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A Novel Condition Monitoring Methodology Based on Neural Network of Pump-Turbines with Extended Operating Range

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***Abstract* – Due to the entrance of new renewable energies, water-storage energy has to be regulated more frequently to keep the stability of power grid. Consequently, pump-turbines have to work under off-design conditions more than before, which will cause more damage and decrease their useful life. Advanced monitoring methodologies that can balance the degradation of machine and revenues to the power plant has been required. To develop an innovative condition monitoring approach, vibration data was collected from different components of a pump-turbine which is running in an extended operating range. The consequences of operating range extension on the vibration of the pump-turbine have been studied by analysing the vibration signatures. The changing rule of the vibration behavior of the machine with the operating parameters has been obtained. An artificial neural network based model has been applied to build an autoregressive normal behavior model. The results indicated that the normal behavior model based on multi-layer neural net has the ability to predict the vibration characteristics of the machine in different operating conditions. This monitoring method can be adapted to the similar type of hydraulic turbine units.**

Keywords* – *Condition monitoring, Pump-turbine, Neural networks, Normal behaviour models.

I. INTRODUCTION

Due to their environment friendly and sustainable characteristics, new renewable energies (NREs) such as wind power, solar power, tidal power and so on are more and more popular. With the scenario of the entrance of NREs, a kind of energy system that can response to the demand of the grid instantly is required. A reversible pump-turbine (RPT) is a high-performance turbine which can switch itself between turbine mode and pump mode by reversing the rotation direction of the runner in a short time[1]. At present, pump-storage is the only system that can store huge amounts of energy[2].

Comparing with the other types of turbines such as Francis and Kaplan turbine, a RPT has a higher rotation speed and suffers higher pressure pulsation due to its special design characteristics. In addition, due to the new demand of energy grid brought by the massive entrance of NREs, RPTs have to increase their start/stop cycles dramatically as well as operate at extended operating condition rather than the best efficiency points (BEPs). In an extreme off-design region, the components of the machine are subjected to strong excitation forces from turbulence, rotor-stator interaction (RSI), vortex, etc. The excessive turbulence and pressure pulsation will generate great vibration and stress on the machine and cause damage[3–5]. When the synchronous precession frequency coincides with one natural frequency of the hydraulic circuit, a hydraulic resonance is induced. The hydraulic resonance will cause hydraulic instability and power swing, endangering the stability of the power grid[6–8]. Lots of cases of damage have been reported due to this new scenario[9,10]. On the other hand, the increased regulation capacity is always translated into a large increase of revenues. Therefore, it’s urgent and necessary to develop advanced monitoring methodology for the maintenance on the machine and maximizing revenues to the power plant. Some artificial intelligent (AI) techniques have been applied on condition monitoring and diagnosis. M. Schlechtingen has applied neural network (NN) on the condition monitoring of wind turbine and detection of the fault[11]. M. Garcia has built an intelligent system based on neural network for estimating the health condition of wind turbine units[12]. AI techniques have also been tried to apply on the condition monitoring and fault diagnosis on hydraulic machines. G.Succi has used NNs to distinguish different flow rates and mechanical conditions of helicopter pump based on experimental data[13]. R. Saeed has used NNs and adaptive neuro-fuzzy inference systems (ANFISs) to predict the operating conditions and crack length of a Francis turbine based on numerical simulation results[14]. Artificial neural works (ANNs) have been widely applied on condition monitoring on different types of machines while it has rarely been applied on the monitoring and diagnosis on PTs, let along the monitoring methodology based on on-site measurement.

In this paper, vibration signals were collected from a prototype pump-turbine. Based on these vibration data, a normal behaviour model is built by means of artificial neural networks due to their ability to model dynamic non-linear industrial processes. The model is able to predict on-line the normal behavior (or reference behavior) expected for each pump-turbine component according to its current operating condition. Based on the normal behaviour model, a predictive operating as well as maintenance scheme can be performed rather than only according to a general guideline. The advanced monitoring system of PTs will guarantee their long life and large benefits.

II. SYSTEM DESCRIPTION

The researched pump turbine unit is a vertical shaft machine with a maximum capacity of 85 MW. It has 7 blades in the runner and 16 vanes in the distributor. The rotating speed is 500 rpm.

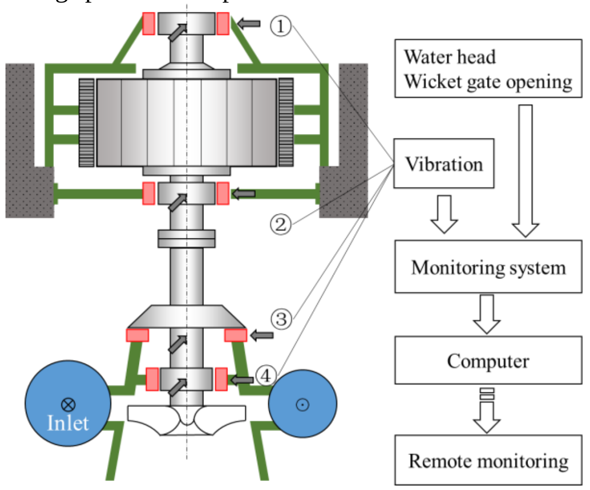


Figure 1 Sketch map of the pump turbine and the monitoring system.

As shown in Figure 1, the accelerometers are mounted on upper generator bearing, lower generator bearing and the turbine bearing. All of the signals generated from the accelerometers as well as parameters related to operation conditions including head level and guide vane opening (GVO) are stored by the monitoring system installed in the unit. Via internet connection, it's possible for a computer that has also installed the monitoring software to remote control or diagnosis.

Over 30 days, 614 operation conditions with different working parameters were acquired and the PT operation and vibration data is used as the research database. During this period of time, the head level varies up and down between 310 m and 340 m while GVO between 20% and 100% (Figure 2). Except head, it is important for us to notice that the output in turbine mode is changing continually in order to match the demand of the electric grid. Being different from the continually changed head level, GVO change dramatically and frequently in turbine mode in order to adjust the output in time. Whereas in pump mode, the GVO degree changes little (from 65.4° minimum to 70.2° maximum) comparing with water head.

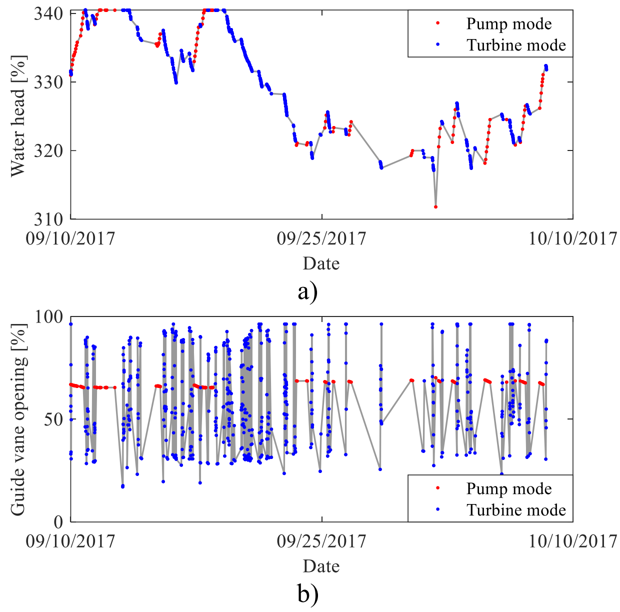


Figure 2 Variation of head level in pumping operation (denoted in red) and in turbine operation (denoted in blue).

III. VIBRATION ANALYSIS

It is well known that the behavior of the structure depends on both the excitation forces and the structure response. Once a defection or damage appears on one of the components of the machine, the excitation forces or/and structure response will change, which may induce the change on vibration. Further inspection can be performed when an abnormal vibration value is detected from the monitoring system. However, the traditional monitoring is only based on the revolution of the vibration level with time, without considering the operating conditions in which they are working. For a PT which is running in an extended range, the type and intensity of excitation forces change dramatically. The structure response (natural frequencies, modal shapes, damping) might even also change with the boundary condition. All of these can be transferred into vibration in the machine behavior. Therefore, it is so hard to predict the machine behavior under off-design operating conditions purely by numerical simulation or model test that it is necessary to perform measurement on a prototype machine to get the real data.

Within deep-part load or over load conditions, the vibration level may reach alarm or even damage level whereas without any damage happens on it. Moreover, the monitoring on vibration overall level is only applied for protection. The damage or defection happens on one part of the machine without having any great influence on the overall level can only be detected from the spectrum. Therefore, it its necessary to build a monitoring system including not only the overall level but also the details of the frequency components for detecting the faults hidden behind the overall level.

Basically, the excitations of hydraulic turbine units are mainly come from hydraulic, mechanical and electromagnetic origin. Mechanical origin excitations are generated by any system with masses in rotation around an axis and are widely existing in rotation machines. In Figure 3 the peak in f_n=8.33Hz is caused by the unbalance of the rotation components.

For PTs, the most important hydraulic excitation is the interaction between the rotating runner blades and the stationary guide vanes, which is known as RSI. The harmonic frequencies excited by RSI are determined as:

$$f_b = n \cdot z_b \cdot f_f \tag{1}$$

Where n is the order of harmonic, z_b is the number of blades, f_f is the rotating frequency. So that in our case f_b=1×7×500/60=58.33Hz and its twice harmonic $2f_b$=1×7×500/60=116.67Hz. Being one of the most important excitation force in PTs, it may lead to fatigue damage in the runner. In Figure 3 the peaks with f_b and $2f_b$ are caused by RSI (a side band of $2f_b$ with a frequency of 116.67+8.33=125Hz has been noticed and it will not influence the amplitude of $2f_b$).

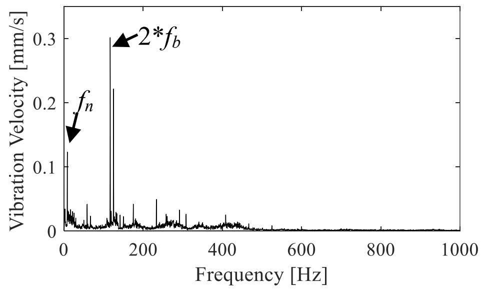


Figure 3 Spectral vibration signature in turbine bearing

Once a mechanical defect or damage appears on any component of PTs, frequency components may have different change in amplitude respectively. It is a complicated work for choosing appropriate indicators from the spectrum for monitoring. In our research, overall level (A_{OL}) and amplitude of f_n (A_{fb}) and twice f_b (A_{2fb}) are chosen as examples for illustrating the feasibility of vibration indicators on building the normal behavior models of PTs.

IV. CONDITION MONITORING WITH ARTIFICIAL NEURAL NETWORKS

Artificial neural network (ANN) is one of the most popular interdisciplinary science that has a large development in recent years. ANN is inspired by biological systems with a large number of neurons collectively performance tasks that even the largest computer has not been able to match. They are parallel computational models comprised of densely interconnected process units, which are called neurons. The networks' learning results are restored within the inter-neuron connection in the form of synaptic weights[15]. Synaptic weights allow the networks to adaptive themselves by "training" instead of "programming" in solving problems, which is the most important feature of ANNs. With this feature, ANNs are very appealing in the cases where one has incomplete or little understanding of the problems to be solved while the existed data can be used for training, such as taxonomic problem, pattern recognition, trend analysis and prediction, etc. Neural Networks Method (NNM) has been widely applied in biology, medicine, finance, industrial engineering and so on. Comparing with linear regression model, NN based model can represent better the vibration signal of PT because the vibration signal contains some nonlinear relationships that linear regression or other regression methods cannot fit so well.

The structure of a neurone is shown in Figure 4. One neuron is a basic information-processing element of an NN. Generally, it is consisted of a set of synaptic weights, an adder and an activation function (or "transfer function")[16].

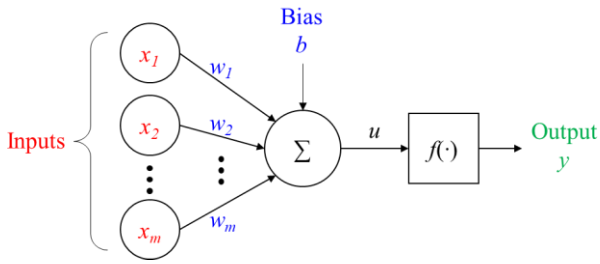


Figure 4 Schematic diagram of one neuron

The neuron depicted in Figure 4 can be described in mathematical terms as the pair of equations:

$$u = \sum_{j=1}^{m} (w_m \cdot x_m + b) \tag{2}$$

and

$$y = f(u) \tag{3}$$

Where x_1, x_2, …, x_m are the input values; w_1, w_2, …, w_m are the respective synaptic weights of the inputs; b is the bias and $f(\cdot)$ is the activation function. Activation functions are usually sigmoid function like tang and exp function which normalize the output of each neuron into a finite range [-1,1] or [0 1]. The normalization helps increase the convergence speed. On the other hand, sigmoid function builds a nonlinear relationship between the input and output which enables the network to approach any nonlinear function. Another characteristic of the sigmoid functions is they are differentiable, which is essential for a BP-NN to correct their synaptic weights by computing the partial derivatives of the error to each weight.

A. Input and output patterns pre-processing

a. Validity check. A simple way for validity check is a data range check. Meanwhile, the other conditions like the consistence between inputs and between inputs and outputs are also need to be checked. In this paper, the extreme outliners and data that has unexpected gradient have been removed. 521 sets of input data have passed the validity check. Especially, for checking the accuracy of the trained network, 20% of the samples have been selected from the whole data set and are used as validation data set. The left 80% samples are used as training set.

b. Data scaling. Data scaling is essential for the pre-processing of the input data because the sigmoid functions are always used as transfer functions and the output is most sensitive to variations of the input values[17]. Each group of input data is scaled within minus one to one with the following equation:

$$X = \frac{2x - x_{max} - x_{min}}{x_{max} - x_{min}} \tag{4}$$

Where x is the observed value of each sample, x_{max} and x_{min} are the maximum and minimum value of each signal respectively, X is the normalized value of observed value x.

B. Building NNs

a. Network topology selection. Backpropagation neural network (BP-NN), which is a typical kind of feedforward neural network (FNN), is a combination of back propagation (BP) algorithm and Multi-Layer Perceptron (MLP) FNN. Gradients are calculated and are used to fix the error of each synaptic weights. The typical structure of BP-NN model applied in this research consists one input layer, one output layer and one or more so-called hidden layers (because these layers do not express themselves to the external environment). Each neuron (or perceptron, cells, units, nodes, processing elements) at subsequence layer is connected by arc (weight) with neurons at prior layer, while neurons in the same layer are independent between each other[18].

b. Numbers of perceptron and layers. It has been proven that a feed forward network with one hidden layer can represent any continuous function. However, there is no generally accepted theory to determine how many hidden neurons are needed in each hidden layer to approximate any given function. It is recommended in [19] that the optimum number of neurons should be found by performing at least 10 runs where only the number of neurons is changed. In our case a single-layer feedforward network with 12 perceptron in the hidden layer is applied, as shown in Figure 5.

According to Section III, A_{OL}, A_{fn} and A_{2fb} are chosen as the examples of the monitoring indicators. The auto-regression normal behavior model is mainly focus on these 3 parameters.

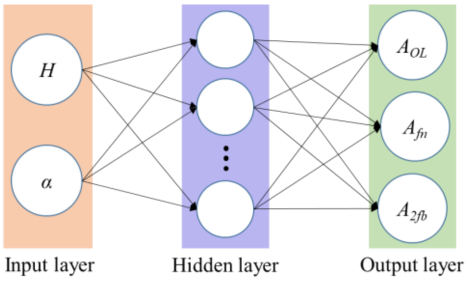


Figure 5 Feed-forward network architecture (Input: head level and GVO; output: head, guide vane opening and vibration overall level; Numbers of hidden layers: 12)

c. Network transfer/activation function. In order to avoid generating extreme values by the neurons, transfer functions are applied in the neurons to limit the permissible amplitude range of the output signal to some finite value[16]. The transfer function, or activation function, is usually a strictly increasing function that exhibits a graceful balance between linear and nonlinear behavior. Sigmoid functions, which have characteristic "S"-shaped curves, are by far the most common form of activation function used in the construction of neural networks. In our case, the log-sigmoid function, which transfer the layer's input into a value between 0 and 1, is chosen as the transfer function:

$$f(x) = \frac{1}{1 + exp^{-x}} \tag{5}$$

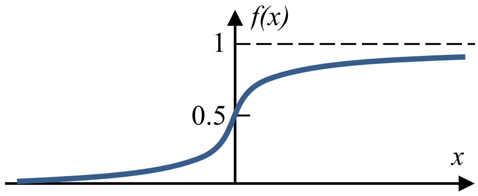


Figure 6 Log-sigmoid function in perceptron

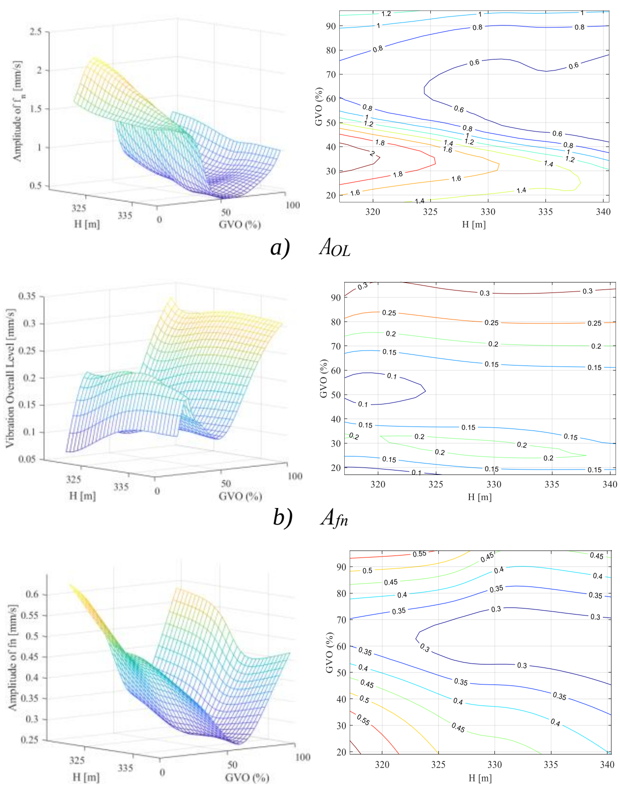
d. Training method. Levenberg-Marquardt backpropagation function is used as the training method in our case. LM algorithm appears to be the fastest method for training moderate-sized feedforward neural networks (up to several hundred weights), although it does require more memory than other algorithms. It has added a damping factor λ into the Gauss–Newton algorithm:

$$x_{k+1} = x_k + [J^T J + \lambda I]^{-1} J^T e \tag{6}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, **e** is a vector of network errors and I is an identity matrix. The advantage of lm algorithm is the scalar λ can be adjusted: when it is large, this algorithm is more like a gradient descent method. While with the proceed of the iteration, λ decreases, which makes it closer to Gauss–Newton algorithm which has a higher accuracy on approximation[20].

V. RESULT AND DISCUSSION

The network was obtained after 2000 epochs training. Beside the existing operating parameters, it is able to respond to any new operating condition within the input range. Given the number of input is only 2 parameters, the variation of each output can be represented in a 3-dimention figure and its contour plot as shown in Figure 7. The PT nomal behavior model representing the variation of overall level A_{OL} versus operating parameters is shown in Figure 7 a) while its sub-models represent the variation of A_{fn} and A_{2fb} are shown in Figure 7 b) and c).



a) A_{OL}

b) A_{fn}

c) A_{2fb}

Figure 7 Vibration amplitude of bearing turbine changing with operating condition (left) and their contour lines plots (right)

The coefficient of determination R^2 is one of the most widely used goodness-of-fit metrics. It represents the proportion of observed variation that can be explained by the simple linear regression model.

$$R^2 = 1 - \frac{\sum[(\hat{y} - y)^2]}{\sum[(y - \bar{y})^2]} \quad (7)$$

Where $\hat{y}$ is the predicted value from the regression model. y is the observed value and $\bar{y}$ is the mean value of y. Whereas the shortage of R^2 is its value always rises with the increase of the number of the input variations. In this paper, the adjusted coefficient of determination R^2_{adj}, which has considered the number of inputs, is used for checking the precision of the trained model in predicting the the vibration characteristics of the operating conditions in validating set.

$$R^2_{adj} = 1 - \left[\frac{(1 - R^2)(n - 1)}{n - k - 1}\right] \quad (8)$$

Where n is the number of the data samples; k is the number of variables in the regression model.
The validating result are listed in Table 1. R^2_{adj} of each indicator is near to 1, which proved that the networks provid fairly good results.

Table 1 multiple determination R^2 of each indicator

Indicator	*Overall level*	f_n	$2*f_b$
R^2_{adj}	0.9426	0.9560	0.7793

On one hand, normal behavior models provide us a reference behaviour expected for each component, according to its current working conditions. The conventional alarm limit is a constant value defined by the same standard. False alarms could be easily happen when the machine is working far away from the BEP. In an extended range, the increase of the overall level might not mean fault but the increase of the excitation forces or the change on the dynamic response.With the normal behavior model, the alarm threshold can be optimized according to the reference vibration levels. Misinformation in fault diagnosis would be decreased.
Comparing with normal behavior model, the sub-models give different vibration ranges and response to the change of operating parameters. The sub-models are useful for improving monitoring ability since they correspond to specific vibration frequencies caused by different damages. When the overall vibration level is within the normal range according to the normal range, sub-models alarm may be triggered by a great change in A_{fn} or the other sub-models.
On the other hand, the normal behavior models are helpful for estimating the remaining useful life (RUL) of the machine by providing the power plant operators information on the distribution of each type of vibration under different operating conditions. For instance, according to Figure 7, in high head condition the machine is more prone to suffer machinery origin damage like bearing damage, etc. since A_{fn} increases with the rise of head while A_{2fb} decrease. According to the normal behaviour models, operators in the power plant can make a plan on the operating condition in which the machine works to control the excitation forces applied on the machine. Some specific impulse or strains can be avoided and the overall RUL of the machine would be extended. According to the operation plan based on normal behavior model, the turbine unit can run in the off-design conditions for a certain time, when there is a demand from the power grid. This reasonable extension will be transferred into a great amount of revenue for the plant without destroying the machine.

VI. CONCLUSIONS AND OUTLOOK

In this paper, vibration signals over one-month monitoring have been obtained from the turbine bearing of a pump-turbine which is working in an extended range. The main excitation forces and vibration of the machine have been analysed.

A single-layer neural network has been designed for building normal behaviour models. Head level and GVO were used as input patterns and vibration overall level A_{OL}, A_{fn} and A_{2fb} are chosen as the monitoring parameters. The prediction result proved that the network provided fairly good results.

Comparing with the conventional monitoring system, the NNs based normal behaviour models have the following advantages:

1) With the normal behaviour models the possibility of monitoring the signal is widely decoupled from the operational mode. Misinformation in fault diagnosis would be decreased.
2) Diagnosis accuracy would be increased since the sub-models focus on specific damage in the machine;
3) Predictive operating plan can be drawn up according to the normal 'damage model' and the requirement from the power grid. the maximum revenue can be achieved within the RUL of the machine.

In the follow-up studies. The effectiveness of damage behaviour models based on more condition indicators (e.g. vortex rope, natural frequency bands) from different components (generator bearings, thrust bearings) of the hydro turbine unit by means of more AI techniques will be researched.

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