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IOT CONDITION MONITORING OF WIND TURBINE GENERATED USING BIG DATA ANALYSIS

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ABSTRACT

Big data refer to the massive datasets that are collected from a variety of data sources for business needs to reveal new insights for optimized decision-making. The wind energy system is the modernization of electrical energy generation systems due to the pollution free nature and the continuous advancement of wind turbine system technologies. Wind energy is used as an alternate form of energy to meet the increasing energy crisis. Wind farms are set up in highly exposed sites. Wind is fluctuating in nature and hence a continuous monitoring system is needed. The wind turbine is used for converting wind energy into a useful form of energy. In this project the various parameters of wind are measured and monitored by setting up an instrumentation system. Due to environmental conditions, the remote location of wind farms, and the vertical height of the nacelle, it is expensive to physically visit wind turbines for maintenance and repair. So, we proposed the system to monitor the status of wind turbine from anywhere in the world using Internet of Things (IoT) technology. In the wind energy surroundings, the application of big data analysis-based decision-making and control are mainly in the following three aspects: data stream side management, storage side management and load side management. The objective of this research is to present a technological framework for the management of large volumes, variety, and velocity of solar system related information through big data tools such as cloud to support the assessment of renewable energy system. The framework includes a modeling of system, storage, management, monitoring and forecast based on large amounts of global and wind energy system.

Keywords: Renewable energy, cloud, Big data and IOT

I. INTRODUCTION

The physical methods rely heavily on numeric whether prediction, which is confined by the sensors and monitoring devices placed within the WPP. The quality of hardware chosen, the parameter settings, the computation time, the time delays, and the sampling rates influence the accuracy of data collected from the WPP. It is easier to predict a single wind turbines performance rather than a whole WPP's power generation. Statistical and neural network methods are based on the historical data and have a low prediction cost. The relationship between input data and output data based on historical measured data is learned and then a nonlinear relationship model between them is built. But when new data not previously included in the training data set is used as input into this kind of model, the prediction error might be large, which is a disadvantage. Different prediction methods mentioned above can be combined as hybrid methods to achieve better prediction results. But this will increase the complexity of the model.

This system focused towards analyzing the big data about power generation of WPP in different periods and environment by using web server (IOT). In this WPP, data of wind information, such as wind speed, wind direction, wind power generation and air pressure are collected by a Plant Information (PI) system, and the output of the entire WPP is monitored by the IoT (Internet of things) system. Raw data from the WPP is processed by a probabilistic neural network (PNN) and then a complex-valued recurrent neural network (CRNN) model is built to predict the total output of the WPP with the following considerations:

- The raw data set will be screened by probabilistic neural network to prepare high quality data for building neural network models;
- The model's inputs do not rely on the data of wind speed and wind direction from all turbines; representative wind turbines can be found to compress the length of the input data;
- The inputs are expressed as complex-valued data (vector representation) which combine wind speed and wind direction;
- The complex-valued recurrent neural network model's time series inputs are generated based on the historical data values of the WPP rather than the predicted values by the model at the previous steps;
- The result to be predicted is the total power generation of the whole WPP rather than outputs of some single wind turbines;

B. Existing system

Renewable energy sources give local communities the opportunity to achieve energy independence in an environmentally friendly way using relatively technically simple solutions. This system presents an analysis of dependence between the capacity of energy storage and its cost and the amount of energy exchanged with the network. Earlier a wind farm was modeled using open meteorological data.

Problem Identifications

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The modeled data are stored in data base with self modeled analysis has been made. The data analyzed in desktop model and private.

C. Proposed system

In this system, an overview of new and current developments in wind forecasting is given where the focus lies upon principles and practical implementations. High penetration of wind power in the electricity system provides many challenges to the power system operators, mainly due to the unpredictability and variability of wind power generation. Although wind energy may not be dispatched, an accurate forecasting method of wind speed measurements can help the power system operators reduce the risk of unreliability of electricity supply. This system gives a method on the categories and major methods of wind forecasting. This system focused towards analyzing the big data about power generation of WPP in different periods and environment by using web server (IOT). In this WPP, data of wind information, such as wind speed, wind direction, wind power generation and air pressure are collected by a Plant Information (PI) system, and the output of the entire WPP is monitored by the IoT (Internet of things) system.

II. LITERATURE SURVEY

Omid Beik[1]This paper discusses wind energy assessment for the largest wind farm in Ontario to-date, Henvey Inlet wind farm (HIWF), which began in 2017 and reached commercial operation in October 2019. The study includes analysis of wind turbine conversion system, wind velocity using measurement towers, wind turbine and wind farm power and energy prosecution. Characteristics of Vestas V136-3.45 that are used in the HIWF are extracted and implemented in the analysis to achieve real-world results. Two analyses approaches are considered, (i) a definite method based on mathematical modelling of wind velocity, power, and energy, and (ii) a statistic analysis based on Rayleigh probability function. Comparison of the results from the definite and probability approach presents a difference of up to 50%. Therefore, although a probability approach may be used for initial analyses of wind energy when choosing a candidate wind farm, the energy output from a wind farm needs to be calculated based on measured and manufacturers data using a definite approach.

MichałGuzek[2]Renewable energy sources give local communities the opportunity to achieve energy independence in an environmentally friendly way using relatively technically simple solutions. This paper presents an analysis of dependence between the capacity of energy storage and its cost and the amount of energy exchanged with the network. Earlier a wind farm was modeled using open meteorological data.

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Huan Long[3]This paper proposes an image-based algorithm for detecting and cleaning the wind turbine abnormal data based on wind power curve (WPC) images. The abnormal data are categorized into three types, negative points, scattered points, and stacked points. The proposed algorithm includes three steps, data pre-cleaning, normal data extraction, and data marking. The negative abnormal points, whose wind speed is greater than cut-in speed and power is below zero, are first filtered in the data precleaning step. The scatter figure of the rest wind power data forms the WPC image and corresponding binary image. In the normal data extraction step, the principle part of the WPC binary image, representing the normal data, is extracted by the mathematical morphology operation (MMO). The optimal parameter setting of MMO is determined by minimizing the dissimilarity between the extracted principle part and the reference WPC image based on Hu moments. In the data mark step, the pixel points of scattered and stacked abnormal data are successively identified. The mapping relationship between the wind power points and image pixel points is built to mark the wind turbine normal and abnormal data. The proposed image-based algorithm is compared with kmeans, local outlier factor, combined algorithm based on change point grouping algorithm and quartile algorithm (CA). Numerous experiments based on 33 wind turbines from two wind farms are conducted to validate the effectiveness, efficiency, and universality of the proposed method.

III.SYSTEM OPERATION

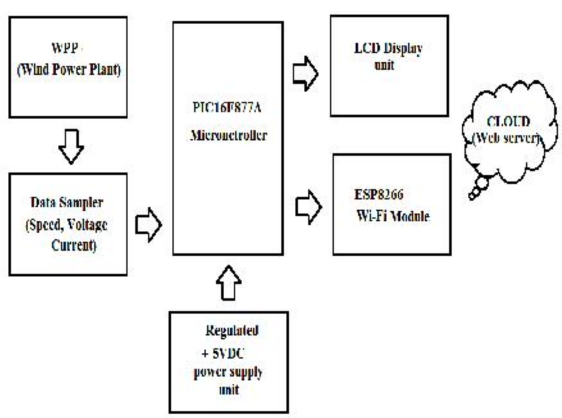

Fig.1 Functional block diagram of the system

This system consists of wind power plant, data sampler, PIC 16f877A microcontroller, +5V power supply unit, LCD display unit and ESP8266 Wi-Fi module. The wind power plant generated the electrical signal according to the air density. In this system we use +12V DC turbine generator. The output of the WPP is applied to input of the sampler unit. The sampler unit is a passive circuit which is used to converts the WPP parameters such as speed, voltage and current into potential value according to the input of ADC (Analog to digital converter) port of PIC microcontroller. The ADC unit receives the signal from data sampler and converts the digital values. The microcontroller is used to converts the data and sends to Wi-Fi module through UART port. The Wi-Fi module receives the data from controller and communicates to web server. The web server data called cloud data or big data which is used to predict and estimate the power generation of the plant. The LCD display unit is used to displays the information about the wind speed in the order of Km/H. [1mv = 1km/H]

IV. HARDWARE DETAILS

A. PIC MICROCONTROLLER

The PIC controller used in our project is PIC16F877A, the pin diagram of which is shown in figure. It is used to energize and de-energize the contactors during the weld and non-weld periods. The internal timer of the PIC microcontroller is used to set time delay between non-weld period and power cut off to the primary of the welding transformer.

The advantages of PIC microcontroller are as follows

- Increased reliability through a small part count.
- Reduced stock levels, as one microcontroller replaces several parts.
- Simplified product assembly
- Greater product flexibility and adaptability
- Rapid product changes or development by changing the program and not hardware.
- Some practical controllers

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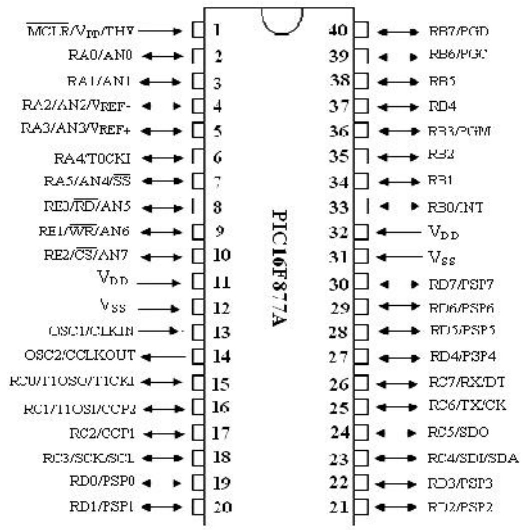

Fig.1 Pin Diagram ofPIC16F877A

This powerful (200 nanosecond instruction execution) yet easy-to-program (only 35 single word instructions) CMOS FLASH-based 8-bit microcontroller packs Microchip's powerful PIC® architecture into an 40- or 44-pin package and is upwards compatible with the PIC16C5X, PIC12CXXX and PIC16C7X devices. The PIC16F877A features 256 bytes of EEPROM data memory, self programming, an ICD, 2 Comparators, 8 channels of 10-bit Analog-to-Digital (A/D) converter, 2 capture/compare/PWM functions, the synchronous serial port can be configured as either 3-wire Serial Peripheral Interface (SPI™) or the 2-wire Inter-Integrated Circuit (I²C™) bus and a Universal Asynchronous Receiver Transmitter (USART). All of these features make it ideal for more advanced level A/D applications in automotive, industrial, appliances and consumer applications.

High-Performance RISC CPU:

- Only 35 single-word instructions to learn
- All single-cycle instructions except for program branches, which are two-cycle
- Operating speed: DC – 20 MHz clock input DC – 200 ns instruction cycle
- Up to 8K x 14 words of Flash Program Memory, Up to 368 x 8 bytes of Data Memory (RAM), Up to 256 x 8 bytes of EEPROM Data Memory
- Pin-out compatible to other 28-pin or 40/44-pin PIC16CXXX and PIC16FXXX microcontrollers

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B. ESP8266

ESP-12E WiFi module is developed by Ai-thinker Team. core processor ESP8266 in smaller sizes of the module encapsulates Tensilica L106 integrates industry-leading ultra low power 32-bit MCU micro, with the 16-bit short mode, Clock speed support 80 MHz, 160 MHz, supports the RTOS, integrated Wi-Fi MAC/BB/RF/PA/LNA, on-board antenna.

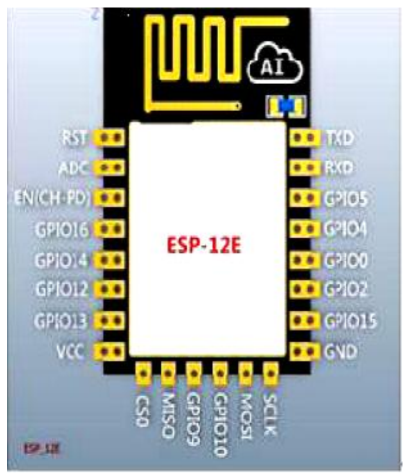

Fig.2 ESP8266 Module

The module supports standard IEEE802.11 b/g/n agreement, complete TCP/IP protocol stack. Users can use the add modules to an existing device networking, or building a separate network controller. ESP8266 is high integration wireless SOCs, designed for space and power constrained mobile platform designers. It provides unsurpassed ability to embed Wi-Fi capabilities within other systems, or to function as a standalone application, with the lowest cost, and minimal space requirement.

Features

- 802.11 b/g/n
- Integrated low power 32-bit MCU, 10-bit ADC, TCP/IP protocol stack
- Integrated PLL, regulators, and power management units
- Supports antenna diversity
- Wi-Fi 2.4 GHz, support WPA/WPA2
- Support STA/AP/STA+AP operation modes
- Support Smart Link Function for both Android and iOS devices
- SDIO 2.0, (H) SPI, UART, I2C, I2S, IRDA, PWM, GPIO

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- STBC, 1x1 MIMO, 2x1 MIMO
- A-MPDU & A-MSDU aggregation and 0.4s guard interval
- Deep sleep power <10uA, Power down leakage current < 5uA
- Wake up and transmit packets in < 2ms
- Standby power consumption of < 1.0mW (DTIM3)
- +20dBm output power in 802.11b mode
- Operating temperature range -40C ~ 125C

CONCLUSION

This system describes a procedure of predicting total output of wind power plant (WPP) by neural networks. Big data analyzing system is applied to classify and screen the raw wind data for the training of data network prediction models. And then certain representative wind turbines were selected as an input data source for modeling and to simplify the input signals to the model. In the last step, based on the previous wind power prediction experience, complex-valued recurrent neural network (CRNN) model was chosen to predict the total output of WPP with high accuracy.

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