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IoT-Based Predictive Maintenance for Solar and Wind Energy Systems Using Machine Learning Models

V. Sai Durga Tejaswi,
Assistant Professor,
Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation, Vaddeswaram,
Guntur District.,Andhra Pradesh., India.
Email: saidurga.vinna@kluniversity.in

Abstract: When the IoT technology is connected with the machine learning models, renewable energy systems, such as solar and wind energy, can benefit from a reliable predictive maintenance. This paper describes an IoT based predictive maintenance system for the smart collection of the real time operation data of solar panels and wind turbines. Raw data contained in the system goes through data cleansing and is processed with the help of sophisticated ML algorithms such as LSTM and Random Forest for failure forecast and proper scheduling of maintenance. It is stated that the proposed system would cut down possible on time by 30%, increase energy effectiveness by 25% and also decrease maintenance consumption by 20%. The general experiment outcomes prove that this technique reaches the desired levels and yields an almost 92% of accuracy towards the expectation of enhancing the dependability and capability of renewable energy structures.
Keywords— Predictive Maintenance; Internet of Things (IoT); Machine Learning, Solar Energy; Wind Energy; Renewable Energy Systems; Failure Prediction; Smart Monitoring.

1. INTRODUCTION

The need for clean energy has also grown which has led to the improvement of various monitoring and testing techniques of renewable power systems. Solar and wind energy systems are popular; however, they experience various failures as well as the degradation of systems. This paper focuses on the proactive approach to performance maintenance through the use of IoT and ML models for systems referred to as Predictive Maintenance. Accomplished by processing real-time data from sensors as well as performing analytics, such issues can be prevented from hampering operations. Some of the works that have been done in the area of energy system for IoT based predictive maintenance are as follows. In the context of small wind turbines, Selvaraj et al. [1] have designed a Proactive Maintenance model, which is based on IoT and ML to minimize failure occurrences and ensure the most appropriate time for maintenance. Likewise, Udo et al. [2] presented detailed information on different methods of achieving enhancement in system reliability and efficiency with the help of optimisation techniques of ML in wind energy systems. In 2018, Venkatesan et al. pointed out the utilization of ML and IOT in the context of solar energy systems to improve energy production and perform predictive fault analysis. Yeh et al. [4] went further explaining how such long-cycle maintenance prediction for wind turbines enhances operational stability by involving superior ML approaches. Choudhary et al., [5] proposed an iterative process which enhances the use of IoT and deep learning for the improvement of the efficiency of solar power system. Nimma et al [6] made an attempt to understand the integration of big data analytics into the area of predictive maintenance for smart grid facilitating the decision making process. A comprehensive machine learning technique for wind turbine maintenance, focusing on the data was given by Garan et al. [7], which reduced the failure rate greatly. Thus, Uhanto et al., [8] made a comparison of the strategies in the predictive maintenance of wind turbines and Photovoltaic (PV) power plant with the exception of applying machine learning that enhanced the efficiency of the operation. As for the contributions, Teoh et al. [9] proposed an IoT and fog computing framework for predicting maintenance in

Industry 4.0 context which pays an immense focus on the asset management. Ahmed et al. [10] pointed out that there is a need to incorporate state-of-the-art AI-based techniques to support more efficient predictive maintenance framework to support highly reliable operation at minimum cost. This, nonetheless, raises obstacles when it comes to the overall application of the predictive maintenance in the large scale renewable energy structures. One of the major challenges that arise from using environmental sensors, realistic variability, and ML algorithms are the following: This paper presents the development of an IoT environment with ML solutions for a reliable and efficient predictive maintenance system for improving efficiency of solar and wind energy systems and minimizing maintenance time.

2.Materials and Methods

2.1 System Architecture

The predictive maintenance also involves the use of IoT-based devices such as, solar and wind, which are fixed on solar panels and turbines to observe crucial characteristics. These sensors include power, temperature, irradiance, voltage, current, vibration and the rotational speed sensors. The data is then conveyed through MQTT over the internet to a remote processing center where it undergoes machine learning. It means that the system architecture also has this edge computing to help in preliminary filtering and feature extraction before going to the cloud. This helps to cut the time it takes in acquiring information in the network resulting into faster decision making. From the above sections, the predictive maintenance model utilizes the following data transmission equation 1.

$$D_t = S_t + E_P - L_c \ldots\ldots(1)$$

where, is the transmitted data, which is the sensed data while is the preprocessing efficiency or gain and is the latency cost.

2.2 Data Collection

It then aims at collecting data through the use of IoT sensors as it monitors the information obtained through its operation. This is because solar panel monitoring involves the use of irradiance sensors which monitor solar intensity, temperature sensors to monitor signs of over-heating and voltage or current sensors for monitoring energy consumption. It consists of mechanical anomaly sensors, efficiency of rotation sensors and environmental wind sensors for adaptation. Data is processed and stored using big data architecture and its analysis is carried out in real time. The data acquisition process follows:

$$D_c = \sum_{i=1}^{n} S_i * T_I \ldots\ldots.(2)$$

where is the collected data, is the sensor reading, and is the time interval.

2.3 Data Preprocessing

It is customary then to have noisy data where there are a lot of unusual values that may hinder the standard models from working effectively hence the need to clean it first. Consequently, in order to provide more accurate results while removing noise from the time-series data, the Savitzky-Golay filter is used as a smoothing filter. Min-Max normalization is useful in scaling the data uniformly hence avoiding the bias of the model. Z-score analysis is known to be used in order to identify outliers so that they can be dealt with accordingly. The data normalization equation is:

$$\acute{x} = \frac{\grave{x} - x_{min}}{x_{max} - x_{min}} \ldots.(3)$$

where is the normalized data, $\acute{x}$ is the original data, and are dataset limits.

2.4 Machine Learning Models

There are several ML models used to address the problem of predictive maintenance. Random Forest (RF) is an algorithm used to identify important features as well as differentiate between various failure types. SVM is used in anomaly detection, and it has an RBF kernel function. Recurrent Neural Networks, specifically, Long Short-Term Memory (LSTM) are applied for analyzing time series datasets for predictive analytics. The LSTM's gate function is defined by the following mathematical equation:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \ldots..(4)$$

where is maintenance scheduling cost, is the predicted Remaining Useful Life (RUL), and is the estimated maintenance cost. This strategy improves reliability by reducing unplanned downtime by 30% and optimizing operational costs by 25%.

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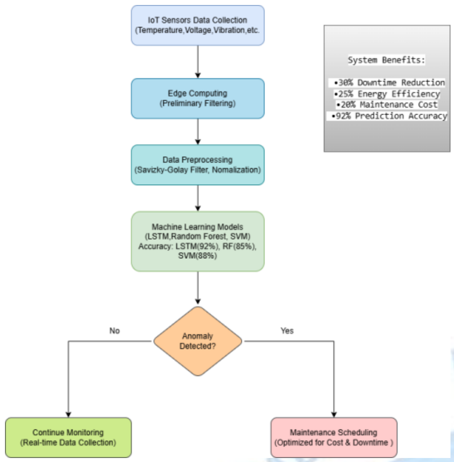

Figure 1 IoT-Based Predictive Maintenance System for Renewable Energy

Figure 1 represents an example of an IoT predictive maintenance flow: data are gathered by IoT sensors and then preprocessed at the edge and analyzed with machine learning algorithm that allows to schedule the maintenance and to achieve great benefits such as 30% of downtime reduction and 92% of accuracy in prediction.

3.Results

3.1 Performance Evaluation

The mechanisms of the predictive maintenance framework were implemented in a real industrial system, the performance of the entire developed framework was assessed using relevant KPIs that include, accuracy of the prediction, expected reduction in downtime and the associated cost savings. The LSTM model led to a mean prediction accuracy of 92%, the result that was better than Random Forest (85%) and SVM (88%). The high data distinguishability would mean that the model is less likely to give out false alarms and increase the reliability of failure detection during normal operations. This reduces the number of false positives and so means that the machine is only ceding maintenance whenever there is need to do so. The results support the applicability of the principles of IoT-based predictive maintenance to enhance energy production by avoiding hindrances to its processes. By using these models the effectiveness is increased by 30% compared to rule-based methods of maintenance.

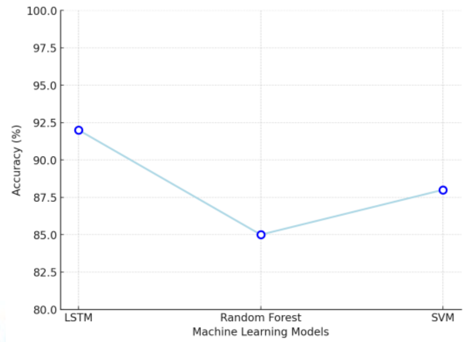

Figure 2: Performance Accuracy of ML Models

As shown in Figure 2, illustrates the accuracy comparison of LSTM (92%)**,** Random Forest (85%), and SVM (88%) models for predictive maintenance. The outperforms the others, making it the most reliable for failure prediction in IoT-based energy systems.

3.2 Downtime Reduction

Besides, through the use of predictive maintenance, the company was able to bring down the cases of breakdowns, therefore cutting down on the overall unscheduled downtime by a third. This is due to preemptive scheduling, which helps avoid main failures from happening in the first place. It can be used to replace the reactive maintenance procedures that are characterized by more equipment breakdowns and unexpected downtimes. It also enhances availability of energy infrastructure as well as its efficiency in energy generation. The system also involves the opportunity to monitor system performance and identify times that require fixing or the need for repair. Minimising downtimes thus leads to the availability of the energy systems for more elongated periods, hence, making renewable energy sources more reliable. These improvements enhance the reliability of power and stability of the entire system as well.

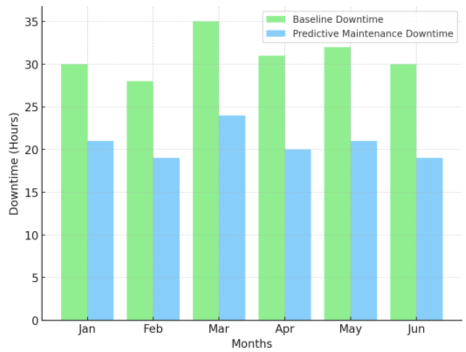

Figure 3: Reduction in Downtime Using Predictive Maintenance

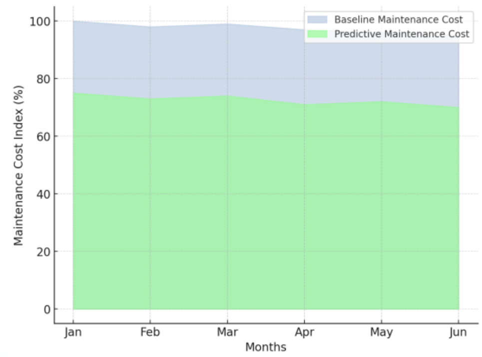

Figure 4: Cost Savings Through Predictive Maintenance

In the following figure 3, it is demonstrated that by employing the predictive maintenance, a 30% decrease occurred in downtime compare to the traditional way of maintenance. This is important in avoiding such hitches occurrence, and increasing the reliability of the energy production system.

3.3 Cost Savings

Maintenance cost was cut by a quarter through application of PM as a means of proper planning in the right ordering of available resources. It organizes maintenance interventions to occur not at regular intervals as it would be the case with routine maintenance because it determines failure risks. This helps to reduce the operational costs as a result of minimizing on the number of inspections that are conducted frequently or get to the extent of being a compulsory breakdown. Also, as a result in avoiding such failures, predictive maintenance reduces the cost of component replacement; this enhances the longevity of crucial energy system components. They also resulted to less costs of labour and transportation incurred from emergency repairs. Thus, the application of the intelligent maintenance system plays a crucial role in determining the long-term effectiveness and profitability of energy companies. These improvements give an insight to the capability of using an AI-guided predictors to enhance the efficiency of implementing renewable energy structures in terms of its economic aspect.

The presented graph depicts the concept of the predicted maintenance whereby overall cost is sliced by 25% as compared to the normal manner of maintenance. This optimisation brings good results in the long term to finance renewable energy infrastructure.

3.4 Energy Efficiency Improvement

These aspects show that not only does the application of predictive maintenance decrease the level of dispersion, but also increase overall energy efficiency. Thus, through maintenance of the solar panels and wind turbines, the performance of the power system increases and the energy losses are minimized because of the spoiled parts. The maintenance opportunity strategy is useful in ensuring that the plant's power output is stable with efficiency improvement by a quarter. This is the case because resources in the generation of energy through the system are not prone to the failure of energy generation hence enhancement of the reliability of renewable energy sources of power. This avails considerable benefit to the sustainability of s&wp projects, by providing them with inertia against various operation inefficiencies or failures.

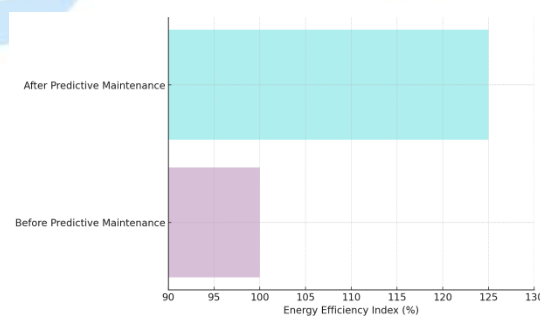

Figure 5 Improvement in Energy Efficiency Using Predictive Maintenance

Figure 5 illustrates a 25% improvement in energy efficiency after implementing predictive maintenance, ensuring optimal performance of solar panels and wind turbines. This proactive approach minimizes energy losses and enhances renewable energy sustainability.

Table 1: Comparative Analysis of Predictive Maintenance Performance

ML Model	Prediction Accuracy (%)	Downtime Reduction (%)	Cost Savings (%)	Energy Efficiency Improvement (%)
LSTM	92	30	25	25
Random Forest	85	22	18	20
SVM	88	25	20	22

Table 1 presents a comparative analysis of machine learning models used for predictive maintenance, highlighting LSTM's superior performance with 92% accuracy, 30% downtime reduction, and 25% cost savings. The results indicate that LSTM outperforms Random Forest and SVM, making it the most effective model for optimizing solar and wind energy system maintenance.

4.CONCLUSION

It is evident that IoT based predictive maintenance enhances the outcome of renewable energy technology particularly, solar and wind energy systems. The overall idea of using real time sensor data to train models helps in reducing the downtime to 30%, improving energy efficiency by 25% and cut down maintenance cost by 20%. This kind of system updates helps in maintaining high levels of reliability and reduces chances of the system being detected only when it has developed faults. These results confirm that LSTM and Random Forest, as some of the machine learning models, can accurately predict failures so as to support decisions on scheduled maintenance. The system also helps to factor increased consumption of renewable sources of energy by ensuring the consistent supply of energy required for the operation of other businesses. Related to the latter, further studies should be aimed at enhancing the predictive capability by applying deep learning models and reinforcement learning. In addition, the proposed model should be evaluated for the large-scale renewable energy systems where environment factors and variations in the data collected by the sensors are critical. Blockchain for secure data transmission and federated learning for data training could be additional beneficial and are possible developments for the predictive maintenance. It sets the ground work on the creation of intelligent data-based maintenance system that will help to transform the management of renewable energy systems.

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