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Development and analysis of an online tool condition monitoring and diagnosis system for a milling process and its real-time implementation †

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Abstract

This paper addresses the development of an online tool condition monitoring and diagnosis system for a milling process. To establish a tool condition monitoring and diagnosis system, three modeling algorithms – an Adaptive neuro fuzzy inference system (ANFIS), a Back-propagation neural network (BPNN) and a Response surface methodology (RSM) – are considered. In the course of modeling, the measured milling force signals are processed, and critical features such as Root mean square (RMS) values and node energies are extracted. The RMS values are input variables for the models based on ANFIS and RSM, and the node energies are those for the BPNN-based model. The output variable is the confidence value, which indicates the tool condition states – initial, workable and dull. The tool condition states are defined based on the measured flank wear values of the endmills. During training of the models, numerical confidence values are assigned to each tool condition state: 0 for the initial, 0.5 for the workable and 1 for the dull. An experimental validation was conducted for all three models, and it was found that the RSM-based model is best in terms of lowest root mean square error and highest diagnosis accuracy. Finally, the RSM-based model was used to build an online system to monitor and diagnose the tool condition in the milling process in a real-time manner, and its applicability was successfully demonstrated.

Keywords: Online tool condition monitoring and diagnosis system; Milling process; Adaptive neuro fuzzy inference system (ANFIS); Back-propagation neural network (BPNN); Response surface method (RSM); Real-time validation

1. Introduction

Recent trends towards the 4th industrial revolution have actively pushed researches on automated and intelligent manufacturing processes based on big data analytics and artificial intelligence [1]. In this context, Prognostics and health management (PHM) researches on machine tool equipment and various mechanical manufacturing processes have recently attracted more attention. Among them, the tool condition monitoring and diagnosis in mechanical machining processes has been of much significance to improve surface quality and dimensional accuracy of machined components, to prevent sudden failure of tool, to minimize unnecessary high number of tool changes, to minimize machine tool downtime, and so forth [2, 3].

While monitoring and diagnosing tool conditions, there are two methods: offline and online. An offline method requires a direct measurement of tool wear during the process, and therefore, the machine must be frequently stopped for the tool to be taken out for the measurement [4]. The offline method is supposed to be more accurate for tool condition monitoring since tool wear is directly measured, but this method is not applicable in an automated manufacturing system. Besides, due to frequent stoppage of whole machining processes, the downtime of machines can be increased, and therefore, productivity can be decreased. When measuring tool wear, an optical microscope and a vision sensor are typically used [5, 6]. A Scanning electron microscope (SEM) can also be used, as well as Energy-dispersive x-ray spectroscopy (EDS) analysis [7].

An online method, which can also be referred to as the indirect method, usually requires measurements of external signals including cutting force, cutting power, spindle current, acceleration, and acoustic emission signals, and those measured signals are processed to be related to tool condition states [8-17]. Thus, additional signal processing techniques should be necessary. In the online methods, whole machining processes

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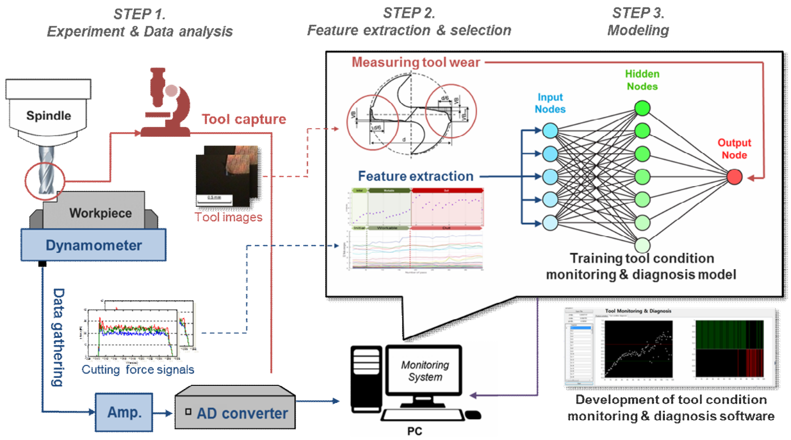


Fig. 1. Schematic diagram of overall methodological framework of the research on an online tool condition monitoring and diagnosis system for milling process.

do not have to be interrupted, while various sensors are used for measuring the abovementioned signals. Therefore, this method can be more effectively incorporated in an automatic manufacturing system without loss of productivity. On the other hand, the existence of noise and drift in measured signals becomes a major drawback of the online method, and it is sometimes necessary to carry out additional signal processing to identify features to be matched with tool condition indices.

In the online methods, a tool condition monitoring and diagnosis model should be properly constructed by applying an appropriate algorithm. Chen et al. proposed the Artificial-neural-networks-based In-process tool wear prediction (ANN-ITWP) system and evaluated it in milling operations [18]. They used a back-propagation ANN model for training the experimental data. In their ANN-ITWP system, the input variables were feed rate, depth of cut and measured average peak force, and the output variable was the tool wear value (V_b). It was reported that the predicted average tool wear errors were within ± 0.037 mm. Lee et al. also used a Back-propagation neural network (BPNN) algorithm to establish the tool condition monitoring and diagnosis model in the micro-grinding process [19]. In their model, the input variables were node energies extracted from the measured tangential grinding force signals by using wavelet packet decomposition, and the output variable was the numerical confidence values for indicating three tool conditions – sharp, middle and dull.

Meanwhile, Malekian et al. investigated the tool wear monitoring method with various sensors, including a force sensor, an acoustic emission sensor and an accelerometer for a micro-milling process [20]. They established a tool wear monitoring model based on a neuro-fuzzy method by training the determining the membership functions and rules. In the course of training, the input variables were the collected sensor signals and cutting condition parameters, and the output variables were numerical values indicating the tool conditions – good, average and bad. Response surface methodology (RSM) could also be an appropriate algorithm for establishing a tool condition monitoring model. In this context, Nam et al. developed the tool condition monitoring and diagnosis model for the micro-drilling process based on an RSM [21]. The input variable was a Root mean square (RMS) value extracted from the measured drilling thrust force signal, and the output response was a confidence value denoting the tool condition of the micro drill. In their research, a k-fold cross validation approach was also applied to improve an accuracy of the model.

In this paper, we developed tool condition monitoring and diagnosis models for milling process based on three methodologies: An Adaptive neuro fuzzy inference system (ANFIS), a Back-propagation neural network (BPNN) and Response surface methodology (RSM). To establish the models, a series of side milling experiments were conducted to machine 40 passes, and the milling forces for each pass were measured. In addition, flank wear values of the endmills after cutting specific milling passes were measured. After examining the measured cutting force signals and flank wear values, three tool condition states, initial, workable and dull, were defined.

For the online monitoring and diagnosis, the measured milling force signals are processed to obtain appropriate features: RMS values and node energy. The RMS values are input variables to the models based on ANFIS and RSM, respectively, and the node energy is an input variable for the BPNN-based model. Meanwhile, as output variables for all three models, the confidence values indicating each tool condition state are used. For the numerical confidence values, 0 is assigned for the initial state, 0.5 for the workable state and 1 for the dull state, respectively.

Each model is validated by conducting milling experiments under the same machining conditions. While investigating the Root mean square errors (RMSEs) and diagnosis rates of each model, it is found that the RSM-based model could be best with smallest RMSE and highest diagnosis rate. Then, the real-time online tool condition monitoring and diagnosis system is realized based on the RSM-based model, and it shows a good applicability to an industrial site with high accuracy and fast processing time. Fig. 1 schematically shows an overall methodological framework of the research in this paper.

Table 1. Experimental conditions.

Milling type	Side milling	
Tool	Carbide twist end mill with Φ12 mm	
Workpiece	Material	S45C steel
	Size	50x120x100 mm
	Hardness	(Brinell) 269
Cutting conditions	Spindle speed	4000 rev/min
	Feed rate	200 mm/min
	Depth of cut	1.8 mm
	Width of cut	3.0 mm
Number of pass	40 passes	
Sampling freq.	10000 Hz	

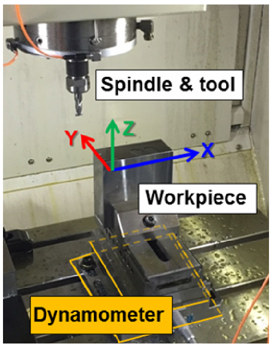


Fig. 2. Photo of an experimental setup of the milling process.

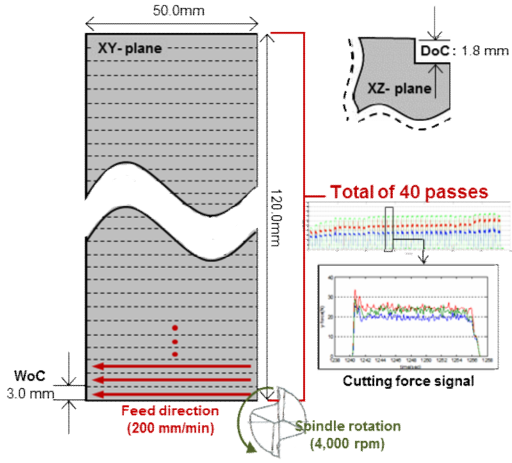


Fig. 3. Schematic diagram of the milling experiments.

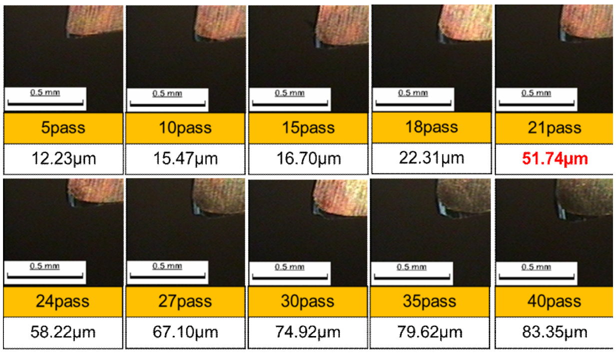


Fig. 4. Photos of the flank wear of endmills after cutting milling passes and their measured values.

2. Milling experiments and tool wear measurement

2.1 Milling experiments

Milling experiments were conducted in the industrial CNC machining center (Doosan Infracore) which has a maximum spindle speed of 8000 rpm. A dynamometer (Type 9265B, Kistler) was installed below a vise holding the workpiece, as shown in Fig. 2, and it measured the cutting forces along X, Y and Z axes. For a tool, the carbide twist end mill (2MEM-120-260-S12, JJ tools) having a diameter of 12 mm, a flute length of 26 mm and an overall length of 75 mm was used. The workpiece material was S45C carbon steel.

To expedite the tool wear progress of the end mill during the experiments, a bit harsher machining conditions were applied, and they are summarized in Table 1. During the side milling experiment, as shown in Fig. 3, the rotating milling tool cut the workpiece 40 times with the same machining conditions and each pass had the same removal volume of 270 mm^3. Thus, a total of 40 profiles of the milling force signals could be gathered.

2.2 Tool wear measurement

For tool wear measurement, ten milling passes, including 5^{th}, 10^{th}, 15^{th}, 18^{th}, 21^{st}, 24^{th}, 27^{th}, 30^{th} and 40^{th} passes were selected among 40 ones. When measuring the tool wear, the milling process was paused after finishing each selected pass, and the tool was detached for the measurement. Therefore, an actual tool condition after such milling pass could be identified. In the above-selected passes, the tool wear measurement interval became shorter after the 15^{th} pass, since the tool wear progressed more rapidly after that pass.

Optical images of the milling tool after cutting each pass were taken by a Charge-coupled device (CCD) camera. From the optical images, flank wear values of each tool were obtained by calculating pixels of the tool images and comparing them with scale bars marked on the pictures. Generally, flank wear is a result of abrasion and adhesion wear of a tool's clearance face contacting with a finished surface, and it is usually considered as an important indicator of milling tool condition [4].

Fig. 4 shows the optical images of the end mills after cutting each pass, and the measured flank wear values are also given. As can be seen in Fig. 4, the measured flank wear values of the milling tool increased as the number of milling passes increased. In particular, after machining the 21^{st} pass, the flank wear value was 51.74 μm, and it was almost twice that after machining the 18^{th} pass – 22.31 μm. Furthermore, the flank wear was intensified faster after the 21^{st} pass, and therefore, it is believed that the significant tool wear of the end mill could have occurred at the 21^{st} machining pass.

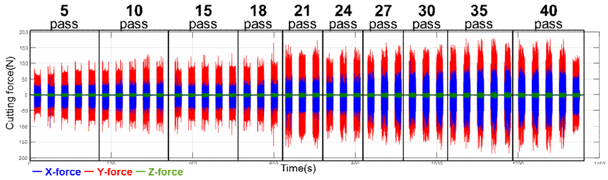


Fig. 5. The measured cutting force signals along X, Y and Z axes for all 40 passes.

3. Feature extraction and correlation with tool condition states

By using a dynamometer, the cutting force signals in each milling pass were captured; the measured cutting force signals along X, Y and Z axes for all 40 passes are given in Fig. 5. In Fig. 5, the signals appearing in red are the milling forces along Y-axis, which was the feed direction, and the blue-colored signals represent those along X-axis, indicating the normal direction. Compared with those two directions, the forces along the axial direction (Z-axis), which is marked by green, are very small, and it is a normal phenomenon in the milling process.

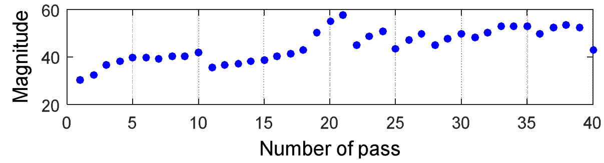
As can be seen in Fig. 5, the measured milling force signals were divided into ten sections according to the milling passes. When observing the magnitudes of measured milling forces in each section, there exists a sudden increase at a section from the 19th to the 21st pass. In particular, the milling forces along with X and Y axes increased significantly in this section. Since the measured tool wear values also increased dramatically in this section, it was believed that the flank wear values were closely related to such measured milling forces. Therefore, we concluded that the measured cutting force signals could be used for indicating the tool wear conditions in the milling process.

On the other hand, in the first section, from the 1st pass to the 5th pass, the measured cutting forces gradually increased, and it is believed that a new endmill had become stabilized by milling the first five passes. Meanwhile, from the 6th pass to the 18th pass, the measured cutting force signals had a nearly constant magnitude, and the measured flank wear values gradually increased, as given in Fig. 5. Thus, in these sections, the milling process could be stable to machine the workpiece.

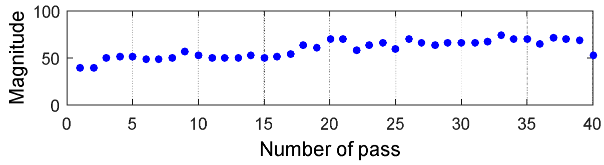
Based on the above preliminary analysis on the measured cutting force signals, various static features including a Root mean square (RMS), a maximum, a variance, a crest factor, a kurtosis and a skewness were considered to be related to tool wear conditions. Among those features, the RMS, maximum and variance values are mathematical values representing the size of a signal, and the crest factor, kurtosis and skewness were those representing the shape of a signal, respectively. More detailed descriptions on each feature are given in Ref. [8]. In Fig. 6, the static features extracted from the measured resultant cutting force signals are given, and they are graphically shown versus the number of passes.

From the previous analysis on the measured cutting force signals in a time domain, the 5th section – from the 19th to the 21st passes – showed a significant increase in their magnitudes. In addition, while analyzing various features given in Fig. 6, the RMS values of the measured resultant forces showed a clear difference before and after the 5th section. Therefore, the RMS values were chosen to be associated with the tool wear conditions.

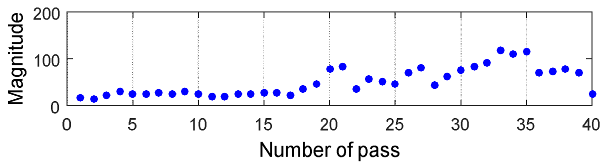
For tool wear conditions of the endmill during the milling process, three states – initial, workable and dull states – were defined along with the milling passes. The first section from



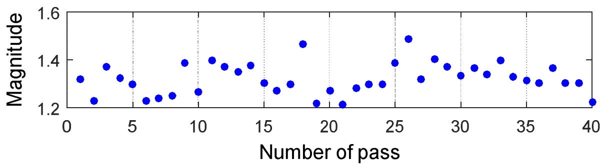
(a) RMS



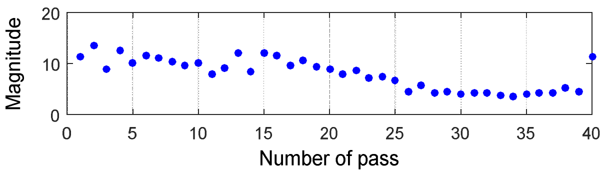
(b) Max



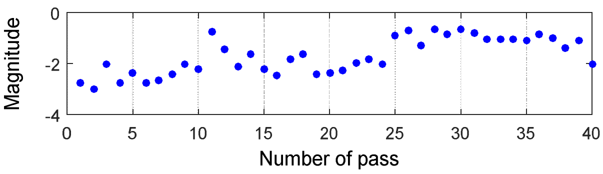
(c) Variance



(d) Crest factor



(e) Kurtosis



(f) Skewness

Fig. 6. The static features extracted from the measured cutting force signals for 40 milling passes.

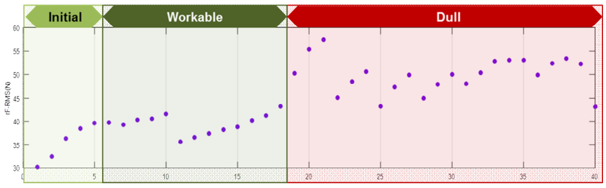


Fig. 7. Initial, workable and dull states of the tool wear conditions versus the number of milling passes.

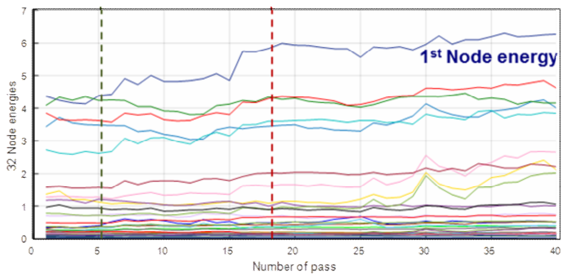


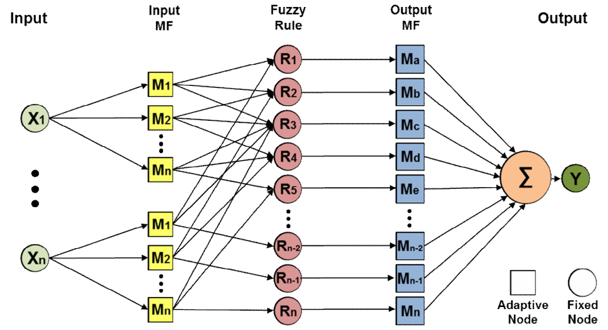
Fig. 8. 32-Node energies of the milling force signals extracted by a WPD method.

the 1st pass to the 5th pass denotes the initial state of the tool wear condition. The next three sections from the 6th pass to the 18th pass do the workable state. Finally, the dull state includes those from the 19th to the 40th passes. Fig. 7 shows a graphical representation of the three states – initial, workable and dull – of the tool wear conditions versus the number of passes by considering the RMS values of the measured resultant cutting forces.

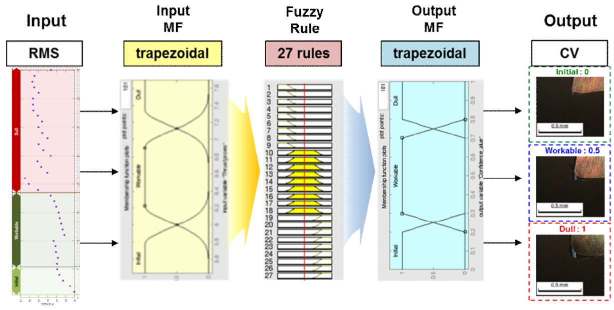
On the other hand, another feature, a node energy, that can be extracted from the measured cutting forces by a Wavelet packet decomposition (WPD) method, was also considered. The WPD method basically divides non-stationary signals into several node energies stored in different frequency bands, and the number of nodes is decided by a level of WPD [22]. In this research, the level of WPD was 5, and thus, total 32 node energies were extracted from the cutting force signals, which are given in Fig. 8. Among them, the first node energy was for the lowest frequency band from 0 Hz to 156.25 Hz, which was calculated by dividing the Nyquist frequency (5000 Hz) by the number of nodes (32). In this frequency band, a rotational frequency of the spindle of 66.67 Hz and a tooth passing frequency of 133.33 Hz were included. Hence, the 1st node energy could well describe a tendency of the tool conditions. As can be seen in Fig. 8, the 1st node energy shows a clear difference in its magnitudes for each tool condition state – initial, workable and dull states.

4. Development of the tool condition monitoring and diagnosis model for milling process

Three modeling methodologies – an Adaptive neuro fuzzy inference system (ANFIS), a Response surface methodology (RSM) and a Back propagation neural network (BPNN) – were applied for developing the tool condition monitoring and



(a) General architecture of an Adaptive neuro fuzzy inference system (ANFIS) algorithm



(b) Schematic of the tool condition monitoring and diagnosis based on an ANFIS algorithm

Fig. 9. General architecture of an Adaptive neuro fuzzy inference system (ANFIS) algorithm and the schematic diagram for the tool condition monitoring and diagnosis model based on an ANFIS.

diagnosis model during the end-milling process. First, the concept of the confidence value was introduced to build the model. Hence, the numerical values of 0, 0.5 and 1 were allocated to the initial, workable and dull states, respectively, and they were considered as output responses for the model. For input variables, the RMS values and node energies extracted from the measured cutting forces were used.

While developing the models, the milling experiments under the machining conditions given in Table 1 were repeated for five times. Then, the RMS values extracted from the measured cutting forces and the confidence values indicating the tool conditions in those five experimental cases were used for building the models.

4.1 Adaptive neuro fuzzy inference system (ANFIS)

The first model was based on an Adaptive neuro fuzzy inference system (ANFIS). An ANFIS is a hybrid intelligent system combining a Fuzzy inference system (FIS) and an Artificial neural network (ANN), so that it takes benefits of both methods – a capability of capturing the vagueness in human decision making for an FIS and a self-learning ability using parallel data processing for an ANN [23, 24]. Therefore, an ANFIS is very useful for establishing a model with a complex data distribution under uncertainty.

However, ANFIS also has a limitation regarding the num-

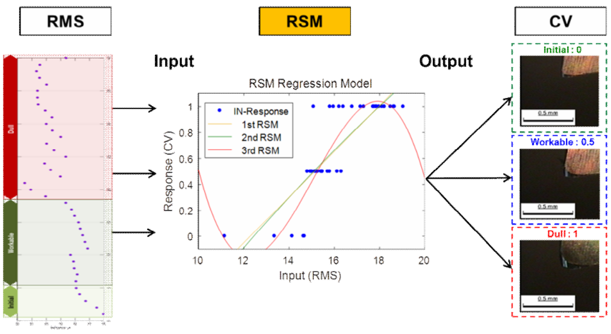


Fig. 10. Schematic diagram for the tool condition monitoring and diagnosis model based on an RSM.

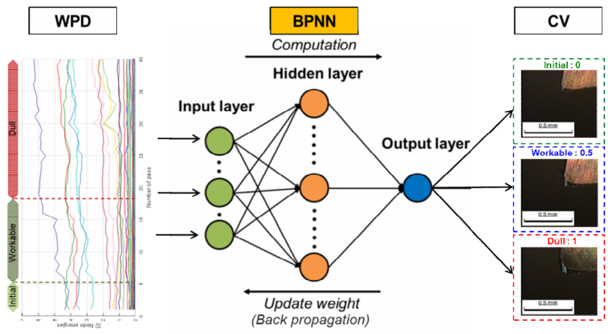


Fig. 11. Schematic diagram for the tool condition monitoring and diagnosis model based on a BPNN.

ber of input layers. As shown in Fig. 9(a), the ANFIS is generally structured down to several adaptive Membership functions (MF) with fixed fuzzy rules, and if the input variables excess 5 layers, the functions become too complicated to ensure an accuracy of output results. In this research, as shown in Fig. 9(b), the trapezoidal membership functions were selected. In such membership functions, the transition regions for the confidence values from 0.2 to 0.3 and from 0.7 to 0.8 were allowed, since the tool conditions of the endmill could be described by a certain percentage of two different states [Jun and Park (2009)]. Thus, the region from 0.2 to 0.3 represented the transition from the initial to workable states, and that from 0.7 to 0.8 denoted the transition from the workable to dull states, respectively. The model converted the input variables – the RMS values of the cutting forces – to the quantitative confidence values in the range from 0 to 1.

4.2 Response surface methodology (RSM)

The second approach was based on a Response surface methodology (RSM) to build the regression model for monitoring and diagnosing the tool conditions. RSM is a collection of statistical and mathematical techniques that is often used when the input variables potentially influence some output responses [25]. In this paper, it is likely that RMS values of the measured cutting forces could have an influence on the tool wear conditions of the endmill. Thus, the RMS values were input variables, and the output responses were the tool conditions that were represented by the numerical confidence values. In addition, the 2nd order regression was considered. Fig. 10 depicts the schematic diagram of the RSM-based tool condition monitoring and diagnosis modeling.

4.3 Back-propagation neural network (BPNN)

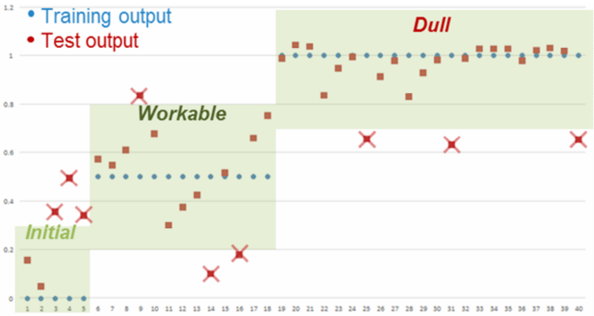
In the third approach, a Back propagation neural network (BPNN) algorithm was introduced to build the tool condition monitoring and diagnosis model. Back propagation is the most extensively used training algorithm for ANN, and its major objective is to modify values of firing strength, generally called weight, using feedbacks on evaluation errors [26, 27]. In this algorithm, 32 node energies that were extracted from the measured cutting forces using a WPD method were input to the input layer, and the numerical confidence values were assigned to the output layer during training the model. In Fig. 11, the schematic diagram for establishing the tool condition monitoring and diagnosis based on a BPNN is given.

4.4 Validation of models and comparative analysis

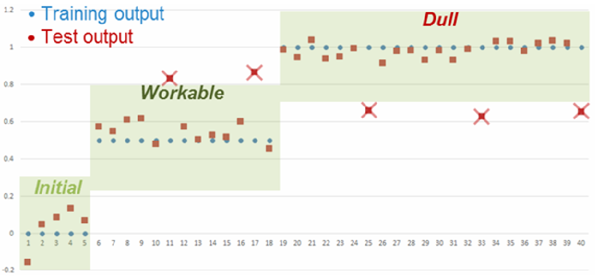
The tool condition monitoring and diagnosis models which were developed by three different methodologies were validated in this section. When validating them, the milling experiment under same machining conditions given in Table 1 was conducted. During the experiment, the RMS values and node energies were extracted from the measured cutting forces, and they were input to the models. Then, the confidence values were computed from the models as output responses. Fig. 12 shows the validation results for three tool condition monitoring and diagnosis models.

After computing the confidence values, we used them to classify three tool condition states. Namely, the confidence values below 0.2 were classified as the initial state; those between 0.3 and 0.7 were the workable state, and those larger than 0.8 were the dull state. As previously described, in the ANFIS-based model, two transition regions are defined. The computed confidence values within those regions can be classified to either tool condition state. Therefore, the confidence values in the range from 0.2 to 0.3 can be classified as either initial or workable state, and those in the range from 0.7 to 0.8 can be either workable or dull state.

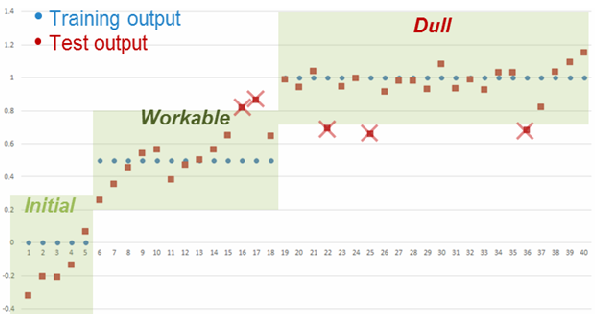
In Fig. 12(a), the validation results from the model based on the ANFIS are given, and those from the models based on the RSM and BPNN are given in Figs. 12(b) and (c), respectively. Meanwhile, the transition regions which were introduced in the ANFIS-based model were also considered for the models based on the RSM and the BPNN, respectively, for consistency. In Fig. 12, the blue circular dots denote the output confidence values during training the models, and the red squares denote computed ones during validating (Testing) them. In particular, the red squares with 'X' marks mean erroneous diagnosis results from the models during the validation.



(a) ANFIS



(b) RSM



(c) BPNN

Fig. 12. Validation results of the tool condition monitoring and diagnosis models based on three methodologies – ANFIS, RSM and BPNN.

As can be seen in Fig. 12, the confidence values indicating the tool wear conditions were computed for each milling pass during the validation, and there were 9, 5 and 5 erroneous diagnosis results for the ANFIS-based, RSM-based and BPNN-based models, respectively. In addition, a level of dispersion seems smallest for the RSM-based model and largest for the ANFIS-based model.

This qualitative discussion can be confirmed by the quantitative results given in Table 2. In Table 2, the diagnosis rates and Root mean square error (RMSE) values for each model are given. As shown in Table 2, the RSM-based model has the highest diagnosis rate and the lowest RMSE value, respectively. Although the BPNN-based model has the same diagnosis rate with the RSM-based model, it has somewhat larger RMSE value. In the case of the ANFIS-based model, it was shown that the diagnosis rate was lowest and that the RMSE value was largest. Thus, the RSM-based model could be more advantageous for monitoring and diagnosing the tool wear conditions by using measured cutting force signals during the milling process in this research.

Table 2. Root mean square errors and diagnosis rates for each tool wear condition monitoring and diagnosis model.

Models	RMSEs	Diagnosis rates
ANFIS	0.675	77.5 % (31/40)
RSM	0.114	87.5 % (35/40)
BPNN	0.138	87.5 % (35/40)

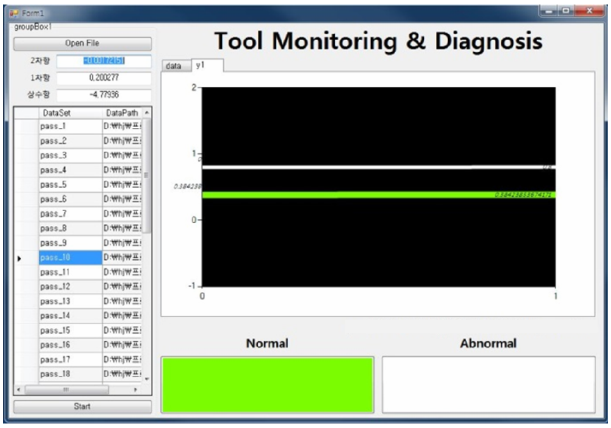
Generally, an RSM can provide quite robust results when input data have a definite trend. On the other hand, an RSM may suffer from a lower accuracy in deduction, if a data distribution is highly complex and imprecise [21]. Meanwhile, the processing time of RSM is usually much faster than the other two approaches considered in this paper. Therefore, the best validation results from the RSM-based model could be obtained in this research, since the RMS values of the cutting force signals in the milling process showed the monotonously increasing trend according to the tool wear progression.

5. Software development and industrial implementation for real-time monitoring and diagnosis

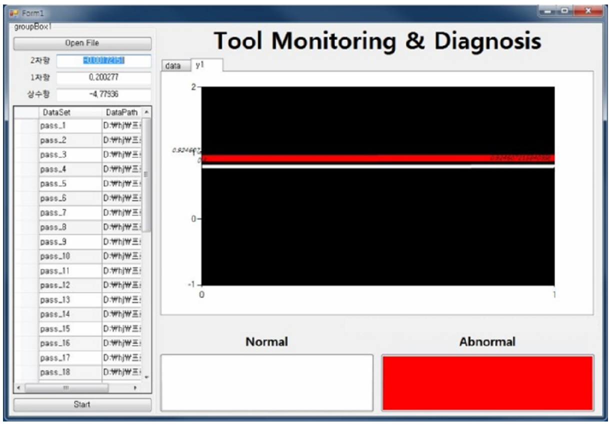
The C sharp programming language was used to develop the real-time tool condition monitoring and diagnosis software for the milling process in an industrial site. As previously discussed, the RSM-based model showed the highest diagnosis accuracy and the lowest RMSE value. Therefore, the software was developed based on the RSM-based model with faster processing time.

During actual industrial implementation of the developed software, the cutting force data start to be collected, as soon as they begin to increase after endmill's contacting the workpiece. Then, their RMS values are calculated and matched with the specific milling pass. Those RMS values are input to the RSM-based model to compute the confidence values indicating the tool wear conditions of the endmill.

In the software, the computed confidence values were used to diagnose the tool conditions. Thus, if the confidence value was larger than 0.8, the tool condition of the endmill was in the dull state and a sign of 'abnormal' was visually given. On the other hand, if the confidence value was smaller than 0.8, the tool wear condition could be in either initial or workable state. Therefore, a sign of 'normal' was visually given in the software. Fig. 13 shows the snapshot photos of the developed software's user interface. As can be seen in Fig. 13, the computed confidence values are graphically shown as lines along with the vertical axes. The numerical confidence values are also given nearby the vertical axes and on the line. For an intuitive information transfer, a line color in the case of the normal tool condition was green, and that for the abnormal tool condition was red, respectively. In addition, the white line lied in the display represents the confidence value of 0.8, which is the threshold value to determine either normal or abnormal state.



(a) Normal tool wear condition



(b) Abnormal tool wear condition

Fig. 13. Snapshots of the tool condition diagnosis results in the software visual interface.

6. Conclusion

Tool condition monitoring and diagnosis models were developed based on three different algorithms – ANFIS, BPNN and RSM – and a comparative analysis was conducted to evaluate each model's performance in terms of an RMSE and a diagnosis rate.

The models based on ANFIS and RSM used the RMS values extracted from the measured milling force signals as input variables. On the other hand, in the case of the BPNN-based model, the node energies were extracted from the milling force signals by a WPD method, and they were used as input variables. The output variables were the confidence values indicating the tool condition for all three models.

It was shown that the RSM-based model was best with lowest RMSE value (0.114) and highest diagnosis rate (87.5 %). Generally, an RSM is quite effective to produce robust results in the case of data sets having a definite trend. Since the tool wear progression showed an increasing trend in the milling process, it is believed that the RSM-based model showed the best result. Meanwhile, the BPNN-based model was second best with same diagnosis rate (87.5 %) with the RSM-based model and a bit higher RMSE value (0.138). Since a WPD method can be applied to highly dynamic data such as the milling force signals in this research, the extracted node energies can be effectively used for input variables for building the BPNN-based model with a good performance.

The RSM-based model that showed the best performance was utilized to develop the software to monitor and diagnose the tool conditions in a real-time environment. Through a series of milling experiments and measurements, the tool condition monitoring and diagnosis model was established, and it was programmed in the embedded system. In this system, the computed confidence value smaller than 0.8 was diagnosed as 'normal', and that larger than 0.8 was diagnosed as 'abnormal'. The developed software system was implemented in an industrial site, and it was demonstrated that a real-time tool condition diagnosis rate was better than 95 %.

Meanwhile, a concept of the confidence value was introduced to indicate the tool conditions of endmills in the milling process. The measured flank wear values were categorized into three tool conditions states – initial, workable, and dull – after examining their magnitudes and increasing trend, and the corresponding ranges of the confidence values for each state were defined. Therefore, machine tool operators could get more intuitive information on the tool conditions and thus make a decision whether the tool should be changed or not more conveniently.

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