Wind turbine fault detection using quantum long-short term memory network

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***Abstract*—Fault detection plays a critical role in ensuring the reliability and safety of wind turbine operation. With the growing availability of operational data, data-driven approaches have become increasingly prevalent. This paper proposes a fault detection method based on the Quantum Long Short-Term Memory network (QLSTM). The model is trained by supervisory control and data acquisition (SCADA) data to capture temporal dependencies among multiple sensor signals under healthy conditions, forming a Normal Behavior Model (NBM). Residuals between predicted and practical measurement values are computed and evaluated using the T-distribution method to establish a threshold for anomaly identification. Experiments conducted on SCADA data show that the proposed method outperforms the conventional LSTM in terms of modeling accuracy, detection sensitivity, and early fault warning capability, achieving a 7.67 hours earlier fault detection and demonstrating the potential of quantum machine learning (QML) in wind turbine condition monitoring.**

***Index Terms*—Wind turbine, condition monitoring, deep learning, quantum machine learning**

I. Introduction

Wind power has become an important part of global renewable energy systems and has seen rapid growth in recent years. According to the Global Wind Energy Council (GWEC), the total installed capacity reached 1021 GW in 2024, and annual additions are still growing steadily [1]. As wind turbines operate in harsh environments, their reliability becomes more of a concern. Components such as gearboxes, generators, and bearings often face failures due to complex loads and harsh conditions, which can lead to unexpected shutdowns or even serious damage [2]. Therefore, improving fault detection is essential to increase availability and thus reduce maintenance costs [3].

In recent years, data-driven methods have become widely used for wind turbine fault detection. Machine learning (ML) models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have achieved good results in learning nonlinear patterns and time dependencies from operational data [4], [5]. However, as model structures grow more complex, their performance gains become limited, while the demand for computational resources rises sharply [6]. This poses challenges for deployment in environments with restricted computing capacity.

Quantum machine learning (QML), which combines quantum computing with learning methods, offers a possible solution to the limitations of conventional machine learning (CML) [7]. QML has shown strong learning and generalization abilities in areas such as finance, image processing, and natural language tasks [8]–[10]. The quantum long short-term memory network (QLSTM) builds on standard LSTM by integrating parameterized quantum circuit (PQC), aiming to improve its ability to model temporal features. Using QLSTM for wind turbine fault detection is therefore meaningful from both theoretical and practical perspectives.

This study presents a wind turbine fault detection approach based on QLSTM. Supervisory control and data acquisition (SCADA) data are first preprocessed by removing outliers and fault points to construct a fault-free time-series dataset under normal operating conditions. QLSTM is then applied to learn temporal dependencies across multiple variables and to build a normal behavior model (NBM). A fault threshold is determined by using a residual-based method grounded in the T-distribution. Experimental results indicate that the proposed approach achieves better performance than conventional LSTM models in terms of R^2, root mean square error (RMSE), and early fault detection, demonstrating its potential for practical application in condition monitoring of wind turbines.

The main contributions of this work are summarized as follows. 1) A novel QLSTM-based NBM framework is proposed for unsupervised fault detection in wind turbines. By embedding PQCs into LSTM gates, the model enhances its capacity to capture long-term dependencies in multivariate SCADA data. 2) A statistically principled fault detection mechanism is developed by combining residuals with a T-distribution-based thresholding method, enabling anomaly detection without reliance on fault labels. 3) The proposed method demonstrates that QML can be effectively applied to wind turbine condition monitoring, providing a generalizable architecture for data-driven modeling and anomaly identification under complex operating conditions.

The rest of this paper is structured as follows. Section II reviews related work on wind turbine fault detection and quantum machine learning. Section III describes the proposed QLSTM-based method, covering model architecture, and fault detection procedure. Section IV reports and analyzes the experimental results. Finally, Section V concludes the paper.

II. Related work

Wind turbine fault detection techniques have mainly relied on expert knowledge and physical models, where dynamic behaviors of wind turbine components are modeled and thresholds are defined for anomaly identification [11]. However, these methods require a deep understanding of system dynamics and are often difficult to generalize under complex and varying operating conditions. With advances in sensor technology, modern wind turbines generate large volumes of high-frequency, long-duration, and multivariate operational data. Signal processing-based approaches have therefore emerged, utilizing techniques such as wavelet transform and fast Fourier transform (FFT) in combination with statistical analysis to achieve an efficient fault detection [12]. Despite their effectiveness in certain scenarios, these methods rely heavily on manual feature extraction and offer limited capability in modeling nonlinear systems, leading to challenges in robustness and generalization under real-world conditions.

To address these limitations, ML algorithms such as support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGBoost) have been introduced. These models are relatively simple in structure and can achieve high classification accuracy and efficiency when combined with well-engineered features [13]. However, the performance of ML models remains highly dependent on feature engineering. They also lack the ability to automatically capture temporal dependencies, making them less effective in scenarios involving complex conditions, compound faults, or long-term time series data.

In recent years, deep learning (DL) methods have been widely applied in wind turbine fault detection. CNN, known for its strength in spatial feature extraction, has been extensively used for modeling vibration signals and image-based monitoring data. In [14], a multi-channel CNN was employed to model three-axis vibration signals for multi-class blade fault identification. In [15], a 3-dimension (3D) CNN was applied to hyperspectral images of turbine blades for surface defect detection. To handle compound fault scenarios, [16] proposed a hybrid architecture combining 3D CNN, attention mechanisms, and LSTM to extract spatiotemporal features, achieving promising results across multiple fault types.

Given the strong temporal characteristics of wind turbine operational data, RNN and its variants have also been widely adopted. In [17], an LSTM-based NBM was constructed and combined with distribution-based divergence measures for unsupervised fault detection. In [5], a CNN-LSTM model with an attention mechanism was designed to enhance feature weighting, significantly improving prediction accuracy. Furthermore, [18] employed a graph attention network (GAT) to model the spatiotemporal dependencies in SCADA data, outperforming CNN-LSTM baselines on multiple metrics. In [19], the robustness and performance of Transformer-based architectures under different feature selection strategies were validated, particularly in terms of F1 score and recall.

Meanwhile, QML has emerged as a promising paradigm in wind turbine condition monitoring. In [20], a hybrid quantum-classical framework was proposed for processing ultrasonic blade images, where quantum neural network (QNN) achieved over 20% higher accuracy than artificial neural network (ANN). In [21], the dimension of SCADA data was reduced via PCA and autoencoders, and the performance of multi-kernel SVMs was compared with quantum SVM (QSVM), reporting 94.5% accuracy for Gaussian SVM and 92.5% for QSVM. Further developments in QML for wind turbine condition monitoring can be found in [22].

These studies have preliminarily demonstrated the feasibility and potential of QML in wind turbine condition monitoring. However, most existing work focuses on benchmarking against classical methods and employs relatively simple QML architectures.

III. Research Method

A. Fault Detection Process

In this study, the NBM serves as the foundation for wind turbine fault detection. The aim of NBM is to capture typical operational patterns under healthy conditions, such that significant deviations between actual measurements and model predictions can be regarded as the potential faults. The complete implementation of the NBM construction, including all model configurations and training settings, is detailed in Algorithm 1. The overall detection process is illustrated in Figure 1. Initially, raw SCADA data are collected and processed through cleaning and variable selection to obtain fault-free samples. These samples are then used to train the NBM, which is implemented using a QLSTM network in this work. Once trained, the model is applied to the test dataset to generate predictions, and the residuals between predicted and observed values are computed. These residuals are compared against the predefined threshold: values exceeding the threshold indicate a fault and trigger an alarm, while values within the threshold range suggest normal operation. This approach enables accurate detection of abnormal behavior and supports the reliable operation of wind turbines.

B. Quantum Long-short Term Memory Network

QLSTM was first proposed in [23] as a hybrid quantum-classical architecture designed to enhance the representational capacity of CML by incorporating PQC, particularly under the constraints of current quantum hardware. While maintaining the overall structure of LSTM, QLSTM replaces the key gating units with PQCs, enabling quantum-enhanced temporal modeling. As illustrated in Figure 2, PQCs are used to replace the forget gate (f_t), input gate (i_t), candidate memory update ($\tilde{C}_t$), and output gate (o_t). At each time step, the input x_t is fed into the corresponding PQC, followed by a nonlinear activation function to control memory and state updates. Specifically, the forget gate is computed by applying a sigmoid activation to the output of $\mathrm{PQC}_1(x_t)$, as shown in Equation (1); the

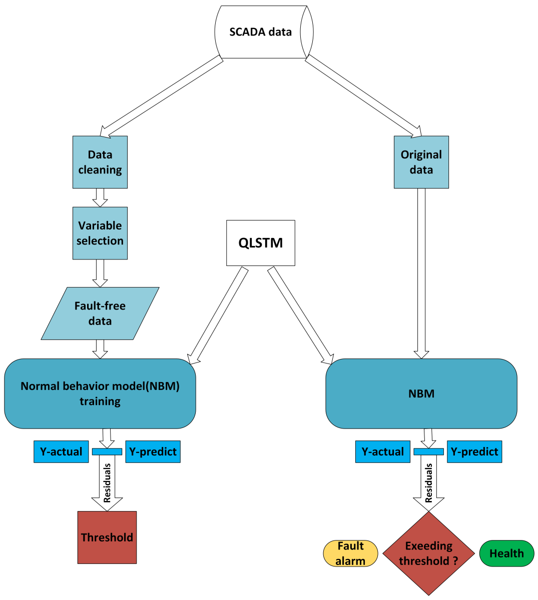

Fig. 1. Process of NBM-based fault detection.

input gate and candidate memory are similarly computed using $\text{PQC}_2(x_t)$ and $\text{PQC}_3(x_t)$, respectively, as in Equations (2) and (3). The cell state is updated by combining the previous memory with the new candidate, as defined in Equation (4); the output gate and final hidden state are obtained using Equations (5) and (6). In these equations, PQC_i denotes the output of the i-th parameterized quantum circuit, σ is the sigmoid activation function, $\tanh$ is the hyperbolic tangent function, and $\odot$ denotes the Hadamard (element-wise) product.

$$f_t = \sigma(\text{PQC}_1(x_t)) \tag{1}$$

$$i_t = \sigma(\text{PQC}_2(x_t)) \tag{2}$$

$$\tilde{C}_t = \tanh(\text{PQC}_3(x_t)) \tag{3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{4}$$

$$o_t = \sigma(\text{PQC}_4(x_t)) \tag{5}$$

$$h_t = \text{PQC}_5(o_t \odot \tanh(C_t)) \tag{6}$$

C. Thresholding Method

In this study, a residual-based thresholding method is implemented using the T-distribution to detect fault. This approach assumes that the model residuals under fault-free conditions follow a Gaussian-like distribution. After training the NBM on healthy data, we obtain the residuals by comparing predicted values and measurement values and then compute their sample mean $\bar{e}$, standard deviation σ, and sample size N. To define

Algorithm 1 Construction of NBM via QLSTM

Require: Fault-free SCADA dataset $\mathcal{D} = \{X, y\}$, where $X \in \mathbb{R}^{N \times d}$ denotes N samples with d variables, and $y \in \mathbb{R}^N$ is the target variable sequence
Ensure: Trained QLSTM model representing NBM

Step 1: Training Environment and Runtime
Hardware: Intel® Core™ i5 - 12600 KF CPU, 64 GB RAM, NVIDIA GeForce RTX 4070 Ti SUPER GPU
Software: Qiskit, TorchQuantum, Pytorch
Approximate training time: 150 minutes per run
Step 2: Data preparation
Select d input variables based on physical relevance to the target y
Set sliding window size $W = 40$, prediction horizon $H = 6$
for $i = 1$ to $N - W - H$ **do**
    Construct input window $X_i \in \mathbb{R}^{W \times d}$ from $[x_i, x_{i+1}, \ldots, x_{i+W-1}]$
    Assign label $y_i = y_{i+W+H}$ {Forecast target H steps ahead}
end for
Step 3: QLSTM network configuration
Initialize a two-layer QLSTM model:
    - First layer: 128 hidden units; Second layer: 64 hidden units
    - Replace all LSTM gates with 6-qubit PQC
    - Activation functions: sigmoid for gates, tanh for memory updates
Step 4: Model Training and Selection
Set batch size = 256, optimizer = Adam, loss function = Mean Squared Error (MSE)
for $j = 1$ to 5 **do**
    Train the QLSTM model on $\{X_i, y_i\}$ using randomly initialized weights
    Evaluate validation performance by computing RMSE_j
end for
Select the model $\mathcal{M}^*$ with the lowest validation RMSE_j
return Final trained QLSTM model $\mathcal{M}^*$ as the Normal Behavior Model (NBM)

a statistical threshold for fault detection, we calculate the upper confidence bound of the residual distribution at a given confidence level $(1-\alpha)$, in this study, the confidence level is set to 99%. This is computed based on the T-distribution as follows.

$$\tau = \bar{e} + \frac{\sigma}{\sqrt{N}} t_{\alpha/2}(N-1) \tag{7}$$

Here, $t_{\alpha/2}(N-1)$ is the critical value from the T-distribution with $N-1$ degrees of freedom. During inference, if a residual exceeds the threshold τ, the corresponding data point is flagged as fault. This method provides a statistically interpretable and computationally efficient thresholding strategy that is well-suited for wind turbine fault detection.

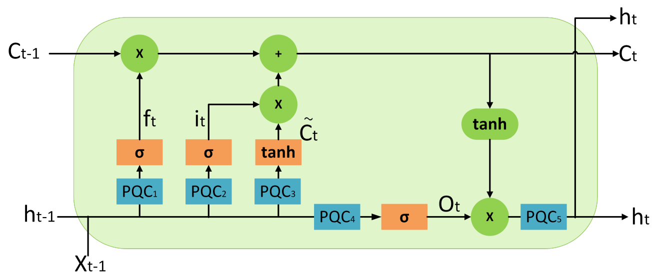

Fig. 2. Structure of QLSTM.

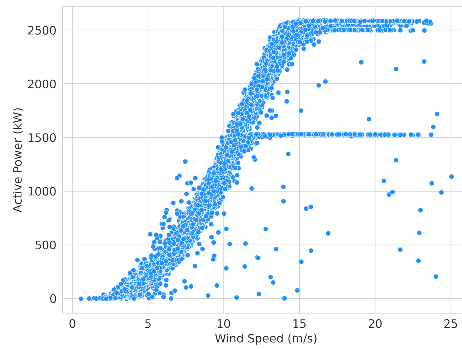

Fig. 3. Original active power vs. wind speed curve.

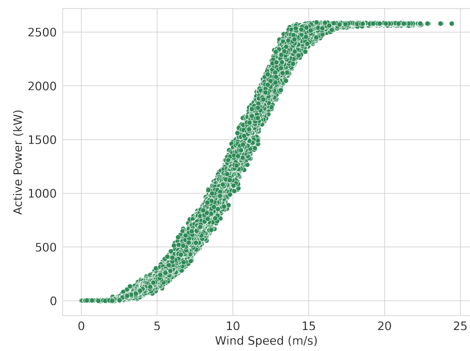

Fig. 4. Fault-free active power vs. wind speed curve.

IV. Experimental Results and Discussion

A. Data Description

The SCADA dataset used in this study was obtained from a wind turbine that experienced an abnormal rise in gearbox oil sump temperature in 2011. The turbine has a rated wind speed of 15 m/s and a cut-out wind speed of 25 m/s. During operation, a gearbox oil over-temperature alarm was triggered at 09:47 on June 4, leading to an emergency shutdown. The SCADA system recorded measurement values at a 2-second interval, which were subsequently averaged and archived at 10-minute intervals. The dataset includes readings from 128 sensors, capturing parameters such as temperatures, pressures, active power, vibrations, wind speeds, and digital control signals.

Figure 3 shows the scatter plot of active power versus wind speed. When the wind speed ranges from 3 m/s to 15 m/s, active power increases accordingly. Beyond 15 m/s, the power output stabilizes around the rated value. Ideally, the power curve should exhibit an S-shaped profile under normal conditions. However, due to the fault, the wind turbine shows underperformance at certain periods when the turbine fails to reach rated power even at the optimal wind speeds, resulting in significant outliers.

To build a reliable NBM, the raw data must be preprocessed to exclude periods associated with alarms or faults. Figure 4 presents the power–wind speed relationship after data cleaning, which more accurately represents the turbine's normal operational characteristics and serves as a robust foundation for model training.

B. Variable Selection

The abnormal rise in gearbox oil sump temperature is typically caused by excessive load, insufficient lubrication, or mechanical damage in gears or bearings, which results in increased frictional heat. As shown in Figure 5 and Figure 6, which present the time-series data of gearbox bearing temperature and oil sump temperature respectively, a sharp increase in bearing temperature can be observed near the fault time point marked by the red dashed line. This sudden rise in bearing temperature subsequently leads to an abnormal increase in oil sump temperature, ultimately triggering the over-temperature alarm. This indicates that the oil temperature anomaly is a consequence of the bearing overheating. Based on this fault mechanism, the gearbox bearing temperature is selected as the target variable for the fault detection model. To improve the performance of the model, variables such as gearbox oil sump temperature, generator speed, gearbox oil pressure, rotor speed, and active power that are closely related to the bearing temperature are selected as input features.

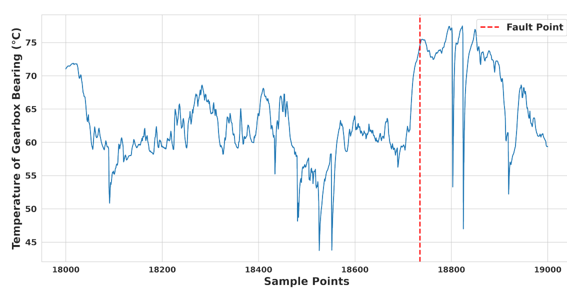

Fig. 5. Time-series data of gearbox bearing temperature.

C. Performance on Test Dataset

On the test dataset, LSTM achieves an R^2 score of 0.9358 and an RMSE of 2.2775, while QLSTM achieves an R^2 score of 0.9446 and an RMSE of 1.9308. Figure 7 illustrates the comparison between the predicted values and measurement values for LSTM and QLSTM. As shown in the figure,

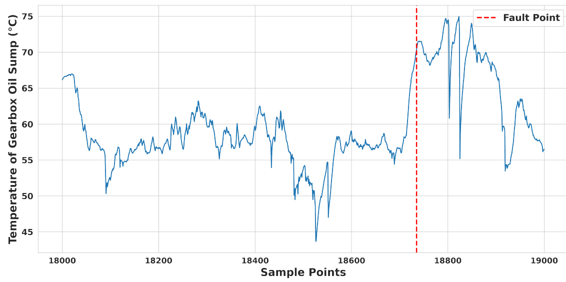

Fig. 6. Time-series data of gearbox oil sump temperature.

QLSTM exhibits better fitting performance on fault-free data, indicating a stronger modeling capability for normal behavior and lower overall prediction error.

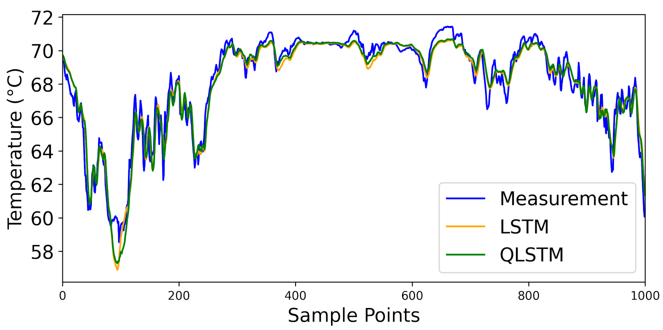

Fig. 7. Measurement values vs. prediction values of LSTM and QLSTM.

D. Fault Detection Performance

As this study targets the gearbox bearing over-temperature fault, the residuals are computed by retaining only the portions where the measurement values exceed the model prediction. Using a thresholding method based on the T-distribution, the fault detection thresholds are determined as 0.4377 for LSTM and 0.4054 for QLSTM, respectively.

The input data for fault detection spans two days prior to the fault occurrence. Figure 8 presents the comparison between the predicted values and measurement values for LSTM and QLSTM, when exposed to raw input containing faults. A noticeable temperature rise begins at the sample point 51850, indicating the onset of abnormal behavior. By comparing the residuals with the respective thresholds, fault conditions can be identified. Figure 9 and Figure 10 illustrate the detection results of both models: QLSTM detects the fault earlier at sample point 51616 (orange vertical line), whereas LSTM responds at 51662. The results clearly show that QLSTM detects the fault 7.67 hours earlier than the conventional LSTM and exhibits higher sensitivity.

E. Discussion

The experimental results provide empirical evidence that the proposed QLSTM model outperforms the LSTM in both prediction accuracy and fault detection sensitivity. On the fault-free test dataset, QLSTM achieves a higher R^2 score and lower RMSE compared to LSTM, indicating stronger generalization capability and a better fit to normal operating patterns. This improved modeling of normal behavior enables more accurate residual computation, which is crucial in residual-based fault detection frameworks.

In the fault detection task, both models apply one-sided residual analysis, focusing exclusively on instances where the actual temperature exceeds the predicted value. This approach corresponds to the physical behavior typically observed in bearing overheating faults. Thresholds for fault detection are

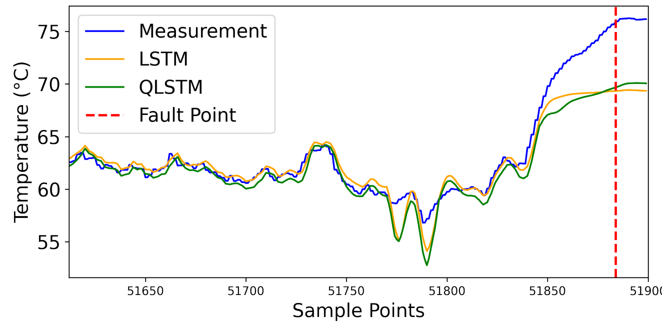

Fig. 8. Measurement values vs. prediction values of LSTM on original dataset.

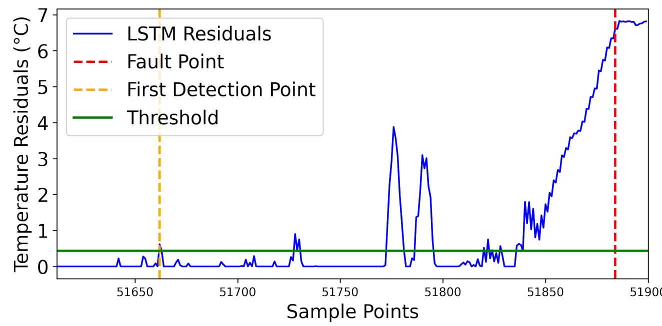

Fig. 9. Fault detection performance of LSTM.

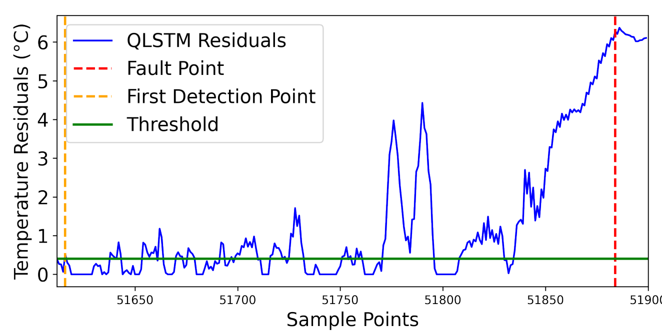

Fig. 10. Fault detection performance of QLSTM.

determined using the T-distribution method, yielding 0.4377 for LSTM and a lower value of 0.4054 for QLSTM. The tighter residual distribution of QLSTM reflects a higher sensitivity to subtle deviations.

More significantly, QLSTM detects the bearing fault 7.67 hours earlier than LSTM, offering a substantial advantage in early fault warning. This earlier detection could provide operators with additional lead time to implement preventative maintenance measures, potentially avoiding more severe mechanical failures. The enhanced responsiveness of QLSTM highlights the potential of QML in condition monitoring of the safety-critical industrial tasks.

While QLSTM demonstrates superior performance, it is important to acknowledge that its advantage partially stems from the expressive power of parameterized quantum circuits, which allow the model to capture complex temporal dependencies with fewer parameters.

V. Conclusion

This paper presents a wind turbine fault detection approach based on the QLSTM. The model is trained to learn the normal operational behavior of wind turbines using SCADA data and to identify deviations indicative of faults through residual-based analysis. A thresholding method based on the T-distribution is employed to determine fault conditions in a statistically robust manner.

Experimental validation demonstrates that QLSTM achieves superior performance over conventional LSTM models, with a higher R^2 score, lower RMSE, and earlier fault detection. Specifically, QLSTM detects gearbox bearing faults one hour earlier than LSTM, demonstrating its enhanced sensitivity and early warning capability. These results underline the practical value of QML in wind turbine condition monitoring.

Future research could investigate the extension of the QLSTM framework to scenarios involving multiple fault types and system components. Additionally, exploring the effects of quantum circuit depth, qubit number, and encoding strategies may offer further insights into optimizing QML architectures for real-world deployment as the quantum hardware matures.

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