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Detection of grinding temperatures using laser irradiation and acoustic emission sensing technique

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This paper presents a new method for the detection of grinding thermal behaviours using a laser irradiation technique. Laser irradiation was initially undertaken in the Lumonics JK704 Nd: YAG laser machine under mimic grinding conditions. Temperature elevation was controlled using laser irradiation by varying the laser energy and laser irradiation time. The signatures of acoustic emission (AE) were recorded as pure thermally induced AE signals. A series of grinding experiments were conducted separately to identify different AE sources during grinding. An artificial neural network (ANN) had been trained to distinguish high and low temperatures using laser thermal AE data. This trained ANN was then used to classify burn and no burn in the grinding zone. The classification accuracy achieved 71% when grinding Inconel718 materials. The novelty of this work is reflected in that the laser irradiation induced thermal AE signals can represent grinding thermal behaviour and can be used for grinding burn detection.

Keywords: Laser; grinding; acoustic-emission (AE); temperature; neural network.

Introduction

Grinding burn is one of the major problems that occurs on a ground surface and results in a thin oxide layer the thickness of which is related to the maximum temperature in the grinding zone. If a grinding wheel is used for a long time in grinding, wheel wear occurs. This leads to less effective grinding so a higher grinding force is required which results in higher grinding temperatures and possible grinding burn. The surface roughness is also directly effected. Monitoring of the thermal behaviour in grinding is therefore important for grinding quality control. There are many sensing techniques used to detect grinding burn as it is the most common type of thermal damage in a machined material surface [1, 2]. Xu and Malkin et al. [3] presented a comparison of methods to measure grinding temperatures. The methods consisted of thermocouple, optical fibre with two colour infrared detectors, and foil/workpiece thermocouple. They found that a foil/workpiece thermocouple works better than other methods and could detect a periodic peak temperature at wheel rotational frequency [3] [4] [5].

An acoustic emission (AE) sensor has a much higher sensitivity and response speed compared to other sensors. Though power and force sensors have been used for grinding burn detection, it is not possible to detect those signal features in a very high frequency range. For this reason, AE sensors have become very popular in recent years for identifying grinding burn in process monitoring. However, most researchers have only used AE signals without distinguishing them as thermally or mechanically induced AE. Chen et al. [6] pioneered the identification of different AE sources in grinding. They suggested the grinding process monitoring should be based on the fundamental process behaviours. Grinding burn detection should be linked to the thermally induced acoustic emission.

Pattern recognition techniques are an important component of intelligent systems and these techniques are used for both data pre-processing and decision making. There have been many different types of classifiers as pattern recognition tools have used in condition monitoring such as artificial neural networks (ANN)[7, 8], Support Vector Machine (SVM) [9] [10] [11], Genetic Programming (GP)[12], fuzzy pattern recognition [13].

Warren Liao, Ting et al. [14] used acoustic emission signals in order to distinguish different states (sharp or dull) of the grinding wheel. The signals were acquired at 1 MHz when grinding alumina with a resin-bonded diamond wheel and an adaptive genetic clustering algorithm was then applied to extract the features. Kwak and Ha et al. [4] detected the grinding burn and chatter phenomena using AE and power sensors. The peak of the root mean square (RMS) and the peak of fast Fourier transform (FFT) were the feature parameters that were extracted from the AE signal and were then used as the input to the neural network. The Neural Network (NN) tools were then used to classify the burn and chatter phenomena with a rate of 95% in terms of correct classification. Wang et al. [1] detected grinding burn from AE signals. The feature parameters included band power, kurtosis, skew and autoregressive coefficients which were extracted from the AE signals. Lezanski [5] presented a paper for monitoring wheel condition using AE signals. A neuro-fuzzy model was used to classify the wheel condition using eight selected features. The features were grinding depth of cut, coolant volume rate, standard deviation of vibration, mean value of vibration and power spectrum, mean value of AE RMS, range of AE RMS and range of RMS of power spectrum. The classification accuracy was reported to be 83.3% at its best performance.

Nickel based super alloys have some characteristics that are responsible for poor machinability. The proportion of nickel is from 38 to 76%. They also contain up to 27% Cr and 20% Co [15]. They have an austenitic matrix, like stainless steel and have a tendency to "work harden". The major reason for the development of these super alloys has generally been for their use in aircraft gas turbine e.g. discs, combustion chamber, bolts, casting, shaft exhaust system, blades, and vanes. Nickel based super alloys such as Inconel718, CMSX4 or MarM002 retain their strength at high temperatures when encountering grinding and machining compared to other materials [16], however, thermal damage to the workpiece in nickel based alloys is a significant problem during grinding.

Liu and Chen et al. [2] investigated grinding burn on CMSX4 materials using AE signals and a thermocouple. In their research, they separated thermal induced AE signals from other AE signals in grinding for the first time by using a laser irradiation simulation method. They obtained a critical grinding burn temperature at 770˚C for CMSX4 materials. By comparing the AE features from the laser irradiation and AE features from the grinding experiment, Chen et al. [6] noticed that the AE signals under different temperatures are made up of different features. However the detection of grinding temperatures by using AE features from the laser irradiation has not been investigated. In addition, the manufacturing industry needs to understand the AE signal features in relation to grinding thermal behaviour (burn).

This paper presents an investigation of grinding behaviour on Inconel718 materials using thermal AE signal signatures. An artificial neural network (ANN) is applied in order to classify the burn and no burn phenomena in the grinding zone. The neural network has been trained for distinguishing high and low temperatures when the laser induced thermal AE data is used as input to the network. Grinding thermal AE data was then used to test the network for further detection of grinding burn.

Laser irradiation tests

The laser irradiation experimental set-up consisted of an AE sensor, thermocouple, preamplifier, USB data logging card, PCI-2 based AE signal processor and specimen (Inconel718 and MarM002). All experiments were undertaken in the Lumonics JK704 Nd: YAG laser machine. An E-type thermocouple, which was located at the centre of the laser beam spot, was tightly fixed on the front surface of the workpiece and an acoustic emission (AE) sensor was placed at the opposite side of the workpiece. The E-type thermocouple covered a temperature range from -40˚C to +900˚C. A schematic diagram of the laser irradiation set up and sensor arrangement is illustrated in Figure 1.

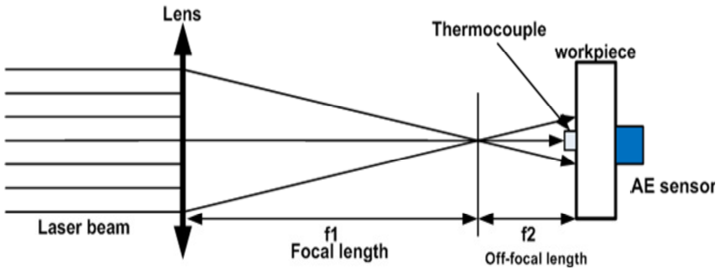


Figure 1: Schematic diagram of laser irradiation optical arrangement.

The parameters used in the laser irradiation experiment are presented in Table 1. The laser power density is a function of the off-focal length. When the laser pulses are focussed at a point on the surface, this can be considered as a point source of heat. When absorbing the laser energy, the workpiece heats up and the subsequent thermal expansion emits acoustic emission waves which are purely related to the material thermal performance. In the laser irradiation tests, three off-focal distances (34mm, 40mm and 46mm) were used to produce pure thermal AE signals under different temperatures.

Table 1: Laser specification.

Laser Parameter	Conditions
Laser	Lumonics: JK 704Nd:YAG
Wave length	1.06 μm
Pulse energy	1.5 J
Maximum peak power	2.5 kW
Irradiation time	0.6 ms
Focal length	120 mm
Light beam diameter	12 mm
Off-focal length	34~46 mm

The results of the calibration temperatures measured from the thermocouples are presented in Table 2. The acoustic emission signal (AE wave) generated by the thermal stress on the workpiece was then converted into a voltage signal which was amplified by the preamplifier and sent to the amplifier in the main processor for further analysis.

Table 2: The calibration temperatures

Laser offset	Inconel718	MarM002
(mm)	(°C)	(°C)
34	698	493
40	324	318
46	174	235

A model of surface temperature has been used based on the thermal energy interaction of the laser irradiation and workpiece surface. If the constant laser energy flux I_0 is absorbed at the workpiece surface and there is no phase change in the material and the heat flows in one dimension then the equation could be written as follows [2, 17],

$$T(0,t) = \frac{2I_0}{K}\eta\left(\frac{kt}{\pi}\right)^{\frac{1}{2}} \qquad (1)$$

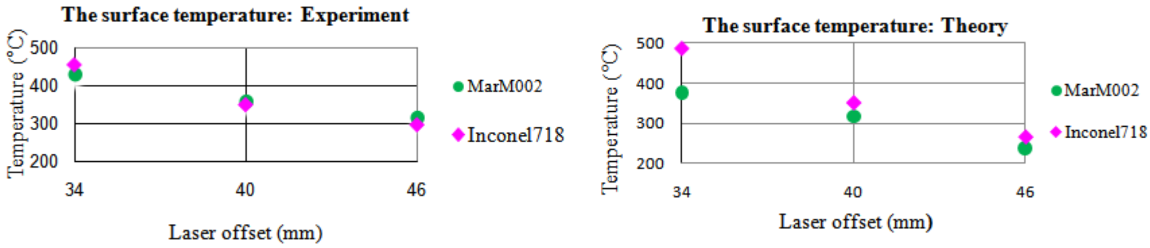
Where, $T(0,t)$ = surface temperature after time t

K = thermal conductivity

k = thermal diffusivity

η = absorption coefficient

The absorption coefficient η can be calculated approximately as 19.16% for a Nd: YAG laser on a nickel based alloy [2, 17]. The laser power flux I_0 can be adjusted by the off-focal distance f_2. The surface temperatures of both the calculated and measured values are shown in Figure 2 (laser energy of 1.5J, pulse width of 0.6 ms and different off-focus lengths). The influential factors resulting in a slight difference between the theory and the experimental values are the laser focal spot size, thermocouple position and laser penetration into these materials. Thermal conductivity (ability to conduct heat) and off-focal distance to these materials also play an important role. If the temperature of the material rises there will be an increase of electron energy exchanges by laser irradiation. The electrons are more likely to interact with the structure of the material rather than oscillate and re-radiate [17].



(a) Temperature calculated (b) Temperature measured

Figure 2: The surface temperatures.

The STFT (Short Time Fourier Transform) signal processing technique is applied to extract thermal features in the acoustic emission signals. The STFT is a form of joint time frequency analysis but it has a major drawback, the window width selected is critical in determining the time and frequency resolution. The Kaiser window function was used to optimise the resolution[18] [19]. The signal features related to high and low temperatures at 34 mm or 46 mm off-focal distances are shown in Figure 3. The signals are sampled at 5 MHz with a Kaiser Filter.

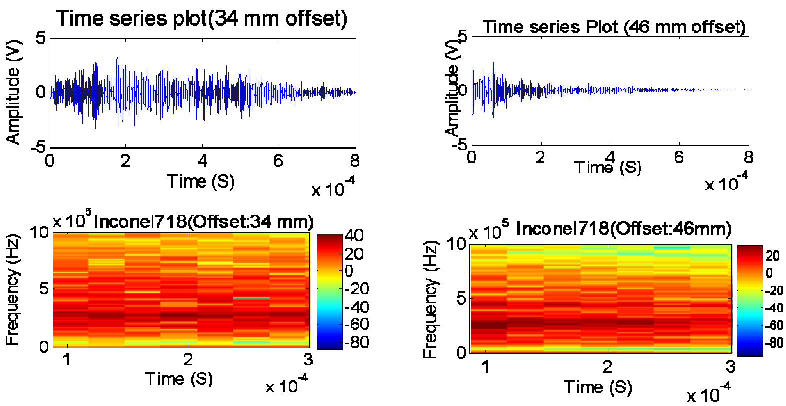


Figure 3: AE signal from laser irradiation, Top: time series data, and down: STFT.

The result is shown in Figure 3 whereby the AE data extracted from 34 mm offset distances has a higher intensity in the 200-250 kHz frequency range than AE data extracted from 46 mm offset distances in the 150-250 kHz frequency range. The AE features, excited by the laser irradiation, cover a range from 100 to 700 kHz.

Grinding experiments

The grinding experiments were undertaken on a Makino A55 machine centre. The acoustic emission (AE) sensor WD-AL04 was placed on the workpiece to detect the AE responses.

The main specification of the AE sensor is presented in Table 3. Grinding was performed with a wheel speed of 35 m/s and depth of cuts at 0.1 mm and 1.0 mm. The feed rate for the workpiece was 1000 mm/min. No coolant was applied in these tests in order to promote burn conditions. If full coolant supply was used then no burn would occur. The extracted AE data was used to identify burn and no burn signatures in relation to depth of cuts.

Table 3: AE sensor specification.

Specification	**PAC WD Sensor**
Sensor number/date	AL04(17/11/04)
Construction	Differential
Sensor drive capability	Up to 100m with w/RG-58 AU cable
Dimension(dia x ht) mm	17*16
Peak sensitivity dB ref. [V/µbar] (dB)	-63.3
Operating frequency range (kHz)	100-1000

From each experiment, the thermal features of the AE signals were extracted from the start, mid and end sections of the AE signal and then applied to FFT for feature recognition. Each set of data, from the start, mid and end sections, include the thermal features of the AE signal which consists of 1024 data points. The features extracted from AE data under 1.0 mm depth of cut represent severe burn on the material while the AE features from data under 0.1 mm depth of cut represent slight burn or no burn. The burn or no burn phenomena on the Inconel-718 workpieces is shown in Figure 4 in relation to AE amplitudes.

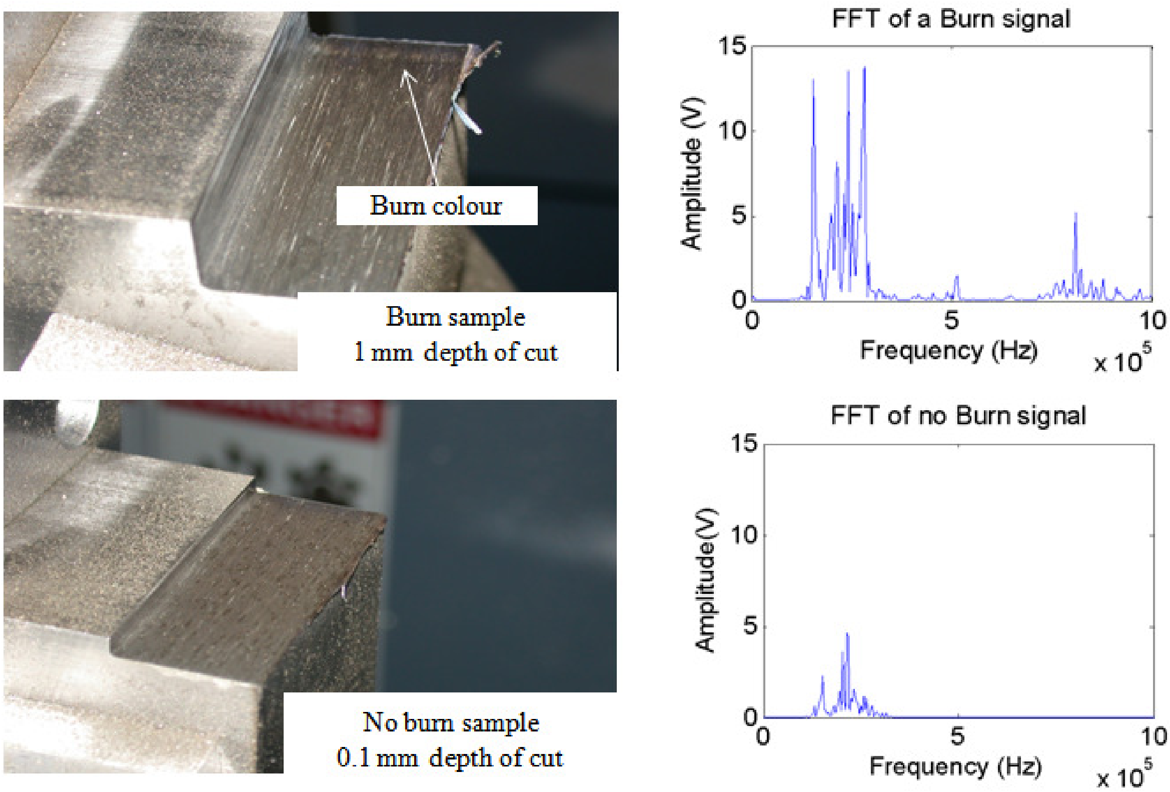


Figure 4 : Grinding burn and no burn phenomena related to 1.0mm and 0. 1mm depth of cuts.

In the burn sample, the burn colours are obviously visible on the workpiece from the middle section to the end section compared to the no burn sample. The intensity of burn is defined by the percentage of burn colour visible on the ground surface. When the temper colour of grinding burn is light brown or pale yellow and only occurs on two segment- areas of the whole surface area, the burn is defined as slight burn (0-2%). When the colour of grinding burn violet and occurs over 20% areas of the whole surface areas, the burn is classed as severe burn (20%) [20].

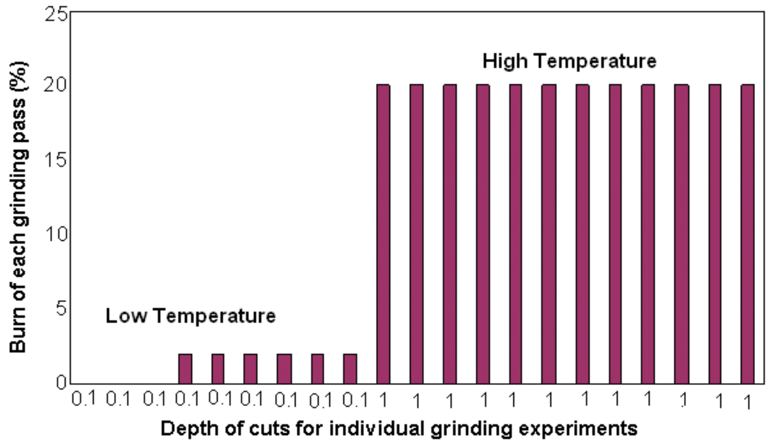


Figure 5: Grinding burn (%) from each grinding pass in relation to 0.1 mm and 1mm depth of cuts (Inconel718).

Figure 5 shows that grinding with a 1 mm depth of cut produces severe burn (the intensities of the burn are 20% at the end of each grinding pass) while a 0.1 mm depth of cut produces slight burn or no burn (the intensities of burn occur at 0-2% at the end of each grinding pass). The grinding burn becomes more severe on the second half of the ground surface. This is due to more friction being present in the wheel loading. The severe burns were certainly much deeper in terms of surface anomalies when compared with the burn in 0.1 mm depth of cuts. These clear features of burn and no burn are a concrete foundation for pattern recognition.

Pattern recognition: Artificial neural network (ANN) approach

The neural network (NN) is a very powerful classification tool that has been used since the 1960s [21]. The advantages of neural networks over pattern recognition are that it can easily constitute optimum nonlinear multi-input functions for pattern recognition and that the accuracy of pattern recognition is easily improved by learning [22]. A back propagation neural network has been applied to identify high and low temperatures in relation to grinding burn. During the ANN training process, the STFT AE data was used as inputs with the outputs being high and low temperatures.

Table 4: Construction of the ANN for temperature indication.

ANN Parameter	Condition
Input size	STFT:256 Neuron
Hidden layer	3
Transfer function for hidden layer	Logsigmoid
Transfer function for output layer	pure linear
Epochs	2000
Learning rate	1.E-10
Momentum	0.95
Goal	1.E-40

The structural parameters of the ANN are presented in Table 4.Once the network has been defined, network architecture can be created and then the network can be trained by optimizing the error function. The training results in Figure 6 show that the straight line matches well with the circular points, where the straight line is defined as the predicted output and circular points are defined as the actual output. The training data set consisted of thermal AE data which were extracted from the laser irradiation tests. The target vector in relation to the network was defined in such a way that the high temperature relating to severe burn was assigned a value of 3 and the low temperature related to normal or no burn condition and was assigned a value of 1. The outputs of the network represented each case correctly, where the values were concentrated at 3 or 1 respectively.

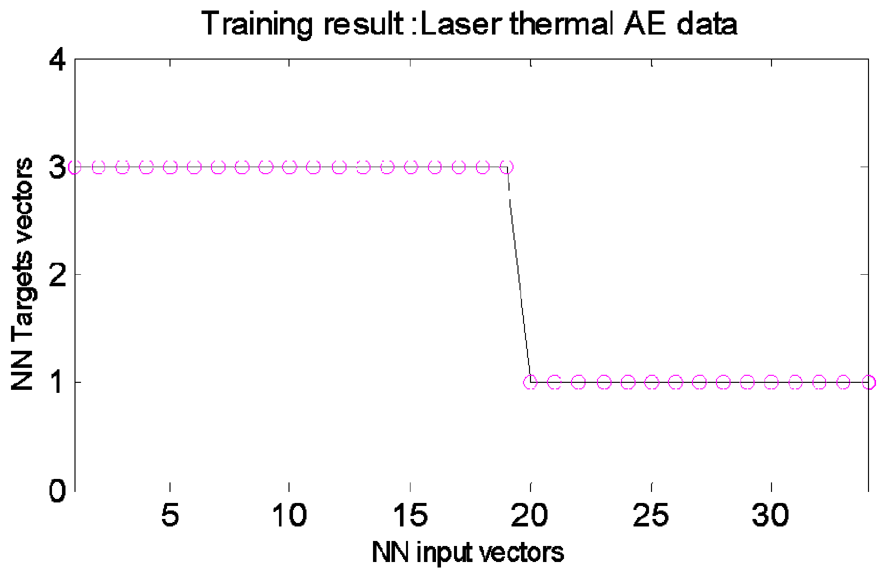


Figure 6: The learnt training set for a NN classification system.

Once the network has been designed and trained by the Laser thermal AE data, it can be tested with AE data extracted from the grinding experiment.The testing result should predict the burn and no burn due to high and low temperatures in the grinding zone.

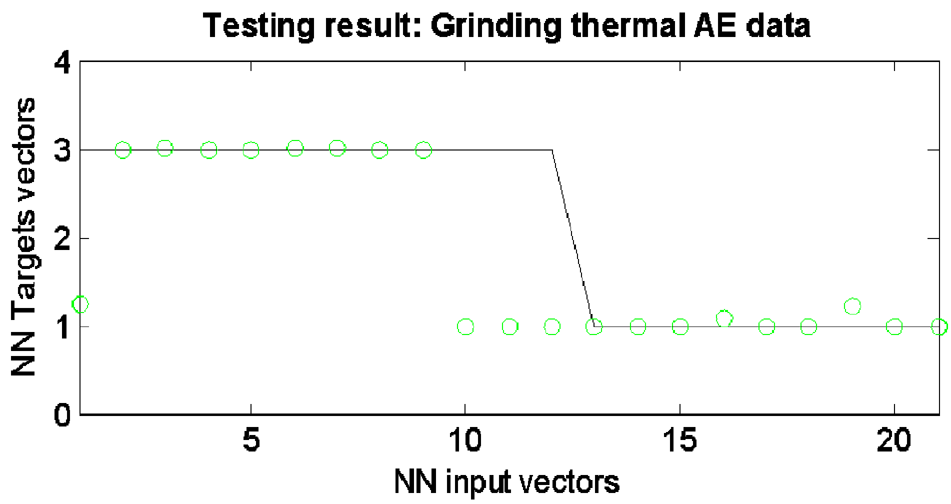


Figure 7: Neural Network verification result of grinding AE data.

The result is shown in the following diagram in the Figure 7, where high temperatures are related to severe burn concentrated at value 3 while low temperature is related to no burn concentration at value 1. There are a few errors shown in Figure 7 which imply the accuracy of using the ANN to judge grinding temperature is about 71.43% (15/21).

Conclusion

This piece of research has demonstrated that it is feasible to detect grinding burn using pure thermal AE signals. This provides a foundation for a new method that utilises an ANN trained from laser irradiation AE data for the monitoring of grinding burn. This may provide a reliable tool for industrial application.

As presented in the paper, using AE and thermocouple sensors, it was possible to detect the thermo elastic wave changes due to different temperature elevations by laser irradiation on the workpiece of nickel based alloys. The surface temperature obtained from laser experiments produced a reasonable agreement with that obtained from theoretical calculations.

The paper has demonstrated that STFT is a useful technique for distinguishing the frequency bands occupied by high and low temperatures in laser irradiation. The STFT were also used to distinguish the frequency bands occupied by the burn and no burn phenomena in grinding. The AE features cover a range from 100 to 700 kHz both in laser irradiation and in grinding.

The experimental results clearly show the trained neural network can distinguish between high and low temperatures on Inconel718 materials due to laser irradiation in 34 mm and 46 mm off-focal distances. By using thermal AE data extracted from grinding 0.1 and 1.0 mm depth of cuts, the ANN can monitor grinding burn with an accuracy of 71%. This confirms that thermal AE signal signature features in laser irradiation can be used for grinding burn monitoring. The AE monitoring system provides critical information to indicate the occurance of grinding burn. The result offers significant benefit to the industrial partners who are expected to benefit through the application of this knowledge. The research can help the manufacturing industry to understand the AE signal features in relation to grinding thermal behaviours.

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