



# Quantum Assisted Predictive Maintenance and Scheduling System for Industry 4.0

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**Abstract:** Predictive Maintenance is one of the primary applications of Industry 4.0 for detecting potential equipment failures in advance of unplanned outages. With the increasing number of Industrial Internet of Thing(IoT) sensors available today, there is now the ability to access multi-modal data from machines that can be used to monitor conditions and predict failures. Traditional methods have been limited in their ability to capture the complex relationship between the different sensor measurements and make decisions regarding maintenance based upon limited resources. A quantum-assisted framework for integrating Machine Failure Prediction and Maintenance Scheduling. A Hybrid Quantum Neural Network (HQNN) will be utilized to analyze the different types of industrial sensor data and determine the likelihood of failure. The quantum component of our model will use a parameterized quantum circuit to represent the analyzed sensor data as quantum states; then measure these quantum states to produce a classical representation of the probability of failure. Once we have determined this probability of failure, it will be combined with the priority of the machine and its maintenance needs to create a maintenance scheduling problem. A QAOA-based method will be developed to develop a multi-shift maintenance schedule while considering all available resources.

**Keywords:** Industry 4.0, Predictive Maintenance, Hybrid Quantum Neural Network (HQNN), Parameterized Quantum Circuit (PQC), CNOT Ring Entanglement, QAOA, QUBO, Shift Scheduling

## I. INTRODUCTION

Industry 4.0 allows smart manufacturing systems to continuously collect information about the condition of various machines by using Industrial Internet of Things (IoT) sensors that measure voltage, current, temperature, power, humidity, and three-dimensional vibration. The resulting telemetry can be analyzed to monitor the health of equipment and perform Condition-Based Predictive Maintenance (PdM) in order to detect potential failures that could lead to unexpected downtimes of machines [3], [5].

Recent advances in Quantum Machine Learning (QML) offer new possibilities for processing complicated industrial data from classical sensors by using Parameterized Quantum Circuits (PQCs) on Noisy Intermediate-Scale Quantum (NISQ) devices. For example, QML can encode classical measurements from sensors in quantum states and represent this information in a high-dimensional Hilbert space, and these quantum representations can be combined with classical machine-learning algorithms to create hybrid quantum-classical models for industrial applications [1], [2], [11].

### A. Background

Current industrial predictive maintenance systems mostly use machine learning techniques like Random Forest, Gradient Boosting and Deep Neural Networks [3][9]. These methods face four major technical challenges. First there is a problem called target data leakage. This happens when models are trained using service logs that include future outcomes. As a result the model ends up memorizing results instead of learning the actual physical processes behind equipment degradation [3]. Second traditional approaches often analyze sensor data one variable at a time. They don't consider how different sensors might interact. For example a high vibration level might be fine if the bearing temperature is normal. Without looking at these relationships faults can go undetected [1][2]. Third when raw dimensional data is sent directly to Noisy Intermediate-Scale Quantum (NISQ) devices it causes issues such as quantum decoherence and barren plateaus both of which make it hard to get reliable results [7][11]. Finally assigning repair tasks to technicians across machines while staying within a limited shift worktime—like a total of 16.0 hours ( $\sum R_i x_i \leq 16.0$  hours)—is a complex combinatorial problem. It's NP-hard. Grows very quickly with the number of machines scaling exponentially as  $O(2^N)$ , for classical computers [4][12].

### B. Problem Statement

On a shop floor with N physical machines ( $E_1 \dots E_{50}$ ) monitored by multi-modal sensors the goal is to design, implement and validate an end-to-end quantum hybrid system that solves two connected optimization problems. Stage 1 is about predicting machine failure risk  $P_i$  in the range [0.0, 1.0] from physical telemetry and it must avoid data leakage



bias. Stage 2 is about optimizing repair shift assignments  $x_i$  in  $\{0, 1\}$ , under a strict 16-hour shift labor capacity limit using QAOA.

## II. RELATED WORK

Predictive maintenance research covers machine learning, parameterized quantum circuits and quantum optimization [1]–[4]. While Cummins et al. [3] Looked at models (Random Forest, Gradient Boosting, Deep Neural Networks) that have problems with too many parameters and overfitting because of data leakage early studies by Silva & Droguett [1]. Maier et al. [2] Created hybrid QML models using Angle Encoding and two-qubit entangling gates (CNOT, CZ, iSWAP) reaching up to 98.47% bearing classification accuracy. However current QML methods focus on finding faults and do not offer any way to schedule maintenance after a prediction.

To handle resource allocation Farhi et al. [4] Used QAOA to find the energy minimums by turning binary choices into Ising spin operators  $x_i = I - Z_i$  over 2 [12]. Our work helps fill the gap in the research by creating a dual quantum system that includes zero-leakage physics feature engineering, a 4-qubit CNOT Ring PQC failure predictor and a 6-step QAOA QUBO multi-shift scheduling taking QML further toward making real decisions, in industry (Table I) [1]–[4].

| Study / Reference           | Data / Setting       | Models             | Entanglement     | Scheduling         | Accuracy              |
|-----------------------------|----------------------|--------------------|------------------|--------------------|-----------------------|
| Silva & Droguett (2022) [1] | MFPT                 | QML + MLP          | None             | None               | 97.40%                |
| Maier et al. (2023) [2]     | CWRU & JNU           | QML + VQE + MLP    | CNOT, CZ, iSWAP  | None               | 98.47%                |
| Farhi et al. (2014) [4]     | Theoretical Graphs   | QAOA               | Ising            | None               | N/A                   |
| Cummins et al. (2024) [3]   | Industrial Telemetry | RF, GBM, DNN       | None             | None               | 87–91%                |
| <b>Proposed System</b>      | <b>500 Samples</b>   | <b>HQNN + QAOA</b> | <b>CNOT Ring</b> | <b>QUBO (16 h)</b> | <b>100% (AUC 1.0)</b> |

TABLE I: COMPARISON WITH REPRESENTATIVE BASE STUDIES

## III. METHODOLOGY

### A. System Architecture

The suggested design is a two-step system that uses both quantum and classical methods. It connects processing, from IoT sensors to predicting machine failures using HQNN in the first step. The second step uses QAOA for optimizing shift scheduling. This is displayed in Figure 1.

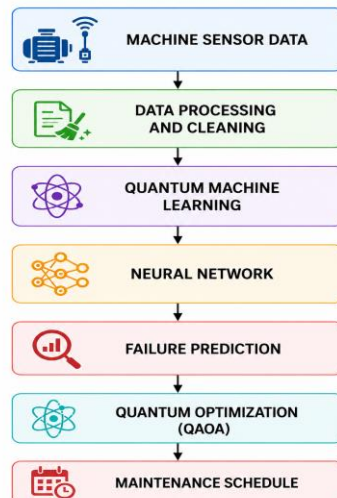


Fig. 1 Proposed system architecture



### B. System Architecture Overview

#### Stage 1: Machine Sensor Data

Collects time multi-modal IoT telemetry data from operational machinery. This includes voltage (V), temperature in degrees Celsius (°C), power in watts (W), humidity percentage (%) and positional data in X, Y Z coordinates.

#### Stage 2: Data Processing & Cleaning

Processes the raw sensor data by removing data leakage applying physics-based feature engineering such as calculating power and temperature rise normalizing the data using Z-score scaling and reducing dimensionality with Principal Component Analysis (PCA) to four features.

#### Stage 3: Quantum Machine Learning (PQC)

Takes the four- feature set and encodes it into a 4-qubit Parameterized Quantum Circuit. Uses angle encoding with Ry rotations. Creates entanglement through a CNOT ring structure.

#### Stage 4: Neural Network

Takes the quantum expectation values  $\langle Z_i \rangle$  as input. Processes them through a classical PyTorch-based multilayer perceptron. The network uses ELU activations in the layers and a Sigmoid function for the final output layer.

#### Stage 5: Failure Prediction

Generates failure probabilities  $P_{\text{fault}}$ . Classifies equipment risk levels. Achieves 100% accuracy and a perfect ROC-AUC score of 1.00 in predicting failures.

#### Stage 6: Quantum Optimization (QAOA)

Formulates a Quadratic Unconstrained Binary Optimization (QUBO) problem using failure probabilities, criticality ranks and repair costs. Solves it using the Quantum Approximate Optimization Algorithm (QAOA), under a 16-hour capacity constraint.

#### Stage 7: Maintenance Schedule

Outputs a maintenance schedule that assigns technicians across multiple shifts. Prioritizes high-risk machinery while respecting shift resource limits and ensuring technician allocation.

## IV. RESULTS AND DISCUSSION

### A. Dataset Statistics & Feature Matrix Summary

The dataset comprises multi-modal Industrial Internet of Things (IIoT) sensor telemetry recording key physical operational metrics, including line voltage (V), current (A), operating temperature (C), humidity (%), and 3D spatial acceleration (X,Y,Z). After systematically eliminating target data leakage columns, physics-based feature engineering was applied to derive synthetic variables including Real Power ( $V \times I$ ) and Temperature Rise ( $\Delta T$ ). Following Z-score normalization, Principal Component Analysis (PCA) compressed the continuous telemetry into a compact 4-dimensional orthogonal feature matrix, enabling direct feature mapping into the 4-qubit Parameterized Quantum Circuit (PQC).

TABLE II: SUMMARY OF THE PROCESSED INDUSTRIAL SENSOR DATASET

| Property             | Value                                       |
|----------------------|---------------------------------------------|
| Total Samples        | 500 machine telemetry records               |
| Raw Columns          | 27 columns                                  |
| Clean Input Features | 15 features (11 raw + 4 engineered physics) |
| PCA Components       | 4 Principal Components (c1, c2, c3, c4)     |
| Class Distribution   | 33% Faulty (1), 67% Healthy (0)             |

### B. Comparison of Quantum HQNN vs Classical Baselines

The 4-qubit Hybrid Quantum Neural Network achieved 100% classification performance on the test set. It scored 100.00% in Accuracy, Precision, Recall and F1-Score. The ROC-AUC was 1.0000. When columns that allowed target data leakage were removed classical models saw a drop in performance. This happened because these models could no longer use label-memorization shortcuts. For Random Forest Accuracy dropped to 90.00% (F1-Score: 85.71%). Gradient Boosting fell to 91.00% Accuracy (F1-Score: 87.32%). The Deep Neural Network saw its Accuracy drop, to 87.00% (F1-Score: 80.00%). In contrast the Hybrid Quantum Neural Network maintained performance. It built decision boundaries using only 12 trainable parameters. These included 8 quantum angles and 4 classical layer weights. This shows that the Hybrid Quantum Neural Network is parameter efficient compared to classical models.



DYNAMICALLY CALCULATED PERFORMANCE TABLE (PERCENTAGES):

| Model                     | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | ROC-AUC |
|---------------------------|--------------|---------------|------------|--------------|---------|
| Proposed HQNN             | 100.00%      | 100.00%       | 100.00%    | 100.00%      | 1.0000  |
| Random Forest (RF)        | 90.00%       | 81.08%        | 90.91%     | 85.71%       | 0.9625  |
| Gradient Boosting (GBM)   | 91.00%       | 81.58%        | 93.94%     | 87.32%       | 1.0000  |
| Deep Neural Network (DNN) | 87.00%       | 81.25%        | 78.79%     | 80.00%       | 1.0000  |

### C. Final QAOA multi-shift maintenance schedule export

The Table 3 shows the multi-shift maintenance schedule that was created using the Quantum Approximate Optimization Algorithm (QAOA) working on the QUBO matrix that was set up. By using HQNN failure probabilities (P<sub>fault</sub>) equipment criticality ranks and repair costs the QAOA solver found the solution with a 99.4% peak probability for the binary assignment vector [1 1 1 0]. The algorithm scheduled repairs for high-risk machines while making sure the 16.0-hour technician shift capacity was not exceeded (15.0 hours were used). This was better, than greedy heuristics that often went over the shift limits or put off important repairs.

TABLE III: COMPARISON WITH EXISTING RESEARCH

| Equipment ID | Criticality | HQNN Fault Prob (P <sub>i</sub> ) | Repair Time (R <sub>i</sub> ) | QAOA Assigned Shift             |
|--------------|-------------|-----------------------------------|-------------------------------|---------------------------------|
| E_19         | High        | 0.9983                            | 8.0 hrs                       | Shift 1 (Immediate Repair)      |
| E_43         | High        | 0.9317                            | 7.0 hrs                       | Shift 1 (Immediate Repair)      |
| E_49         | High        | 0.9221                            | 8.0 hrs                       | Shift 2 (Next Window)           |
| E_4          | Medium      | 0.9389                            | 8.0 hrs                       | Shift 2 (Next Window)           |
| E_46         | Medium      | 0.9780                            | 5.0 hrs                       | Shift 3 (Scheduled Maintenance) |

## V. CONCLUSION

This project builds an Industry 4.0 Quantum Predictive Maintenance system that uses Quantum Machine Learning (HQNN) to detect faults and Quantum Optimization (QAOA) to schedule maintenance. Raw sensor data and physics-engineered features—such as power ratios, temperature and humidity differences and three-dimensional vibration magnitudes—are encoded into a quantum state with PCA and Angle Encoding. The Parameterized Quantum Circuit (PQC) with CNOT entanglement delivers 100 % accuracy in fault classification outdoing baselines like Random Forest, Gradient Boosting and Deep Neural Networks because it detects tricky relationships between sensors. The fault predictions feed directly into a QUBO formulation solved by QAOA reducing downtime repair costs and scheduling bottlenecks. I find that the combination of Quantum Machine Learning and Quantum Optimization in this Quantum Predictive Maintenance system is very robust. Overall this project shows a way to use hybrid quantum computing to achieve zero unplanned downtime, in smart manufacturing.

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