中國機械工程學刊第四十二卷第五期第 461~470 頁(民國一百一十年)
Journal of the Chinese Society of Mechanical Engineers, Vol.42, No.5, pp. 461~470 (2021)

PCD Milling Cutter Remaining Useful Life Prediction for Titanium and Aluminum Mirror Milling by Using S2S-LSTM Deep Learning Technology

Shang-Liang Chen *, Kuei-Ming Lee **, Yen-Hsiang Huang ***, Yu-Ting Lu ****, Yu-Fu Lin *****and Ho-Chuan Huang ******

Keywords：Deep Learning, LSTM, Mirror Milling, S2S, RUL.

ABSTRACT

Both the titanium alloy and aluminum alloy cutting by using Polycrystalline Diamond (PCD) milling cutter for obtaining mirror milling surface results are important processing technologies in the industry. To improve the production efficiency or enhance the cutting performance of this cutting technology, the Remaining Useful Life (RUL) prediction of PCD milling cutter becomes one of the major issues nowadays. The Sequence to Sequence Long Short-term Memory (S2S-LSTM) is used in this research as the prediction model to carry out PCD milling cutter's RUL prediction, and two times of PCD milling cutting experiments for titanium and aluminum alloy are designed and carried out. In the experiments, the data of the vibration signal, sound signal, and the surface roughnesses of the workpieces are measured and used as the datasets. The prediction model yielded F1-scores of 98.1% and 95.8% by using the validation datasets of the two experiments. The proposed model is also compared with other AI (Artificial Intelligent) models, such as RNN (Recurrent Neural Network), GRU (Gated Recurrent Unit), and LSTM under the same batch size, epoch, learning rate, and other hyper-parameters.

Paper Received January, 2021. Revised June, 2021. Accepted August, 2021. Author for Correspondence: Shang-Liang Chen.

* *Professor, Institute of Manufacturing Information and Systems, National Cheng Kung University, Tainan, 70101, R.O.C.*
** *Graduate Student, Institute of Manufacturing Information and Systems, National Cheng Kung University, Tainan, 70101, R.O.C.*
*** *Section Director, Micro Mechanical Manufacturing R&D Department, Metal Industries Research & Development Centre, Kaohsiung, 811, R.O.C.*
**** *Engineer, Micro Mechanical Manufacturing R&D Department, Metal Industries Research & Development Centre, Kaohsiung, 811, R.O.C.*
***** *Associate Professor, Department of Intelligent Commerce, National Kaohsiung University of Applied Sciences, Kaohsiung, 824, R.O.C.*

INTRODUCTION

Nowadays, materials commonly used in the high-tech industry such as titanium (Ti) alloy and aluminum (Al) alloy require excellent surface roughness on specific occasions, and mirror milling has become an important method to achieve that quality. The cutter of the mirror cutting machine has a significant influence on the quality of the finished product, which needs to be replaced from time to time due to the accumulation of wear with the increase of processing time. In the current manufacturing industry, the experience and judgment of engineers are usually taken as the basis for the timing of cutter replacement. However, the timing of cutter replacement will even affect the overall efficiency of production. If the wear is too serious and the cutter is not replaced immediately, the quality of the product will be reduced. On the other hand, if the cutter is replaced too early, it does not meet the cost considerations. Besides, the production line has to be suspended for each tool change, which will reduce production efficiency and cause losses to the industry.

To achieve high production efficiency, the RUL prediction of mirror milling cutter has become an important issue. The cutter usually used in mirror milling for Ti and Al alloy is a high hardness diamond cutter, PCD, or cubic boron nitride cutter, etc. E. Kaya's research results show that the cutting results of PCD cutter for mirror surface cutting have better quality (Kaya et al, 2020). Therefore, PCD milling cutter is selected as the experimental cutting tool in this research.

Many previous researchers have investigated this topic and focused on this issue for getting a better cutter RUL prediction method. For example, A. Heng calculated RUL time by applying the sensing data related to tool life into the calculation of neural network algorithm (Heng et al, 2009). M. Kious used the wear degree on the flank of a cutting tool as the RUL evaluation basis and divided the wear of the flank into initial wear, normal wear, and damage wear

(Kious et al, 2010). To reduce the difficulty of measuring wear loss on the flank, Tobon-Mejia measured the surface roughness of the cutting result and used it as the evaluation basis for cutting tool RUL calculation (Tobon-Mejia et al, 2012). Mirror milling is defined as cutting results with a surface roughness between 0.08 μm to 0.8 μm Ra value (Lindvall et al, 2020). In this study, the surface roughness of mirror milling is also used as the evaluation definition for PCD cutter RUL calculation.

Recently, the usage of deep learning technology has risen to prominence once again due to advancements in hardware, data collection ability, and innovations in deep learning algorithms (An et al, 2019). For the applications of deep learning technology, the algorithm used to build the prediction model must match the actual physical phenomena. Therefore, it is an important issue to apply appropriate algorithms to the physical phenomena of the problem to be predicted (Yu et al., 2019).

Some researchers have already studied the RUL prediction of cutting tools by using artificial intelligence. Benkedjouh used SVR (support vector regression) to predict the amount of wear and the RUL of cutting tools (Benkedjouh et al, 2015). Drouillet used artificial neural networks to predict the RUL of milling cutters (Drouillet et al, 2016). Tobon-Mejia developed a two-stage RUL prediction algorithm based on a dynamic Bayesian network (Tobon-Mejia et al, 2012). Wu proposed a multi-sensor information integration system for online RUL prediction for machine tools based on an adaptive network fuzzy reasoning system (Wu et al, 2018). However, none of the scholars mentioned above have taken into consideration the time sequence characteristics of the sensing data used, which creates a greater discrepancy between the predictions made and the actual results. To overcome the above problem, a time-series model is used in this study to predict cutting tool RUL.

To have the temporal characteristics of the sensing data which is more in line with the model characteristics of some applications, the LSTM of the temporal prediction model is used as the elevation basis for obtaining better model prediction accuracy. Ahmed Elsheikh used the Bi-LSTM model to predict the RUL of turbofan engines. It is reported that the number of network layers and the neurons can be adjusted to optimize model accuracy (Elsheikh et al, 2019). Wennian Yu used an LSTM model to predict tool RUL, in which model training was carried out under the condition of Epoch and hyper-parameters varied (Yu et al, 2019). Bin Zhang used an LSTM model to predict rolling bearing RUL. In this study, no data preprocessing method is used, and the accuracy of the model was about 94.967% (Zhang et al, 2019).

Pingyang Lyu used S2S-LSTM architecture to predict gas leakage (Lyu, 2020) and compared the mean absolute error (MAE) with other architectures, the results are reported to be obviously better than those of other architectures. Zenghui An (2020) also used the S2S-LSTM framework to predict the rolling bearing RUL and obtained 93.5% model accuracy, which is better than that of other deep learning models. However, the above research used accuracy as the basis to evaluate the model, and this method could not truly display the performance of the model.

To improve the performance of deep learning models in target prediction applications, the S2S-LSTM architecture is used in this research to predict the RUL of PCD cutters in mirror milling. For getting better model performance, hyper-parameters such as epoch, batch size, and learning rate are varied and considered. Besides, F1-Score is used as the basis in this research for judging the model to evaluate more realistic model performance.

METHOD

The system structure of this study is shown in Figure 1, which can be divided into two parts.

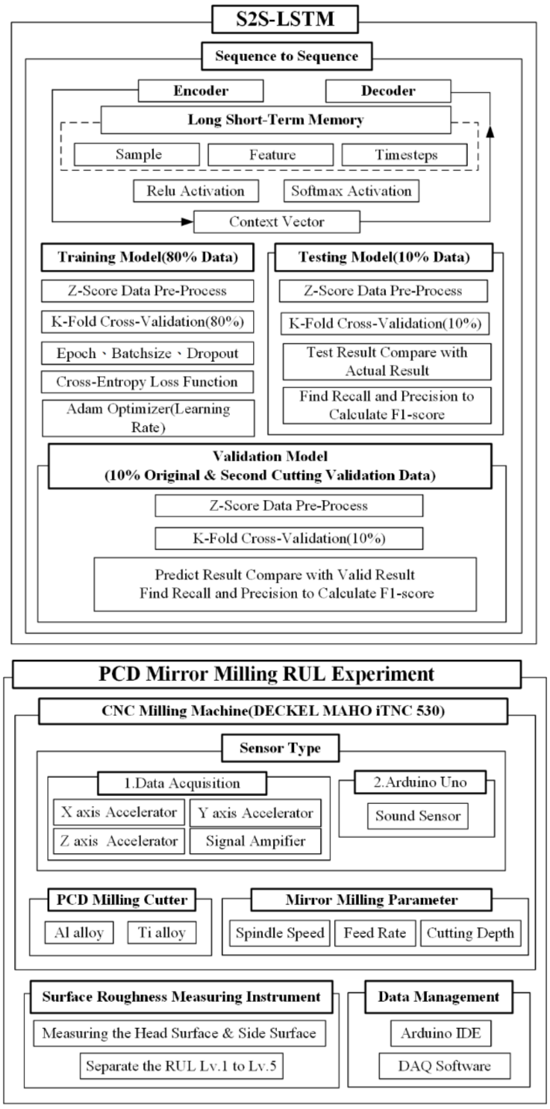

Fig. 1. System structure.

The first part is the functional modules related to experimental design for the RUL prediction for PCD milling cutter in Ti alloy and Al alloy mirror milling. The planning for the RUL prediction experiment planning of PCD cutters during mirror milling includes cutting experiment design, practical mirror milling, sensor data measurement, and surface roughness measurement. The vibration data is collected from a three-axis accelerometer sensor on the spindle. The sound sensor is attached to the cutter's handle to collect the sound data during cutting. The Ti alloy and Al alloy are selected and machined with a PCD milling cutter with mirror milling cutting parameters, and the spindle speed, feed rate, and cutting depth are fixed. The surface roughness of the cutting result surface is measured by a CMM machine. The measured results are classified according to their mirror level. The CNS10793 standard defines the mirror levels of mirror surface roughness. The mirror levels will be further used in the dataset for training and testing.

The second part of this study is S2S-LSTM model construction. The collected sensor data is programmed into a data format that is readable by the model. For pre-processing the data, the Z-Score data and K-Fold data segmentation are then applied to the data here. The data is further split into training, testing, and validation datasets. The S2S-LSTM model will be supplied for subsequent calculation. With the deep learning model of S2S-LSTM established, the LSTM model is embedded in the encoder and decoder architecture of S2S to predict the RUL of PCD cutters. LSTM parameters are set, including Sample, Feature, Timesteps, etc. The accuracy of the model can be increased through the above-mentioned hybrid technology. The Relu activation function is used for data filtering between models. In the output layer, a Softmax activation function is used to distribute the output probability value to the RUL label category of the PCD cutter. The hyper-parameters such as Epoch, Batch size, and Dropout are used to test the model's F1-Score. In this study, the Cross-Entropy loss function is used to calculate the deviation of the model. The Learning Rate of Adam optimization function is used to optimize the accuracy of F1-Scores.

The overall process in this study is shown in Figure 2. An accelerometer is installed on the spindle of the three-axis direction and acquires data through a DAQ. A sound sensor is installed at the base of the knife holder. And data is transmitted to a computer through an Arduino. This completes the setup of the experiment equipment, and mirror milling experiments are then carried out. The surface roughness of the finished workpieces is measured. The sensor and surface roughness measurement data are integrated into the format of three accelerometer sensor data, and one each of sound sensor, and surface roughness data. This facilitates data reading for the deep learning model.

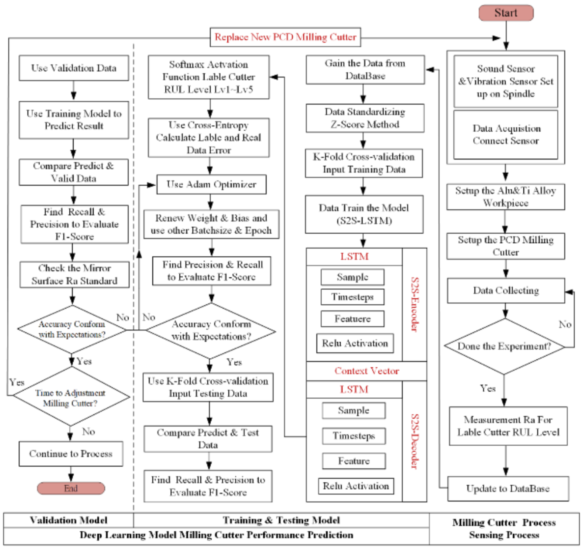

Fig. 2. System Flowchart.

The above sorted datasets are retrieved and preprocessed through Z-Score data normalization, reducing the difference between data so that training for the prediction model goes more smoothly. In this study, the K-Fold method is used to divide the data into three parts consisting of: 80% training set, 10% test set, and a 10% validation set. Among the models implemented by S2S-LSTM in this study, S2S has the functions as both encoder and decoder while LSTM is used as the neuron of S2S to complete calculations calculate between neurons. In addition, hyper-parameters such as Epoch, Batch size, and Learning Rate are adjusted to conduct model tests to improve the F1-Score. At last, the 10% validation set data is used to calculate Recall and Precision, and to carry out the calculation of the F1-Score for the prediction model. The model is designed to predict the RUL of PCD cutters under mirror milling conditions.

PCD Cutter RUL Experiment and Planning of Life Index

In this study, a DMU-ITN530 three-axis milling machine is used for cutting, a PCD cutter with an external diameter of 10 cm is used as the experiment subject, and Al and Ti alloys are used as cutting materials. The mirror milling parameters obtained from the literature are set as the machining parameters of this study. The parameters include spindle speed, cutting depth, and feed rate. In this study, accelerometer sensors and sound sensors are arranged on the spindle and knife handle of the machine tool. The signals from the above sensors are collected through a DAQ and Arduino to upload to the database. During mirror milling, an RUL prediction model is constructed for PCD milling cutters. Measuring the surface roughness of the cutting workpiece is used as the RUL judgment basis for PCD cutters. The planning is shown in Figure 3.

In this study, Al and Ti alloys are used for experimental cutting. The material size is 100mm long, 120mm wide, and 100mm high. The three-view diagram of the material before cutting, as shown in Figure 4(a). The clamping position of the workpiece is shifted 20mm upwards from the bottom, which is set as the safety plane. The down milling feed direction cutting movement is 50% of the cutter diameter. The design of this cutting experiment is based on the concept of terraces. The surface roughness of each terrace can then be measured. The change in tool wear can be shown and recorded and the RUL of PCD milling cutters under mirror milling condition can be deduced. The three-view diagram of the material after cutting, as shown in Figure 4(b).

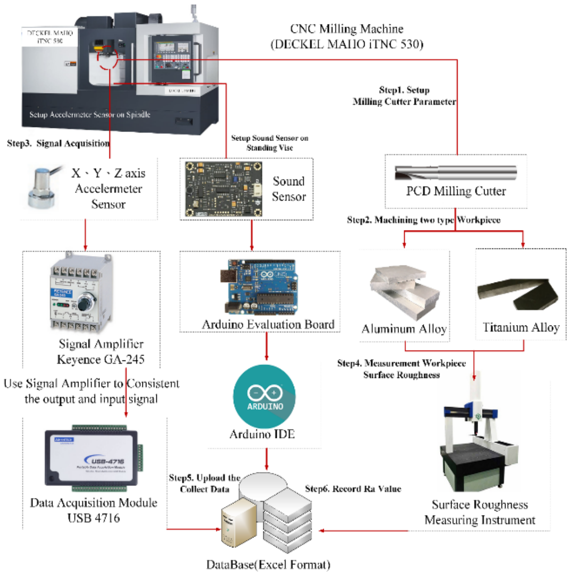

Fig. 3. RUL experiment flowchart for PCD milling cutter in mirror milling.

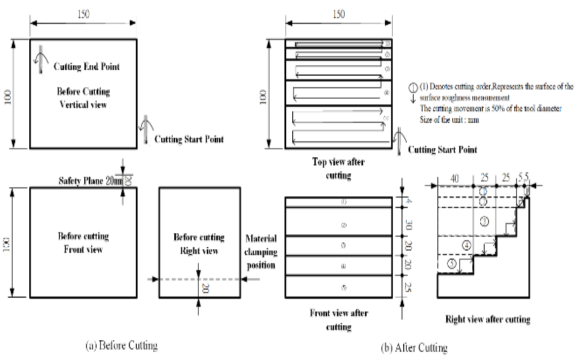

Fig. 4. Milling design drawing for experiment.

PCD milling cutters are considered very suitable for mirror milling, and it is pointed out in the literature that better cutting performance can be obtained. Thus, PCD milling cutters are selected for use in this study. In this study, the milling experiments of Al and Ti alloys are carried out with a PCD milling cutter combined with mirror milling parameters. The cutting parameters include spindle speed, cutting depth, and feed rate, as shown in Table 1. The material parameters of PCD milling cutters used in this study include the coefficient of friction, coefficient of elasticity, Vickers hardness, and coefficient of thermal expansion, as shown in Table 2.

Materials commonly used in high-tech industries, 6063-T6 aluminum alloy and Ti6Al4V titanium alloys, are used in this research. Aluminum alloy is often used in sheet metal and metal crafting industries, while titanium alloys are commonly used in aerospace and medical industries. Both materials require extremely high surface roughness for specific applications. That is why this study chooses to use the surface roughness of mirror milling grade as the criterion of tool. In this study, material selection and experimental cutting are carried out based on the workpiece material parameters in Table 3.

Table 1. Parameter setup of Mirror milling experiment.

	Spindle Speed(rpm)	Cutting Depth(mm)	Feed Rate(mm/t)
Case Al alloys	15000	0.1	0.1
Case Ti alloys	10000	0.05	0.05

Table 2. PCD milling cutter material

Material of Cutter	Coefficient of Friction	coefficient of Elastic	Vickers Hardness	Thermal Expansivity
PolyCrystalline Diamond	0.3	630Gpa	6000	0.9×10^{-6}

Table 3. Material parameter of workpiece

Workpiece material	Poisson's ratio	Density	Coefficient of Young's	Vickers Hardness
6063-T6 Al alloy	0.35	2.7 g/cm³	69 Gpa	92
Ti6Al4VTi alloy	0.37	4.5 g/cm³	110 Gpa	457

In this study, the surface roughness of mirror milling is used as the hierarchical classification of the RUL of a PCD cutter, shown in Table 4. Lv.1-Lv.4 mirror milling is defined as surface roughness ranging from 0.08μm to 0.8μm, corresponding to grade 0.1a to 0.8a in the Ra standard of CNS10793. In order to identify specifications beyond the specular cutting standards, Lv.5, which is 1.6a, is included in the standard table, bringing the total categories in this study to five. The surface roughness is measured through mirror milling experiments of Al and Ti alloys, and the PCD milling cutter RUL can be estimated. The cutting results and the estimated RUL of PCD milling cutters are presented in Table 4.

Table 4. PCD milling cutter RUL indicator.

PCD milling cutter RUL level	Surface Roughness	PCD milling cutter RUL
Lv.1	0.1a	(Obtained by cutting experiment)
Lv.2	0.2a	(Obtained by cutting experiment)
Lv.3	0.4a	(Obtained by cutting experiment)
Lv.4	0.8a	(Obtained by cutting experiment)
Lv.5	1.6a	(Obtained by cutting experiment)

S2S-LSTM Model Architecture and Construction

In this study, S2S-LSTM deep learning technology is used as the algorithm basis, and its prediction model architecture is detailed in the following four aspects:

Data sorting: Vibration and sound sensing signals are collected into a database via sensors and microcontrollers. The Z-Score method is used to standardize the data, narrowing the data gap in the model calculation process. The use of the Z-Score method can accelerate the network solution speed. The data is then validated using the K-Fold method, splitting the data set into 80% training, 10% testing, and 10% validation sets.

Model establishment: In this research, the S2S-LSTM architecture is used to build a hierarchical deep learning model. Data compression and prediction is established by building the encoder and decoder functions in S2S model. When S2S is used in tandem with the LSTM model, invalid data can be filtered out and gradient disappearance can be prevented.

Training model: An LSTM network is imported into the encoder and decoder architecture of S2S as neurons. Through the encoder, input data is compressed into the Context Vector and would become the input data of the decoder. Then, the Softmax activation function is used to predict the context of input data. The loss function of the prediction model is finally calculated using Cross-Entropy, and the accuracy is optimized by the Adam Optimization function. As a result, the model with the highest accuracy and lowest loss function is obtained by adjusting the hyper-parameters such as Epoch, Batch size, and Learning Rate.

Model evaluation and validation: To verify the high reproducibility of the S2S-LSTM prediction model implemented in this research, two times cutting experiments are performed, and the model is validated through validation datasets from both experiments. The Precision and Recall values obtained from the predicted and actual data are calculated by F1-Score to analyze whether the accuracy of the S2S-LSTM prediction model is acceptable.

Data Pre-processing

In data pre-processing, the input data required for the prediction model is transferred to the database and its data format is unified. Vibration and sound signal are used as features of the model, and their parameter correlation format is shown in Table 5. The standard deviation of data with different formats and levels is calculated by Formula 1, and then Z-Score is calculated by Formula 2 to achieve data pre-processing.

Table 5. Input parameter specification of sensor.

Dataset	Range Measure	Units
Accelerometer Sensor Value	-5v~5v	Voltage
Sound Sensor Value	30db~130db	Decibel

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1}} \ . \qquad (1)$$

$$Z = (X_i + \bar{X})/SD \ . \qquad (2)$$

Model Training

For target prediction using deep learning technology, a model must be built and trained first. The model training process is shown in Figure 5. Eighty percent of the original data will be pre-processed to generate the input data required by the model. LSTM parameters, including Sample, Timesteps, and Feature, should be set when the model is built, and the Softmax activation function should be used to predict the output target. The results of the prediction correspond to the level of surface roughness defined in this research.

After the prediction, the Cross-Entropy loss function is used to calculate model errors, and the Adam Optimization function was used to optimize model parameters. To test the changes of F1-Scores under different conditions of S2S-LSTM models, this study sets multiple Epochs, Batch sizes, and other hyper-parameters when building the model.

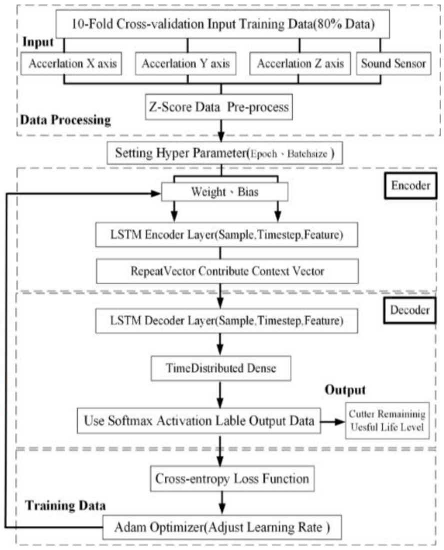

Fig. 5. Flowchart of S2S-LSTM training model.

Model Testing and Validation

The model testing process is shown in Figure 6., and the validation process is shown in Figure 7. The trained S2S-LSTM model is then used to predict the target, and its F1-Score is calculated to observe whether the accuracy of the model is as projected, reaching 95% or more.

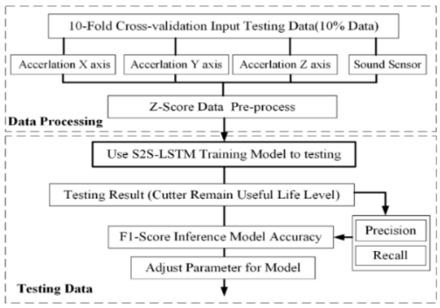

Fig. 6. Flowchart of S2S-LSTM testing model.

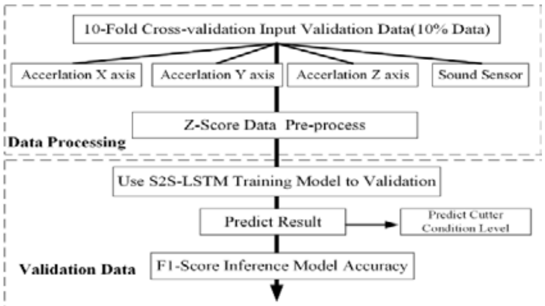

Fig. 7. Flowchart of S2S-LSTM validation model.

Hyper-parameters Adjusting

By adjusting hyper-parameters (such as Learning Rate, Batch size, and Epoch), the model index F1-Score is optimized, and the correlation between different hyper-parameters and accuracy is analyzed. The setting of hyper-parameters is shown in Table 6. The F1-Score of S2S-LSTM and other time-series models in Table 6 are compared to analyze the difference under the same hyper-parameters condition.

Table 6. S2S-LSTM hyper-parameters & Time-series F1-Score Comparing

Hyper Parameter	**Learning Rate**	**Batchsize**	**Epoch**	**Encoder、Decoder Layer**
Design Value	(0.01, 0.001)	(64, 128, 256, 512)	(2, 10, 50, 100, 200, 500)	3
Model F1-Score Compare				
Type	S2S-LSTM	LSTM	GRU	RNN

Model Accuracy Evaluation

After the model is built, the accuracy of the model should be calculated to show its advantages and disadvantages. The purpose of the F1-Score is to obtain the difference between model accuracy and the actual situation after the completion of the test model. Formula 3 and Formula 4 are used to calculate the Precision and Recall. Its F1-Score calculation is shown in Formula 5, The relationship between TP, FP, TN, and FN in the formula is shown in Table 7. Precision is defined as the ratio between actual and predicted positive results and the total events. The Recall is defined as the ratio between actual and predicted positive results and the total predicted events. F1 is the indicator score of the model, with the best score being 1 and the worst score being 0.

$$precision = \frac{TP}{TP + FP} \quad (3)$$

$$recall = \frac{TP}{TP + FN} \quad (4)$$

$$F_1 = \left(\frac{recall^{-1} + precision^{-1}}{2} \right)^{-1} = 2 \cdot \frac{precision \cdot recall}{precision + recall} \quad (5)$$

Table 7. Definition of Recall and Precision

	True conditions	**False conditions**
Predict conditions	TP(True Positives)	FP(False Positives)
Predict conditions	FN(False Negatives)	TN(True Negatives)

SYSTEM TESTING AND ANALYSIS

Experimental environment construction and development tools

The DECKEL MAHO iTNC 530 three-axis milling machine is used for mirror milling experiments of Al and Ti alloys, and a three-axis accelerometer and sound sensor are used for data acquisition. The surface roughness of the cutting result is measured by a CMM machine, and a dataset is established for training and validation. The experimental environment and equipment setup are shown in Figure 8.

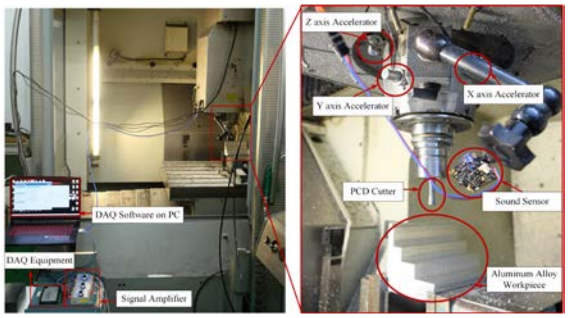

Fig. 8. Experiment environment and equipment erection diagram

PCD Milling Cutter RUL Prediction Data Acquisition

This study sets up a three-axis speed gauge sensor on the spindle to collect vibration signals during the cutting of Al and Ti alloys, and a DAQ will record and send data back to the computer. The vibration and noise signals of the Ti alloy cutting are shown in Figure 10 and Figure 11. The vibration signals of the vibration sensor in Figure 10 show that the triaxial accelerometer detects more vibrations as the cutting time increases. The sound sensor signal acquisition figure in Figure11 shows a significant change in the sound signal at the mid-cutting stage, and the surface roughness of the interval increased from 0.139μm to 0.366μm.

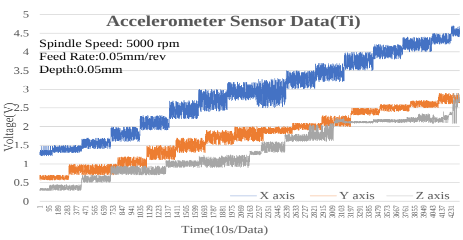

Fig. 10. An accelerometer sensor signal for titanium alloy cutting.

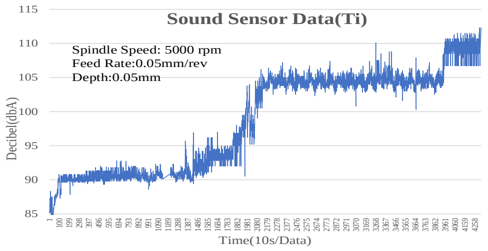

Fig. 11. A sound sensor signal for titanium alloy cutting.

The sound sensor is set up on the knife handle to collect noise signals during Al and Ti alloy cutting, and the sensor data is transmitted back to the computer through an Arduino. The surface roughness measurements are taken for Al and Ti alloys after milling. Data for each terrace is recorded and classified according to the surface roughness criteria of mirror milling, as shown in Table 8 below.

Table 8. Surface roughness measurement for cutting experiments (μm)

Step	Al alloy end surface	Ti alloy surface	Al alloy side surface	Ti alloy side surface
1	0.092	0.079	0.21	0.301
2	0.189	0.139	0.32	0.54
3	0.392	0.227	0.55	0.66
4	0.568	0.366	1.63	1.24
5	0.828	0.796	None	None

Test and analysis of prediction models

The sensing data and surface roughness levels of Al and Ti alloys are modeled. The sensor data is used as the input data and the surface roughness level is used as the output data. The highest F1-Score is tested by adjusting the Learning Rate, Batch size, and Epoch, as shown in Table 9.

Table 9. Adjust hyper-parameter include Batchsize、Epoch and LR to calculate F1-Score

Aluminum Alloy						
Batchsize	Epoch2	Epoch10	Epoch50	Epoch100	Epoch200	Epoch500
64	30.25%	47.25%	89.35%	90.54%	91.85%	93.21%
128	32.56%	58.69%	89.78%	91.21%	92.63%	95.68%
256	34.56%	59.87%	89.65%	92.43%	98.63%	97.21%
512	35.63%	49.91%	91.37%	92.85%	95.87%	96.31%
Titanium Alloy						
Batchsize	Epoch2	Epoch10	Epoch50	Epoch100	Epoch200	Epoch500
64	38.23%	45.21%	87.35%	90.21%	92.39%	95.67%
128	30.21%	46.32%	88.21%	90.51%	92.14%	96.39%
256	32.21%	47.21%	88.97%	91.03%	95.26%	97.68%
512	34.58%	48.42%	89.92%	92.52%	95.68%	97.31%

RESEARCH RESULTS AND DISCUSSIONS

Relationship between PCD milling cutter wear and surface roughness

The PCD milling cutter is used for mirror milling of Al and Ti alloys. The relationships between microscope imaging and tool wear of PCD milling cutters are shown in Figure 12 and Figure 13, and the relationships between the tool wear and the surface roughness are shown in Table 10 and Table 11. In Figure 12 and Figure 13, sub-pictures (a) to (d) represent the process of cutting tools from factory new, initial wear, normal wear to serious wear. It can be seen that the surface roughness and tool wear are directly related to the tool lifespan.

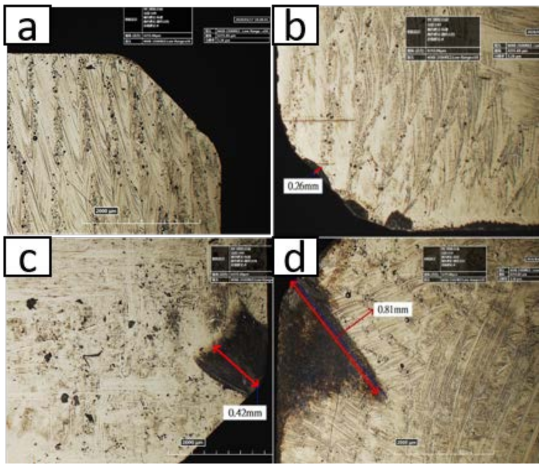

Fig. 12. The relationship between microscope imaging and tool wear of PCD milling cutters for cutting Al alloy.

Table 10. The relationship between the surface roughness and the wear of Al alloy in PCD cutting

	The New	initial wear	Normal wear	Serious wear
Surface Roughness	0.092 μm	0.189 μm	0.392 μm	0.828 μm

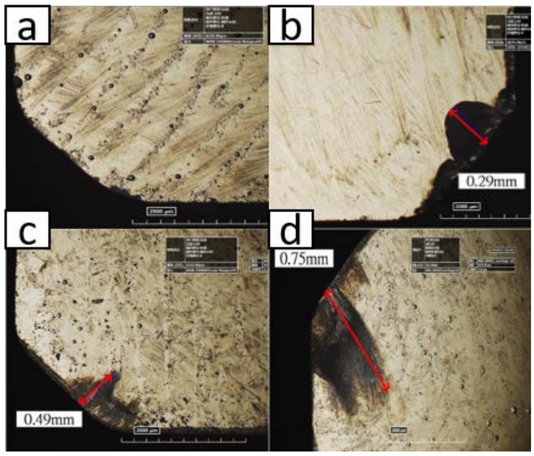

Fig. 13. The relationship between microscope imaging and tool wear of PCD milling cutters for cutting Ti alloy.

Table 11. The relationship between the surface roughness and the wear of Ti alloy in PCD cutting

	The New	initial wear	Normal wear	Serious wear
Surface Roughness	0.079 μm	0.139 μm	0.227 μm	0.796 μm

PCD milling cutters RUL prediction table

The S2S-LSTM model proposed in this research is applied to predict the RUL of PCD milling cutters in mirror milling, and the results are shown in Table 12. The surface roughness Ra of mirror milling is used to divide the tool lifespan into five levels, from lv. 1 to lv. 5. The table can be used to judge the RUL of the PCD milling cutter when mirror milling, to facilitate the optimization of the processing or overall production line scheduling.

Table 12. PCD cutter are used to measure the cutting life of Al and Ti alloys mirror milling

PCD milling cutter (Al alloy)			PCD milling cutter (Ti alloy)		
RUL level	**Ra**	**RUL**	**RUL level**	**Ra**	**RUL**
Lv.1	0.1a	10hr~12hr	Lv.1	0.1a	16hr~18hr
Lv.2	0.2a	5hr~10hr	Lv.2	0.2a	14hr~16hr
Lv.3	0.4a	96min~5hr	Lv.3	0.4a	5hr~14hr
Lv.4	0.8a	33.6min~96min	Lv.4	0.8a	40.8min~5hr
Lv.5	1.6a	Replce immediately	Lv.5	1.6a	Replce immediately

S2S-LSTM compared to other time-series architecture

As shown in Table 13 and Table 14, the proposed S2S-LSTM time-series architecture is compared to other time-series architectures include LSTM, GRU, and RNN in terms of the accuracy of RUL prediction. According to Table 13(a), it can be seen that the S2S-LSTM realized in this study can reach a 98.63% F1-Score by using Al alloy end face data for prediction, and its F1-Score is much higher than the other three time-series models. According to Table 13(b), it can be seen that the S2S-LSTM realized in this study can reach a 97.68% F1-Score by using the end face data of Ti alloy for prediction, and the accuracy of the F1-Score is ten percent higher than that of the other three time-series models.

Table 13. S2S-LSTM compare to other time-series by using Al & Ti alloys end surface data

	Al alloy end surface cutting data(a)				Ti alloy end surface cutting data(b)			
Model	S2S-LSTM	LSTM	GRU	RNN	S2S-LSTM	LSTM	GRU	RNN
Precision	0.9	0.88	0.82	0.84	0.92	0.89	0.83	0.80
Recall	0.9	0.9	0.85	0.86	0.92	0.87	0.81	0.83
F1 Score	98.63%	88.98%	82.63%	84.94%	97.68%	87.98%	85.02%	81.47%

As shown in Table 14(a), the S2S-LSTM realized in this study can reach a 95.98% F1-Score by using aluminum alloy side data for prediction, which is much higher than the other models. It can be seen from Table 14(b) that the S2S-LSTM realized in this study can reach a 98.61% F1-Score by using the side data of titanium alloy for prediction.

Table14. S2S-LSTM compare to other time-series by using Al & Ti alloys side surface data

	Al alloy side surface cutting data(a)				Ti alloy side surface cutting data(b)			
Model	S2S-LSTM	LSTM	GRU	RNN	S2S-LSTM	LSTM	GRU	RNN
Precision	0.92	0.87	0.78	0.82	0.93	0.89	0.82	0.84
Recall	0.93	0.89	0.82	0.83	0.95	0.92	0.85	0.86
F1 Score	95.98%	84.65%	79.37%	82.49%	98.61%	90.05%	83.47%	84.98%

To examine the high reproducibility of the proposed model, the second cutting experiment was also carried out in this research. In this experiment, a new PCD milling cutter is used, and the second set of data is constructed by cutting another piece of Al alloy with the same processing environment and parameters. As a result, a 95.8% model F1-Score was obtained by importing the collected data into the S2S-LSTM model. It is evident that the S2S-LSTM prediction model verified by the data from the second experiment has a high F1-Score, which proves that the model is highly reproducible.

SUMMARY

S2S architecture and LSTM network are taken as the technical core of deep learning in this study. An RUL prediction framework for PCD cutters in mirror milling conditions is proposed. The vibration and sound signals of aluminum and titanium alloys cutting using a PCD milling cutter are collected by using a three-axis accelerometer and a sound sensor. Under mirror milling conditions, a PCD milling cutter RUL level table is realized. The S2S-LSTM deep learning framework is implemented in this study for model training, testing, and validation. By comparing the predicted data with the actual data, the F1-Score of the model reaches as high as 95%.

According to the analysis methods and experimental results mentioned in this study, the following points can be summarized:

1. The data which are imported into the prediction model are collected and analyzed through sensors. Through experiments, the PCD milling cutter is used to predict the RUL of titanium and aluminum alloys.
2. In this study, a three-axis milling machine was used for aluminum and titanium alloy cutting under mirror milling conditions. The PCD milling cutter conforms to the RUL range of mirror milling.
3. The prediction model of S2S-LSTM architecture is implemented. The vibration and sound data serve as input data and the measured surface roughness is taken as output data. The model is trained, tested, and validated with a model validation F1-score of 93.63%. To verify that the model implemented in this study is highly reproducible, the secondary cutting data is used to validate the model, with an F1-Score of 95.8%.

The future prospects of this study are as follows:

1. Image detection of surface roughness can be introduced into this study. The surface roughness can be measured in real-time during cutting allowing the time between RUL levels to be more accurate.
2. Wireless sensor technology can be used. By uploading the collected data to a cloud database, RUL predictions can be made remotely.
3. Deep learning algorithms are constantly being

updated. This prediction architecture can be imported into other novel algorithms, achieving faster operations and higher accuracy along with other benefits.

ACKNOWLEDGMENT

This research is financial supported by the research program of the Ministry of Science and Technology. (Project number MOST 107-2221-E-006-230-MY2). Special thanks to Kaohsiung Metal Industry Research and Development Center for experiments and data collection to allow this research to be completed successfully.

REFERENCES

An, Zenghui, et al. "A novel bearing intelligent fault diagnosis framework under time-varying working conditions using recurrent neural network." ISA transactions 100 (2020): 155-170.

Benkedjouh, Tarak, et al. "Health assessment and life prediction of cutting tools based on support vector regression." Journal of Intelligent Manufacturing 26.2 (2015): 213-223.

Drouillet, Cyril, et al. "Tool life predictions in milling using spindle power with the neural network technique." Journal of Manufacturing Processes 22 (2016): 161-168.

Elsheikh, Ahmed, Soumaya Yacout, and Mohamed-Salah Ouali. "Bidirectional handshaking LSTM for remaining useful life prediction." Neurocomputing 323 (2019): 148-156.

Heng, Aiwina, S. Zhang, and A. C. Tan. "et Mathew, J.(2009)." Rotating machinery prognostics: State of the art, challenges and opportunities. Mechanical Systems and Signal Processing 23: 724-739.

Kaya, Eren, and İrfan Kaya. "Tool wear progression of PCD and PCBN cutting tools in high speed machining of NiTi shape memory alloy under various cutting speeds." Diamond and Related Materials (2020): 107810.

Kious, M., et al. "Detection process approach of tool wear in high speed milling." Measurement 43.10 (2010): 1439-1446.

Lindvall, Rebecka, et al. "Performance and wear mechanisms of PCD and pcBN cutting tools during machining titanium alloy Ti6Al4V." Wear (2020): 203329.

Lyu, Pingyang, et al. "LSTM based encoder-decoder for short-term predictions of gas concentration using multi-sensor fusion." Process Safety and Environmental Protection 137 (2020): 93-105.

Tobon-Mejia, D. A., Kamal Medjaher, and Noureddine Zerhouni. "CNC machine tool's wear diagnostic and prognostic by using dynamic Bayesian networks." Mechanical Systems and Signal Processing 28 (2012): 167-182.

Wu, Jun, et al. "Multi-sensor information fusion for remaining useful life prediction of machining tools by adaptive network based fuzzy inference system." Applied Soft Computing 68 (2018): 13-23.

Yu, Wennian, II Yong Kim, and Chris Mechefske. "Remaining useful life estimation using a bidirectional recurrent neural network based autoencoder scheme." Mechanical Systems and Signal Processing 129 (2019): 764-780.

Zhang, Bin, Shaohui Zhang, and Weihua Li. "Bearing performance degradation assessment using long short-term memory recurrent network." Computers in Industry 106 (2019): 14-29.

S2S-LSTM 深度學習技術於鈦及鋁合金鏡面切削之 PCD 銑刀剩餘壽命預測

陳響亮
國立成功大學製造資訊與系統研究所

李桂銘
工業技術研究院機械與機電系統研究所控制核心技術組機電控制整合部

黃彥翔
國立成功大學製造資訊與系統研究所

呂育廷 林彧甫
金屬工業研究發展中心模具與精微加工組

黃河銓
國立高雄科技大學智慧商務系

摘 要

在製造業中，使用多晶鑽石(polycrystalline diamond, PCD)銑刀對鈦合金、鋁合金進行鏡面切削是重要的加工技術，而為了提高生產效率、改善鏡面切削技術，PCD 端銑刀的剩餘使用壽命(remaining useful life, RUL)預測亦成為了重要的議題。本研究設計並進行了數次鈦合金和鋁合金的 PCD 銑削實驗，於實驗中收集振動及聲音訊號以作為 RUL 預測的資料集。本研究使用 S2S-LSTM 深度學習技術建構 PCD 銑刀 RUL 預測的模型，

於初次實驗中以驗證集數據進行預測得到 98.1% 的 F1-Score。於第二次實驗中，本研究以相同加工參數進行銑削實驗並以提出的 S2S-LSTM 模型對驗證集進行預測，得到的 F1-Score 則為 95.8%。此外，本研究亦在相同的超參數條件下(相同的 Batchsize、Epoch 及 Learning Rate 等)，與其他 AI 模型如 RNN、GRU 及 LSTM 進行了 F1-Score 的優劣比較。