Development of Surface Roughness Prediction and Monitoring System in Milling Process

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ABSTRACT

High surface quality is an important indicator for high-performance machining during the manufacturing process. The surface roughness generated in machining can be affected by cutting parameters and machining vibration. To achieve processing efficiency, monitoring surface quality within the desired range is important. This study aimed to develop a surface roughness prediction system for the milling process. The predictive model was established based on data collected from machining experiments with the response surface methodology. The surface roughness is related to independent variables, including cutting parameters and machining vibration, in terms of nonlinear functions by regression analysis and the neural network approach, respectively. To be implemented in a CNC milling machine for online application, a predictive model was introduced in the Virtual Machine Extension (VMX) intelligent software development platform. This model can acquire the cutting parameters from the controller via the Open Platform Communications Unified Architecture (OPCUA) interface as well as the vibration features from the sensory module. The system can calculate the roughness based on these data and issue alert when the predicted value exceeds the preset threshold or abnormal vibration is detected.

Keywords-artificial neural networks; cutting conditions; machining vibration; surface roughness

I. INTRODUCTION

With high demand of processing efficiency and high quality, high speed machining technology has been widely applied in the cutting process of machine components used in aerospace industry and 3C industry among others. In addition to high material remove rate, high surface quality is another important indicator in the manufacturing process for achieving high performance machining. Machining quality basically can be characterized by surface roughness. Basically, poor surface roughness will affect the tribological characteristics of the contact surfaces, wear behavior, and the fatigue strength of components [1-3]. The surface roughness generated on the machined parts can be influenced by many factors such as geometry and material of cutter, workpiece material, cutting parameters, coolant conditions, machine conditions, etc. [4-7]. Cutting parameters such as axial depth of cut, spindle speed, and feed rate were shown to have great impacts on surface quality [8-10]. The optimization of cutting conditions is a prerequisite for producing better surface accuracy [11-14]. Therefore, monitoring the surface quality within the desired range is of great importance and worthy of investigation. For this purpose, authors in [14] proposed a two-pronged approach combining Machine Learning (ML) and Nondominated Sorting Genetic Algorithm (NSGA-II) to model and optimize surface roughness and tool flank wear. The experimental verification showed that the absolute percentage errors of roughness and flank wear were 2.5% and 1.5%, respectively. Authors in [15] applied multivariable regression analysis to establish a prediction model of surface roughness based on the cutting parameters, tool wear and tool vibration. They found that feed rate is the main factor affecting surface accuracy, and spindle speed is the main factor affecting tool vibration in machining. Authors in [16] proposed a multi-objective optimization algorithm to minimize vibration amplitude and surface roughness. The objective functions and the second-order response surface models for surface roughness and vibration amplitude were created by performing regression analysis based on experimentally collected data. Authors in [17] also presented regression models in the form of nonlinear polynomial function and power-law functions to predict the surface roughness of milled surface, which were verified with higher prediction accuracy of about 90%. These studies show that the influence extent of cutting parameters on the surface roughness is different, which is dependent on machine spindle tool system, geometry characteristics and material of the cutter, workpiece material and selected cutting parameters in the experimental conditions. On the other hand, the high-speed cutting process is prone to induce chattering phenomena by the excitation of cutting force under inappropriate cutting parameters. Chatter vibration will adversely affect the surface quality and dimension accuracy of the workpiece, and cause noise and premature tool failure. In order to avoid chatter vibration, an appropriate cutting condition is necessary, which basically can be determined by the machining stability of the cutter. A cutting condition within a stable region can ensure machining without chatter and hence improve surface quality. In addition, critical cutting parameters with larger cutting depth can achieve maximum removal rate with high efficiency, but it may lead to poor surface quality due to excessive tool vibration or wear damage. Therefore, monitoring of the workpiece surface accuracy and tool damage are major concerns [18-21]. Authors in [18-19] applied sensing modules to measure the tool vibration and to detect possible damage of the tool. Authors in [21] developed a dynamic monitoring system of surface roughness by applying a neural network model. The roughness prediction model was established based on spindle speed, depth of cut, feed rate, and tool vibration in X and Z axes. Authors in [22] reported that workpiece surface morphology is affected by the vibration of the cutter in machining. They found that an increased cutting force with an increasing cutting depth and feed rate leads to higher vibration, and it accordingly augments surface roughness. Authors in [23-25] reported that surface roughness is greatly affected by the vibration amplitude of the machine tool and the axial cutting depth. The vibration levels are closely related to the cutting parameters and they become greater with an increase in the cutting speed and feed rate. Authors in [26] considered the influence of machining vibration on surface quality when establishing the surface prediction model. The input variables included cutting parameters, tooling condition, and tool vibration and were assessed in the turning process.

For improving machining quality, it is important and necessary to develop a reliable prediction model of the surface roughness, which can help engineers to detect the variation of the surface quality in process and further confirm whether the workpiece really meets the accuracy requirements without off-line physically measurements. Online monitoring can help to immediately prognose the poor accuracy causes, making improvements and adjustments of cutting parameters, and enhance machining efficiency. This concept is also an important core technology for the development of intelligent manufacturing. Based on this concept, this study aims to develop an online surface quality monitoring system, attempting to predict the surface roughness variation in milling machining considering the machining vibration, which may be affected by tool wear with machining cycles. In this study, a series of machining experiments were conducted under various combinations of cutting conditions. The dataset collected from the experiments, including machining parameters and vibration features of the spindle tool and surface roughness of the machined parts, were used to establish the prediction model by multivariable linear regression analysis and artificial neural network modeling. Finally, a monitoring system, including the data sensing modules and data processing software, was constructed and implemented in the milling machine. The system can automatically detect the vibration state and predict the variation of surface roughness in process.

II. EXPERIMENTAL CONFIGURATION AND PROCESS

Figure 1 shows the machining experiments conducted on a vertical milling machine, in which a tungsten carbide end cutter with a diameter of 10 mm and 60 mm overhang was installed in spindle with the BT tool holder. The workpieces are Al6061 aluminum alloy blocks with dimension of 150 × 150 × 80 mm. The machining process was carried out by full slot milling on the workpieces along the X-direction under different cutting parameters. In order to establish a surface roughness predictive model, valid for low speed rough machining and high speed finish machining, the cutting parameters, such as cutting depth, spindle speed, and feed rate were defined in a wide range with several levels as presented in Table I. The axial cutting depth (Z) was 1, 1.5, 2.0, 2.5, 3.0, 3.5 and 4.0 mm. It was defined in the stable region based on the machining stability lobe diagram of the cutter. There are 168 machining conditions defined by the different levels of cutting parameters, including 8 spindle speeds, 3 feed rates, and 7 cutting depths.

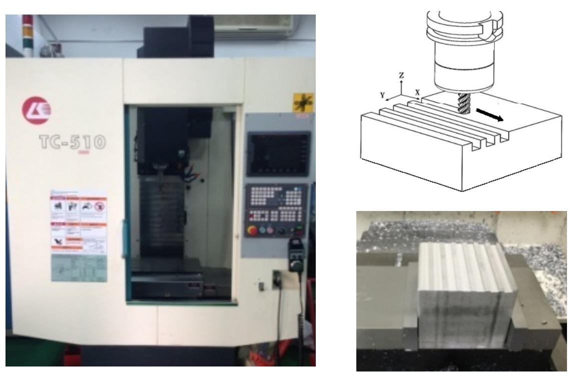

Fig. 1. Machining test and workpiece.

TABLE I. CUTTING PARAMETERS AND THEIR LEVELS

Parameters	Symbol	Levels
Spindle speed (rpm)	S	3000, 4000, 5000, 6000 7000, 8000, 9000, 10000
Cutting depth (mm)	Z	1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0
Feed rate (mm/flute)	F	0.05, 0.075, 0.10

To assess the vibration of the spindle tool in machining, accelerometers (Wilcoxon, Model 787, 500 mV/g, 22kHz) were mounted on the spindle housing to measure the vibration signals in X, Y, and Z directions simultaneously. For each slot machining, the Root Mean Square (RMS) value of the vibration signals during the milling period was calculated for further data analysis. For each machined slot, the surface roughness value (Ra) was measured at 5 equally spaced points along the feeding direction with a white light interferometer (Zygo, NewView™ 8000 Series). The mean value of the 5 measurements was calculated and collected along with the cutting parameters for subsequent analysis. The morphologies of machined surfaces and the vibration spectrum of the milling tool under specific machining conditions are illustrated in Figure 2. For example, for machining at cutting depth of 1.0 mm and speed of 4000 rpm, the surface roughness was measured as 0.834 µm. When cutting depth was increased to 2.0 mm at 7000 rpm, the roughness Ra was 2.227 µm.

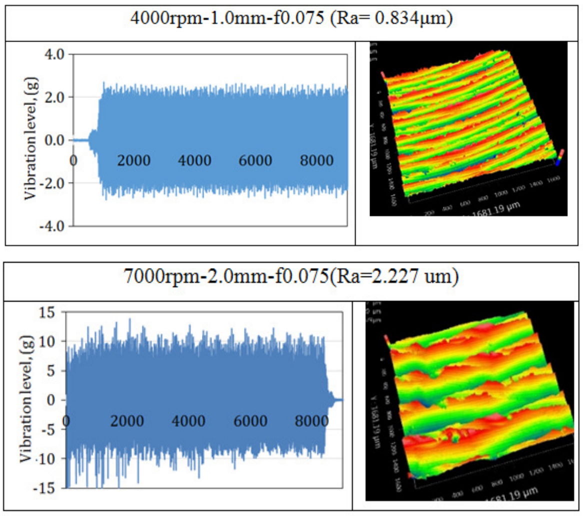

Fig. 2. Surface morphologies and vibration spectrum.

III. MODEL DEVELOPMENT

A. Regression Analysis

Basically, the roughness generated on the machined surface is mainly determined by the cutting parameters and can be affected by tool vibrations induced during the machining process. The dependence of surface roughness on the process parameters can be mathematically formulated in different functions through multivariable regression analysis. Based on previous studies [17, 27], the surface roughness (Ra) can be successfully related to various parameters such as axial cutting depth (*Z*), spindle speed (*S*), feed rate (*F*), and machining vibration (V_b) by a nonlinear model in the form of a power law formula:

$$\mathrm{Ra} = CZ^{\beta_1} S^{\beta_2} F^{\beta_3} V_b^{\beta_4} \tag{1}$$

The power-law model can be expressed in logarithmic transformation form:

$$\ln\mathrm{Ra} = \ln C + \beta_1 \ln Z + \beta_2 \ln S + \beta_3 \ln F + \beta_4 \ln V_b \tag{2}$$

The influences of the parameters and their interactions on the surface roughness were considered. The regression coefficients β_i (i = 0, 1, 2) are to be estimated from the experimental data by the method of least squares regression analysis.

B. Artificial Neural Network Model

Artificial Neural Networks (ANNs) have been recognized as a powerful tool to establish a high nonlinear correlation between dependent and independent variables and the interactive effects among variables. In this study, cutting parameters, such as spindle speed and cutting depth were selected at 8 and 7 levels, respectively. This eventually yields the nonlinear characteristic of the surface roughness with cutting parameters. Therefore, ANN modeling approach was employed to establish the predictive model of surface roughness [27-30]. A three layered ANN with one input layer, one hidden layer, and one output layer was considered the appropriate architecture to model the surface roughness during the machining process. The variables or the neuron used input layer are spindle speed, feed rate, axial cutting depth, and machining vibration of the spindle tool. The target to be predicted in the output layer is the surface roughness of the machined parts. The neuron in hidden layer provides the relationship between the input and the output layers and delivers the processed data from the neurons in the input layers to neurons in the output layer. A general form characterizing the relationship between input data and the neurons in the hidden layer is given by:

$$x_{hidden,j} = \sum_{i=1}^{n} W_{ij} u_i + \theta_j \tag{3}$$

where W_{ij} is the weight coefficient between the input and the hidden neurons, u_i is the value of the input, and θ_j denotes the biases of the hidden neurons.

The effectiveness of ANN models is dependent on various characteristics such as network architecture, activation functions, and training algorithms. Essentially, the Multilayer Perception (MLP) network was used to establish the predictive model, which was trained with the application of the Broyden–Fletcher–Goldfarb–Shanno (BFGS) method, conjugate gradient, and the steepest descent training algorithm. Another ANN network is the Radial Basis Function (RBF) network, which has equivalent capabilities to the MLP model, but with faster training [30]. To realize the best network, the activation functions—Rectified Linear Unit (ReLU), tanh, logistic were chosen based on their ability to introduce non-linearity and facilitate learning complex patterns of the data. A trial and error scheme was used to determine the appropriate number of hidden neurons. Further, the error function was used to determine errors between the actual and the calculated values during learning, testing, and validation:

$$Errors = \sum_{i=1}^{N} (y_i - t_i)^2 / N \tag{4}$$

The prediction performance of the regression models can be evaluated with the Root Mean Squared Error (*RMSE*), determination coefficient (*R*), and Mean Absolute Percentage Error (*MAPE*):

$$RMSE = \left(\left(\sum_{i=1}^{N} |t_i - y_i|^2 \right) / N \right)^{1/2} \tag{5}$$

$$R^2 = 1 - \left(\sum_{i=1}^{N} (t_i - y_i)^2 / \sum_{1}^{N} (y_i)^2 \right) \tag{6}$$

$$MAPE = \sum_{i=1}^{N} ((t_i - y_i)/t_i) \times 100)/N \tag{7}$$

where t is the target value, y is the predicted value, and N is the number of samples.

IV. RESULTS AND DISCUSSIONS

A. *Variation of Surface Roughness*

Variations of the surface roughness with changing of cutting parameters are illustrated in Figure 3. In addition to fewer samples with significant roughness generated at certain cutting parameter value, the roughness value of all machined surfaces essentially ranges from 0.6 to 3.7 μm, depending on the cutting conditions used in machining. At specific speed, poor surface roughness was generated under a larger cutting depth (Figure 3(a)). At a certain cutting depth, there is no significant trend in the effect of spindle speed on the surface roughness, but it is clearly shown that when machining was conducted under speed between 6000 and 8000 rpm with cutting depth above 3.0 mm, the surface roughness increases significantly.

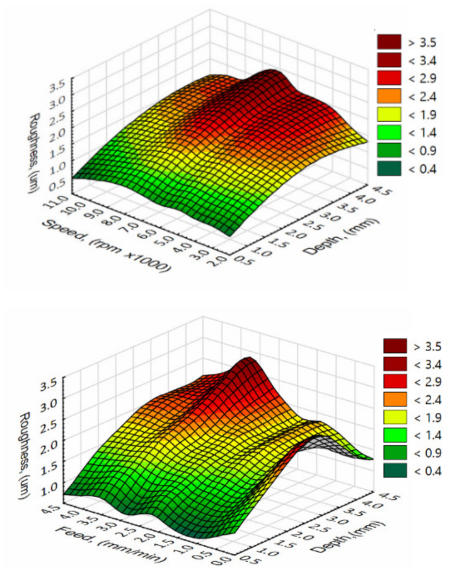

Fig. 3. Distribution of surface roughness under different cutting conditions: (a)speed and depth, (b) feed and depth.

Figure 3(b) shows the surface roughness generated at different feed rates and depths. Obviously, the surface finish produced under high feed rates (> 2500 mm/min) and spindle speeds between 6000 and 8000 rpm is significantly worse. Similarly, the surface finish produced by high feed rates (>2500 mm/min) and spindle speeds between 6000 and 8000 rpm is also significantly worse. Overall, the surface roughness increases as the depth of cut increases. A higher feed rate generates higher roughness on the machined surface, which means that the feed rate has a certain influence on the surface roughness. Basically, appropriate values of spindle speed, feed rate, and depth of cut can be selected to improve the machining quality and processing efficiency from the response surface plot against different combination of the cutting parameters.

B. *Variation of Machining Vibration*

Figure 4 shows the variation of the machining vibration generated at different cutting conditions. When the specific speed is 6000 to 8000 rpm and the depth of cut is above 3.0 mm, the vibration of the tool increases significantly, resulting in a significant increase in surface roughness. The same phenomenon of significant increase in tool vibration was observed for high feed rate (> 2500 mm/min) and large depth of cut (> 2.5 mm), affecting the machining quality with higher roughness value.

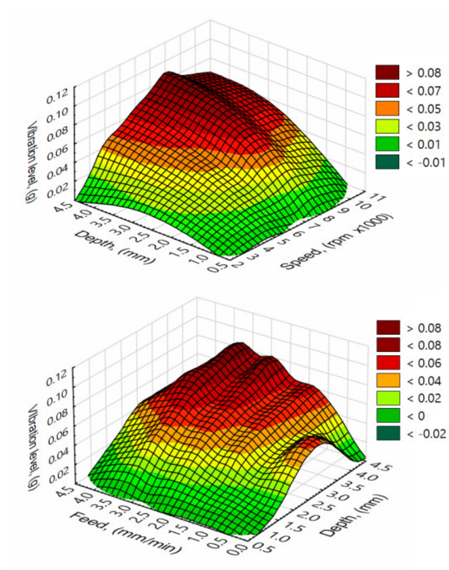

Fig. 4. Response surface of tool vibration under different conditions: (a) speed and depth, (b) depth and feed.

C. *Regression Model of Surface Roughness*

From the statistical analysis based on the experimental results, the influence of machining parameters and tool vibration on the surface quality of the workpiece was clearly examined. The statistical coefficients of regression analysis are shown in Tables II. The resulting regression equation of surface roughness is:

$$\text{Ra} = 20.345 Z^{0.24585} S^{0.6628} F^{0.4907} V_b^{0.20573} \tag{8}$$

It should be noted that the regression model in explicit form clearly shows the influence of the individual parameters and their interactive effects on surface roughness. The spindle speed has a negative effect on roughness, while the cutting depth and feed rate show a positive influence. In other words, the roughness shows a tendency to increase with the increase of feed rate or cutting depth, but it decreases with increasing spindle speed. The scatter plots between the measured roughness and the predicted values of all 168 samples are shown in Figure 5, which indicates the close correlation between them. The correlation coefficient between the measured and the predicted values is around 0.79 and the average prediction error is 14.5%. The results demonstrate that the regression model based on cutting parameters (spindle speed, cutting depth, and feed rate) and machining vibration displays certain accuracy in predicting the surface roughness. This also indicates that the tool vibration induced in machining process substantially affects the surface quality of the machined parts.

TABLE II. REGRESSION PARAMETERS OF NONLINEAR POWER-LAW Ra MODEL

Parameter	Coefficient	Standard deviation	P-value
Intercept	3.01287	0.45928	6.81E-10
Cutting depth (*Z*)	0.24584	0.04472	1.46E-07
Spindle speed (*S*)	-0.6628	0.06959	2.25E-17
Feed rate (*F*)	0.49073	0.05326	1.52E-16
Vibration (V_b)	0.20577	0.02853	1.95E-11

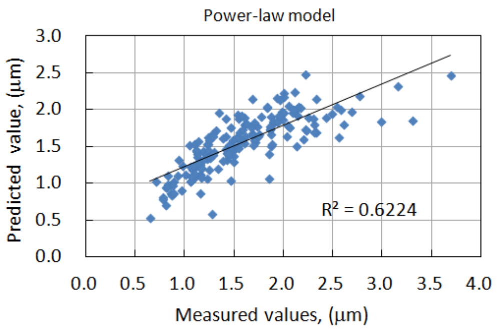

Fig. 5. Comparison of the surface roughness between measurements and regression predictions.

D. ANN Predictive Model

A dataset collected from machining tests was used to create the ANN predictive models, in which 80% of the records were selected for model training, 10% of the records were used for testing, and the rest for validation. The ANN modeling was conducted utilizing MLP and RBF networks, respectively by Statistica Neural Networks software [31]. After many attempts, the ANN models were evaluated by observing prediction performance and correlation coefficient. In the MLP architecture, the activation functions, logistic and tanh are found to have good performance, enhancing the learning efficiency and accuracy. RBF networks typically have three layers: an input layer, a hidden layer with a non-linear activation function, and a linear output layer. To initialize the network, the weights are set to random values. Subsequently, through the application of a training algorithm, these weights are iteratively adjusted until they converge to specific values employing the training algorithm and activation functions. This iterative process refines the network, enhancing its ability to accurately model and learn from the training data.

In this study, four ANN models with optimum performance were selected, as listed in Table III. The ANN models are labeled with the number of neurons in each layer, and the optimized number of neurons in the hidden layer. For example, MLP 4-14-1 and MLP 4-30-1, were optimized with 14 and 30 neurons in the hidden layer, respectively. The sensitivity levels of the constructed ANN input parameters are also given in Table III. Essentially, a parameter with small sensitivity value has more influence on the output parameter and a parameter with larger sensitivity value shows less influence. As a whole, the spindle speed has the larger sensitivity values.

TABLE III. SENSITIVITY LEVEL OF THE INPUT VARIABLES OF THE SELECTED ANN MODELS

ANN model	Sensitivity of input variables			
	Speed (rpm)	**Feed (mm/min)**	**Depth (mm)**	**Vibration level (g)**
MLP 4-14-1	6.687	5.540	4.014	2.278
MLP 4-16-1	7.506	7.473	4.697	2.877
MLP 4-22-1	5.370	5.290	5.792	3.649
MLP 4-30-1	5.453	5.032	5.407	2.194

Figure 6 depicts the variations of MSE values of the MLP network with the training cycles. It was found that MLP networks with activation functions tanh and logistic show similar learning efficiency with slow convergence performance (around 120 epochs). Both activation functions yield a good convergence to small prediction errors of about 0.002. Besides, the changes of error functions for training and testing dataset are relatively consistent. This indicates that there is no obvious over- or under-fitting problem in establishing MLP predictive models with tanh and logistic functions.

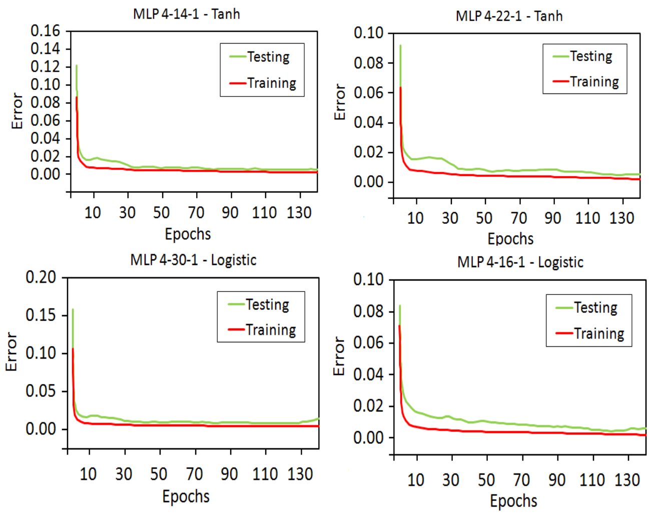

Fig. 6. Variations of the loss function of different MLP networks.

The variations of the MSE value of RBF networks with training cycles are shown in Figure 7. The RBF models show an efficient learning rate with fast convergence performance (around 20-30 training cycles) which is faster than that of the MLP networks. According to the training results presented in Figures 6 and 7, both MLP and RBF models are well trained. However, the prediction error of RBF models is around 0.01, which is higher than that of the MLP models, indicating that the MLP network has better fitting capability to the dataset. In addition, the number of neurons slightly affects the convergence process. Basically, more neurons increase the complexity of the model, easily generating the over-fitting problem. But this phenomenon was not observed in the MLP and RBF models considered in this study. As seen in Table IV, the prediction performance of the ANN models does not reveal any substantial variation across different configurations of hidden neurons.

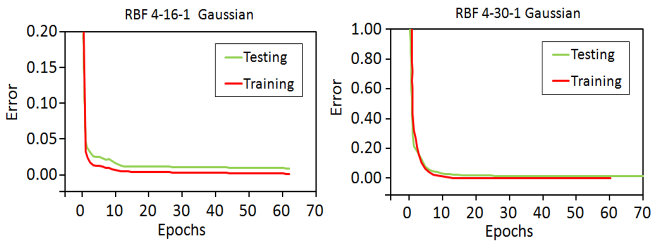

Fig. 7. Variations of the loss function of different RBF networks.

Figure 8 shows the comparison between the measured surface roughness and the predicted values of all samples, clearly indicating that roughness values predicted by the MLP models agree well with the measurements.

The prediction performance of the ANN models, evaluated in terms of determination coefficient R, RMSE, and MAPE, can be seen in Table IV. The values of R for the 4 MLP models with training, validation, and testing data are in the range 0.887–0.937, which means that for the selected ANN models, the MAPE of all datasets is about 9.47– 12.5% and the RMSE around 0.21-0.30. Nevertheless, for the RBF models, the MAPE and RMSE values are around 15.3–20.8% and 0.3–0.458, respectively. Comparing the statistical values listed in Table IV, the MLP models have significantly higher prediction accuracy than the RBF models. This result indicates that the MLP network is more suitable for establishing a predictive model based on the collected dataset from the machining process with a wide range of cutting conditions. This conclusion is similar to the findings reported in [30]. In addition, comparisons of prediction accuracy of multiple regression models and ANN models clearly reveal that the ANN models provided better results with higher accuracy of around 90%.

TABLE IV. STATISTICAL VALUES OF ANN MODELS

ANN model	Training dataset			Validation dataset			Testing dataset			Activation function	
	R	RMSE	MAPE	R	RMSE	MAPE	R	RMSE	MAPE	Hidden layer	Output layer
MLP 4-14-1	0.908	0.216	10.10%	0.897	0.298	11.80%	0.909	0.300	9.47%	Tanh	Logistic
MLP 4-16-1	0.902	0.222	11.64%	0.880	0.253	10.78%	0.937	0.290	11.54%	Logistic	Identity
MLP 4-22-1	0.900	0.224	10.73%	0.908	0.270	10.69%	0.928	0.270	9.99%	Tanh	Logistic
MLP 4-30-1	0.886	0.238	12.02%	0.910	0.297	9.64%	0.903	0.290	12.50%	Logistic	Identity
RBF 4-16-1	0.799	0.300	16.80%	0.816	0.330	20.80%	0.784	0.458	18.20%	Gaussian	Identity
RBF 4-30-1	0.781	0.310	15.30%	0.795	0.325	19.00%	0.782	0.447	17.90%	Gaussian	Identity

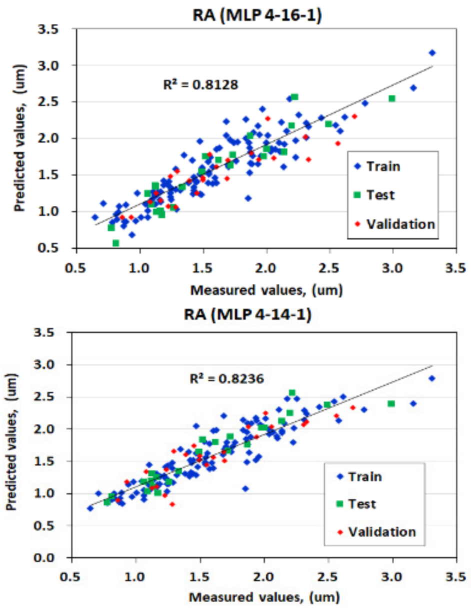

Fig. 8. Surface roughness value comparison between measurements and ANN predictions.

E. Model Verification

Additional machining experiments were carried out to validate the prediction model of surface roughness. Cutting operation was processed under different speeds, cutting depths, and feed rates, which were defined in the high stable region based on the stability lobes diagram [17]. Details of the cutting parameters are given in Table V. It should be noted that the dataset collected for model verification was not included in model training. Surface roughness was measured for each machined surface. As illustrated in Figure 9, the surface roughness under cutting depth of 3.5 mm and speed of 5500 rpm was measured as 1.668 µm. For cutting depth of 2.5 mm at a speed of 7500 rpm, the measured Ra was 1.985 µm.

TABLE V. EXPERIMENT PARAMETERS AND THEIR LEVELS.

Parameter	Level 1	Level 2	Level 3
Spindle speed (*S*, rpm)	5500	7500	9500
Cutting depth, (*Z*, mm)	1.5	2.5	3.5
Feed rate, (*F*, mm/min)	0.05	0.075	0.1

The roughness values obtained by prediction and measurement are summarized in Table VI, which also compares the prediction results of regression models and the selected ANN models.

TABLE VI. DATASET FOR MODEL VERIFICATION

No	Cutting parameters			Measured vibration	Measured Ra (μm)	Predicted Ra (μm)	
	Depth	Speed	Feed			Power law	ANN model
1	1.5	5500	2200	0.026	1.59	1.54	1.63
2	2.5	5500	2200	0.051	1.92	2.00	2.09
3	3.5	5500	2200	0.087	2.45	2.43	2.57
4	1.5	7500	3000	0.071	1.98	1.79	2.13
5	2.5	7500	3000	0.068	2.07	2.01	2.16
6	3.5	7500	3000	0.063	2.19	2.16	2.17
7	1.5	9500	3800	0.027	1.64	1.41	1.51
8	2.5	9500	3800	0.050	1.97	1.82	1.80
9	3.5	9500	3800	0.068	2.21	2.10	2.11
10	1.5	5500	1650	0.023	1.19	1.30	1.27
11	2.5	5500	1650	0.036	1.44	1.62	1.49
12	3.5	5500	1650	0.052	1.67	1.90	1.73
13	1.5	7500	2250	0.057	1.46	1.49	1.43
14	2.5	7500	2250	0.079	1.99	1.81	1.87
15	3.5	7500	2250	0.121	2.60	2.14	2.58
16	1.5	9500	2850	0.030	1.29	1.25	1.18
17	2.5	9500	2850	0.065	1.56	1.67	1.43
18	3.5	9500	2850	0.074	1.64	1.86	1.67
19	1.5	5500	1100	0.018	1.01	1.02	0.88
20	2.5	5500	1100	0.022	1.01	1.21	1.02
21	3.5	5500	1100	0.031	1.10	1.40	1.19
22	1.5	7500	1500	0.035	1.17	1.11	0.87
23	2.5	7500	1500	0.052	1.49	1.36	1.43
24	3.5	7500	1500	0.063	1.88	1.53	1.50
25	1.5	9500	1900	0.021	0.98	0.96	0.93
26	2.5	9500	1900	0.047	1.35	1.28	1.02
27	3.5	9500	1900	0.055	1.66	1.43	1.19
					MAPE	8.87%	8.11%
					RMSE	0.179	0.169
					R	0.916	0.946

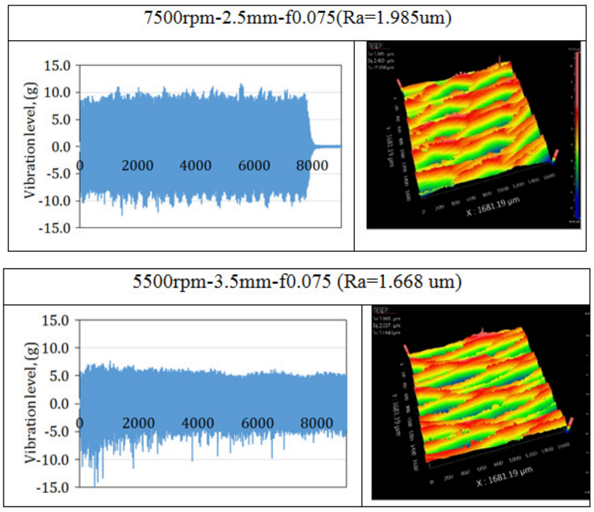

Fig. 9. Surface morphologies and vibration spectrum.

As shown in Figure 10, the correlation coefficients for ANN and regression models range between 0.946 and 0.916, which means that the predictions are in good agreement with the measurements for the verification dataset. Besides, based on *MAPE* and *RMSE* values, it is found that the ANN and regression models can predict roughness with high prediction accuracy of about 92%. Basically, the ANNs can generate different models based on the training data and training algorithm, yielding different prediction results. The number of neurons in the hidden layer will affect the prediction error and overall prediction performance. The verification tests again demonstrate that the established predictive models based on the machining parameters and vibration assessed from the milling process can accurately forecast the surface roughness generated at various cutting conditions.

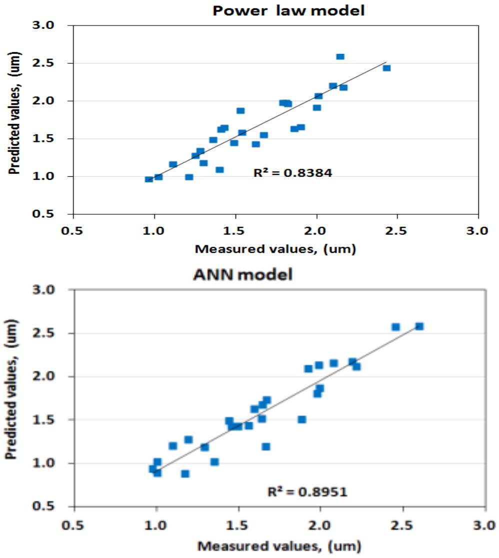

Fig. 10. Surface roughness comparison between measurements and predictions.

V. CONSTRUCTION OF THE MONITORING SYSTEM

In order to achieve online machining monitoring and real-time prediction, the processing parameters must be obtained from a controller. At present, the VMX intelligent software development platform developed by the Industrial Technology Research Institute in Taiwan can be connected to different controllers. The monitoring APPs developed with C language were implemented on the IIOT-VMX system in an industrial PC, including the data processing module and the surface roughness predictive model. The cutting parameters and various servo parameters in the controller can be easily accessed through the OPCUA communication interface. In addition, the machining vibration can be acquired from the accelerometers mounted on the spindle through a data acquisition device. The surface roughness model can be established through ANNs or regression analysis for model training and verification. In the milling process, the processing parameters and real-time vibration signals and features, which were fed as inputs into the prediction model, were directly extracted and processed. As illustrated in Figure 11, the user can preset the desired roughness and threshold of the vibration levels. The cutting parameters assessed from the controller and the time domain vibration levels in the 3 axes are simultaneously displayed on the screen. To monitor the variation of machining quality during the milling process, the system continuously outputs the roughness based on the input parameters with vibration features. At the same time, the system will issue an alert signal when the predicted roughness exceeds the threshold or vibration abnormalities are detected.

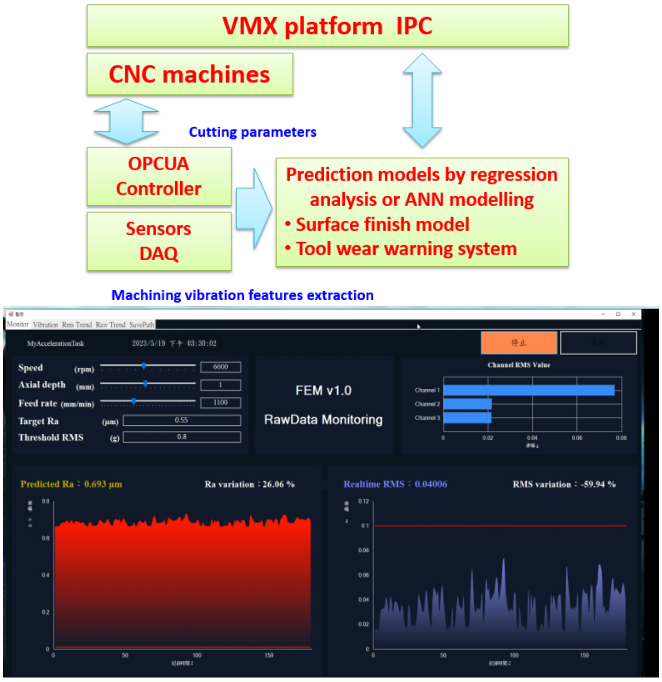

Fig. 11. Schematics of the surface quality monitoring system and the visualization interface.

VI. CONCLUSION

This study aimed to develop an online surface quality monitoring system, attempting to predict the variation of the surface roughness based on the cutting parameters and the vibration features during milling machining. Based on the acquired results, the following conclusions can be drawn:

- The cutting parameters for establishing the prediction model should be defined within the stable boundaries of the stability lobes diagram. This can ensure practical applicability for a variety of cutting process from low speed rough machining to high speed finishing machining.
- A surface roughness predictive model can be well developed by regression analysis with nonlinear power-law function or an MLP network with adequate defined training algorithm and activation functions, yielding superior prediction accuracy about 90%.
- The vibration assessed from the machine tool is a critical factor influencing surface roughness. It should be integrated along with the cutting parameters in the predictive model of the surface quality of the machined parts.
- The predictive model and the data processing module were integrated into the IIOT-VMX platform. This platform facilitates direct assessments of cutting parameters through the OPCUA interface and captures vibration features via a sensory module on the spindle tool. Subsequent testing results demonstrated the system's effectiveness, establishing its potential as an online surface quality monitoring system for practical machining processes.

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