Fault Diagnosis Technique for Hydroelectric Generators using Variational Mode Decomposition and Power Line Communications

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Abstract. With the increasing proportion of Hydro generator units in the whole power grid and its aging infrastructure, it becomes increasingly important hot topic for our next generation smart grid to complement a real-time fault diagnosis in Hydroelectric Generators. In this paper, we propose a road-map towards this issue. To this end, Variational Mode Decomposition method and other signal processing algorithms, such as Multi-dimension Permutation Entropy and fuzzy C-means clustering algorithm and so on, are developed and power line communication technique is used. Computer simulations results show that our proposed diagnostics solutions successfully empower Hydroelectric Generators to independently predict and identify the three different most commonly faults.

1. Introduction

The safety operation of Hydro generator are becoming more and more important, and higher requirements are put forward for the maintenance, operation and management of Hydro generator. Once an accident occurs, it will affect the normal operation of the unit, and seriously damage the Hydro generator unit, even affect the safety and stable operation of the power grid and cause casualties.

The implementation of status monitoring and fault diagnosis can monitor the operation status of the equipment carefully and detect abnormal or hidden dangers in time. When the equipment accident occurs, the safety and reliability of power plant operation can be greatly improved and the loss of failure can be reduced to the lowest level, it limits the accident to a minimum level. At the same time, fault diagnosis can also maximize the utilization rate of equipment and minimize the loss, thus reducing the maintenance workload, and also preventing the occurrence of man-made failures due to unnecessary maintenance, Thus productivity can be improved.

The power line communication (PLC) uses the existing power cables, which is designed to transmit the electric power, for data communication, and some PLC systems have already been employed by power distribution automation systems and even Hydro generator systems. Using PLC systems for Hydro generator automation and diagnosis is a very attractive alternative solution or a supplement to traditional methods.
2. Analysis of Vibration Causes and fault diagnosis road-map

2.1. Analysis of Vibration Causes
There are many reasons that may cause vibration in hydropower units. The main sources of vibration interference of hydropower units come from three aspects: hydraulic aspect, mechanical aspect and electrical aspect. They interact with each other and often interweave together to form coupled vibration makes it difficult to identify faults. The possible sources of vibration described as follows:
- First hydraulic aspect: The Karman Vortex Street, Draft tube vortex belt and the jet-flow in axial-flow water turbine may causes various vibration;
- Secondly mechanical aspect: Vibration of unit caused by mass imbalance of rotating part of unit; The excessive bearing clearance may also generate vibration, Excessive Fineness of Spindle and Insufficient Stiffness of Shaft; Excessive Fineness of Spindle and Insufficient Stiffness of Shaft.
- Thirdly electrical aspect: Unbalanced magnetic, pull Polar Frequency Vibration Caused by Loosening of Stator Core Composite Joint and Negative Sequence Current and Stator Core Laminates loosen, resulting in gaps between the laminates

2.2. Layout of Vibration Measuring Points for Hydroelectric Generators
The complexity of vibration causes determines that the arrangement of vibration measurement points for hydroelectric generating units needs to be as complete as possible. In this research, we use vibration sensor and pendulum sensor to measure vibration signal synthetically. Magnetoelectricity sensor are employed as vibration sensor, which measures the absolute motion of the machine relative to the ground, is also called inertial or seismic sensor. Firstly, the fixed seat is welded at the measuring point, and then the sensor is fixed on it. The vibration sensor is divided into two types, horizontal and vertical. These two type of Magnetoelectricity sensor are installed as Fig 1

![Figure 1. Horizontal and vertical magnetoelectricity vibration sensor](image)
The pendulum sensor is a non-contact measurement and is fixed by a bracket. The Pendulum and bond phase sensors are installed as Fig 2

![Figure 2. Pendulum and bond phase sensor.](image)

2.2.1. The road-map of our fault diagnosis solution.
In this part, we present the fault-diagnosis road-map that we propose for Hydro generator based on PLC system as follows (Fig.3). Vibration data are collected by sensors and integrated in the junction box, then transmitted through power line communication equipment. Then vibration data are recognized and classified by intelligent algorithm to complete fault diagnosis.
3. Fault diagnosis algorithm

In this section, the vibration data are recognized and classified by intelligent algorithm as software section shows in Fig.3. Then the vibration data are first decomposed into different Intrinsic Mode Function (IMF) by Variational Mode Decomposition (VMD) algorithm in frequency domain.

3.1. Variational Mode Decomposition

The VMD decomposition method transfers the process of vibration data signal to the framework of variation, and introduces Lagrange penalty factor to transform unconstrained into constrained. The alternating direction method is used in algorithm multipliers to find the optimal solution of the adaptive vibration signal decomposition. If the vibration data is supposed to be decomposed (by VMD) into a set of IMFs as $u_k(t)$, the set of central frequency is $\{\omega_1, \omega_2, \ldots \omega_s\}$. Then, math model of constrained variational problem can be expressed as

$$\min \left\{ \sum_k \left[ \int (\delta(t) + \frac{L}{\pi t}) \ast u_k(t) \right] e^{-j\omega_k t} \right\}$$

subject to $\sum_k u_k(t) = f$

By introducing a penalty factor $\alpha$ at quadratic and a Lagrange multiplier operator $\lambda(t)$, the constrained variational problem in (1) will become a non-constrained optimal problem as

$$\min \{ \sum_k \left[ (\delta(t) + \frac{L}{\pi t}) \ast u_k(t) \right] e^{-j\omega_k t} + \lambda(t) - f(t)\}$$

subject to $\sum_k u_k(t) = f$

ADMM method is used to solve the problem mentioned overhead, and the saddle point in the extended Lagrange expression is sought by alternating updates and sums. Fourier equidistant transformation is used to transform equation (2) into frequency domain, through repeated iteration, the solution of the quadratic optimization problem in vibration signal decomposition can be obtained as

$$u_k(\omega) = \frac{\hat{f}(\omega) e^{-j\omega_k} + \hat{\lambda}(\omega)}{1 + 2\alpha(\omega - \omega_k)^2}$$

Based on the same idea, the central frequency can be calculated as follows.

**Figure 3.** Fault-diagnosis road-map.
3.2. Multi-dimension Permutation Entropy

After the vibration signals are decomposed by VMD algorithm, and the MPE algorithm will be used for effective feature extraction. Permutation Entropy Applied to No-stationary Vibration Signal Analysis of Hydroelectric Generators. Given the IMF feature sequence \( \{X(i), i = 1, 2, \cdots, n\} \), each extent of IMF is 1 to \( n \), the phase space is reconstructed and the following matrix is obtained as

\[
\begin{bmatrix}
  x(1) & x(1+\tau) & \cdots & x(1+(m-1)\tau) \\
  \vdots & \vdots & \ddots & \vdots \\
  x(j) & x(j+\tau) & \cdots & x(j+(m-1)\tau) \\
  \vdots & \vdots & \ddots & \vdots \\
  x(K) & x(K+\tau) & \cdots & x(K+(m-1)\tau)
\end{bmatrix},
\]

\( j = 1, 2, \cdots, K \) (5)

In the formula, the embedding dimension is \( m \), the delay time is \( \tau \). \( K = n - (m - 1)\tau \) and After a complex reordering, calculate the probability of each symbol sequence appearing as \( P_1, P_2, \cdots, P_K \). The ranking entropy of each symbol sequences can naturally be defined as following formula by the shape of Shannon entropy.

\[
H_p(m) = \sum_{j=1}^{K} P_j \ln P_j
\]

The permutation entropy of every subsequence is obtained, and the permutation entropy of subsequences are assigned to a data point in the middle of the subsequence. By analogy, the change of permutation entropy of the signal can be obtained.

3.3. Principal Component Analysis & fuzzy C-means clustering

Principal Component Analysis (PCA) is used to reduce the dimension of the above feature information, and fault samples are obtained and divided into the training samples as well as test samples. Then the training samples and test samples are substituted into fuzzy C-means clustering algorithm (FCM) for fault identification and classification.

4. Measured signal & Computer Simulation

Measured signal is obtained from hydropower station X, which is located in the Liuguang section of the junction of Qianxi County and Xiuwen County, Guizhou Province. It is the third cascade hydropower station on the main stream of Wujiang River, about 82Km from Guiyang Highway. The installed capacity of the power station is \( 3 \times 200 \) MW. 1 # Unit turbine is a vertical axis metal spiral case mixed flow type, runner diameter is 5.9m, spiral case and draft tube are made of metal, turbine guide bearing is above the top cover. The generator is a three-phase synchronous generator, which adopts the static excitation mode of thyristor and the fully enclosed circulating air cooling system with air cooler. The generator adopts a half umbrella structure with a guide bearing. The thrust bearing and the guide bearing share an oil groove, which is located below the rotor and the upper guide bearing is above the rotor. Three Typical Fault Signals are obtained as Fig.4
Figure 4. Three Typical Fault Signals.

After that MPE results are calculated as Fig. 5

Figure 5. MPE results of Three Typical Fault Signals.

After MPE feature extraction, 32 groups of 64 data samples were randomly selected as training samples, and the remaining 32 groups were test samples. The training samples are input into the fault diagnosis model established in this paper for learning and training. Finally, the test samples are input to complete the fault diagnosis and recognition. Fault classification results after FCM are shown as Fig. 6. The graph shows that the test fault signal can be correctly identified.

Figure 6. Test Fault Signals Fault & classification results after FCM.

| Table 1. The classification results of fault diagnosis. |
|--------------------------------------------------------|
| Fault type 1 | Fault type 2 | Fault type 3 |
| Number of Tested samples | 32 | 32 | 32 |
| Number of erroneous classifications | 2 | 0 | 1 |
| Accuracy rate | 93.75% | 100% | 96.9% |
5. Conclusion
In this research, we have presented solutions to enable Hydro generator to independently detect and classify different kinds of faults using power line communications and intelligent algorithm combination. We tested our proposed fault diagnosis solutions with real measured fault information. Computer simulation results show that it is a feasible and effective solution for fault diagnosis issue in Hydro generator.

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