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Study of spindle power data with neural network for predicting real-time tool wear/breakage during inconel drilling

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ABSTRACT

Digital manufacturing systems are determined to be a major key to enhance productivity and quality mainly due to real-time process monitoring and control capability with instant data processing. During machining, such systems are anticipated to excerpt reliable data within a short time-lapse, monitor tool wear progress, anticipate its wear and breakage, alert the machinist in real time to avoid unexpected failure of tool or machine, and help obtaining quality products. This is vital, especially, when drilling Ni-/Ti-based superalloys because catastrophic failure and premature breakage of tools occur in random manner due to aggressive welding and chipping of tool including the rake and/or flank faces and tool corner.

Nowadays, spindle power data are easy to collect directly from modern machine tools and can be made available in production floor for such real-time data processing. This work aims to evaluate spindle power data for real-time tool wear/breakage prediction during drilling of a Ni-based superalloy, Inconel 625. Experiments were performed by varying speed and feed. Spindle power data were collected from the power meter (also called load meter) to feed into the neural network (NN) for functional processing. To understand the reliability of the spindle power data, force data were also collected and compared. The results show that the trends of these two different types of data over cutting time are similar for any feed and speed combinations. The error in NN prediction from actual wear was found to be between 0.8–18.4% with power data as compared to that between 0.4–17.9% with force data. Findings suggest that spindle power data integrated with the artificial intelligence (NN) system can be used for real-time tool wear/breakage monitoring and process control, thus appreciate digital manufacturing systems.

1. Introduction

In recent years, the manufacturing world has made considerable progress towards digital intelligent manufacturing technologies and systems – from data processing to shop floor data mining to final products [1]. Many different intelligent hardware and software, including sensors and data acquisition (DAQ) systems are being developed to improving both manufacturing productivity and product quality [2,3]. Nonetheless, a syndrome called "DRIP – Data Rich Information Poor" is still common to engineers and machine operators at the manufacturing shop floor [4]. A majority of data are analyzed offline by researchers or engineers rather than machine operators, which slows down productivity. Analyses are performed mainly by developing analytical force and wear models or statistical tool life models based on experimental data, such as force, wear, and surface metrology. However, in a production line, *e.g.*, in machining, there is a serious need of intelligent manufacturing systems that can automatically collect reliable data during machining, monitor tool wear progress based on the collected data, anticipate wear and breakage, alert the machinist in real time to avoid unexpected tool failure, and help to obtaining quality products.

Drilling is counted to be one-third of all machining operations [5] and usually comes last in the entire process. It is therefore critical for this process to be as precise and optimized as possible. Drill wear monitoring is very important since worn tools affect hole quality (*e.g.*, cylindricity, circularity, surface roughness), and product life [6]. The problem becomes more critical when machining superalloys, such as, Ni- and Ti-based alloys that possess unique physical and metallurgical properties [7–9]. Due to mainly poor machinability, significant chip welding at the cutting edge, and

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twisted flutes with limited channel size for evacuating long curled chips, drilling tools can become unstable (bend and vibrate) at any moment. While drilling these superalloys with comparatively longer but thinner tools, the problem becomes even more critical. This ultimately leads to chipping at the rake and/or flank faces, premature tool breakage at the weakest location (usually on shank) of the drill bit, and even partial destruction of the manufactured part. Such nature of tool failure is often random and highly uncertain in machining superalloys [10]. A recent related report on drilling operation is as follows [11]: "*A drill breaks and then the reamer tries to do its job, and it breaks, too. On a machine running unattended, a tool wears prematurely and creates thousands of bad parts. A large, high-priced indexable tool hits a misaligned part and destroys itself... But tool breakage and wear can be unpredictable*."

So, in such machining processes, both analytical and empirical methods that are developed based on either classical mechanics or experimental cutting force and wear data, *etc.* are not suitable to assess tool life/wear and product quality [12]. Moreover, in a real production setup, it is desired to have a smart manufacturing system that does not demand special setup (*e.g.*, force dynamometer) and time during the processing of thousands of complex 3D parts while also monitoring and controlling the process at the same time.

Modern machine tools are provided with a built-in spindle power sensor that is very cheap and does not interfere with the operation setup [1]. Spindle power data are easy to collect and can be deployed for real-time digital manufacturing systems. Machining power (consumed by the AC motor) is directly proportional to its torque resulting in a correlation between the power and the cutting forces. Thus, the power sensor is found to be correlated with tool wear [13,14]. With the smart use of this sensor data, a machine could automatically sense the tool condition if a tool breaks and wears, then shut down itself or load a new tool. In a research led by Shao et al. [15], a threshold updating strategy for tool condition monitoring (TCM) is presented that can deal with variable cutting operations during milling. The power sensor is mainly used as a complementary sensor for systems, such as sensor fusion combined with a neural network, to improve signal reliability, and help TCM to reach good results [16]. For turning, spindle power was also used for detection of critical amount of tool wear (VB_{max}), and the successful classification rate was 96%. However, the use of power sensors in manufacturing is still very limited for TCM, especially, tool wear/breakage prediction (TWBP). Moreover, since premature tool breakage and catastrophic chipping are common but random when drilling superalloys, the use of in-process power data for real-time TCM/TWBP and early predication of sudden breakage is vital.

The aim of this work is to evaluate the usefulness of spindle power data for real-time tool wear/breakage prediction (TWBP) instead of using force data that are impractical in production floor. Study was performed for drilling of a Ni-based superalloy, Inconel 625 – a very demanding material in critical applications, such as, aerospace, chemical, and oil production industries. Experiments were performed by varying speed and feed parameters. Spindle power data were collected from the machine power meter (also called load meter) to verify their relationship with the associated cutting force data. Power data were then fed into the neural network (NN) for functional processing, thus to predict tool wear progress, life and premature breakage with a preset threshold value.

The remainder of the paper is presented as follows. Section 2 focuses on the overview of the data collection technologies and the NN technique used in manufacturing, followed by the experimental setup and procedure in Section 3. Section 4 evaluates the use of spindle power data in manufacturing. Section 5 presents the NN processing technique with data, followed by conclusions in Section 6.

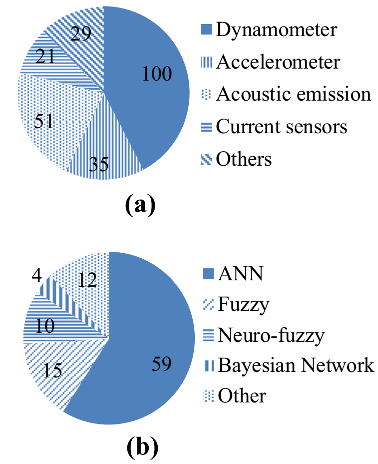

Fig. 1. Previous research studies on (a) output response methods; (b) use of artificial intelligence (AI) in intelligent manufacturing [3].

2. Study background

Data acquisition systems (DAQs) for machining involve both hardware and software. In hardware, while force dynamometer was the obvious instrument as a part of the machining data system, it is being replaced by intelligent but low-cost and quickly installable built-in sensors in the present era of digital manufacturing systems. Similarly, in software, some artificial intelligence (AI) methods that could be implanted for online data processing are now taking the place of offline data processing media like spreadsheets. This section presents an overview of the machining DAQs and the NN technique simplified for processing machining tool wear data.

2.1. Machining data acquisition systems

Several measurement technologies are implemented to predict tool wear indirectly (see Fig. 1(a)). For decades, piezo sensor-based dynamometers have proven to be the best method to gather force data and to monitor a cutting process with cutting force levels [3]. However, it does not support current digital manufacturing systems. Primarily, in production lines, where compound machining operations are performed for thousands of products, there is no scope to accommodate such dynamometer in the setup. However, tool wear and life monitoring in each operation is highly important. Even for the offline lab-based fundamental data analysis, a custom setup is always demanded for collecting data. Also, for dynamometers, the related DAQs and their maintenance are relatively expensive. Microscopic measurement of tool wear cannot be deployed in online tool condition monitoring (TCM) or TWBP. An accelerometer is an option to detect tool vibration and breakage, but it: i) works in a specific range of machining speed, ii) is sensitive to mounting position, and iii) is sensitive to environment (coolant, chip strike). Acoustic emission (AE) sensors, which work based on microstructure change of materials due to noises occur at the tool-workpiece interface during the material removal process, are recently employed in TCM [17,18]. Although they are cost effective and easy to install, but are not recommended for a production environment since calibration is very important to avoid overload and non-voluntary noises. Also, the mounting condition and the location of such sensors affect the data values.

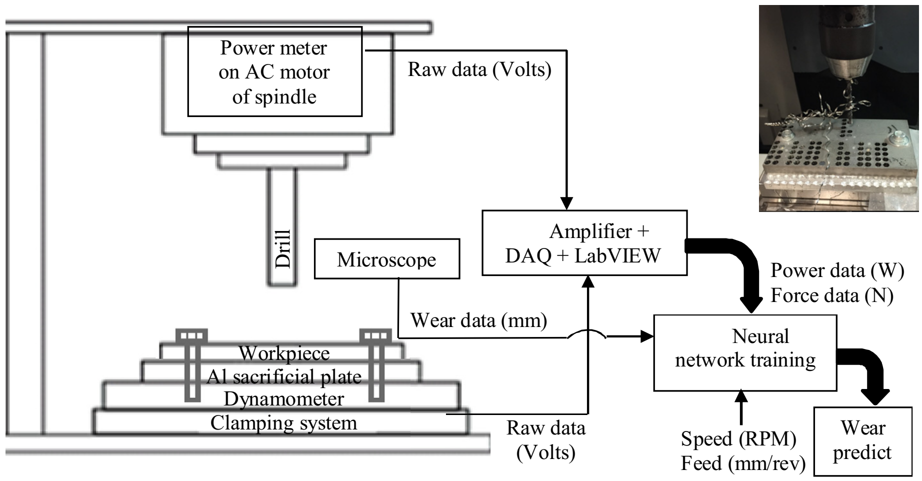

Fig. 2. Overall drilling setup and data processing with the NN technique (inset: tool-work).

As such, new sensors like spindle power senor are developed aiming to install on the rotating spindle where machining interference is not an issue and the data can safely and easily be collected for in-process TCM/TWBP [11]. Many modern machine tools such as Okuma, Moriseiki, HAAS, and so on are provided with built-in power sensors. It is high time to leverage this technology into the digital manufacturing systems.

2.2. Neural network technique overview

Artificial intelligence, such as neural networks, fuzzy logic [19], genetic algorithms [20], and Bayesian networks [21] are used in stochastic machining processes (see Fig. 1(b)). Neural networks (NNs) can be used to solve curve-fitting problems because functions can be stored [22]. The objective is to identify and create a relationship between the input and the output data. When the relation is modeled with the necessary accuracy, the NN can be used as a function approximation. Instead of experimental data used in non-physics-based fitting methods, such as polynomial fitting that offers model trend, NNs work based on experience from these data. With experience, NNs can implicitly detect complex nonlinear relationships between dependent and independent variables, and their interactions [23]. Once the NN is trained with at least one data set, it should be able to predict the future output approximately during the process like machining. However, since NN techniques assume the forecasting results based on the received data characteristics and size, error on predicted results may be larger in the beginning of the process due to a smaller data size received. Continuous feeding of the data helps the NN acquire more experience for a better prediction of the future output (converging error trend). An extensive history of NNs can be found in the literature [24], and the advantages are outlined in [12,23]. Explicit limitations include its “black box” nature, computational burden with software requirement like MATLAB, proneness to over-fitting, and the empirical nature of model development [23]. Also, if the environment changes, for instance, noise or new coolant during machining, data should be reproduced and loaded for the training, at least one new set to start.

Neural networks (NNs) are less common amongst drilling ones as that compared to milling applications. In drilling, NNs are used to monitor workpiece vibration, surface roughness [25], circularity, cylindricity [6] and wear (mostly edge and flank). In order to train a network, a number of different inputs including standard machining input parameters (spindle speed, feed rate) and output parameters such as vibration signals, thrust force, torque, motor current or chip thickness can be considered [26,27]. In the present study, the NN technique is extended to be used to predict tool wear and to detect breakage before it happens using the spindle power data. As it is able to map arbitrary input-output, the multi-layer perception (MLP) is used to deal a variety of problems. The NN MLP structure and the NN technique in manufacturing data processing are simplified in this study as provided in Appendix A.1 and A.2.

Three different well-accepted NN algorithms including Levenberg Marquandt (LM), Conjugate Gradient Descent (CGD), and Bayesian Inference (BI) are used in this study to perform data analysis for the set of equations shown in Appendix A. With NNs, data have to be split in three categories:

i) Training data: Network is trained, and different weights are calculated and optimized.
ii) Validation data: Network generalization is quantified. This data set is used to halt training when error stops decreasing.
iii) Testing data: Precision of the NN is evaluated with error values.

3. Machining setup and experimentation

Drilling experiments are performed on a 3 axis vertical machining center, *Okuma Millac 44V*. A schematic of overall drilling setup with an inset of the actual tool-workpiece zone is shown in Fig. 2. An Inconel 625 plate of 200 mm × 100 mm × 12.7 mm is drilled using heat resistant, chip clearing, and uncoated cobalt steel jobbers' drills that are recommended for drilling nickel alloys. The drill geometry is as follows: parabolic flutes, 5.95 mm dia, 135° point angle, 55.88 mm drill depth, and 92.08 mm overall length. Based on the literature for Inconel drilling, three spindle speeds (S1:400, S2:500, S3:600 rpm) and four feed rates (F1: 0.05, F2:0.075, F3:0.1 mm/rev) are selected to construct a design matrix of experiments, and that to obtain the best data sets possible for the neural network training. Experiments were conducted with a water soluble coolant at 7% concentration.

Note that some preliminary experiments with parameters within the above mentioned range were conducted to observe tool wear progress and premature tool breakage (at tool faces or shank), and related power and force increase level. The main purpose was to determine a threshold force and/or power level (%increase w.r.t. to a fresh tool) between continuous tool wear and sudden premature breakage. It was performed in order to avoid tool breakage and machine tool crush (spindle bearing). Thus, this study was limited to predict tool wear values before the catastrophic tool failure.

Fig. 3. Drilling wear measurement locations.

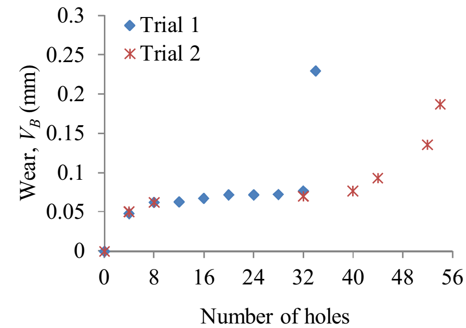

Fig. 5. Flank wear for two drilling trials at the same conditions of 500 rpm and 0.1 mm/rev.

As seen in Fig. 2, the workpiece plate was placed on a sacrificial supporting plate of aluminum; then these two plates together were fastened on the top of the *Kistler dynamometer 9257B* using two bolts, one on each end. The force data were directed to an *NI DAQ* card *via* a charge amplifier (*type 5010*). The machine has a power meter on its AC motor that runs the spindle. The power meter line was connected to the same DAQ card. The force and power (P) were collected using *LabVIEW* software in terms of newton (N) and watt (W). With *LabVIEW*, the power data were collected AC mode. To measure the flank wear level (VB) at different locations of both the cutting edges, a *Mitutoyo MF* series (integrated with a *Moticam 380* camera) and/or a *Dynolite Pro camera microscope AM413TA* were used. Tool flank wear was

measured at the locations of four maximum peak wear points in each side at an interval of four holes until the tool life (see Fig. 3). The tools were checked more frequently (1 or 2 holes) at the end of tool life in order to avoid catastrophic failure. A total of two points per side is sufficient in the measurement of tool wear, but preliminary drilling experiments revealed welding or built up edge that sometimes cover a consequent portion of the flank. In literature, usually 4–6 points are recommended [5]. Wear measurement is defined by an average value of all measured points on both the sides. Tool life criteria is selected based on some preliminary experiments and is explained in the next section.

4. Machine spindle power data in process analysis

As stated in Sections 1 & 2, several offline and online technologies may be used for tool condition monitoring (TCM), particularly, tool wear/breakage prediction (TWBP). This study focuses on understanding if the spindle power data that are readily available and easily extractable from a data cable connected with the rotating spindle can reliably be used for real-time TCM during machining. This section presents drilling tool wear behavior for Inconel 625, spindle power data at different cutting conditions, and power and force data relationship to evaluate reliability of the power data for machining process.

Tool wear has a direct relationship with both the spindle power and the cutting force. Thus, it is necessary to understand the wear behavior of a tool during drilling, especially, super alloys. As shown in Figs. 4 and 5, similar to previous studies, tool wear behavior usually follows three stages before failure: i) initial flank wear appears from the first hole and progresses extremely fast until 4–8 holes with a typical amount of about 0.05 mm, ii) steady wear state survives until 0.085–0.1 mm of wear level, and iii) critical/catastrophic wear or tool breakage happens at the tool wear of 0.3 mm or before. Chipping usually was observed in later moments of the steady wear region on the flank. However, when chipping on the rake appears abnormally early, the tool wear was found to be accelerated. Flank wear is observed to be inconsistent towards the center of the drill as compared to the outer edge of the drill (see Fig. 5). Also, if none of the sides is chipped in earlier stage, flank wear progress is usually found to be consistent for each side until the steady wear state.

Fig. 5 presents maximum tool wear value (average of 4 maximum wear locations) against number of holes for two trials at the same condition of 500 rpm and 0.1 mm/rev during the drilling of Inconel 625. It is very interesting to observe that there is a difference of 20 holes between two trials – one tool survived up to 34 holes while the other tool up to 54 holes. Though both the tools were following the same steady wear until 33 holes, the tool flank for the first trial suddenly chipped and damaged at the 34th hole as opposed to the other tool that was still able to produce holes and failed by following the conventional wear behavior in machining. This reveals that there is a high uncertainty of tool failure/wear during the drilling of Inconel 625 due to the causes stated in Abstract and Introduction sections. Fig. 6(a) and (b), respectively, depict such a behavior of tool wear with a sudden steep rise of about 3 times of both the spindle power (from an average of 230 W to 795 W) and the thrust cutting force (from an average of 964 N to 2650 N). It can be noted that the power values appear in both positive and negative as they are captured in the AC (alternating current) mode – positive indicates the drill bit engages the workpiece while negative indicates the release from the hole. The sudden drop and rise behavior of power and force values recognizes failure/breakage of the tool. From some preliminary experiments including this trial No. 2, it was also noticed that most tools catastrophically failed or broke on the shank (tool body) after 20–30% of the power and the

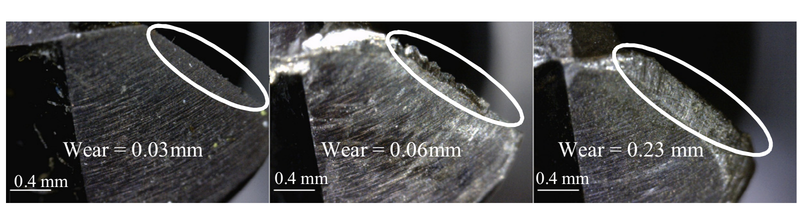

Fig. 4. Three stages of flank wear at 500 rpm and 0.1 mm/rev after (a) 4 holes (b) 12 holes, and (c) 34 holes.

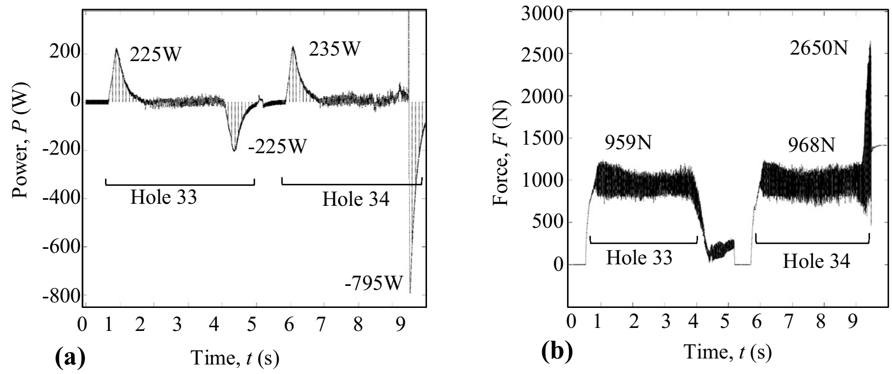

Fig. 6. Tool failure observed with: (a) power and (b) force signals at hole 34 when drilling at 500 rpm, 0.1 mm/rev.

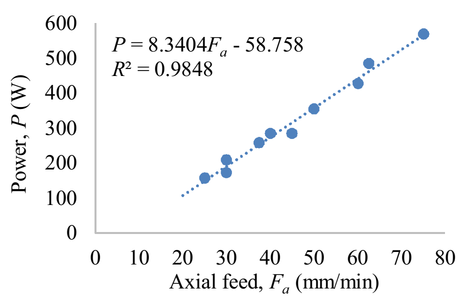

Fig. 7. Power values against axial feeds for 10 drilling tests (at beginning of the steady wear).

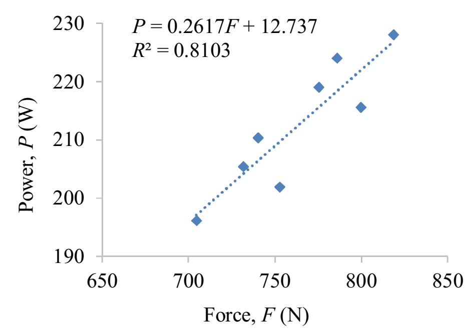

Fig. 9. Power and force relationship from drilling experiments of Inconel 625.

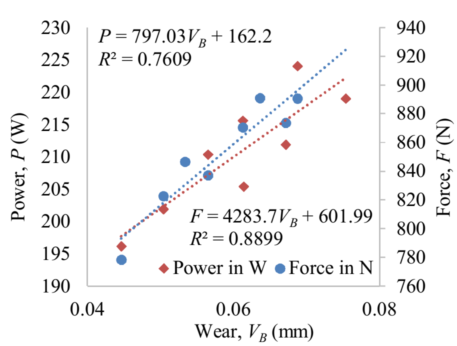

Fig. 8. Force and power as function of wear for 500 rpm and 0.075 mm/rev.

force increase from the initial value. Therefore, the tool life in this study was determined based on the average/maximum flank wear value of either 0.3 mm or a force and power level of 20% increase of the initial value, whichever happened earlier.

In this study, spindle power data were collected with the voltage setting in the AC mode due to AC (alternating current) coupling. However, the power data in the DC (direct current) mode were also available. For reference, the relationship between the collected AC and DC power data from the spindle is provided in Appendix A.2. Maximum spindle power (AC) values are plotted against different axial feeds (=rpm x feed rate) of the drill across the plate thickness of one hole at the beginning of the steady wear (5th or 6th hole), as depicted in Fig. 7. A line is fitted to the data points. It is seen that there is a linear relationship between the power and the axial feed (mm/min) of the tool. From the regression analysis of the data points, the value of R^2 = 98.48% reveals that the linear curve fits with the data points very well. Thus, the real-time power data extracted from the spindle load meter during drilling can be reliably used for online TCM.

Fig. 8 shows both the power and the force data points at different flank wear values measured for a particular drilling condition of 500 rpm and 0.075 mm/rev. It is obvious that force, and thus power increases with the progression in tool wear. The relationship between the thrust cutting force and the power for the same drilling condition is presented in Fig. 9. The relationship is linear, which is theoretically true. However, the regression line at R^2 = 81.03% reveals that there is a little discrepancy in this response.

Also, in Fig. 8, linear regression line for the power data are found to result in R^2 = 76.09%, as compared to that for force data at R^2 = 88.99%. So, from both Figs. 7 and 8, it may be assumed that the power data are not as accurate as the force data. This is coherent with the fact that, due to the static condition of the dynamometer setup, the force data are considered to be the most reliable in machining research. A little inaccuracy in the power data may be due to the power loss factor on the spindle as it rotates. There is a loss of information when sensing and capturing power due to the damping effect of the rotor caused by its considerable inertia drowning smaller variations in tool wear. Therefore, the main problem with this technology [3] is spindle and motor inertia. Also, chip clogging that happens with different amounts on the drill flutes at different wear levels can also cause a variation of power data (measures on momentum or drilling torque in x-y plane). On the other hand, the force data are obtained from the dynamometer that is static and rigid as clamped with vise on the machine. Moreover, chip clogging would barely affect the cutting force data measured in the thrust direction (z-axis). Though the thrust force data points can be considered to be more accurate to the regression line, a difference of 5–14% (reliability measures with the R^2 value) between the force and power data points calculated for all different tests indicates that the power data can still be considered for data analytics in NN-based TCM. Further work on the spindle load meter system (hardware) in machining can enhance the accuracy of spindle power data values.

In summary, there is a linear proportional relationship of the power and the force with the level of tool wear during the drilling of Inconel 625. Tool failure/breakage is uncertain with respect to the number of holes from one to another test under the same cutting condition; thus there is a need for real-time in-process TCM/TWBP system, instead of ideal lab-based cutting force data. Since the power data are found to be reliable considering the trade-off between the inaccuracy (by R^2 value comparison with the force data) and the simplicity of such DAQ system to be applied in an industrial environment (can be extracted directly from the machine tool during machining using a simple and inexpensive method), they can be used for real-time TCM during machining. In order to do that, the power data should be processed by an artificial intelligence technique like the NN technique described in Section 2.2. The next section presents the real machine spindle power data processing using the NN technique for implementing an on-line TCM when drilling a Ni-based superalloy, Inconel 625. Also, it was observed that, the tool is about to break once the power/force reaches to 120–130% with respect to the power/force value measured at the first hole (fresh tool). Thus, either a power or force value of 120% was considered to be the threshold to predict tool wear in this study.

5. Wear prediction with power data using NN technique

5.1. Sampling

Sample size of a data set is selected by the user based on the importance of testing. For instance, a larger sample size to train the network will help increase precision, but decrease the accuracy of the validation. There is a compromise that has to be made between a more precise evaluation of the performance of the network and the power prediction. In this study, a sample size of 36 wear data values is selected from five different drilling conditions: i) 400 rpm, 0.075 mm/rev; ii) 400 rpm, 0.1 mm/rev; iii) 500 rpm, 0.05 mm/rev; iv) 500 rpm, 0.075 mm/rev; v) 600 rpm, 0.075 mm/rev. Then the NN technique was randomly applied based on the standard *MATLAB* sampling distribution: i) training: ~70% (26 out of 36), ii) validation: ~15% (5 out of 36), and iii) testing: ~15% (5 out of 36).

5.2. Algorithm

In order to find the most precise algorithm, the three major ones presented by *MATLAB* including Levenberg Marquandt (LM), Conjugate Gradient Descent (CGD), and Bayesian Inference (BI) are used in this study (refer Section 2.2). These algorithms are compared for a number of five neurons. Performance of sample regression is evaluated in terms of the mean square error (MSE) and the *R* values. Table 1 shows that the performance of all three algorithms applied to the 36 samples of tool flank wear data. It is found that the Levenberg-Marquardt algorithm performs the best in terms of pure error performance, *i.e.*, lower MSE and larger *R* values. This indicates that, as compared to the other two methods, the LM method has trained and managed the most successful cases to model most of the variation in the input values. However, no other criterion such as computing time was considered in this study. Note that, initially, it would take a little longer time to build or train a neural network. However, once implemented in a production line, it would take only a fraction of a second to obtain the result from basic matrix calculations in computer when applying a few neurons.

Table 1
Performance comparison of three NN algorithms.

	Training		Validation		Testing	
Algorithm	MSE (10^{-5})	*R* (%)	MSE (10^{-5})	*R* (%)	MSE (10^{-5})	*R* (%)
LM	2.23	85.5	2.33	92.2	11.8	94.0
CGD	3.9	83.3	0.86	85.3	12.7	98.4
BI	3.1	83.0	0	0	2.9	92.5

Table 2
Influence of number of neurons on precision level in NN.

	Training		Validation		Testing	
Neuron	MSE (10^{-5})	*R* (%)	MSE (10^{-5})	*R* (%)	MSE (10^{-5})	*R* (%)
5	2.2	85.5	2.3	92.2	11.8	94.0
8	2.1	88.3	3.5	87.2	10.0	83.5
10	4.4	82.2	4.9	89.2	1.1	91.8
12	3.3	82.8	1.0	94.2	3.5	87.4

5.3. Number of neurons

The Precision level of the output prediction improves with the number of neurons, but with a demand of comparatively a longer time. A smaller number of neurons make a consistent, robust but less precise NN. Table 2 depicts the MSE and the R values at different number of neurons. It is seen that a NN with five neurons works the best considering both the validation and the testing parts together,

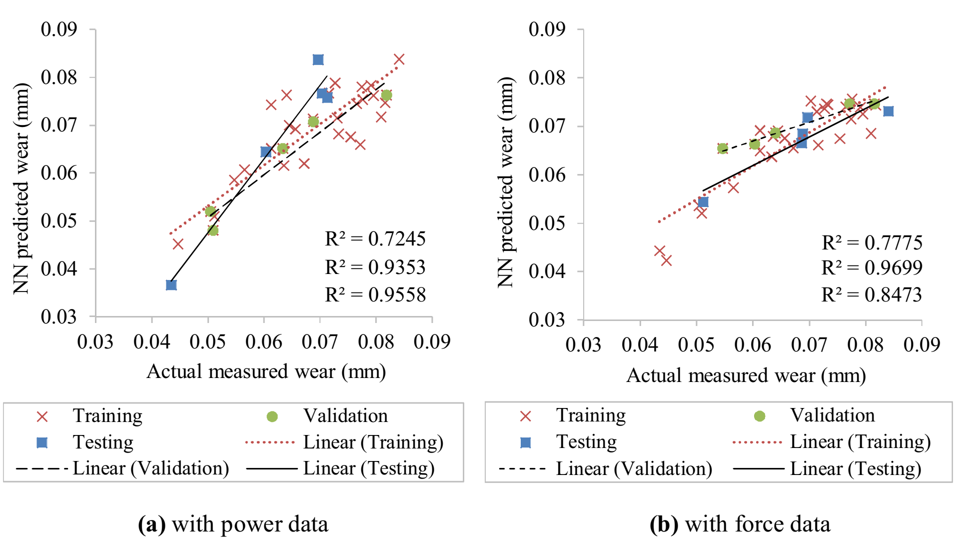

Fig. 10. Power and force predictions at different drilling conditions (400 rpm, 0.075 mm/rev; 400 rpm, 0.1 mm/rev; 500 rpm, 0.05 mm/rev; 500 rpm, 0.075 mm/rev; 600 rpm, 0.075 mm/rev).

Table 3
Comparing power and force based on error percentage.

	Number and percentage of samples within error range				Error	
	<4%	4–8%	8–12%	>12%	Average (%)	Min-Max (%)
Power	13	12	5	6	6.86	0.81–18.40
Force	16	9	8	3	6.09	0.44–17.94

Table 4
Power and force errors and *R* values from the NN technique.

	Power		Force	
	MSE (10^{-5})	*R* (%)	MSE (10^{-5})	*R* (%)
Training	2.23	85.5	2.3	90
Validation	2.33	92.2	4.2	99
Testing	11.8	94.0	2.8	92

but without much compromise in the training part, and this was considered in the present study of tool wear/breakage prediction during the drilling of Inconel 625.

5.4. *Tool wear prediction*

From 36 wear data samples at five different conditions as stated before, training was performed using MATLAB with NN LM algorithm on 26 samples, followed by validation and testing procedure for 5 data samples each. For the three inputs (drilling conditions with speed and feed rate, and either power or force), the wear value was predicted (or tested) based on the training and the validation. Fig. 10(a) depicts the estimated wear values against the actual measured wear data for different particular conditions, when power was considered. Fig. 10(b) shows the actual and predicted wear values with respect to the force values with the other two drilling input parameters. The values of R^2 are shown for all three stages in the figure. Though the R^2 value is less than 80% during the training stage for both the power and the force data, it was improved during the validation and the testing stages. When considering the testing stage, the R^2 values for power and force are found to be 95.58% and 84.73%, respectively. This analysis indicates that the power data are useful in machining process.

With the limited data analysis, the R^2 values in the testing stage indicate that the power data is better than the force data. This finding seems to be a little bit contradictory when considering the results shown on the force and power relationship against the drilling conditions (see Section 4). In order to verify this contradiction, error percentage of the predicted wear with respect to the actual wear, and the average, minimum and maximum errors are considered to be analyzed, as shown in Table 3. Moreover, the MSE and the *R* values for both the power and the force values are predicted based on the NN LM algorithm, as presented in Table 4. These two tables show that the force data are still more precise than the power data. This agrees with the results shown in Section 4. But, as per reliability, the power data are found to be highly competitive to the force data based on these analyses. The power data can well predict the wear at different conditions within the error range of 0.8–18%, and out of 36 samples, 25 samples are found to be within 8% error. This suggests that the power data have high potential to be utilized in the practical machining environment where the tool failure is uncertain (*e.g.*, Inconel drilling) and power data can easily be extracted from the spindle load meter to transform in to the intelligent machining system that adopts artificial intelligent techniques in the shop floor for real-time tool condition monitoring.

6. Conclusions

In this work, spindle power data are evaluated and analyzed for real-time tool wear/breakage monitoring during drilling of a Ni-based superalloy, Inconel 625 at different drilling conditions. The main aim was to determine if the power data, which are simple, sensible in production floor (Watt format) and inexpensive to extract from a machine load meter, are useful in industrial environments where a force dynamometer (ideal for lab tests only) cannot be used. Force data were also collected and analyzed for comparison with the power data. Based on the findings, the following points can be concluded:

1. During the drilling of materials, especially superalloys like Inconel 625, the power and the force rise very steeply in a sudden indicating that the tools can fail in a premature stage. This shows the importance of applying TCM in real industry environment.
2. Power is found to be linearly proportional to the axial feed of the drill bit and the data are highly reliable based on the R^2 value (98.48%) that measures the reliability of data.
3. Also, both the power and the force data have a linear proportional relationship with respect to the tool flank wear value. The R^2 value reveals that the force data are more accurate (88.99%) than the power data (76.09%). Power loss due to the damping effect of the rotor, spindle and motor inertia, as well as chip clogging on the drill flutes while progressing towards the plate thickness could cause such loss of accuracy when considering the power data.
4. Power and force data are found to have an obvious linear relationship ($R^2 = 81.03\%$) with the experimental data, which encourage to simply use the power data in manufacturing processes.
5. When using neural networks for wear prediction, the Levenberg Marquart algorithm is found to be the best option when compared to Bayesian Inference and the Conjugate Gradient Descent algorithms. In addition, the optimal number of neurons is predicted to be 5 in this application.
6. While predicting tool wear based on 36 power data samples received from five different drilling conditions, the NN is found to well predict the actual measured data with the error range of 0.8–18%. Out of 36 samples, the error for 25 samples was found to be within 8%. Also, the R^2 value for the testing stage is found to be about 95%. This reveals that the power data are useful to be implemented for real-time TCM during machining, such as drilling.

In this study, a drill size of 5.95 mm was used, which is considered to be thin for drilling Inconel. Further analysis of power data could be performed for larger diameters (rigid and strong) for improving the reliability factor when predicting real-time tool wear/failure with NN technique.

Appendix A.

A.1 NN MLP Structure

A multi-layer perception is built of several layers of nodes as shown in Fig. A1. In the first 'Input' layer, external information of independent variables, *e.g.*, feed rate, drill speed, drill angle, power consumption, material is received as input nodes. The last 'Output' layer receives the predicted results as output nodes (*e.g.*, wear, roughness, burr height, circularity). The hidden intermediate layer

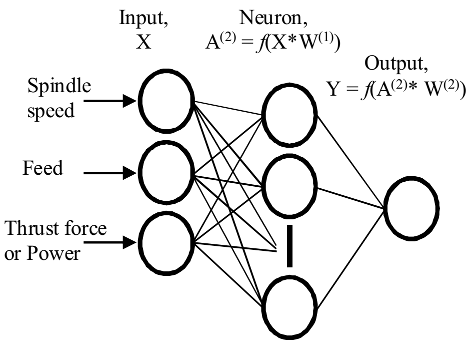

Fig. A1. Multi-layer perception (MLP) structure in the NN technique.

(usually only one but never more than two) applies the activation functions and passes on the data to the next layer.

A.2 NN Technique in Manufacturing Data Processing

There are different types of entities in the NN technique [28]. Synapses refer to the line that connects two neurons and are expressed as:

$$Synapse, Z : Input\ value, X \times Weight, W \tag{A-1}$$

The weights are coefficients that are applied to the data. The NN algorithm investigates the optimal combination of weights in order to correlate the calculated output with the real output as closely as possible. Neurons are the entities where the activation function is applied to the values as follows:

$$neuron : activationf \left(\sum output\ of\ all\ synapses \right) \tag{A-2}$$

The activation function works as the transfer function defining the relationship between input and output at the level of a neuron. In theory, a differentiable function can qualify as an activation function even though it is usually bounded, monotonically increasing and differentiable. Among four types of functions, the sigmoid or logistic function: $f(x) = \frac{1}{1+e^{-x}}$ is used in this study as it is the best choice for all hidden and output nodes [29].

In order to predict tool wear, the NN has to be trained first with a primary set of data. Suppose a problem with three input parameters (speed (S) in RPM, feed (F) in mm/rev, power (P) in W) and one output parameter (wear (V_B) in mm). For instance, to predict the wear of three different combinations of feed, speed and power, the matrixes are expressed as follows:

$$input, X = \begin{bmatrix} S11 & F12 & P13 \\ S21 & F22 & P23 \\ S31 & F32 & P33 \end{bmatrix}; output, Y = \begin{bmatrix} V_{\boldsymbol{B}1} \\ V_{\boldsymbol{B}2} \\ V_{\boldsymbol{B}3} \end{bmatrix} \tag{A-3}$$

For each input and output parameter, data when input into the NN have to be normalized so that different scales and orders of magnitude (*e.g.*, speed at 400 rpm and feed rate at less than 1 mm/rev) do not influence the weights calculations. Data normalization is performed in order to obtain a range from 0.1 to 0.9 [30]:

$$D = 0.1 + 0.8 \times \frac{x - \min}{\max - \min} \tag{A-4}$$

Mathematically, neural networks are nothing but input matrixes being multiplied by weight matrixes and put through activation functions. Once the data are normalized, the matrix is fed into the network. In the first synapse, a weight matrix (3 × 3) is selected based on the size of the input matrix, but an inverse of that matrix. The matrix expression for the first synapse of the network is:

$$Z^{(2)} = X \times W^{(1)} \tag{A-5}$$

The first neuron is obtained where the sigmoid activation function is applied:

$$a^{(2)} = f\left(Z^{(2)}\right) \tag{A-6}$$

On the second synapse, the second set of weights is applied. The second weight matrix is a 3 × 1 matrix (based on the expected output matrix), thus the second synapse can be expressed as:

$$Z^{(3)} = a^{(2)} W^{(2)} \tag{A-7}$$

Finally, in the last neuron, the second activation function is applied. The calculated output matrix, *i.e.*, the prediction of different outputs using the NN technique is:

$$\hat{Y} = f(Z^{(3)}) \tag{A-8}$$

In order to predict the output, the network has to be trained, and the correct matrixes have to be used as explained above. Training the network means reducing the error between the real output value and the NN prediction, and finding the optimal combinations of weights for every level. A convex quadratic cost function, J, as expressed below, can be used for monotonous progression of the function on both sides of the optimum.

$$J = \sum \frac{1}{2} \times \left(real\ output, Y - calculated\hat{\ } output, \hat{Y} \right)^2 \tag{A-9}$$

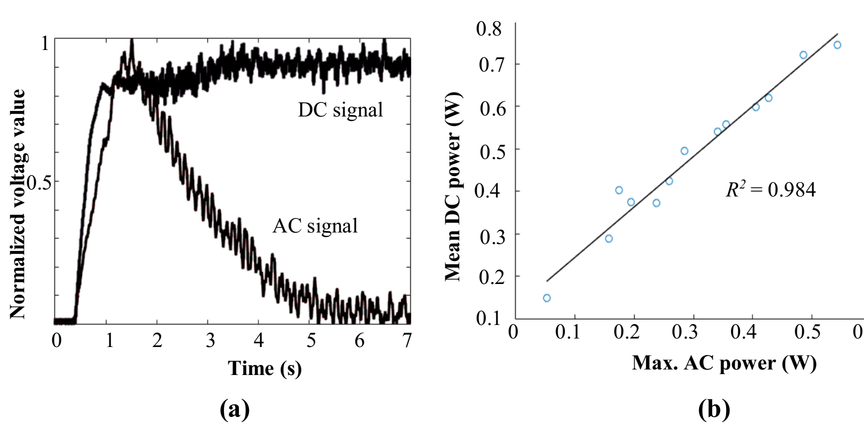

Fig. A2. AC *vs.* DC power data relationship during drilling of Incolen 625: (a) AC *vs.* DC power values at 1200 Hz sampling rate, b) ratio of the values.

A.3 Power Data: AC vs. DC

Fig. A2 shows the relationship between the AC and DC power data received from the spindle power sensor. It seems that the maximum value of AC power is close to the DC power value. The ratio of the maximum AC power value to the mean DC power value was found to be about 1.18, though some spikes of the DC power value reaches to the AC maximum value. However, there is a linear relationship between these two modes with R^2 value of 0.984. Thus, for in-process TCM or TWBP, both AC and DC power values can be used.

References

[1] Lynn R, Chen A, Locks S, Nath C, Kurfess T. Intelligent and accessible data flow architectures for manufacturing system optimization. Adv Prod Manage Syst 2015;459:27–35.
[2] Ertekin YM, Kwon Y, Tseng TL. Identification of common sensory features for the control of CNC milling operations under varying cutting conditions. Ident Common Sens Features Control CNC 2003;43(9):897–904.
[3] Abellan-Nebot J, Subirón F. A review of machining monitoring systems based on artificial intelligence process models. Int J Adv Manuf Technol 2009;47(1):237–57.
[4] Sobel J. Manufacturers Struggle to Turn Data Into Insight; 2016. http://www.huffingtonpost.com/techonomy/manufacturers-struggle-to_b_5992058.html (downloaded on March 31 2016).
[5] Liu HS, Lee BY, Tarng YS. In-process prediction of corner wear in drilling operations. J Mater Process Technol 2000;101(1–3):152–8.
[6] Gowda BMU, Ravindra HV, Ullasa M, Prakash NGV, Ugrasen G. Proc Mater Sci 2014;6:1780–7.
[7] Nath C, Brooks Z, Kurfess TR. Machinability study and process optimization in face milling of some super alloys with indexable copy face mill inserts. J Manuf Process 2015;20:88–97.
[8] Nath C, Rahman M. Effect of machining parameters in ultrasonic vibration cutting. Int J Mach Tools Manuf 2008;48:965–74.
[9] Nath C, Kapoor SG, DeVor RE, Srivastava AK, Iverson J. Design and evaluiation of an atomization-based cutting fluid spray system in turning of titanium alloy. J Manuf Process 2012;14:452–9.
[10] Chen YL. Study on wear mechanisms in drilling of Inconel 718 superalloy. J Mater Process Technol 2003;140(1–3):269–73.
[11] How It Works – Tool Monitoring, Today's Machining World Archive; 2007. http://todaysmachiningworld.com/magazine/how-it-works-tool-monitoring/ ; March 2007; 3 (03).
[12] Drouillet C, Karandikar J, Nath C, Journeaux AC, El-Mansori M, Kurfess T. Tool life predictions in milling using spindle power with the neural network technique. J Manuf Process 2016;22:161–8.
[13] Lee B, Tarng YS. Application of the discrete wavelet transform to the monitoring of tool failure in end milling using the spindle motor current. Int J Adv Manuf Technol 1999;15(4):238–43.
[14] Du R, Liu Y, Xu Y. Tool condition monitoring using transition fuzzy probability. The 3rd International Conference on Metal Cutting and High Speed Machining 2001:375–93.
[15] Shao H, Wang HL, Zhao XM. A cutting power model for tool wear monitoring in milling. Int J Mach Tools Manuf 2004;44(14):1503–9.
[16] Ghosh N, Ravi YB, Patra A, Mukhopadhyay S, Paul S, Mohanty AR, et al. Estimation of tool wear during CNC milling using neural network-based sensor fusion. Mech Syst Signal Process 2007;21(1):466–79.
[17] Li XL, Yuan ZJ. Tool wear monitoring with wavelet packet transform—fuzzy clustering method. Wear 1998;219(2):145–54.
[18] Li XL, Dong S, Yuan ZJ. Discrete wavelet transform for tool breakage monitoring. Int J Mach Tool Manuf 1999;39(12):1935–43.
[19] Zadeh L. Is there a need for fuzzy logic? Inf Sci 2008;178(13):2751–79.
[20] Nama JS, Kim DH, Chung H, Lee SW. Optimization of environmentally benign micro-drilling process with nanofluid minimum quantity lubrication using response surface methodology and genetic algorithm. J Clean Prod 2015;102:428–36.
[21] Karandikar J, Abbas AE, Schmitz TL. Tool life prediction using Bayesian updating. Part 1: Milling tool life model using a disccrete grid method. Precis Eng 2014;38(1):9–17.
[22] Theodosis P. Neural networks: interpolation and curve fitting 2007; 2007.
[23] Tu J. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. J Clin Epidemiol 1996;49(11):1225–31.
[24] Zhang G, Patuwo EP, Hu MY. Forecasting with artificial neural networks: the state of the art. Int J Forecasting 2016;199814(1):35–62.
[25] Rao KV, Murthy BSN, Rao NM. Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network. Measurement 2014;51:63–70.
[26] Abu-Mahfouz I. Drilling wear detection and classification using vibration signals and artificial neural network. Int J Mach Tools Manuf 2003;43(7):707–20.
[27] Xu J, Yamada K, Seikiya K, Tanaka R, Yamane Y. Effect of different features to drill-wear prediction with back propagation neural network. Precis Eng 2014;38(4):791–8.
[28] Coolen A. A Beginner's Guide to the Mathematics of Neural Networks. King's College London; 1998.
[29] Goh A. Back-propagation neural networks for modeling complex systems. Artif Intell Eng 1995;9(3):143–51.
[30] Panda SS, Singh AK, Chakraborty D, Pal SK. Drill wear monitoring using back propagation neural network. J Mater Process Technol 2006;172(2):283–90.