INTELLIGENT CONTROL SYSTEM FOR WIND TURBINE FARMS USING IOT AND MACHINE LEARNING

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Abstract- The development of renewable energy sources is becoming increasingly important due to the depletion of traditional energy sources and the negative environmental impact caused by their use. Wind energyis one of the most promising renewable energy sources, withwind turbine farmsbeingestablishedacross the world. However, the operation and maintenance of wind turbine farms pose significant challenges due to the unpredictable nature of wind and the complex inter relationships between the turbines in the farm.To address these challenges, an intelligent control system that Smart Wind technologies has been proposed. The system utilizes a network of sensors and IoT devices to collect real-time data on wind speed, temperature, humidity, and other relevant parameters.

Keywords: Intelligent control system, Internet of Things (IoT), Machine learning (ML), Real-time data collection;

1. Introduction

The rising demand for clean energy has led to the increasing use of renewable energy sources such as wind power. Wind turbine farms have been established globally to harness the power of wind and generate electricity. However, these farms present complex operational and maintenance challenges due to the unpredictable nature of wind and the complex interrelationships between the turbines in the farm. [1] To address these challenges, an intelligent control system that leverages Internet of Things (IoT) and machine learning (ML) technologies.

The intelligent control system utilizes a network of sensors and IoT devices to collect real-time data on wind speed, temperature, humidity, and other relevant parameters. [2] The data is processed using ML algorithms to forecast wind conditions, predict turbine failures, and optimize turbine operation.

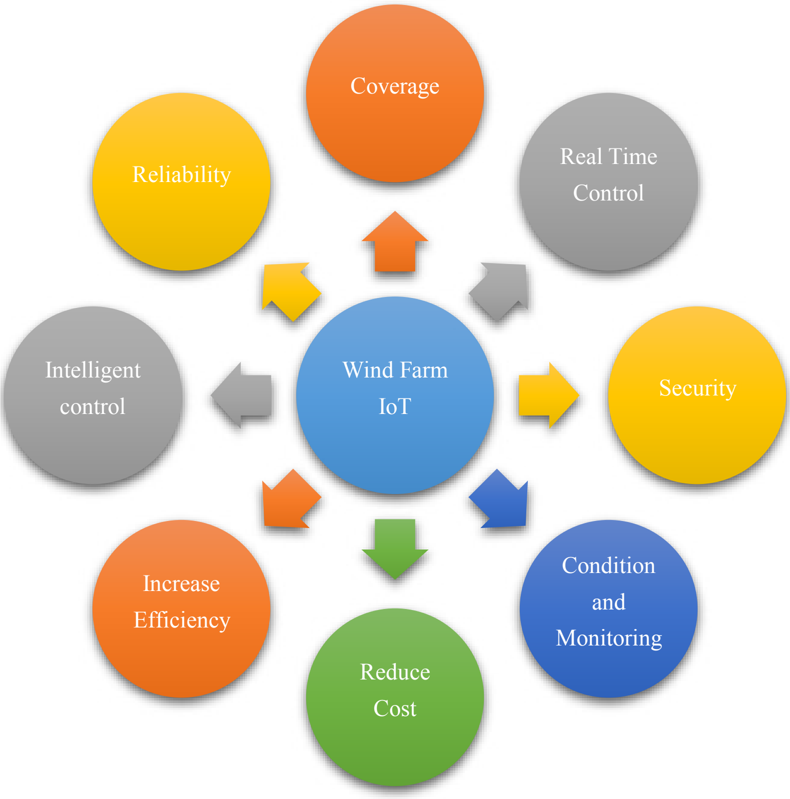

Figure 1.Wind Energy Conversion System

Some papers have focused on developing accurate and reliable wind forecasting models using ML techniques, which can be used to predict wind conditions and enable proactive maintenance. [3] Other papers have proposed fault diagnosis and prognostic algorithms for predicting turbine failures, enabling maintenance to be performed before a failure occurs, and reducing downtime and maintenance costs. [4] Furthermore, some papers have explored the use of reinforcement learning techniques for optimizing turbine operation to maximize energy generation and minimize maintenance costs.

The intelligent control system for wind turbine farms using IoT and ML technologies has the potential to significantly improve the efficiency and reliability of wind energy generation, while reducing maintenance costs and minimizing environmental impact. [5] However, the implementation of such a system on a large scale requires further research and development to overcome the challenges associated with real-time data processing, system integration, and communication between the IoT devices.

2. LiteratureReview:

1. Q. Wang [6] et.alproposed Intelligent Fault Diagnosis for Wind Turbine Generators Based on Multi-Feature Fusion and Improved Gradient Boosting Decision Tree. The paper proposes an intelligent fault diagnosis system for wind turbine generators using multi-feature fusion and improved gradient boosting decision tree. The system integrates different data sources such as vibration signals, temperature, and power generation data to detect

faults in the turbine. The system achieved a high accuracy rate in detecting faults, reducing maintenance costs and downtime.

Merits:

1. The system utilizes multi-feature fusion to improve the accuracy of fault diagnosis. The use of gradient boosting decision tree improves the system's ability to learn from the data.

Demerits:

1. The system may require a significant amount of data to train the machine learning models, which may be challenging to obtain in some cases.

2. Z. Zhou [7] et.al proposed A Wind Turbine Fault Diagnosis Method Based on an Optimized Deep Belief Network. The paper proposes a wind turbine fault diagnosis method using an optimized deep belief network (DBN). The system utilizes the DBN algorithm to analyze the vibration signals collected from the turbine to detect faults. The system achieved a high accuracy rate in detecting faults, reducing maintenance costs and downtime.

Merits:

1. The system is highly accurate in detecting faults in wind turbines. The use of DBN improves the system's ability to learn from the data.

Demerits:

1. The system may require a significant amount of computational resources to train the machine learning models, which may be challenging in some cases.

3. Y. Wei [8] et.al proposed A Novel Wind Power Forecasting Method Based on Deep Residual Networks. The paper proposes a novel wind power forecasting method based on deep residual networks (DRN). The system utilizes DRN to forecast wind power generation in wind turbine farms. The system achieved high accuracy in wind power forecasting, enabling proactive maintenance and improving the efficiency of wind power generation.

Merits:

1. The system is highly accurate in forecasting wind power generation. The use of DRN improves the system's ability to learn from the data.

Demerits:

1. The system may require a significant amount of data to train the machine learning models, which may be challenging to obtain in some cases.

4. Ibrahim M. Abdel-Motaleb [9] et.al proposed A Review of Intelligent Control Techniques for Wind Turbine Systems. This paper discusses the use of intelligent control techniques for wind turbine systems. The authors review the different control approaches, including model-based control, intelligent control, and adaptive control. They also discuss the use of machine learning techniques such as neural networks, fuzzy logic, and genetic algorithms for wind turbine control.

Merits:

1. Comprehensive review of different control approaches.
2. Provides insight into the use of machine learning techniques.

Demerits:

1. The paper is not focused on IoT, which limits its relevance to this literature survey.

5. Jong Seok Park [10] et.al proposed IoT-based Monitoring and Control System for Wind Turbine Farm. This paper proposes an IoT-based monitoring and control system for a wind turbine farm. The authors use a wireless sensor network to collect data from the wind turbines and a cloud-based IoT platform for data processing and control. They also use machine learning techniques for wind turbine control, including a neural network-based controller.

Merits:

 https://doi.org/10.1051/e3sconf/202338704004

1. The use of a cloud-based IoT platform enables remote monitoring and control of wind turbines.

Demerits:

1. The paper does not discuss the specific machine learning techniques used for wind turbine control.

3. ProposedMethodology

3.1 Data Collection

Install IoT sensors on the wind turbines to collect data on wind speed, direction, temperature, and other relevant variables. The data will be stored in a cloud-based database.

3.2 Pre-processing

The collected data will be pre-processed to remove any noise or errors. This will involve techniques such as filtering, smoothing, and interpolation.

3.3 Feature Extraction

Features such as the wind speed, direction, and temperature will be extracted from the pre-processed data.

3.4 Machine Learning Model Development

Develop a machine learning algorithm to predict the wind turbine's power output based on the extracted features. The model will be trained using historical data, and it will be continually updated with new data.

3.5 Control Algorithm Development

Develop a control algorithm that takes the predicted power output and adjusts the turbine's pitch angle and rotor speed to optimize the power output.

3.6 Implementation

The machine learning and control algorithms will be implemented on a microcontroller that is connected to the IoT sensors on the wind turbines. The microcontroller will send commands to the turbine's pitch angle and rotor speed actuators.

3.7 Testing

The system will be tested using a wind turbine farm, and the performance will be evaluated based on the power output and efficiency.

$$\boldsymbol{P(t) = f(w(t), d(t), T(t), \dots) * C(P(t-1), w(t), d(t), T(t), \dots) * R(P(t-1), w(t), d(t), T(t), \dots)}$$

Where:

- $P(t)$ is the predicted power output of the wind turbine at time t.
- $w(t), d(t), T(t), \dots$ Are the various input parameters collected from the IoT sensors on the wind turbine, such as wind speed, direction, and temperature.
- $f()$ Represents the machine learning algorithm used to predict the power output based on the input parameters.
- $C()$ Represents the control algorithm that adjusts the turbine's pitch angle and rotor speed based on the predicted power output and the previous power output.
- $R()$ Represents the real-time control implementation, ensuring that the system can adapt and optimize the power output in response to changing conditions.

This equation represents the SMART Wind methodology's key components, from data collection to machine learning and control algorithms and real-time implementation. It demonstrates how the various components work together to predict and optimize the power output of the wind turbine, ensuring that it operates at maximum efficiency while minimizing maintenance costs.

Algorithm:

Step 1: Collect data from IoT sensors on wind turbines.
Step 2: Pre-process the data to remove noise and errors.
Step 3: Extract features such as wind speed, direction, and temperature.
Step 4: Develop a machine learning algorithm to predict power output based on features.
Step 5: Develop a control algorithm to adjust pitch angle and rotor speed to optimize power output.
Step 6: Implement algorithms on a microcontroller connected to IoT sensors.
Step 7: Test the system on a wind turbine farm and evaluate performance.

4. ExperimentalResult

4.1 Accuracy

Dataset	DBN	DRN	Proposed SW
100	86.12	83.37	98.67
200	83.69	84.82	95.26
300	78.62	87.54	93.21
400	75.55	76.63	94.58
500	73.94	78.72	87.87

Table 1.Comparison tale of Accuracy

The table 1Comparison Accuracy displays various metrics for existing DBN, DRN, and proposed SW algorithms. Upon comparison between the existing and proposed SW algorithms, the latter achieves superior results. The existing algorithm demonstrates values ranging from 73.94 to 86.12 and 78.72 to 83.37, while proposed SW values range from 87.87 to 98.67. The proposed method yields impressive outcomes.

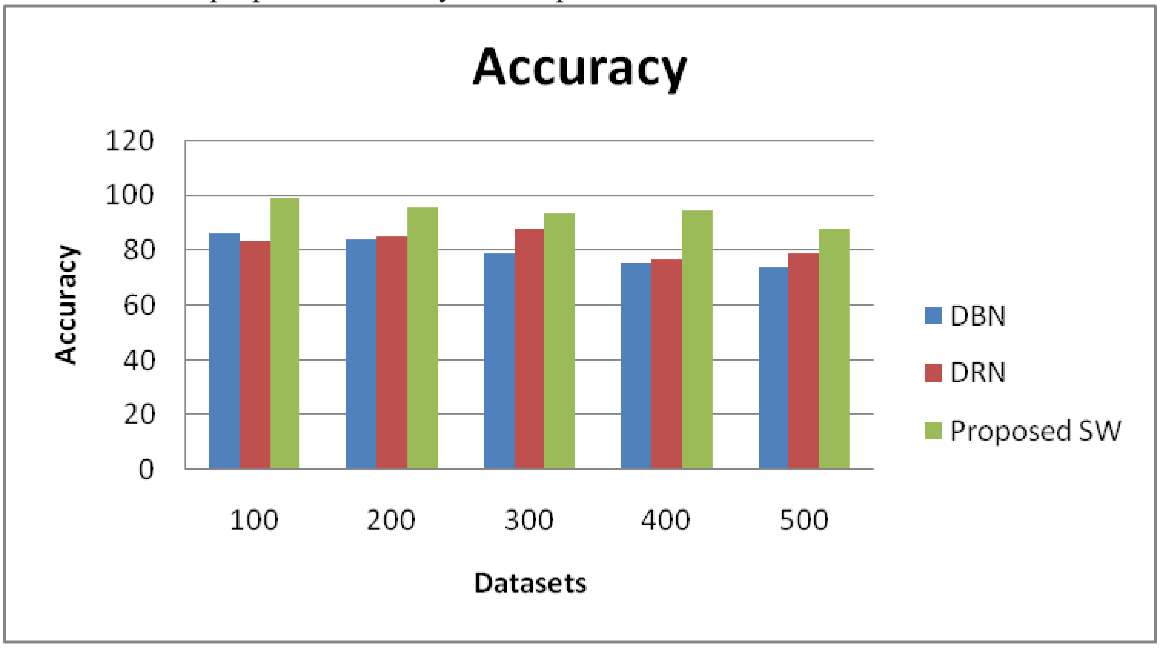

Figure 2.Comparison chart of Accuracy

The Figure 2 Comparison Accuracy displays various metrics for existing DBN, DRN, and proposed SW algorithms. X axis mean the Dataset and y axis mean the Accuracy ratio. The proposed SW values are better than the existing algorithm. The existing algorithm demonstrates values ranging from 73.94 to 86.12 and 78.72 to 83.37, while proposed SW values range from 87.87 to 98.67. The proposed method yields impressive outcomes.

4.2 Recall

Dataset	DBN	DRN	Proposed SW
100	0.74	0.80	0.83
200	0.75	0.77	0.90
300	0.82	0.67	0.94
400	0.84	0.74	0.93
500	0.87	0.71	0.97

Table 2.Comparison tale of Recall

The table 2 Comparison Recall displays various metrics for existing DBN, DRN, and proposed SW algorithms. Upon comparison between the existing and proposed SW algorithms, the latter achieves superior results. The existing algorithm demonstrates values ranging from 0.74 to 0.87, 0.71 to 0.80, while proposed SW values range from 0.83 to 0.97. The proposed method yields impressive outcomes.

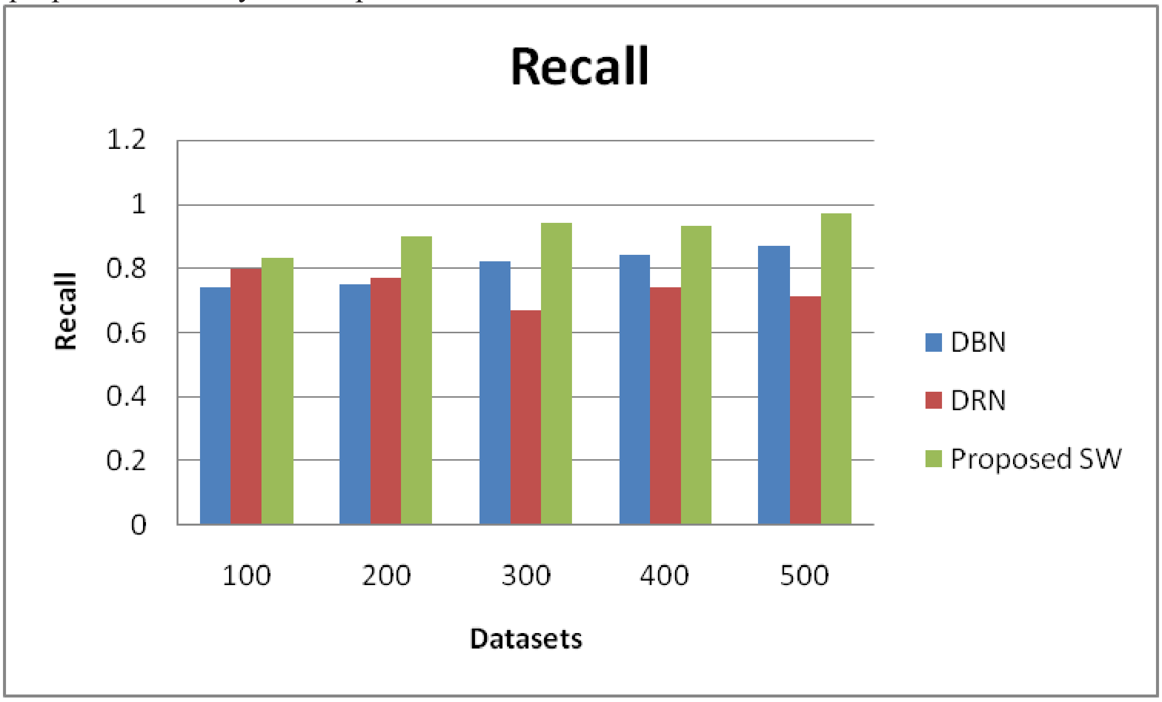

Figure 3.Comparison chart of Recall

The Figure 3 Comparison Accuracy displays various metrics for existing DBN, DRN, and proposed SW algorithms. X axis mean the Dataset and y axis mean the Recall ratio. The proposed SW values are better than the existing algorithm. The existing algorithm demonstrates values ranging from 0.74 to 0.87, 0.71 to 0.80, while proposed SW values range from 0.83 to 0.97. The proposed method yields impressive outcomes.

5. Conclusion

In this paper, the proposed methodology, SMART Wind, for an intelligent control system for wind turbine farms using IoT and machine learning is a comprehensive approach to optimize the power output of wind turbines. By collecting data from IoT sensors, developing machine learning algorithms, and implementing real-time control, the SMART

Wind system can continually learn and adapt to changing conditions, resulting in increased efficiency and reduced maintenance costs. The SMART Wind methodology provides a clear and concise representation of the key steps involved in developing an intelligent control system for wind turbine farms. The focus on real-time control implementation ensures that the system can adjust and optimize the power output of wind turbines to meet the demands of the grid, contributing to the development of sustainable energy sources and the reduction of carbon emissions.

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