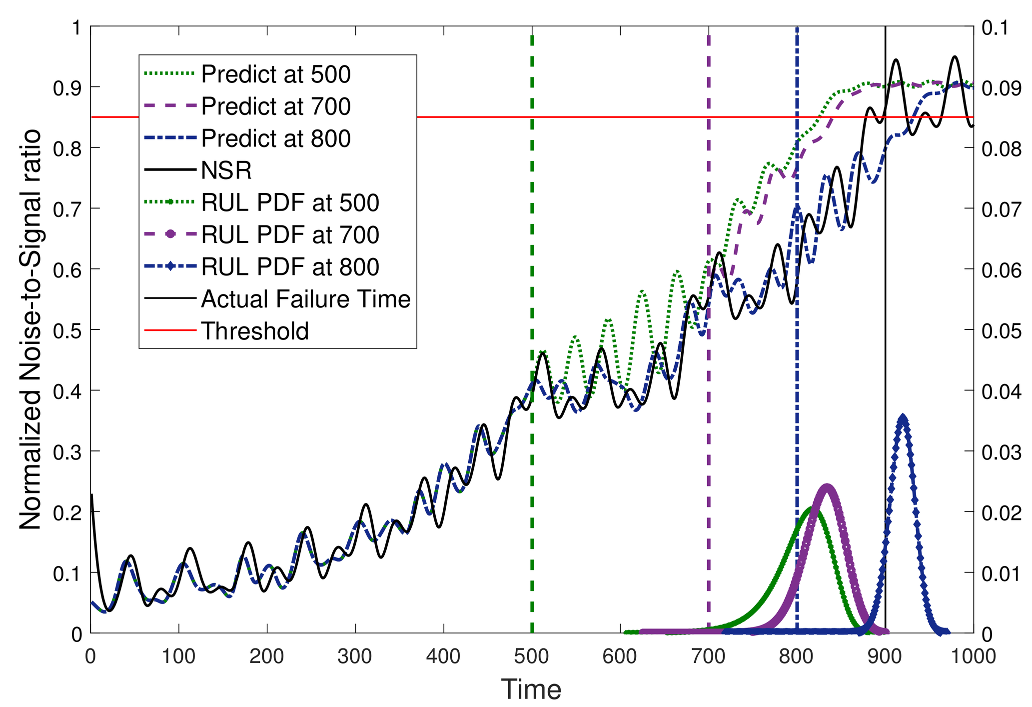

Figure 4: Predicted PDFs of the RUL at different time instants

Fig. 4 shows the PDF of the RUL prediction at time index of 500, 700, 800 using the proposed framework. The peak of each PDF curve represents the highest probability of the predicted failure time. As time goes on, more particles predict the RUL gathering to the peak of PDF. The peak of the PDF predicted at 800 is closed to 900, which is the actual failure time when the NSR reaches 0.85, indicating that the RUL prediction precise has positive correlation with the time. The reason lies in is that the ANFIS and PF methods have the ability to use new fault features to improve its accuracy in the RUL prediction as time goes on.

Data

The dataset for evaluation is generated by a recently developed high-fidelity MHK simulation platform [1]. The AeroDyn, ElastoDyn, ServoDyn and InflowWind modules are used with input parameters setting from a 20 kW MHK turbine located at the Southeast National Marine Renewable Energy Center (SNMREC).

Conclusion

This paper proposed a RUL prediction framework for MHK turbine blade under imbalance fault based on ANFIS and PF approaches. Considering the fault information is typically weak in the power signal, a novel NSR was defined for fault feature extraction. Additionally, the PF algorithm was implemented to predict the RUL PDF of the turbine blade based on the learned degradation model using ANFIS. Experimental Results have shown that the proposed method can effectively obtain the RUL of the turbine blade, and the prediction becomes more accurate as time goes on.

References

[1] Y. Tang, J. VanZwieten, B. Dunlap, D. Wilson, C. Sultan, and N. Xiros, "In-stream hydrokinetic turbine fault detection and fault tolerant control - a benchmark model," in *American Control Conference (ACC), 2019.* IEEE, 2019.

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