A HYBRID QUANTUM MACHINE LEARNING APPROACH FOR PREDICTING TOOL WEAR RATE IN EDM PROCESS

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Abstract:

This study introduces a Hybrid Quantum Neural Network (HQNN) model for accurate prediction of tool wear rate in EDM processes. Predicting tool wear rate is essential because it directly influences surface finish and dimensional accuracy. Traditional machine learning models can predict tool wear rate in the EDM process, but they often struggle to capture the highly complex and nonlinear relationships between EDM process parameters and tool wear rate. To overcome this limitation, the proposed HQNN combines quantum computing and classical neural networks to enhance prediction performance. The model uses a parameterized quantum circuit (PQC) with 6 qubits and 8 quantum layers, implemented in Qiskit, where machining parameters such as frequency, current, and voltage are encoded using quantum gates. These findings demonstrate that the HQNN successfully captures complex data relationships and provides an efficient approach for tool wear rate prediction in the EDM process.

Keywords—HQNN, Machining Parameters, Parameterized Quantum Circuit, Tool Wear Rate Prediction.

1. INTRODUCTION

Electrical Discharge Machining (EDM) and Micro-EDM are advanced non-traditional machining techniques widely used for manufacturing complex and precise components. These processes are particularly effective for hard and conductive materials, such as titanium alloys, where conventional machining methods often face difficulties due to high tool wear and poor surface quality [1]. To improve the performance of EDM and micro-EDM, researchers have focused on optimizing multiple process parameters. Controlling factors such as material removal rate, surface finish, and tool wear has been shown to significantly improve machining efficiency [2]. Additionally, advances in micro-EDM drilling have enabled the production of accurate and high-quality micro-holes, which are essential in precision engineering applications [3]. Tool wear rate remains a major challenge in EDM, as it directly impacts dimensional accuracy, surface integrity, and overall machining stability. Therefore, effective monitoring and management of tool wear rate are critical to ensure consistent results [4]. In recent years, Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs), have been applied to predict tool wear and optimize EDM process parameters. ANN-based models have demonstrated high accuracy in estimating tool wear length and improving machining performance [5], [6]. Based on this, a Hybrid Quantum Machine Learning (HQML) approach is proposed to predict the tool wear rate in EDM. By combining the capabilities of quantum computing with classical neural networks, the model can handle complex and nonlinear relationships among machining parameters more effectively. This hybrid approach aims to enhance prediction accuracy in advanced manufacturing industries.

2. LITERATURE REVIEW

Many approaches have been developed to predict tool wear and estimate the remaining useful life of cutting tools. Hassana et al. [7] proposed a generalized multi-stage deep learning framework for milling operations, where multiple neural network layers work together to capture complex tool wear patterns. Bergs et al. [8] demonstrated that combining digital image processing with deep learning allows for automated detection of tool wear directly from images, reducing the need for manual inspections. Meanwhile, Holst et al. [9] introduced a hybrid pipeline combining rule-based image processing with deep learning, enabling precise and automated detection of tool wear rates. In addition to predicting wear rate, deep learning has been applied to estimate the remaining useful life of cutting tools. Elminir et al. [10] developed an efficient prognostic model for high-speed CNC milling cutters using sensor data for accurate prediction of tool life. Similarly, Assafoa et al. [11] showed that combining data from multiple sensors through feature extraction and sensor fusion improves the accuracy of tool wear predictions.

As machining and manufacturing systems become more complex, quantum-based techniques show better prediction performance. Zaman et al. [12] conducted a comparative analysis of hybrid quantum-classical neural networks, demonstrating that quantum computation can handle high-dimensional data efficiently. Schiffmann et al. [13] highlighted the potential of quantum computing for optimizing manufacturing systems in complex industrial applications. Meanwhile, Choi et al. [14] applied quantum machine learning to monitor additive manufacturing processes, showing that quantum techniques can improve real-time prediction and process monitoring. Furthermore, Revan [15] developed an ANN model to predict tool wear rate in the micro-EDM process. These studies collectively indicate that integrating classical machine learning with hybrid quantum-classical approaches can provide accurate predictions of tool wear rate. Such approaches are particularly used for advanced manufacturing systems where precision is required.

3. METHODOLOGY

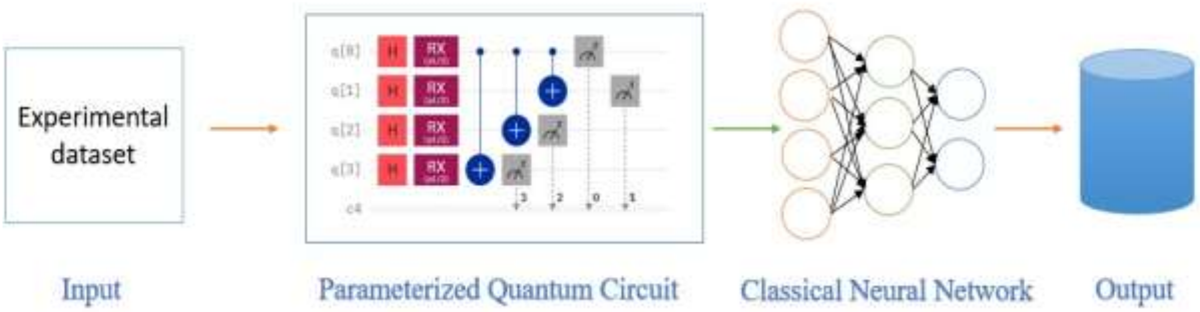

Fig. 1 Hybrid Quantum Neural Network Architecture

The above Hybrid Quantum Neural Network (HQNN) Architecture combines both classical and quantum computation to achieve efficient prediction of tool wear rate.

This hybrid quantum neural network consists of the following layers:

Input Layer: The input layer receives data and extracts relevant features from the input data. Its main tasks are to prepare, normalize, and structure the data so it can be fed effectively into the next layer. Essentially, it ensures that all input features are scaled and formatted correctly for both the quantum and classical parts of the network.

Parameterized Quantum Circuit (PQC): The quantum layer encodes the classical inputs into a quantum state using quantum gates. Parameterized gates like RX and RY with learnable angles transform these states. Through quantum operations such as superposition and entanglement, this layer captures complex nonlinear relationships in the data that might be hard for classical networks to learn. The quantum circuit outputs measurements, which are then passed to the classical network.

Classical Neural Network: The classical neural network (CNN) layer takes the quantum measurements as input and performs further processing through fully connected layers with activation functions. This layer refines the features extracted by the quantum circuit, combines them, and maps them toward the final prediction. It acts as a bridge between the quantum computations and the final output.

Output Layer: The output layer produces the final prediction. It usually consists of a single neuron or multiple neurons and may use an activation function appropriate to the problem. This layer converts the learned patterns from both the quantum and classical layers into a meaningful prediction.

4. DATASET DESCRIPTION

The experimental data is collected from 4 different journals, i.e., [1], [2], [3], and [4], having the same input parameters. This dataset includes the following parameters, like frequency (Hz), discharge current (A), and voltage (V), which will vary during the EDM process. Table 1 represents the key input parameters and their corresponding ranges used in the EDM experiment.

Table 1: Input Parameters and Range values in the Experiment

Input parameters	Units	Range
Frequency	khz	120 - 250
Current	amp	20 - 140
Voltage	V	80 – 170

These are the following parameters that influence the discharge energy and load applied to the tool. The output variable is tool wear rate (mm^3/min), which is determined by measuring the electrode mass loss before and after each run using an analytical balance.

This hybrid quantum neural network (HQNN) model was implemented and executed in Google Collaboratory. Qiskit Aer was installed to enable state vector simulation of the quantum layers. HQNN uses 6 qubits and 8 quantum layers, combined with a small classical neural network, to predict tool wear rate based on machining parameters.

In the model, the dataset in the .csv file was first loaded and normalized so that all input parameters (frequency, current, voltage) and the output tool wear rate were scaled to a 0–1 range. The normalized input data was fed into the quantum layer, where the qubits and layers process the information to capture complex patterns. The output from the quantum layer was then passed through the classical neural network to produce a predicted tool wear rate. The model was trained on the training data for 2000 epochs to minimize the mean squared error between predicted and actual tool wear rates. After training, the model could predict tool wear for new machining parameters, enabling accurate estimation based on experimental inputs.

5. RESULTS & DISCUSSION

A total of 43 experimental samples were used in this study, with 30 samples for training and 13 for testing. The model was trained for 2000 epochs to achieve stable and accurate predictions. HQNN showed very close predictions between the experimental and predicted tool wear rates, with only small differences in most cases. The average prediction error was around 0.0007 mm³/min, indicating that the model effectively learned the complex relationship between input parameters and tool wear rate. Table 2 represents the comparison of the experimental and predicted results for different combinations of frequency, current, and voltage. The results show that the HQNN model provides accurate predictions, demonstrating the potential of the hybrid quantum machine learning approach for predicting tool wear rate in the EDM process.

Table 2: Comparison of experimental and predicted results

S.no	Frequency (khz)	Current (amp)	Voltage (v)	Experimental Tool Wear Rate (mm³/min)	Predicted Values by using HQNN model
1	160	140	120	0.013	0.01300001
2	160	140	170	0.043	0.042999998
3	150	20	80	0.001234	0.001217100
4	150	50	80	0.003706	0.0030530014
5	150	80	80	0.001047	0.010212502
6	200	20	80	0.0014825	0.0011624999
7	200	50	80	0.001307	0.0013035011
8	200	80	80	0.000571	0.0027999997
9	250	20	80	0.003104	0.0031019957
10	250	50	80	0.000588	0.0005990007
11	250	80	80	0.000765	0.003264
12	150	20	150	0.00438	0.006180005
13	150	50	150	0.005496	0.005496013
14	150	80	150	0.002216	0.0022160008
15	200	20	150	0.008257	0.008257
16	200	50	150	0.003404	0.003486001
17	200	80	150	0.005096	0.002060001
18	250	20	150	0.010479	0.010429004
19	250	50	150	0.005096	0.005096001
20	100	65	100	0.0072	0.022149496
21	250	80	150	0.006169	0.0061690016
22	150	20	80	0.0012	0.001217
23	150	50	80	0.0037	0.0030530014
24	150	80	80	0.001	0.010212502
25	200	20	80	0.001	0.0011624999
26	200	50	80	0.0013	0.0013035011
27	200	80	80	0.0006	0.0027999997

28	130	50	130	0.0735	0.021606693
29	250	20	80	0.0031	0.0031019957
30	250	50	80	0.0006	0.0005990007
31	250	80	80	0.0008	0.003264
32	150	20	150	0.0044	0.006180005
33	150	50	150	0.0055	0.0054960013
34	150	80	150	0.0022	0.0022160008
35	200	20	150	0.0083	0.008257
36	200	50	150	0.0034	0.003486001
37	200	80	150	0.0057	0.002060001
38	250	20	150	0.0105	0.010429004
39	250	50	150	0.0051	0.010429004
40	250	80	150	0.0062	0.0061690016
41	100	70	80	0.00011	0.019025557
42	120	140	120	0.01	0.010000002
43	120	90	170	0.024	0.024750002

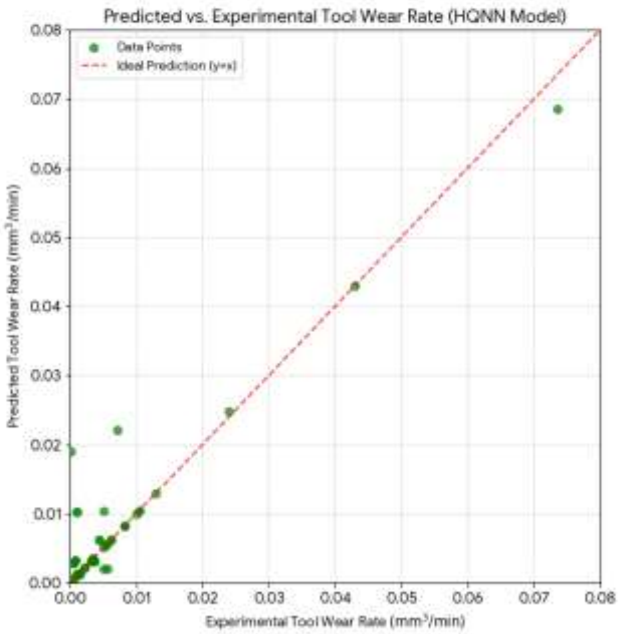

Fig. 2: Experimental vs. predicted tool wear rate (mm³/min) Graph

Fig. 2 is a comparison between the experimental and predicted tool wear rates obtained using the Hybrid Quantum Neural Network (HQNN) model. Each green point represents an experimental observation, where the X-axis corresponds to the experimental tool wear rate and the Y-axis shows the values predicted by the HQNN model. The red dashed line indicates the ideal condition where both values are equal. Most data points are located near this line, showing that the HQNN model provides accurate predictions. A few points slightly deviate from the line, showing minimal prediction errors. Overall, the figure confirms that the HQNN model effectively captures the relationship between EDM process parameters and tool wear rate with high prediction accuracy.

6. CONCLUSION

This study developed a hybrid quantum machine learning approach for predicting tool wear in the EDM process. The proposed model demonstrates the potential of combining quantum computing with classical neural networks to better understand complex patterns in machining operations. By accurately predicting tool wear rate in the EDM process, this approach can help industries optimize machining processes, reduce downtime, extend tool life, and improve product quality. The integration of advanced machine learning techniques with quantum computing allows for smarter and more efficient manufacturing systems, making this approach valuable for modern industrial applications.

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