Implementation of Remote Condition Monitoring System of Offshore Wind Turbine Based on NI WSN

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Abstract

The national capacity around the world has focused to the development of renewable energy in order to respond to energy, environment, security and economic. Among them, the unit price of wind turbine was reduced by technical maturity. So, the comparative advantage against other renewable energies can be achieved because of proximity to the unit price of the existing fossil fuel. In other words, the wind turbine is the only alternative energy that can ensure that a competitive price is equal to the fossil fuels in the short term. The onshore wind turbine has difficulty to secure additional location by the depletion of good location and the increase in civil complaint. The korea also has factors of problem such as limitation of locational condition and noise. Therefore, it is essential to advance to the sea. However, the mechanical and electrical allowance that components of wind turbine must withstand was increase in a corresponding degree. Therefore, the possibility of failure was increased, and then the secondary damage by limited access caused additional costs by locating offshore. In this paper, in order to diagnose fault in advance and ensure the reliability of large wind turbine located in the sea, we took advantage of the condition monitoring system (CMS). In other words, we propose effective monitoring and control system by integrating the CMS and SCADA systems based on LabVIEW. First, the remote monitoring system based on PC using the ethernet gateway of wireless sensor network (WSN) should be constructed in order to overcome the environment of positional constraints. And then we collect measured signal data from distributed nodes of the installed WSN within wind turbine farms and extract feature information of the classified fault and normal signals pattern through Wavelet Analysis. The extracted feature information is used as the input of neural network learning. When the error signals have arisen in the wind turbine farms, it is possible that alarm is happen, and condition is controlled through the automatic fault diagnosis. In addition, simple faults as well as complex faults that occur over a long time can be diagnosed early.

Keywords: *wind turbine condition monitoring system, wireless sensor network, wavelet transform, neural network, automatic failure diagnosis, LabVIEW*

1. Introduction

Due to the maturity of wind turbine technology, the unit cost of wind power was decreased. Therefore, the unit cost of wind power is similar to the cost of existing fossil fuels compared to other renewable energy. Global action is also starting to address the issue of global warming. Thus, there was emerged wind power, for existing fossil-fuel energy sources of alternative energy. Over the past 20 years due to advances and matures in technology, wind turbines have become greater, and unit cost of wind power is falling. Therefore, unit costs of wind power are similar to existing fossil fuels, compared with other renewable energy costs. However, a larger turbine inevitably increases the height of the tower and blade length. Also, the components of wind turbine increase mechanical and electrical permit capacity. Consequently, it is inevitable problem that increased failure rate of turbine [1-2]. In Korea, the existing requirements for wind power have the difficulties on limitation of location and issues such as noise pollution. A power wind turbine needs greater capacity to ensure affordability in the market. Therefore, expansion into sea is necessary, but there are some problems for the operation of large wind turbines at sea. First, mechanical and electrical failures are increased for larger wind turbine. Second, due to the constrained access environment by locating sea, the additional costs occur in secondary damage. Therefore, monitoring technology of wind turbine is essential for usability and reliability [3-5]. In this paper, failure of the wind turbine is determined through signal analysis based on wavelet transformation. In addition, real-time signal was analyzed by wavelet transformation. Feature information of classified signal pattern through signal analysis had been learned by using neural network algorithm to design the automatic fault diagnosis system.

2. Condition Monitoring Techniques of Wind Turbine

2.1. Description of Condition Monitoring System

The surveillance system of wind power is classified into supervisory control and data acquisition (SCADA) system and condition monitoring system (CMS). The SCADA system remotely performs control function of wind turbine in conjunction with turbine controller. And, it is essential component to consist of wind power system. However, the current wind turbines are difficult to identify the operating condition because SCADA systems are made differently per the turbine manufacturer [6].

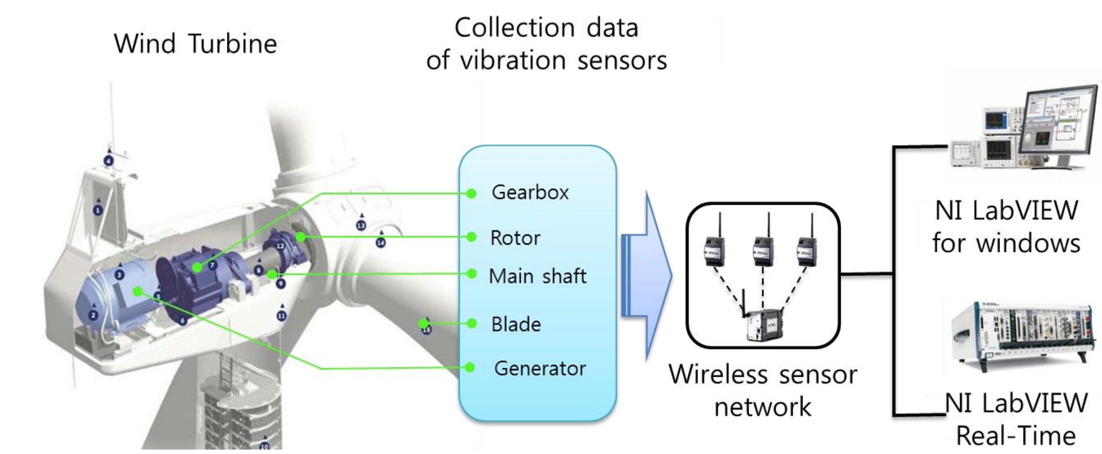

Figure 1. Structure of the system

The other hand, the CMS is prevention system that diagnoses malfunction in advance by closely monitoring, analyzing and predicting component of wind turbine. In the past, the CMS was regarded as an optional component. In case of large and wind turbine located sea, the CMS is recognized as an essential component because of a matter of credibility. In this paper, the stator current of induction motor was used as the input signal. Because the signal analysis of large offshore wind turbines is constrained. Overall, we must ensure the reliability by suggesting automatic fault diagnosis system based on CMS through neural network on the feature information of signal patterns and signal analysis using the wavelet transform.

2.2. The data collection and analysis

The structure of the data collection and analysis system is shown in Figure 1. We used the multiple sensors to collect vibration data of wind turbine parts. Then the collected data would be transferring to the central monitoring server by NI WSN system. In the central monitoring system, we used the wavelet transform and neural networks learning algorithm for data analysis.

2.2.1. Wireless sensor network: With LabVIEW WSN, you can embed decision making on NI WSN measurement nodes, so decisions can be made autonomously without transmitting the stimulus and response to and from a host computer or embedded controller. A wireless sensor network consists of three main components: nodes, gateways, and software, are shown in Figure 2.

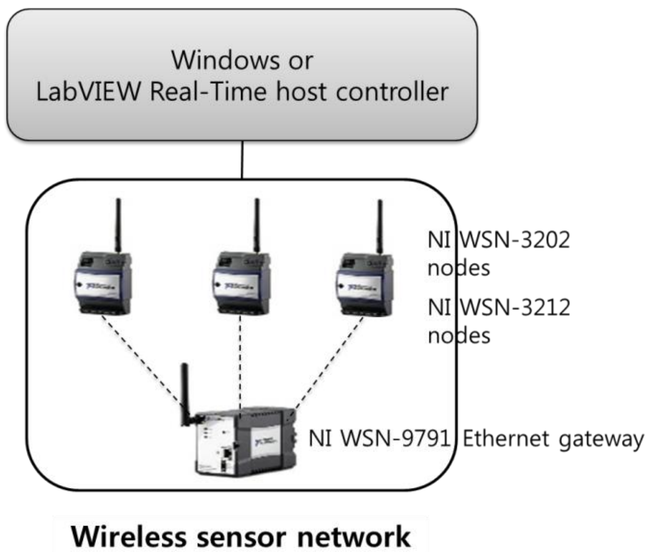

Figure 2. Wireless Sensor Network Platform

The spatially distributed measurement nodes interface with sensors to monitor assets or their environment. The acquired data wirelessly transmits to the gateway, which can operate independently or connect to a host system where you can collect, process, analyze, and present your measurement data using software. Routers are a special type of measurement node that you can use to extend WSN distance and reliability. For the measurement node, NI WSN-3202 and NI WSN-3212 were applied in our project. They connected with multiple sensors and data acquisition being executed.

The NI WSN-3202 measurement node offers four ±10 V analog input channels with selectable input ranges and four bidirectional digital channels that you can program for event detection or local control. And the NI WSN-3212 measurement node provides four 24-bit thermocouple input channels and four bidirectional digital channels that you can program for event detection or local control.

The NI WSN-9791 Ethernet gateway is a pass-through device that must be connected to a host system. This gateway has a 2.4 GHz, IEEE 802.15.4 radio to collect measurement data from the sensor network and a 10/100 Mbit/s Ethernet port to provide flexible connectivity to a Windows or LabVIEW Real-Time host controller. In our project, two NI WSN-3202 models and one NI WSN-3212 model were used as measurement and acquisition nodes, and pass-through those data to LabVIEW software in Windows by an NI WSN-9791 Ethernet gateway.

2.2.2. Wavelet Transform for Fault Signal Analysis: The wavelet analysis [7-8] appeared by integrating special techniques individually developed to meet special purpose belonging to signal processing system. Basic techniques of computer vision using multi-resolution analysis method, sound and video compression using sub-band coding technique and applied mathematics using wavelet series are developed recently into wavelet theory's special applications. The wavelet transform can understand that input signals are separated into the set of the basis function. The set of basis function used to wavelet transform can be obtained through expansion, reduction and parallel transference of time axis about basis function of wavelet. Basis function of wavelet indicates band-pass filter of special form. And the relative bandwidth invariability of wavelet transform is satisfied by expansion and reduction of temporal axis about wavelet basis function. Thus, the scale is called instead of frequency band in wavelet transform. Unlike Fourier transform, wavelet transform includes high resolving ability about scale of signal. Therefore, wavelet transform is time–scale transform as below

$$\phi_{ab}(x) = 1/2\phi((x-b)/a), \tag{1}$$

where 'a' means expansion and 'b' which means movement indicates the temporal position.

The more 'a' is increased, the more resolution of frequency is increased. The scaling is expanding or reducing signal. Large-scaling signal is expanded. And small scaling signal responds to the compression.

Integration for entire signal of Fourier transform causes high-frequency component by diversion in the finite space, it's difficult to handle flexibly non-stationary function because the analysis about variation of frequency has limit. To overcome these demerits, various analytical methods were devised and wavelet transform among the rest is efficiently used [4]. After studying orthogonal basis functions, discrete wavelet transformation (DWT) is developed. DWT indicates two-space of separated frequencies for the signal analysis as below

$$x(t) = \sum_{n=-\infty}^{\infty} a_{0,n}(t), g_{0,n}(t) + \sum_{j=0}^{\infty}\sum_{n=-\infty}^{\infty} d_{j,n}(t), h_{j,n}(t), \tag{2}$$

where $a_{0,n}(t)$ is approximation component of the signal, and $g_{0,n}(t)$ represents low-pass filter (LPF). $d_{j,n}(t)$ is detail component, and $h_{j,n}(t)$ conducts high-pass filter(HPF).

In Figure 3, g[n] is the low-pass approximation coefficient, h[n] is the high-pass detail coefficient. It is possible to regenerate two-band about the filtering signal. In other words, if separation of 2-level is finished, the original signal is separated into frequency of four bands [5].

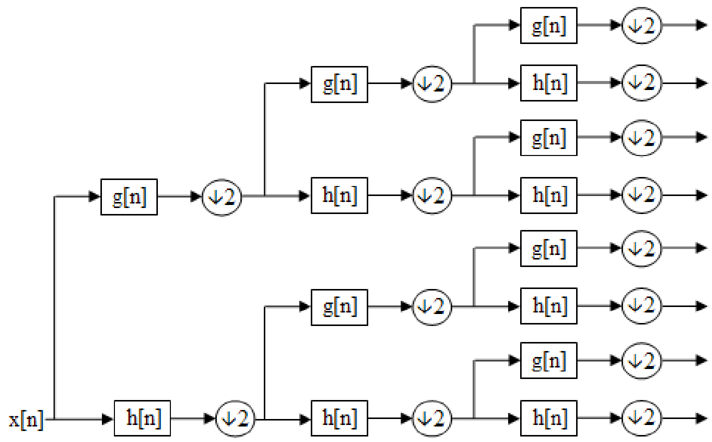

Figure 3. The Wavelet Transform with 2-Level

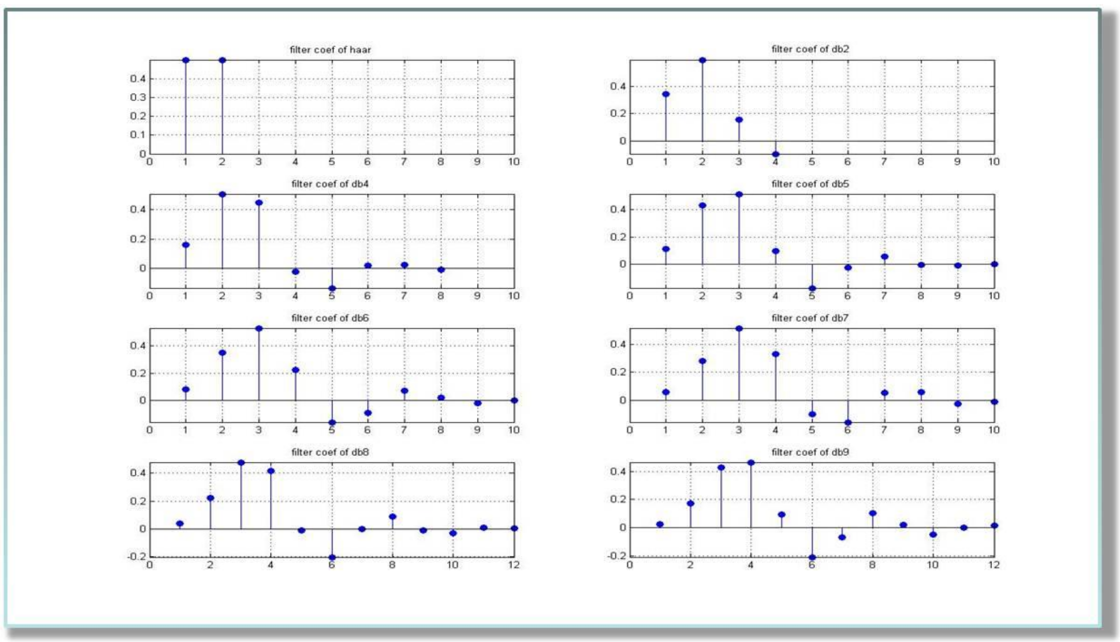

Figure 4. Db(N) DWT Filters

There is very wide variety of wavelet filter according to its purpose. Figure 4 shows the coefficients of the filter increase in accordance with N value of Db(N). In this paper, Db(4) is used to analyze input signal of generator's current removed noise, and an example shown in Figure 5. Very short basis functions need to suggest discontinuity of input signal, and very long low-frequency basis functions need to analyze frequency accurately. We simultaneously use two basis functions based on Daubehies wavelet. So, we easily can get the ambiguous feature information on the signal analysis of time-frequency domain.

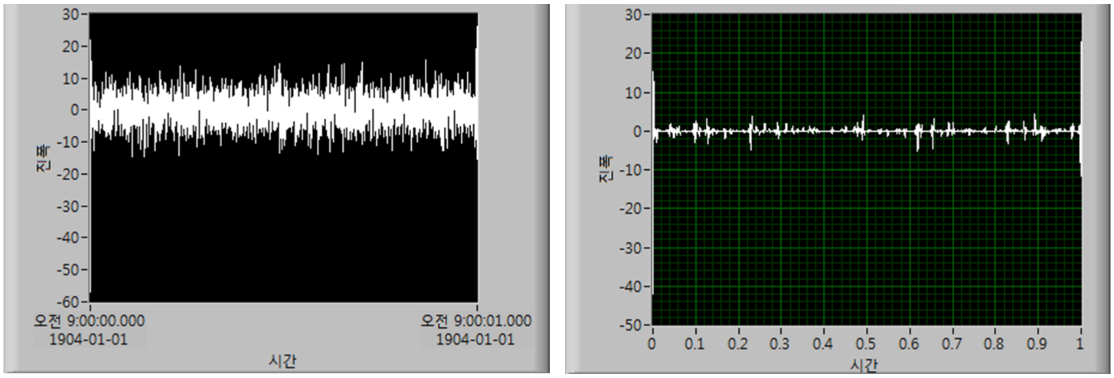

Figure 5. The results of Wavelet Transform

3. Neural Network Modeling

It is an animal characteristic of neural network, mathematical model for distributed parallel processing algorithms. Such networks depend on the complexity of the system, by adjusting the internal connected relationships between a large number of nodes, so as to achieve the objective of dealing with information.

The primary function of neuron calculates input and weighted summing NET of connection strengths in artificial neural network. And the output comes out by the activation function. Therefore, output of neuron is different depending on the activation function.

The most simple activation functions are step and sigmoid function. When the input is over the threshold value, the output is a function that is activated as 1. The sigmoid function for the change of the value has a form to infinitely approach 0 and 1. In other words, the sigmoid function linearly translates disorderly nonlinear values in neural network model [9].

4. BP Algorithm

The back propagation(BP) algorithm which also called error back propagation algorithm, proposed by Rumelhart and McCelland-led team of scientists in 1986, is used to be applied multiple neural network. BP is universal neural network algorithm used to various fields.

Figure 6 shows a three-tier structure of BP neural network. The renewal of the connection strength is most important in the learning algorithm. The BP algorithm consists of the forward step and the backward step. As with other neural network learning algorithm, the learning is made by renewal of the connection strength. The input layer enters classified signal pattern through signal analysis into neural network. And it is multiplied with connection weights connected to the hidden layer. The multiplied values are passed to hidden layer. Through repetition of this process, the output of output layer is obtained. And error is calculated through the subtraction of the output and the target data [10].

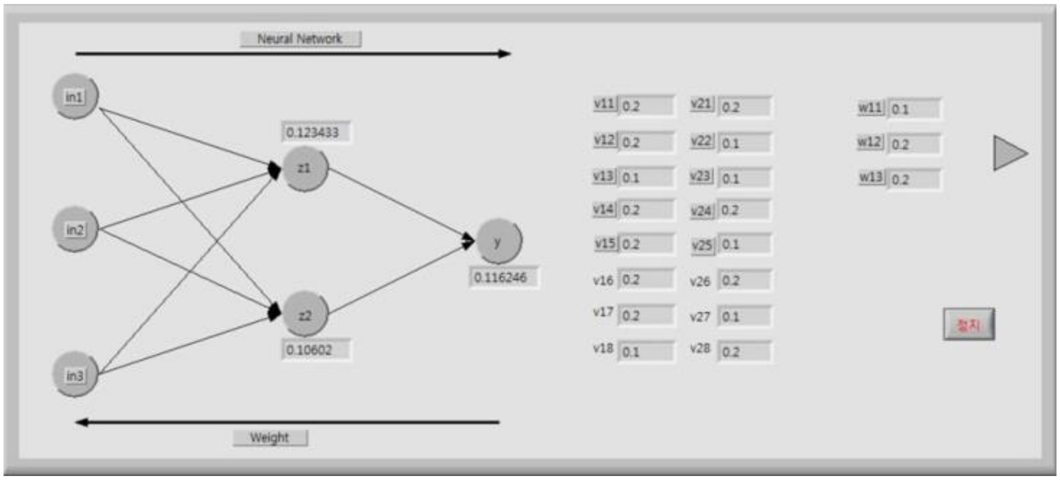

Figure 6. Neural Network Processing

5. Experimental Results of Automatic Fault Diagnosis System

In this paper, to implement automatic fault diagnosis of offshore wind turbine, we conducted an experiment to improve the reliability by suggesting neural network algorithm and wavelet transform based on CMS for signal analysis.

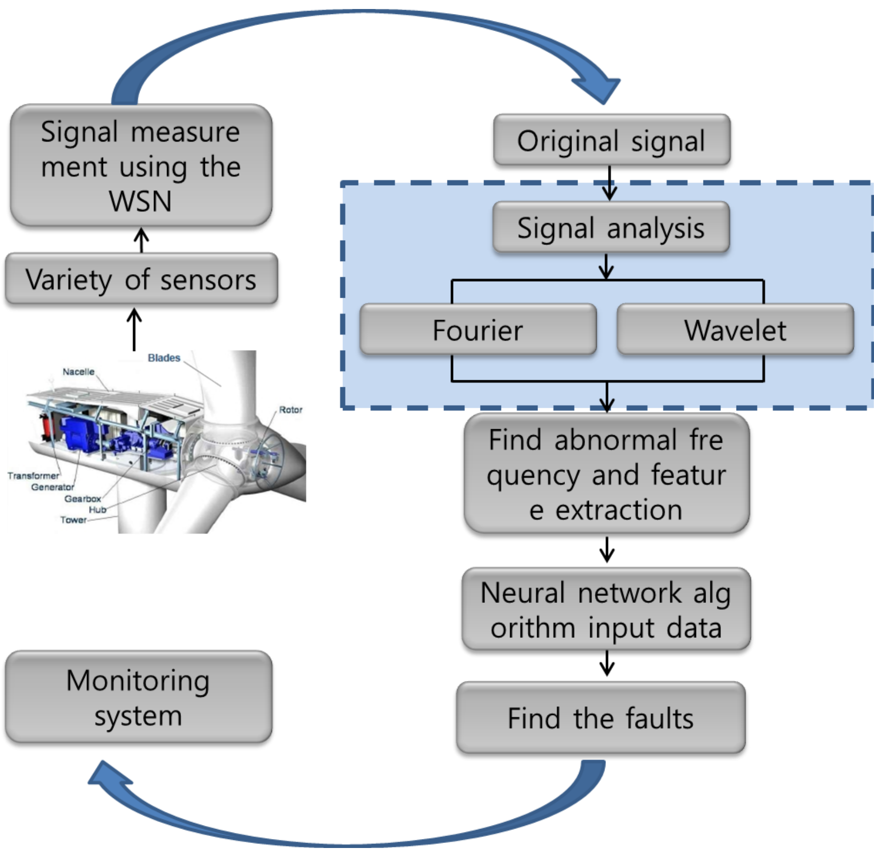

Figure 7. The Diagram of CMS for Wind Turbine

Figure 7 shows the overall system of automatic failure diagnosis through learning using feature information of classified signal pattern. First, that is a data acquisition. In this part, the variety of sensors was used to collect the data from wind turbine, and the collected data would be transferred to the central monitoring system by NI WSN platform. Second part is signal analysis. For signal analysis, we used the wavelet and fourier transform [11] to extract the feature information of vibration signals of the wind generator, and their results were compared in our experiment. And then the extracted feature information was used as the input layer of neural network learning. When the error signals have arisen in the wind turbine farms, it is possible that alarm is happen, and condition is controlled through the automatic fault diagnosis. To obtain fault diagnosis signal, the system simulated 300rpm to 500rpm as the main speed of the generator. There were four simulated fault statuses, including the bearing misalignment fault, unbalanced rotor fault, bad bearing lubrication, and stator fault. Table 1 shows the diagnosis results of the learning rates for wind generator faults, respectively. From the results of the table shown, the proposed method using the wavelet transform was better than method using fourier transform to extract the feature of signal data for neural network learning.

Table 1. The neural network learning rate for wind generator faults

	Fourier Transform + Neural Network	**Wavelet Transform + Neural Network**
bearing misalignment fault	92%	95%
unbalanced rotor fault	95%	95%
bad bearing lubrication	92%	98%
stator fault	88%	97%
normal status	98%	98%

6. Conclusions

In this paper, we extracted peak value of classified signal using peak detection function based on LabVIEW for extraction of feature information. And, extracted feature information is used as input to the learning of neural network algorithm to implement automatic failure diagnosis system of offshore wind turbine. In this study, we early diagnose a complex fault signal that occurs over a long time rather than a simple failure. And there are aims to reduce secondary damage. The experimental results of the neural network learning through the wavelet analysis are higher than the neural network, which using a Fourier transformer. This means that analysis ability is superior in signal analysis.

This system will be developed to work in real-time and will become a more reliable system. The final purpose of this system can be applied to many areas of the industry, and can accomplish important work in the faults diagnosis of wind turbine. Also, we look forward to applying to a variety of monitoring environments.

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