Study of milling machining roughness prediction based on cutting force

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Abstract. Cutting parameters can be properly adjusted to increase machining precision, to enhance cutting efficiency, and to reduce cost. These parameters are generally chosen according to the recommended data from the tool maker’s technical manual with the synergy of the operator’s experiences. However, inappropriate parameters selection might not only damage cutter and the machine tool, but also worsen the surface roughness of the workpiece. Researches on improving surface roughness has been studied over the years, for example, on the optimization of cutting conditions, vibration measurement and analysis, and cutting forces measurement and analysis, to name only a few. However, most of them must have sensors installed on the machine tool for data collection before the analysis. This will increase the cost. Furthermore, the measurement of cutting force needs to have dynamometer which is not only expensive but is also not appropriate to be installed on a small-sized machine tool. This research focused on establishing the relationship between the cutting force and the surface roughness for the workpiece machining in a small-sized machine tool. In order to calculate the cutting force, cutting force coefficients were obtained based on the cutting test on the other machine tool rather than the small-sized machine. Tapping test was also conducted to obtain the frequency response function of the machine. The cutting forces were calculated based on the cutting force coefficients and the frequency response function. The calculated cutting forces were then converted through the proposed methodologies into eleven characteristic values. Finally, two commonly used machine learning algorithms, multivariate linear regression and generalized regression neural network were adopted for regression analysis to establish the relationship between the cutting forces and the surface roughness. The results have shown that the prediction by generalized regression neural network is better than that of multivariate linear regression. The major contribution of this paper is that appropriate algorithms have been studied, compared and verified so that the relationship between cutting force and surface roughness can be established. This means that surface roughness can be estimated based on the calculated cutting forces incorporating the machine tool’s frequency response function.

1. Introduction

During the cutting process, the changes of cutting force during the machining will affect the stability of the whole machine. In severe cases, it will worsen the quality of the workpiece, incur fast tool wear, affect the reliability, shorten useful life of the machine, and directly reduce production efficiency.
Smith and Tlusty [1] had shown that the analysis of “stability lobe diagram” is more important in high-speed milling, because there is a wide and highly stable cutting area during high-speed milling. Chiou, Chung and Liang [2] used a dynamometer to verify and analyse the chatter stability diagram and found that the tool wear loss could be calculated using the Coriolis force equation to obtain a difference in feed rate, which indirectly affects the damping coefficient and the cutting force. Tlusty and Andrews [3] developed processing technology for automatic detection; they used three kinds of sensors to detect cutting force, vibration and sound wave, respectively. Experimental analysis of turning and milling results showed that the cutting force sensor is the best because the chatter is more difficult to measure than that of vibration signal. Cutting forces was able to very clearly distinguish Chatter. Taylor [4] found the cutting chatter is mainly caused by the discontinuous cutting, the periodic cutting force and the mechanical parts of the machine tool (such as a part of the table and the drive system) are caused by the same natural frequency. Smith et. al [5] discussed the stability of cutting after changing the tool length - after the tool holder holds the tool, the length of the tool extends outward. When the tool is clamped on the spindle, it is like a cantilever beam structure. When the external length of the tool is different, the rigidity of the machine structure is also different. Because the tool, workpiece and machine tool structure form a closed system during cutting. If the external length of the tool is different, it directly changes the stability of cutting, and also changes the rigidity of the cutting process. When the tool overhang is longer, the main stable processing area becomes narrower, and it has no effects on the depth of cut.

Since stable and unstable cutting will affect the processing quality, in order to achieve the required upper quality level, the processing parameters are usually adjusted that the optimized application parameters could be obtained. The most commonly used method is the trial-and-error method of empirical rules, but the use of this method will conduct actual processing cutting and testing, and therefore, it is not only time-consuming but also waste of materials. Milton [6] discussed various phenomena and interactive effects in cutting. It was mentioned that cutting was a highly nonlinear behaviour. Davim [7] provided surface detection methods, from the earliest offline surface measurement to online direct surface measurement, and to online indirect surface measurement. Dimla, Lister and Leighton [8] organized various tool monitoring methods for cutting, and proposed analysis from multi-sensors through signal feature analysis by the use of neural network to find key features. Lauro, Brandao, Baldo, Reis, Davim [9] organized the commonly used methods and theories for cutting, signal acquisition, signal processing, and signal analysis cutting. Varghese and Radhakrishnan [10] discussed the integration of multiple sensors. It used the binary value of the root mean square of capacitive, inductive, and optical distance sensors as input. The binary values of the median, root mean square, and average roughness of the surface roughness were the output. A feed forward back propagation neural network was constructed. The number of neurons was tested in three hidden layers, and the surface roughness was predicted successfully by the experiment with the error less than 20%. Hossain, Amin and Patwari [11] only used the spindle speed, feed rate, and cutting depth as the input, and the surface roughness as the output; a two-layer Log sigmoid hidden layer with genetic algorithm (GA), the feedforward back-propagation neural network model was successfully constructed for nickel-aluminium alloy end milling. The error was below 8.3%, which showed that even under the condition of insufficient information, the function approximation ability of the neural network still has reliability. Wang [12] used spindle speed, feed rate, depth of cut and workpiece acceleration value as input, and surface roughness as output. A feed-forward backward neural network with LS-SVR algorithm was constructed. The obtained average relative error (ARE) by least square vector regression neural network is about 7%. Azlan, Habibollah and Safian [13] optimized the processing parameters through GA, found the best cutting conditions could be used to obtain the smallest surface roughness value. Ilhan and Mehmet [14] used artificial neural networks (ANN) and multiple regression methods to simulate the surface roughness prediction of AISI 1040 steel. The input parameters include cutting speed, feed rate and cutting depth, and the output was the surface roughness value. It was clearly seen from the results that ANN algorithm could optimize the processing parameters and reduce the surface roughness value compared with the multiple regression
model. Reddy [15] used composite materials (GFRP) for cutting, and found key factors through neural network algorithm. After analysis, it was found that cutting speed and cutting depth are important factors affecting surface roughness, which were 26.84% and 40.44%, respectively. Grynal, Srinivasa and Rashmi [16] thought that surface roughness prediction was too complicated because there were uncontrollable factors such as the impact of blade wear and machining vibration in the cutting process. Therefore, neural network algorithm (ANN), radial basis function neural network (RBFNN) and Summation Wavelet-Extreme Learning Machine (SW-ELM) were used to predict surface roughness. The research results showed that SW-ELM had a higher prediction accuracy. Gopan, Leo and Surendran et. al. [17] claimed that there were high requirements for surface roughness in the field of wear. Therefore, prediction of the surface roughness through neural network algorithm (ANN) were researched, but the ANN was easy to fall into the local solution. The optimization of ANN model through genetic algorithm (GA) could have a greater improvement in the accuracy of ANN. Titus, K., R. S., Prabhu, Sivakumar, Devaraj and Sathiskumar [18] developed neural network models for composite materials. Each input parameter is checked by using the ANOVA method, and then the material removal rate (Material Removal Rate, MRR) and surface roughness (Ra) were predicted by a neural network algorithm. According to the above literatures, the prediction of surface roughness is very important for a machined component but it seems that study on a small-sized machine has not been studied yet. This research is therefore aimed for predicting the surface roughness (Ra) by using neural network algorithm based on dynamic cutting forces according to the stable and unstable cutting through the SLD.

2. Dynamic cutting force operation process and method
In the machining process of a machine tool, the cutting energy of the machine is dispersed and the tool vibration is caused, which causes the unstable phenomenon of the cutting system and affects the surface of the workpiece. This phenomenon is called chatter. Generally self-excited chatter can be divided into three categories, the Regenerative Chatter, the Mode Coupling Chatter, and the Friction Chatter (Friction Chatter). Regenerative chattering is the most common case. It is due to the wavy surface left by the tool during the previous cutting, which causes unstable phenomena in the closed loop system of cutting and machine structure. On the surface of the workpiece, deeper cuts marks will be produced, resulting in a larger roughness on the surface of the workpiece, and fast tool wear. Such a vicious cycle will eventually cause damage to the tool, workpiece and even the machine. Therefore, this paper calculates the dynamic cutting force through the cutting force methodology [19]. The working process is shown in figure 1, and it includes two parts: (1) cutting experiment, and (2) machine tapping test.

![Figure 1. Flow chart of dynamic cutting force operation.](image-url)
2.1. Cutting experiment

The cutting experiment is used mainly to obtain six cutting force coefficients (CFCs) - Kae, Kac, Kre, Krc, Ktc, and Kte. These CFCs are then saved into cutting force coefficient (CFC) database. This research will establish the cutting force coefficients for Cu material. The tool type is shown in table 1.

The cutting experiment is Down-milling, the cutting depth is 0.5mm, and the spindle speed is 5120 rpm. According to the use of CuPro [19] software, five experiments are conducted, as shown in table 2, in order to obtain the average cutting force and establish a linear regression model (as figure 2). The linear regression equations are shown from equation (1) to (3).

\[
\text{Avg}(F_x) = a_x F_x + b
\]

(1)

\[
\text{Avg}(F_y) = a_y F_y + b
\]

(2)

\[
\text{Avg}(F_z) = a_z F_z + b
\]

(3)

Avg() is the average cutting force, \(F_x\) is the cutting force in the x direction, \(F_y\) is the cutting force in the y direction, \(F_z\) is the cutting force in the z direction. \(a_x\) is the slope in the x direction. \(a_y\) is the slope in the y direction. \(a_z\) is the slope in the z direction. \(b\) is a constant.

| Table 1. Tool type. |
|---------------------|
| Tool type | Solid carbide mill |
| Tool diameter | 3 mm |
| Tool material | Tungsten Carbide |
| Angle | 25° |
| Number of flutes | 2 |
| Cutter type | Flat-end |

| Table 2. Cutting force experiment table. |
|---------------------|
| Test no. | Feed per flute (mm/min) | Feed rate (mm/min) |
| 1 | 0.012 | 123 |
| 2 | 0.014 | 143 |
| 3 | 0.016 | 164 |
| 4 | 0.018 | 184 |
| 5 | 0.02 | 205 |
Figure 2. Regression model of average cutting force.

Next, the CutPro software was used to calculate the six CFCs through the average cutting force regression model, as shown in Equation (4) to Equation (9).

\[
K_{xc} = \frac{-4a_x F_y}{Na} \tag{4}
\]
\[
K_{xc} = \frac{-4a_x F_x}{Na} \tag{5}
\]
\[
K_{sc} = \frac{a_x F_z}{Na} \tag{6}
\]
\[
K_{sa} = \frac{a_y F_z}{Na} \tag{7}
\]
\[
K_{te} = \frac{-a_x F_z}{Na} \tag{8}
\]
\[
K_{se} = \frac{2a_x F_z}{Na} \tag{9}
\]

where \(N\) is Blade count, and \(a\) is Depth of cut.

It is found that these CFCs could be calculated if \(a_x, a_y, a_z\) are known. And \(a_x, a_y, a_z\) are the slopes of the linear regression equations. Therefore, as long as the slope could be obtained, the CFCs tend to be consistent, and the results of SLD and dynamic cutting force will also be similar to each other.
2.2. Machine's Frequency Response Function (FRF)
This research uses the impact hammer and acceleration sensor, as shown in figure 3, to obtain the vibration signal of the machine. The Frequency Response Function (FRF) could then be calculated from CutPro software.

After established the cutting force coefficient and the FRF of the machine, the stability lobe diagram (SLD) and dynamic cutting force could be calculated next. The SLD shows the relations between the depth of cut and the spindle speed with stable and unstable zones. This is important information for the machining processes, because it is necessary to avoid machining in the unstable zone. In addition, the generation of dynamic cutting forces is also important for the subsequent introduction of machine learning algorithms to calculate surface roughness.

![Figure 3. Machine tapping test.](image)

3. Space problem of small machine.
This research adopted a small turning and milling centre (TA20) manufactured by Arix Machinery Co. Ltd. The correlation between the cutting force and the surface roughness is calculated and predicted through adopted AI algorithms. The performance, specifications and dimensions of the machine are shown in table 3 and figure 4.

| Table 3. Small turning and milling centre (TA20). |
|-----------------------------------------------|
| **TA20**                                      |
| Controller                                    | Syntec 220MA-5 |
| Work space (mm)                               | 400*300*100    |
| X/Y/Z axis travel (mm)                        | 100/200/200    |
| X/Y/Z axis fast speed (m/min)                 | 10/10/10       |
| Max spindle speed (rpm)                       | 30,000         |
| Spindle motor output (kw)                     | 1              |
The dynamometer models used in this research are Kister 9265B and 9443B, the size of it is 220 mm * 100 mm * 186 mm, as shown in figure 5.

It can be seen from table 3 and figure 4 that the Kister dynamometer (9265B and 9443B) is too large to be installed in the work space of TA 20. This will lead to the problem that the cutting force signal cannot be obtained by cutting test in TA 20. Therefore, this study used the CFCs obtained based on the cutting tests on the other industrial machine tools, and then apply it to the small machine (TA20). In this way, the dynamic cutting force signal is obtained, and the surface roughness could be estimated for the subsequent machine learning algorithm.

4. Surface roughness processing experiment
Since the output end of the machine learning algorithm is surface roughness (Ra) value, therefore, this research carried out cutting experiments on the TA 20 so as to measure the machined surface roughness; the experimental parameters include processing speed and cutting depth, as listed as follows:
- Cutting speed (rpm): 5000, 7000, 9000, 11000, 13000, 15000, 17000, 19000.
- Depth of cutting (mm): 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5.

The tool type is shown in table 1. The workpiece is mainly copper rod, with a diameter of 20mm and a length of 100mm. Before the cutting processing, the copper rod was milled into a slope to facilitate subsequent surface roughness measurement. The machining experiment is carried out by milling in the Y direction, and eight layers of steps were cut on the inclined plane, and the cutting depth equals to the cutting width; and the eight layers of steps corresponded to the depth of cut, as shown in figure 6.
The total cutting experiment has a total of eight processing speeds and eight cutting depths, and then sixty four processing experiment data were obtained. Next, measure the surface roughness (Ra) of the workpiece through the surface roughness instrument produced Mitutoyo, model SJ-410, as shown in table 4.

### Table 4. Workpiece surface roughness (Ra).

| Cutting Speed (rpm) | Ap 0.1mm | Ap 0.3mm | Ap 0.5mm | Ap 0.7mm | Ap 0.9mm | Ap 1.1mm | Ap 1.3mm | Ap 1.5mm |
|---------------------|----------|----------|----------|----------|----------|----------|----------|----------|
| S5000               | 1.21     | 1.31     | 3        | 4.55     | 4.93     | 2.96     | 6.73     | 3.63     |
| S7000               | 0.31     | 1.147    | 0.797    | 2.807    | 2.261    | 4.2      | 4.34     | 4.72     |
| S9000               | 0.26     | 0.53     | 0.6      | 1.19     | 1.94     | 3.31     | 4.07     | 4.61     |
| S11000              | 0.242    | 0.9885   | 0.564    | 0.9515   | 1.127    | 1.425    | 1.39     | 0.675    |
| S13000              | 0.222    | 0.5115   | 0.537    | 0.9643   | 1.109    | 0.794    | 1.3935   | 1.011    |
| S15000              | 0.293    | 0.289    | 0.5785   | 1.1795   | 1.8675   | 1.174    | 1.4187   | 1.3585   |
| S17000              | 0.2287   | 0.4675   | 0.9507   | 0.8737   | 1.0973   | 0.6255   | 1.0105   | 0.963    |
| S19000              | 0.639    | 0.4633   | 0.5175   | 0.6955   | 0.78     | 0.905    | 1.289    | 0.9705   |

Since the maximum cutting depth of the processing parameter is already the radius of the tool, the vibration caused by the processing will increase with the cutting depth, and the vibration will also be greater. If the blade frequency of this vibration is just at the natural frequency of the machine, resonance phenomena or chatter will be induced, and the surface quality of the cutting workpiece will deteriorate as the vibration amplitude increases. Next, this research will try to find out the stable zone and the unstable zone from the SLD, and examine the relationship between the processing parameters and the SLD.
5. Stability Lobe Diagram (SLD) to analysis
Because the small machine cannot have a Dynamometer installed. So, the CFCs came from the other industrial normal-sized machine. Large industrial machines include the vertical machine centre by Tongtai since the worktable area is enough to setup the Kister dynamometer. The cutting force coefficient experiment were carried out and established. Therefore, based on the dynamic cutting force operation process (figure 7), this study obtained the CFCs from the VC608 machine centre, and then transferred to the TA20 processing machine, as shown in table 5 and figure 7.

|   | Ktc  | Krc  | Kac  | Kte  | Kre  | Kae  |
|---|------|------|------|------|------|------|
|   | 1567.32 | 695.04 | 216.75 | 2.71  | 7.03  | -3.11 |

![Figure 7. VC608 average cutting force regression model.](image)

Next, according to the dynamic cutting force operation flow, the FRF of the TA20 machine is obtained, as shown in figure 8. If the cutting frequency is the same as or close to the natural frequency, resonance will occur. At this time, if the rigidity of the machine is not good enough, chatter will occur, resulting in an increase in poorer surface roughness. The quality of the workpiece will decline, and even cause problems such as machine damage and tool damage. So, this figure will be able to provide users’ reference so as to avoid the natural frequency.

Because the surface roughness processing experiment used eight different speeds for machining, and the cutting width (Ae) is equal to the cutting depth (Ap) processing parameter. Therefore, in this study, CutPro will create a stability lobe diagram (SLD), examines the stable zone and unstable zone, and to mark them as shown in figure 9 to figure 16. Due to the influence of the machine's FRF, the maximum depth of cut and the stable depth of cut are also different due to the difference in processing speed and cutting width. For example, the processing speed is 5000rpm, the blade frequency is 166.67Hz, and the natural frequency is listed as follows:

- The 5th edge frequency 833Hz is close to the natural frequency in the y direction (825Hz).
- The 18th blade frequency 3012Hz is close to the natural frequency in the y direction (3012Hz).
When the tool blade frequency is close to the natural frequency, the maximum allowable depth of cut will be reduced. That is, the stable zone will also be limited. Next, according to the cutting depth range of the SLD, there are a stable zone and an unstable zone at different speeds, and the arrangement is shown in Table 6. It can be known from this table that at the processing speeds of 13000 rpm, 15000 rpm and 19000 rpm, due to the influence of the machine FRF, that the maximum cutting depth will be extended to 0.9 mm.
In this study, SLD was used to obtain stable depth of cut, maximum depth of cut, stable zone and unstable zone. Combined with the surface roughness (Ra), the trend between SLD and surface roughness (Ra) will be shown. However, due to errors in measurement, this study will use polynomial regression equations to solve. First, the surface roughness (Ra) in the stable zone was assumed to be polynomial regression (the trend of Ra in the stable zone has reproducible characteristics), as shown in figure 17. In addition, because the unstable zone contains chattering and instability, and contains randomness problems. So, it is not considered to do polynomial regression.

Table 6. The range of stable zone and unstable zone at different speeds.

| Cutting Speed (rpm) | Stable zone Ap (mm) | Unstable zone Ap (mm) |
|---------------------|---------------------|-----------------------|
| S5000               | 0.1 ~ 0.7           | 0.9 ~ 1.5             |
| S7000               | 0.1 ~ 0.7           | 0.9 ~ 1.5             |
| S9000               | 0.1 ~ 0.7           | 0.9 ~ 1.5             |
| S11000              | 0.1 ~ 0.7           | 0.9 ~ 1.5             |
| S13000              | 0.1 ~ 0.9           | 1.1 ~ 1.5             |
| S15000              | 0.1 ~ 0.9           | 1.1 ~ 1.5             |
| S17000              | 0.1 ~ 0.7           | 0.9 ~ 1.5             |
| S19000              | 0.1 ~ 0.9           | 1.1 ~ 1.5             |

Figure 13. S13000 (Stable and Unstable zone).

Figure 14. S15000 (Stable and Unstable zone).

Figure 15. S17000 (Stable and Unstable zone).

Figure 16. S19000 (Stable and Unstable zone).
This experiment used the parameter that the cutting width (Ae) is equal to the cutting depth (Ap), so the effective material removal area “Ae * Ap” was used for correlation. Then the polynomial regression equation in the stable zone is numerically normalized to the minimum value (ex: S5000, Ap 0.1mm) and maximum value (ex: S5000, Ap 0.7mm) in the stable zone of Ae*Ap. Arrange it as shown from figure 18 to figure 25.

**Figure 17.** S5000 Ra polynomial regression.

**Figure 18.** S5000 Ra tend analysis.

**Figure 19.** S7000 Ra tend analysis.

**Figure 20.** S9000 Ra tend analysis.

**Figure 21.** S11000 Ra tend analysis.
In this study, the Normalized Root-Mean-Square Deviation (NRMSD) formula was used to calculate the accuracy rate, as shown in Equation 10 and Equation 11. The accuracy rate calculated by the NRMSD formula were interpreted here as the confidence level.

\[
\text{NRMSD}(\%) = \left(1 - \frac{\text{RMSD}}{Y_{\text{max}} - Y_{\text{min}}} \right) \times 100\% 
\]

\[
\text{RMSD} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Y_i - \bar{Y}_i)^2} 
\]

Where \(Y_{\text{max}}\) – Maximum of measured value (ex: Ra or \(Ae*Ap\));
\(Y_{\text{min}}\) – Minimum of measured value (ex: Ra or \(Ae*Ap\));
\(N\) - Total count;
\(\bar{Y}_i\) - measured value (as calculated from the polynomial regression equation).

Since the machining state has stable cutting and unstable cutting and the NRMSD can be calculated separately for both, as shown in table 7. It can be seen from the table that in the stable zone, there is an average confidence level of 92.97%, while in the unstable zone, there has only 63.02% confidence level. This is because the random phenomenon occurs in unstable cutting, which it is difficulty for SLD to achieve a higher accuracy. Next, the machine learning algorithm will be followed to establish and predict the dynamic cutting force and surface roughness (Ra).
### Table 7. NRMSD in the stable and unstable zone.

| Cutting Speed (rpm) | Stable (%) | Unstable (%) |
|---------------------|------------|--------------|
| 5000                | 99.15      | 92.55        |
| 7000                | 97.7       | 80           |
| 9000                | 99.58      | 96.29        |
| 11000               | 88.9       | 29.38        |
| 13000               | 90.59      | 79.12        |
| 15000               | 97         | 87.29        |
| 17000               | 91.76      | 27.97        |
| 19000               | 79.11      | 11.54        |
| **Average:**        | **92.97**  | **63.02**    |

6. Machine learning algorithms predict surface roughness (Ra)

According to Fayyad, Piatetsky-Shapiro and Smyth [18], the process of defining machine learning knowledge discovery includes Data Selection, Data Processing, Data Transformation, Data Mining, and Interpretation and Evaluation. There are five major steps, and gradually establish the relationship between the surface roughness (Ra) and then prediction.

6.1. Data selection

According to the dynamic cutting force operation flow, through the MAL Lab's CutPro software [19]. The dynamic cutting force has eight different cutting speeds (rpm) and eight cutting depths (Ap), and can be calculated with a total of sixty four data.

6.2. Pre-processing

Since these 64 data are cutting force signals (time-domain signals) and subsequent algorithm analysis cannot be performed. At this stage, the feature extraction will be performed to facilitate algorithm analysis. This study uses Equations (12) to (23) to extract dynamic cutting, but because the dynamic cutting force contains three axes, all three axes must be extracted. After feature extraction, the data matrix size is 64*33.

\[
\text{Mean Value (MV)} = \sum_{i=1}^{N} \frac{y(i)}{N} \quad (12)
\]

\[
\text{Mean Square Error (MSE)} = \sqrt{\sum_{i=1}^{N} (y(i) - \text{MV})^2} \quad (13)
\]

\[
\text{Square Mean Root (SMR)} = \left( \sum_{i=1}^{N} \frac{|y(i)|}{N} \right)^{\frac{1}{2}} \quad (14)
\]
6.3. Data transformation
Since thirty-three features are not conducive to analysis, this study uses PCA (Principal Component Analysis) for dimensional reduction, as shown in table 8. In the nineteenth principal component (PC No.), the cumulative contribution ratio can reach 100%, so the data is reduced to a matrix size of 64*19.

Dimension reduction of data was through PCA, and then machine learning algorithms was used; and the algorithm chose linear and nonlinear algorithms such as the multivariate linear regression (MLR) and generalized regression neural network (GRNN). However, because the GRNN algorithm uses the Gaussian function as the basis for prediction, it is easily affected by other value ranges (such as other cutting speeds or cutting depths), and then it decreases accuracy. Therefore, this study used linear interpolation, that is, at the same processing speed that between the previous cutting depth and the next cutting depth, it used linear interpolation and insert eight data. So, it extends to 568 data, that the matrix size is 568*19. This approach will reduce the learning bias of the GRNN algorithm.

6.4. Data mining
In the research of pattern recognition in the machine learning, the data set is often divided into two subsets: a training set and a validation set. The former is used to build a model, and the latter is used to

\[
\text{Square Mean Root (SMR)} = \left( \frac{1}{N} \sum_{i=1}^{N} |y(i) - \bar{y}| \right)^2
\]  

\[
\text{Maximum Absolute Value (MA)} = \max |y(i)|
\]  

\[
\text{Skewness Factor (SF)} = \frac{\sum_{i=1}^{N} (y(i) - \bar{y})^3}{(N-1) \times \text{MSE}^3}
\]  

\[
\text{Kurtosis Factor (KF)} = \frac{\sum_{i=1}^{N} (y(i) - \bar{y})^4}{(N-1) \times \text{MSE}^4}
\]  

\[
\text{Crest Factor (CF)} = \frac{\text{MA}}{\text{RMS}}
\]  

\[
\text{Margin Factor (MF)} = \frac{\text{MA}}{\text{SMR}}
\]  

\[
\text{FC} = \frac{1}{N} \sum_{i=1}^{N} S(f)
\]  

\[
\text{Root Mean Square Frequency (RMSF)} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (S(f))^2}
\]  

\[
\text{Root Variance Frequency (RVF)} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (S(f) - FC)^2}
\]
evaluate the accuracy of the model in predicting unknown samples. K-fold Cross Validation is a more commonly used verification method. The method is to randomly divide the data into k sets, and then use a certain set as a validation, and the remaining k-1 sets as training, so repeat until each set is regarded as the verification information. The final result (Prediction results) is compared with the ground truth (Performance Comparison), as shown in figure 26. In this study, 10-Fold Cross Validation were used to establish 10 sets of training data sets and validation data sets.

| PC No. | Variation | Variation (%) | Cumulative contribution ratio (%) |
|--------|-----------|---------------|-----------------------------------|
| 1      | 24.6121   | 74.5822       | 74.58                             |
| 2      | 3.9817    | 12.0657       | 86.65                             |
| 3      | 2.8461    | 8.6244        | 95.27                             |
| 4      | 0.6927    | 2.0991        | 97.37                             |
| 5      | 0.3029    | 0.9178        | 98.29                             |
| 6      | 0.2020    | 0.6120        | 98.9                              |
| 7      | 0.1591    | 0.4821        | 99.38                             |
| 8      | 0.0953    | 0.2887        | 99.67                             |
| 9      | 0.0418    | 0.1265        | 99.8                              |
| 10     | 0.0271    | 0.0820        | 99.88                             |
| 11     | 0.0171    | 0.0518        | 99.93                             |
| 12     | 0.0071    | 0.0214        | 99.95                             |
| 13     | 0.0044    | 0.0133        | 99.97                             |
| 14     | 0.0030    | 0.0090        | 99.98                             |
| 15     | 0.0021    | 0.0064        | 99.98                             |
| 16     | 0.0015    | 0.0046        | 99.99                             |
| 17     | 0.0013    | 0.0040        | 99.99                             |
| 18     | 0.0011    | 0.0034        | 99.99                             |
| 19     | 0.0006    | 0.0017        | 100                               |
| ...    | ...       | ...           | ...                               |
| 33     | 0.0004    | 0.0011        | 100                               |
In this research, according to 10 sets of data sets and machine learning algorithms, the relationship between dynamic cutting force and surface roughness (Ra) was established. This research chose multivariate linear regression (MLR) and generalized regression neural network (GRNN) algorithms to learn training data sets and predict validation data sets. The prediction results of these algorithms are shown in figure 27 and figure 28.

**Figure 26.** k-Fold Cross Validation.

**Figure 27.** MLR results.

**Figure 28.** GRNN results.
After the machine learning algorithm targets 10 sets of verification data sets were collected, the NRMSD was used to calculate, as shown in Equation (10). The average accuracy of the MLR algorithm is 58.66%, while the average accuracy of the GRNN algorithm is 88.69%. Obviously, it could be known that the data is not linear, but it is a non-linear data type. So, the GRNN algorithm has a great contribution on the prediction of non-linearity. In addition, on the results of the GRNN algorithm, it is also clear that the performance of the TA20 machine is a low torque and high speed. So, when the processing speed is 11000rpm, the prediction accuracy of the surface roughness (Ra) can be above 85% and the maximum error is below 0.893mm. And in the unstable zone, it can also have a higher accuracy than the stability lobe diagram (SLD).

6.5. Interpretation and evaluation

The respective execution results of the MLR algorithm and the GRNN algorithm must estimate indicators to obtain the accuracy rate of the two algorithms for the data set. The evaluation indicators were aimed at inputting the same data into different algorithm models and giving quantitative indicators of the results. In evaluation indicators, most of them can only partially reflect the model performance. If the evaluation indicators could not be used reasonably, the problems could not be found with the model itself, and the wrong conclusions might be concluded. Therefore, this research calculated the accuracy of MAPE (Mean Absolute Percentage Error) through Equation (24).

\[
\text{MAPE} = 100\% \times \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\text{actual}(i) - \text{predicted}(i)}{\text{actual}(i)} \right| 
\]  

(24)

The prediction results of the two algorithms (MLR and GRNN) were calculated by Equation (10) to calculate NRMSD and Equation (24) to calculate MAPE, as shown in figure 29 and figure 30. Combining the analysis of the two evaluation indicators (NRMSD and MAPE), the GRNN algorithm is better than the MLR algorithm, and can improve the accuracy of the SLD in the unstable zone.

\[\text{Figure 29. The accuracy of the prediction of the each cutting speed in NRMSD.}\]

\[\text{Figure 30. The accuracy of the prediction of the each cutting speed in MAPE.}\]
7. Conclusion
Since it is generally not able to install dynamometer on a small machine such as the TA20, the cutting force could not be measured during the machining. Therefore, this research has successfully generated dynamic cutting force signals of the small machine according to cutting force coefficients obtained from the cutting test on the other industrial machine tool, and also the small machine’s FRF. The calculated cutting force have been found to be able to approximate the cutting force signal of the physical dynamometer on a small machine (TA20). In this research, the actual machining was conducted on the small machine and the machined surface Ra was measured, and the roughness prediction algorithm has been established by using multivariate linear regression (MLR) and generalized regression neural network (GRNN). It is concluded that the GRNN (non-linear) algorithm is better than MLR (linear) in the predicted accuracy. From another perspective, the dynamic cutting force was adopted to analyse this study, and some use machine learning algorithms such as GRNN were used for prediction. The accuracy rate of the surface roughness prediction could be reached to that of more than 80% (NRMSE and MAPE), which means that the proposed methodology is useful for surface roughness prediction on small machines or machines that cannot have a dynamometer installed.

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