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# TOWARDS SUSTAINABLE AND INTELLIGENT MACHINING: ENERGY FOOTPRINT AND TOOL CONDITION MONITORING FOR MEDIA-ASSISTED PROCESSES

Reducing energy consumption is a necessity towards achieving the goal of net-zero manufacturing. In this paper, the overall energy footprint of machining Ti-6Al-4V using various cooling/lubrication methods is investigated taking the embodied energy of cutting tools and cutting fluids into account. Previous studies concentrated on reducing the energy consumption associated with the machine tool and cutting fluids. However, the investigations in this study show the significance of the embodied energy of cutting tool. New cooling/lubrication methods such as $WS_2$-oil suspension can reduce the energy footprint of machining through extending tool life. Cutting tools are commonly replaced early before reaching their end of useful life to prevent damage to the workpiece, effectively wasting a portion of the embodied energy in cutting tools. A deep learning method is trained and validated to identify when a tool change is required based on sensor signals from a wireless sensory toolholder. The results indicated that the network is capable of classifying over 90% of the tools correctly. This enables capitalising on the entirety of a tool's useful life before replacing the tool and thus reducing the overall energy footprint of machining processes.

Nomenclature

| **Abbreviation** | **Definition** |
|---|---|
| $Al_2O_3$ | Aluminium oxide |
| CMQL | Conventional minimum quantity lubrication with rapeseed oil |
| CNN | Convolutional neural network |
| CVD | Chemical vapour deposition |
| $E_c$ | Coolant/lubricant energy footprint |
| $E_{cdis}$ | Energy footprint for disposal of water-based cutting fluids |
| $E_{CM}$ | Cumulative energy footprint of machining |
| $E_{cpro}$ | Energy footprint for production of coolant/lubricant |
| $E_m$ | Machine tool energy consumption |
| $E_{pm}$ | Primary material energy footprint |
| $E_t$ | Energy footprint of cutting tools |
| FFT | Fast Fourier Transform |
| Flood | Water-based emulsion 7% concentration |
| HPC | High performance cutting |

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| | |
|---|---|
| HSM | High speed machining |
| LCA | Life cycle assessment |
| MQL | Minimum quantity lubrication |
| OA4% | MQL with 4% $Al_2O_3$ suspension in oil |
| OA50% | MQL with 50% $Al_2O_3$ suspension in oil |
| OD | MQL with 50% PCD suspension in oil |
| OG | MQL with 1% graphite suspension in oil |
| CMQL | MQL with rapeseed oil |
| OW | MQL with Oil-water mixture |
| OWS | MQL with 4% WS2 suspension in oil |
| $P_{coolant\ pump}$ | Coolant pump's power consumption |
| $P_{compressed\ air}$ | Power consumption for producing compressed air for machine tool |
| $P_{machine\ tool}$ | Machine tool's power consumption |
| PCD | Polycrystalline diamond |
| PVD | Physical vapour deposition |
| SVM | Support vector machines |
| SDGs | United Nation's sustainable development goals |
| TCM | Tool condition monitoring |
| $VB$ | Average tool flank wear |
| WC-Co | Tungsten carbide with cobalt binder |
| $WS_2$ | Tungsten disulphide |

## 1. INTRODUCTION

The United Nation's Sustainable Development Goals (SDGs) have identified a set of objectives to ensure economic, environmental and societal prosperity across different countries. Some of the main drivers for achieving these goals are access to clean energy, responsible consumption and production and minimised environmental impacts (air, land and marine) [1]. Global warming and the declaration of Climate Emergency by the United Nations has necessitated the need for minimising the greenhouse gas emissions from energy sources, specifically electricity generation. However, the path to zero-emission electricity requires significant time, investment and innovations. Reducing energy consumption can support and facilitate the path towards a zero-emission future. Over 40% of the global electricity is consumed by industry [2] and 7% of that is used for operating machinery [3]. Machining remains the most used manufacturing process for producing precision engineering components and has a significant role in the global economy. Figure 1 illustrates the revenue from machining for a number of countries in 2018. Electrical energy is used for operating machine tools and their pumps for delivering cutting fluids. Several analytical, numerical and experimental models have been developed for predicting and optimising the direct energy consumption in machining [4]. Shao et al. [5] proposed a virtual model for performing life cycle assessment (LCA) and energy consumption analysis for decision making in machining. They highlighted the need for data regarding the impacts of cutting tools and cutting fluids. Kara and Li [6] found an empirical model to correlate machining energy consumption with cutting parameters with 90% accuracy. The common recommendation of these energy models is that reduced energy consumption can be achieved by increasing material removal rate. However, increased material removal rate can have a detrimental impact on the tool life. This has necessitated the use of cutting fluids.

Cutting fluids have been widely used to enhance machining performance in terms of tool life and workpiece surface integrity. Flood cooling using water-based emulsions is the most common machining environment used in industry. However, their effectiveness is limited in high performance cutting (HPC) and high speed machining (HSM). In these scenarios, they fail to effectively penetrate the cutting zone and lubricate the contact surfaces. In addition, the Leidenfrost effect can reduce the cooling effect of water-based cutting fluids [7]. As a result, a similar performance is achieved to that of dry machining. Water-based cutting fluids have been repeatedly identified as one of the major sources of environmental impacts of machining. The main evidence supporting these claims is the fact that a large quantity of cutting fluids is used in flood cooling and that water-based cutting fluids are susceptible to bacterial and fungi growth, which can lead to a number of occupational health diseases [7, 8]. This has led to numerous innovations in coolant and lubricants for machining as an alternative to flood cooling. One such innovation is defined as media-assisted machining which includes high pressure cutting fluid, cryogenic machining, minimum quantity lubrication (MQL), etc [9].

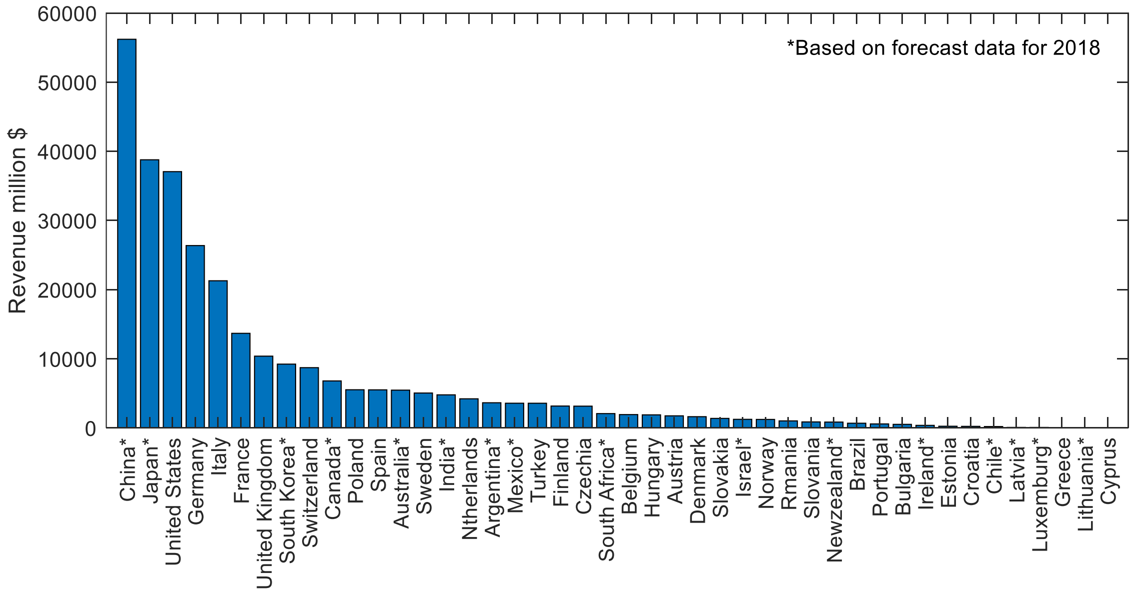


Fig. 1. Revenue from machining in 2018 in various countries based on [10]

Cryogenic machining and MQL are often referred to as sustainable or environmentally friendly alternatives to conventional flood cooling due to the elimination of the use of large quantities of water-based cutting fluids. However, there are limited studies investigating the whole life cycle of the fluids. Instead, the majority are focused on gate-to-gate analysis. In MQL, a small amount of lubricating oil, typically 20–100 ml/hr, is sprayed into the cutting zone through pressurised air. In order to improve the biodegradability of the process, vegetable-based oils are used in-lieu of mineral oil. However, MQL is generally considered a lubricating method and the cooling is limited to forced convective heat transfer through pressurised air. As a result, in some cases, MQL fails to deliver similar or superior performance to that of flood cooling [11, 12].

To improve the lubricating and cooling performance of MQL, nano fluids are used by dispersing micro and nano particles in the lubricating oil. Various metal oxide particles, graphene, carbon nanotube and solid lubricants have been tested in different vegetable oils. The addition of solid nanoparticles to the lubricant oil generally enhances the cooling performance of the oil. They can also improve lubrication due to their geometry by rolling and ploughing or by chemically reacting with the workpiece/cutting tool [9]. Despite the potential technical advantage of nanofluid MQL, the health and safety issues related to spraying nanoparticles are generally overlooked. Nouzil et al. [13] performed a thorough review of the toxicity of various nanoparticles used for nanofluid MQL. They concluded that transition metal dichalcogenides such as $MoS_2$ and $WS_2$ have the least toxicity compared to other nanoparticles. Salem et al. [14] performed a cradle-to-gate LCA of various nanofluid MQL with different particles as well as conventional flood cooling and MQL with vegetable oil. Their analysis showed that conventional flood cooling has the lowest impact followed by MQL with vegetable oil. Nanofluid MQL with multi-walled nanotube and $Al_2O_3$ dispersed in rapeseed oil showed the highest single-score impact for human health, ecosystem quality, climate change and resources.

The global cutting tool market was estimated to be ~$76 billion in 2022 and is expected to reach over $79 billion in 2023 [15]. About 80% of the cutting tools used in industry are made from cemented tungsten carbide and tungsten carbides form about 64% of the global tungsten consumption [16]. During machining, the cutting tool experiences thermomechanical and chemical wear. After a certain criterion for flank wear is reached, the cutting tool is replaced to prevent damage to the workpiece and ensure process efficiency. However, this requires constant interruption of machining process and monitoring the tool wear using optical methods. In industrial applications, this is very time consuming and not viable. Instead, statistical process monitoring based on historical data is used for determining the tool life and replacing the cutting tools.

In machining high value and/or safety critical products, tool wear induced damage to the workpiece can be expensive. In finish machining of near-net-shaped components such as those made by forging or additive manufacturing, the parts have a high value even prior to machining. Any damage to the part during machining can be detrimental. Tool life is specifically short in machining difficult-to-machine materials such as titanium and nickel alloys, which increases the frequency of tool change. In these scenarios, conservative measures are taken and cutting tools are often replaced prematurely to prevent tool wear induced damage to the parts. In practice, only 50-80% of a tool's useful life is utilised [17]. This not only increases the machining costs but also wastes the material and energy used in the production of cutting tools.

Being able to detect the exact time that a cutting tool needs replacing enables maximising the utilisation of cutting tools and reducing the environmental impacts related to the manufacture of cutting tools. Teti et al. [18] provided a comprehensive overview of process monitoring technologies including tool condition monitoring (TCM) in machining. Various direct and indirect methods have been investigated for TCM. Direct methods include optical microscopes and image processing techniques [19] as well as white light and laser scanners. Indirect TCM relies on other quantities such as cutting forces, vibrations, temperature, spindle power/current, etc [20]. In-process on-machine direct TCM methods have obvious limitations due to the need for line-of-sight access to the cutting tool. The cutting tool can be obscured by cutting fluids, cutting chips and the part geometry. Additionally, in milling operations, the cutting tool is rotating at high speeds which requires high sampling rate sensors and data acquisition systems. These limitations have shifted the research mainly towards indirect TCM methods. Tool wear is directly related to the cutting forces and therefore other parameters derived from cutting forces i.e. acceleration, bending moment, power, etc. Vibrations and acoustic emissions have also been investigated for TCM [21]. As the tool wear increases, the cutting forces and therefore power consumption increases. This provides an opportunity for TCM. In repetitive processes using identical setups, and tool and workpiece geometries and materials, thresholding has been used for detecting cutting tools' end of life. However, tool wear and its relationship with cutting forces and other parameters is less deterministic. It is affected by small variations in the cutting tool and workpiece material properties. This has led to the development of more complex methods for TCM using various sensor signals to establish a direct correlation between cutting signals and tool wear conditions [18]. In recent years, feature extraction from the sensor signals and the use of machine learning has gained popularity in this field [20].

Researchers have studied TCM applications to accurately predict tool conditions to optimise tool change decisions. Kolny et al. [22] developed a system for TCM by monitoring a machine tool's power consumption and identifying anomalies in the power consumption signal. Segreto et al. [23] utilised cutting force, acoustic emission and vibration to assess the tool condition via neural network pattern recognition. Shen et al. [24] investigated different regression algorithms to predict tool wear condition under different machining conditions. Hassan et al. [25] proposed a sensor-based tool wear monitoring applying the wavelet scattering convolution neural network. A comprehensive review of advanced tool monitoring techniques can be found in reference [26]. As presented in these references, the goal is to maximise productivity and optimise tool change decisions, which ultimately leads to increased productivity in cutting tool management.

The energy footprint of machining consists of the machine tool's power consumption as well as the energy used for the cooling/lubrication system and the cutting tools. However, these are often investigated and analysed individually. Indeed, energy is used for producing the cutting tools and the coolant/lubricants, and for operating coolant/lubricants during machining. Apart from electricity, most machine tools also require compressed air. This is often overlooked in energy analysis. There is a lack of study on the overall energy footprint and environmental impact of various machining processes. Gate-to-gate analysis for reducing the overall energy footprint of a process or its environmental impact can be misleading or contradictory to the overall aim of minimising the burden to nature and the global resources. Reducing energy or resource consumption within the boundaries of a study may only shift the energy and resource consumption elsewhere. For instance, increasing material removal rate to reduce machining energy consumption per part can lead to increased cutting tool consumption and hence the energy used for producing cutting tools. The main aim of this paper is to identify the overall energy footprint in media-assisted machining. Whilst the technical performance of these methods in terms of tool life and part surface integrity may be known, their environmental viability is still not clear. In addition, considering the embodied energy in the cutting tools and cooling/lubrication systems as well as the energy consumption of the machine tool will help to identify the main drivers for reducing the total energy footprint of machining. Cutting tools are often replaced early to prevent tool wear induced damage to the workpiece. This can increase the impact of cutting tools' embodied energy on the overall machining energy footprint.

In this paper, firstly, the energy footprint of machining is investigated in end milling of Ti-6Al-4V titanium alloy used in the aerospace industry employing three distinct cooling/ lubrication methods. These are: flood cooling (Flood), conventional MQL with vege-table oil (CMQL), and MQL with tungsten disulphide ($WS_2$) in vegetable oil (OWS). For energy footprint analysis, the machine tool's energy consumption and the embodied energy in cutting tools and cutting fluids has been investigated. Secondly, a method is proposed for tool condition monitoring. It uses sensor signals from a wireless sensory tool holder which are transformed into scalograms using continuous wavelet transform. The scalograms are then used for training and testing a CNN deep learning network to determine the state of the cutting tool, so that the use of the tool life can be maximised to reduce the overall energy footprint of machining.

Following this section, the experimental data used for the energy footprint analysis and training the deep learning network is presented. The data including tool life and power consumption are used in the Section 3 for analysing the energy footprint of machining using dry cutting with compressed air, flood cooling and MQL with oil and with $WS_2$-oil suspension. The bending moment sensor signals from the experiments are used in Section 4 for processing, training and testing of a CNN network. This is followed by a thorough discussion of the findings. Finally, the concluding remarks are presented.

## 2. EXPERIMENTAL DATA

The experimental data for this investigation was taken from the results in [27, 28] on end milling of Ti-6Al-4V titanium alloy using different cooling and lubrication conditions. In [27], a new cooling and lubrication method was introduced combining tungsten disulphide ($WS_2$) microparticles and rapeseed vegetable oil for minimum quantity lubrication (MQL), referred to as OWS. As shown in Table 1, this method was compared with conventional MQL using the same nozzle with only rapeseed oil (CMQL). In addition, dry cutting with compressed air at 0.5 MPa (Air) and flood cooling using water-based emulsion at 7% concentration (Flood) were used for comparison.

Table 1. Various cooling/lubrication conditions considered [27]

| | Coolant/lubricant |
|---|---|
| Flood | Flood cooling with water-based emulsion at 7% concentration |
| Air | Dry cutting with compressed air |
| CMQL | MQL with rapeseed oil |
| OWS | MQL with 1%wt $WS_2$ microparticles suspended in rapeseed oil |

Tool life, power consumption and bending moment were reported at 150 m/min cutting speed and 0.03 mm/tooth feed rate, with 3 mm axial and 4 mm radial depth of cut. A 5 flute solid tungsten carbide end milling tool with 12 mm diameter, 83 mm length and TiSiN coating was used for each experiment. Tool wear was measured periodically by interrupting the machining process and using a digital microscope. The experiments were concluded when 300 μm average flank wear criterion was reached. A Hioki 3169 power analyser was used for measuring the machine tool's power consumption during the experiments at 1 Hz sampling rate. A Spike wireless sensory tool holder allowed for measuring and monitoring the cutting tool bending moment during the experiments at 2.5 kHz sampling rate. The investigations in [27] showed that using OWS can improve the machining performance for Ti-6Al-4V. The experimental results for tool wear, power consumption and bending moment are shown in Fig. 2. Further details can be found in [27].

| | | | |
|---|---|---|---|
| **Tool** | 5 flute solid tungsten carbide | **Workpiece** | Ti-6Al-4V |
| **Cutting speed** | 150 m/min | **Axial depth of cut** | 3 mm |
| **Feed rate** | 0.03 mm/tooth | **Radial depth of cut** | 4 mm |

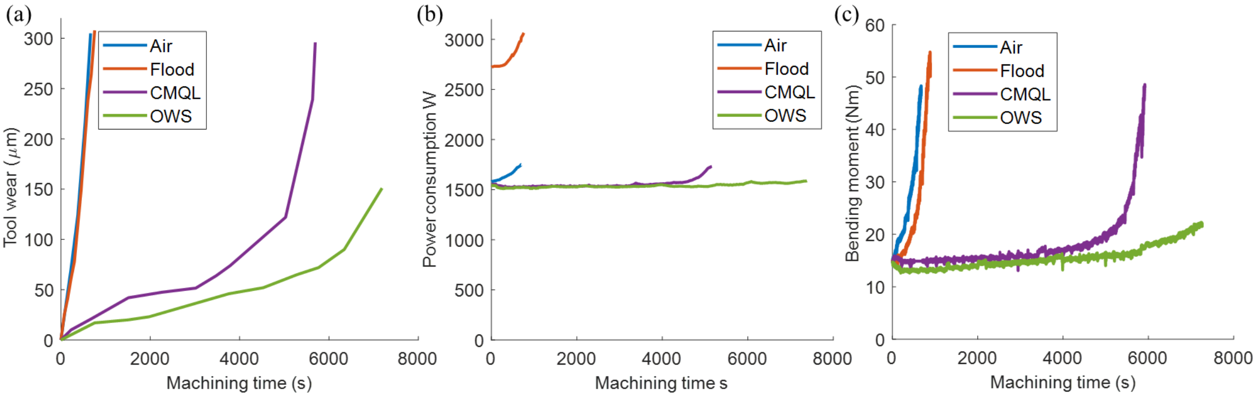


Fig. 2. Average (a) tool wear, (b) power consumption and (c) tool bending moment using various cooling/lubrication methods in end milling Ti-6Al-4V alloy adapted from [27]

## 3. ENERGY FOOTPRINT ASSESMENT OF MACHINING

### 3.1. TUNGSTEN CARBIDE CUTTING TOOL

Tungsten carbide with cobalt binder (WC-Co), also known as cemented carbide, is the most used cutting tool material in industry. The global demand for tungsten was estimated to be 119.2 kT in 2022 [29] and tungsten carbide forms about 64% of the total demand for tungsten [16]. The global reserve of tungsten is about 3.8 million tonnes [30] and the production of primary tungsten is led by China, Vietnam and Russia, respectively [31]. Surprisingly, only 46% of the tungsten carbides and 55% of tungsten carbide tools are currently recycled [32]. Cobalt is used as a binder material in WC-Co cutting tools and is designated as a critical raw material by the European Union [33]. The global reserve for cobalt is 8.3 million tonnes and the demand has increased over the past decade led by electric car battery production [34]. Over 70% of the global cobalt is mined in the Democratic Republic of Congo.

Producing the WC-Co material is the most energy intensive step in the production of cutting tools. Rief et al. [35] provided a breakdown of the process for producing WC-Co rods for cutting tools with their associated energy consumption. Kirsch et al. [36] included the embodied energy of the primary material and calculated a 90 MJ/kg embodied energy for WC-Co rods. Rajemi et al. [37] used 400 MJ/kg for analysing the embodied energy of cutting tools. These are lower than the values identified in a later study by Furberg et al. [38], as shown in Fig. 3. Approximately, 146 g of WC-Co is used for producing a typical cutting tool of 12 mm diameter used in this investigation. This equates to an average ~70 MJ energy footprint for producing WC-Co material but can be as high as 107 MJ in a zero-recycling scenario or as low as 19 MJ if a fully recycled material is used.

The production of solid end mill tools involves grinding the tool geometry from a rod of WC-Co material with the final tool weighing approximately 108 g. Based on the literature [36], the embodied energy due to grinding can be approximated to be 23.5 MJ and 0.03 MJ for drag finishing. The energy consumption for coating varies between chemical vapour deposition (CVD) and physical vapour deposition (PVD) methods, with CVD reportedly having a significantly higher energy consumption. The overall capacity of the coating machine also impacts the embodied energy of the tools. Generally, tools coated using machines with a larger capacity have a lower energy footprint. For this study, the energy consumption for coating was based on the analysis by Kirsch et al. [36], equivalent to 2.64 MJ per tool. Using the suggestions by Furberg et al. [38] for non-Chinese WC-Co, the cutting tool used in this study has a total embodied energy of ~84 MJ. However, there are uncertainties in this value, and it can be as high as 128 MJ or as low as 39 MJ if a fully recycled material was used.

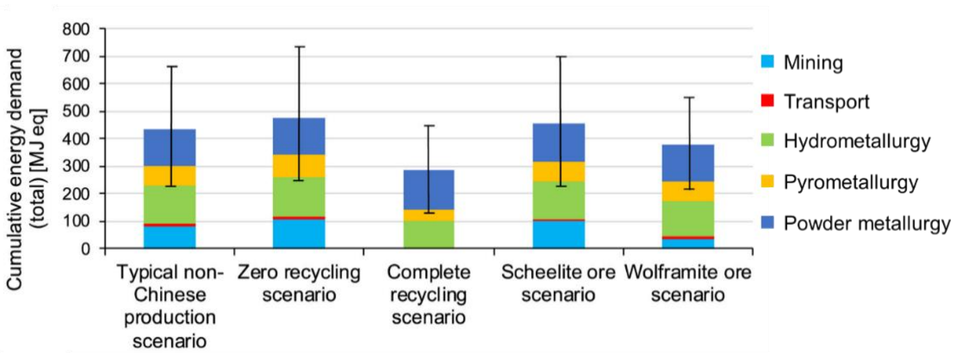


Fig. 3. Energy demand for producing cemented carbide in various scenarios [38]

### 3.2. ENERGY FOOTPRINT OF COOLANTS/LUBRICANTS

The energy footprint of the coolant/lubricant methods $E_c$ used in this study includes the energy footprint of the primary materials ($E_{pm}$), the energy used for producing the coolant/lubricant ($E_{cpro}$) and for their disposal ($E_{cdis}$):

$$E_c = E_{pm} + E_{cpro} + E_{cdis} \tag{1}$$

Water-based cutting fluids used for flood cooling are emulsions of oil in water typically at 3–10% concentration. They contain oil, emulsifiers, surfactants, extreme pressure additives, bactericides, fungicides, corrosion inhibitors, etc. The exact composition of water-based cutting fluids is usually a proprietary material of the manufacturers and not publicly available. In this regard, most studies use the environmental impacts of mineral oil for the analysis. More detailed investigations also include the impact of surfactants [39]. Typically, 1-10% anionic and/or non-ionic surfactants are used in formulating emulsion oils. The embodied energy of surfactants is relatively large, ranging from 41.4 MJ/kg to 76.6 MJ/kg [40]. Raimondi et al. [41] calculated the embodied energy of petroleum-based lubricants at 62.194 MJ/kg, whilst Skerlos et al. [39] and Clarens et al. [42] identified a value of 2400 MJ/year for a tank of 208 l. In contrast, Alswat and Mativenga [43] used 11.1 MJ/l for water-based cutting fluids. Jensen [44] concluded that 2922.48 MJ is used for producing emulsion oil for 3 $m^3$ water-based emulsion at 5% concentration. The disposal energy for emulsion cutting fluids has been estimated to vary between 0.17 MJ/l and 0.4 MJ/l, depending on the method which excludes the transportation [43, 45].

In this study, for Flood experiments, the machine tool has a tank of 250 l filled with emulsion at 7% concentration and the cutting fluid is typically replaced once a year. A coolant pump is used for recirculating the cutting fluid. The power consumption of the coolant pump was measured to be 1.05 kW which equates to 62.7 kJ for a minute of machining. The values identified by Pusavec et al. [45] and Alswat and Mativenga [43] for embodied energy of water and emulsion concentrate were used, taking surfactant and disposal energy into account. This leads to a total of 315.4 MJ embodied energy for the emulsion cutting fluid over a year. Assuming 252 working days and an 8 h shift per day, the energy footprint of the cutting fluid excluding the coolant pump equates to less than 3 kJ per minute of machining. This can be further reduced if multiple shifts are used in a day. In contrast, taking non-material cutting times into account, the energy footprint will be higher.

In all MQL scenarios of Air, CMQL and OWS, 6.1 $m^3$/h compressed air at 5 bar was used. With a compression efficiency of 75%, the embodied energy of the compressed air was estimated to be ~0.54 MJ/$m^3$. However, there are systems with lower efficiencies, and leakage and pressure drop can increase the energy footprint of compressed air. This is in agreement with the analysis by Ginting et al. [46]. The energy consumption for generating compressed air during the 95 min tool life in CMQL is 5.2 MJ. The impact of the rapeseed oil is more complex. It is a combination of multiple parameters depending on farming practices and the geographical region where the rapeseed is grown. This includes the farming machineries and their associated diesel and electricity consumption, use of fertilisers and pesticides and the yield per hectare. The footprint of rapeseed oil produced in the UK has been estimated to be 2.1 kg $CO_2$ eq/kg [47]. The equivalent embodied energy of rapeseed oil has been estimated to be between 19 MJ to 33 MJ per litre [48, 49], which equates to 32 kJ/min to 55 kJ/min given 100 ml/h flow rate in CMQL. In this study, a value of 50 kJ/min for rapeseed oil was considered.

The $WS_2$ used in OWS experiments has a high embodied energy of 0.84 MJ/g [50]. At a concentration of 1% $WS_2$ in rapeseed oil and flow rate of 100 ml/hr, the embodied energy of the $WS_2$-rapeesed oil mix equals to 8 MJ over the 128 min lifespan of the tool. The energy for producing compressed air in OWS was estimated to be ~7 MJ.

The various parameters used for calculating the energy footprint of various elements of machining using different cooling/lubrication methods are summarised in Table 2. As shown in Fig. 4, by only considering the impact of machining environment, using compressed air as a coolant appears to have the lowest energy footprint of 55 kJ for a minute of machining, followed by Flood with 65 kJ. In comparison, CMQL and OWS require 105 kJ and 117 kJ energy, respectively. The fact that the coolant in the machine tool recirculates for a year, significantly minimises the energy footprint for production and disposal of the cutting fluid during its lifetime compared to MQL systems where the lubricant is consumed. The main contributor to the impact of flood cooling is the energy required for running the coolant pump. In contrast, the energy demand in MQL is equally divided between compressed air and vegetable oil production. Reducing the air pressure and flow rate in MQL and using more efficient air compressors can potentially reduce the energy demand of compressed air production. Nevertheless, generating compressed air remains inefficient with the majority of the energy used transforming into heat. Improved farming practices, reduced pesticide and fertiliser consumption and electrification of farming machinery can further reduce the energy consumption for producing vegetable oils. Alternative oils from algae also have the potential to minimise competition with food supply.

Table 2. Tool life and energy footprint of various elements for machining experiments

| | Flood | Air | CMQL | OWS |
|---|---|---|---|---|
| Tool life (min) | 14.5 | 11.6 | 95 | 128 |
| Average Machining Power consumption (kW) | 1.77 | 1.65 | 1.55 | 1.55 |
| Emulsion production (MJ/l) | 0.86 | - | - | - |
| Emulsion disposal (MJ/l) | 0.4 | - | - | - |
| Vegetable Oil (MJ/l) | - | - | 30 | 30 |
| Air (MJ/m$^3$) | - | 0.54 | 0.54 | 0.54 |
| Coolant pump (kW) | 1.05 | - | - | - |
| $WS_2$ (MJ/g) | - | - | - | 0.84 |
| Cutting tool (MJ) | 83.95 | 83.95 | 83.95 | 83.95 |

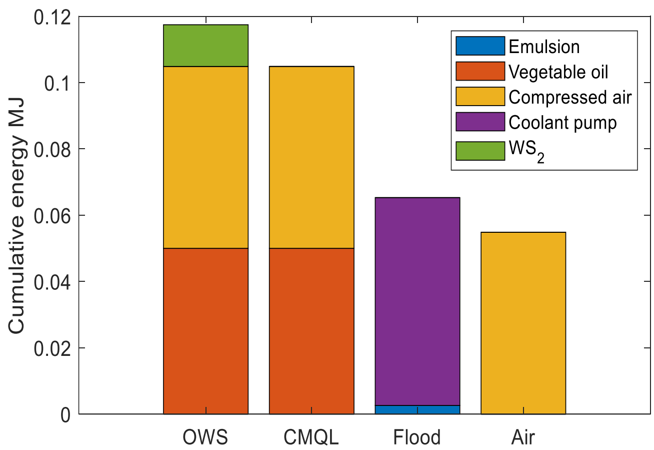


Fig. 4. Energy demand of various cooling/lubrication methods for a minute of machining

### 3.3. CUMULATIVE ENERGY FOOTPRINT OF MACHINING

The cumulative energy footprint of machining ($E_{CM}$) is the summation of the total energy consumed by the machine tool during machining ($E_m$), the energy for delivering coolant/lubricant ($E_d$), and the energy used for producing the consumables used during machining i.e. cutting tools ($E_t$) and cutting fluids ($E_c$):

$$E_{CM} = E_m + E_t + E_c + E_d \tag{2}$$

Each of these energies may represent a cumulative energy consumption of multiple components and processes. In addition, the embodied energy of machine tool and tooling (fixtures, tool holders, etc.) and their share for a specific product or unit volume of machining can be taken into account. However, they are considered non-consumables and have a long lifespan. Hence, their share on the energy footprint is negligible. Additionally, the energy requirements for the transportation of the parts and consumables can be included.

The direct power consumption of the machine tool is affected by tool wear and increases as the tool wear progresses, as shown in Fig 2b. In the case of flood cooling (Flood) with water-based emulsion coolant at 150 m/min cutting speed, the measured machine tool power consumption was 2.82 kW, which also includes the power consumption of the coolant pump (1.05 kW). The machine tool also requires compressed air for operation. This is separate from the compressed air used for cooling/lubrication. The power consumption for generating air for the machine tool is estimated at 1.5 kW. The integration of the measured power consumption curve (Fig. 2b) and the compressed air generation, excluding the power consumption of the coolant pump over time, provides the machine tool energy consumption during the life of the tool:

$$E_m = \int_{t_0}^{t_{VB=0.3}} (P_{machine\ tool} - P_{coolant\ pump} + P_{compressed\ air})dt \tag{3}$$

where $t_0$ is the time zero when a new tool is used, $t_{VB=0.3}$ is the time when average tool flank wear (*VB*) reaches 0.3 mm, $P_{machine\ tool}$ is machine tool's overall power consumption, $P_{coolant\ pump}$ is the coolant pump's power consumption, and $P_{compressed\ air}$ is the power consumption for producing compressed air used by the machine tool.

Equation (3) yields 2.85 MJ energy consumption for running the machine tool and material cutting during the 14.5 min tool life in Flood. In contrast, the energy footprint of the emulsion including the coolant pump and cutting tool is ~0.95 MJ and 84 MJ, respectively. It clearly shows the significant impact of the cutting tools in the cumulative energy footprint of machining.

The machine tool energy consumption in Air was equivalent to 2.19 MJ during a tool life of 11.6 min. When CMQL is used, the tool life is significantly increased to nearly 95 min, leading to 17.37 MJ energy consumption by the machine tool over the lifespan of the cutting tool. The overall energy footprint for machining in CMQL was estimated to be 111.3 MJ during the 95 min tool life, including the energy consumption for cutting tools and the coolant/lubrication system.

The longest tool life of 128 min was associated with OWS, when a suspension of $WS_2$ in oil was used. The machining energy consumption including the energy for generating compressed air was estimated to be 23.4 MJ. This led to a 110.9 MJ cumulative energy footprint for machining over the lifespan of the cutting tool when the impact of cutting tool and cooling/lubrication was taken into account.

Figure 5 illustrates the energy footprint and specific energy footprint of machining using various cooling/lubrication methods per unit time of machining, when the embodied energy of cutting tools and the energy consumption of the machine tool is taken into account. Extending the tool life can significantly reduce the overall energy footprint of machining. Nevertheless, the embodied energy in the cutting tool remains dominant. OWS delivered the lowest energy footprint for a minute of machining compared to CMQL and Flood cooling, despite higher energy requirements for producing $WS_2$, vegetable oil and compressed air. The overall energy demand in OWS is ~6.9 times lower than that of Flood. It is also 20% lower than CMQL.

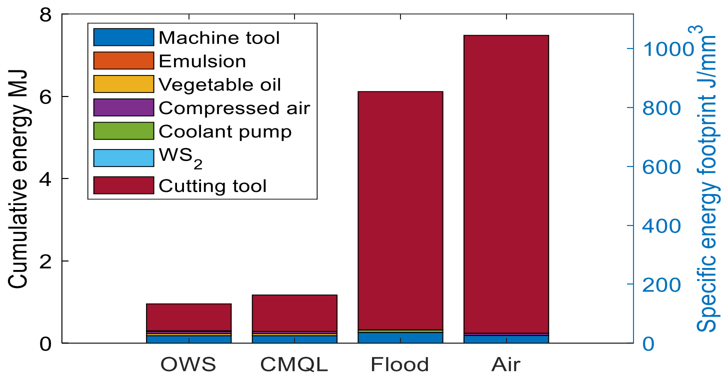


Fig. 5. Cumulative energy footprint for 1 minute of machining and specific energy footprint using various cooling/lubrication methods for end milling Ti-6Al-4V

As shown in Fig. 6, irrespective of the machining condition and extending tool life, the energy embodied in cutting tools dominates the overall energy footprint of machining.

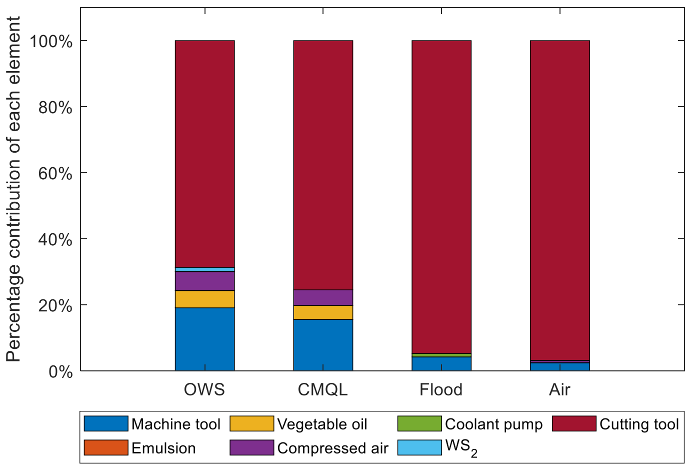


Fig. 6. Percentage contribution of various elements to the cumulative energy footprint of machining during the lifetime of a cutting tool using different cooling/lubrication methods

It forms 69%, 75%, 96% and 97% of the overall energy footprint of machining in OWS, CMQL, Flood and Air, respectively. This indicates the importance of extending the tool life, as well as utilising the entirety of a tool's useful life prior to replacement with a new tool to prevent wasting the embodied energy in cutting tools. It highlights the need for a TCM system capable of detecting the exact time that a tool needs to be replaced before it damages the workpiece, but not before the maximum tool life is utilised.

## 4. TOOL WEAR DETECTION USING CONTINUOUS WAVELET TRANSFORM AND CONVOLUTIONAL NEURAL NETWORKS

As highlighted above, a significant portion of the total machining energy footprint is due to the embodied energy of the cutting tools prior to machining. As such, replacing the cutting tools early based on the users' experience or historical data can lead to inefficient use of the cutting tools. This is also synonymous to wasting the tools' embodied energy, further increasing the energy footprint of machining. Development and implementation of intelligent TCM systems utilising machine learning and real time sensor signals offers significant potential benefits in enhancing productivity and sustainability in cutting tool usage. They can potentially detect the exact time that the cutting tools need replacing to ensure maximum utilisation of a tool's useful life.

In this section, a tool wear detection method for end milling tools is proposed using the tool bending moment signal collected from a wireless sensory tool holder. The bending moment signal is pre-processed and transformed into images for deep learning using continuous wavelet transform. A convolutional neural network (CNN) model is trained and tested for classifying the condition of the cutting tool based on the bending moment signal.

For the purpose of tool wear detection, the bending moment signal from the Spike sensory tool holder was used. The data was obtained from experiments performed by Shokrani et al. [28] on various cooling and lubrication methods, Table 3, for machining Ti-6Al-4V alloy at two cutting speeds of 150 m/min and 200 m/min. The feed rate and axial and radial depth of cut were kept constant at 0.03 mm/min, 3 mm and 4 mm, respectively. The experiments involved six cooling/lubrication methods: (i) MQL with rapeseed oil, (ii) 50% $Al_2O_3$ suspension in oil (OA50%), (iii) 4% $Al_2O_3$ suspension in oil (OA4%), (iv) 50% PCD suspension in oil (OD), (v) 1% graphite suspension in oil (OG) and (vi) oil-water (OW). Additionally, the data for CMQL and Flood from [27] was used as explained in Section 2. In both experiments, the machining experiments were periodically interrupted and the tool flank wear was measured using a digital microscope. Further details can be found in [27] and [28].

Table 3. Various cooling /lubrication conditions used by Shokrani et al. [28]

| | Lubricant |
|---|---|
| MQL | MQL with Rapeseed oil |
| OA50% | MQL with $Al_2O_3$ nanoparticle at 50% concentration in rapeseed oil |
| OA4% | MQL with $Al_2O_3$ nanoparticles at 4% concentration in rapeseed oil |
| OD | MQL with Polycrystalline diamond (PCD) at 50% concentration in rapeseed oil |
| OG | MQL with Graphite at 1% concentration in rapeseed oil |
| OW | MQL with 50% mixture of water and oil |

The bending moment of the cutting tool was recorded throughout the experiments in *X* and *Y* directions in the cutting tool coordinate system. Given the rotation of the cutting tool, the coordinate system also rotates with respect to the machine tool's coordinate system but is stationary with respect to the end milling tool's cutting edges. The resultant bending moment can be calculated from the *X* and *Y* bending moment signals using Pythagorean theorem. Figure 7 illustrates an example bending moment signal in *X* and *Y* directions as well as the resultant bending moment of the tool for a machining pass. As demonstrated in Fig. 2, the bending moment of the tool increases as the tool wear progresses. The bending moment is directly related to the cutting forces. Monitoring the magnitude of the cutting forces and therefore tool bending moment can indicate the state of the tool wear. However, this method is dependent on the cutting parameters and fails to account for the variability in material properties and cutting geometry. Moreover, the bending moment is also influenced by the tool's overhang length.

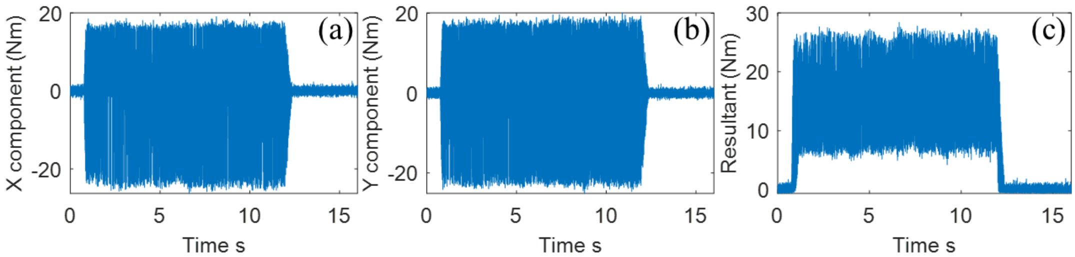


Fig. 7. Bending moment signal in (a) X and (b) Y direction and (c) the resultant signal for an example machining pass

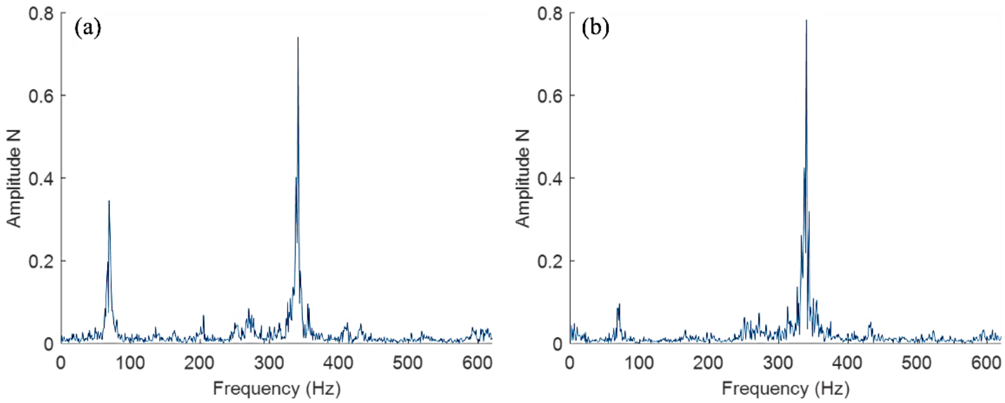


Fig. 8. Fast Fourier transform of example bending moment signals for a (a) new tool and a (b) worn tool

Instead of the analysing the signal magnitude in the time domain, the analysis can be performed in the frequency domain by performing the Fast Fourier Transform (FFT) of the signals as shown in Fig. 8. The comparison between a new tool (a) and a worn tool (b) indicates differences in the sensor signal in frequency domain. The two major peaks in the signal for a new tool (Fig. 8a) are associated with the spindle speed and the tool passing frequency, which is the engagement frequency of the cutting edges. As shown in Fig. 8b, the tool passing frequency becomes more prominent as the tool wear increases.

Plotting the bending moment of the tool in the *X* axis against the *Y* axis reveals more details. As shown in Fig. 9 (a) and (b), the magnitude of the bending moment in both *X* and *Y* directions is larger for a worn tool than a fresh tool. The star-like graph also resembles the cutting edges of the five flute tool, indicating the peak bending moment when each cutting edge engages with the workpiece. The standardised *X* and *Y* components of the bending moment are shown in Fig. 9 (c) and (d) for a new and worn tool, respectively. Local standardisation removes the impact of signal magnitude for comparison. A circle is fitted to show the perimeter of the peak bending moment. The location of the peak bending moment changes as the tool wear progresses. As the cutting edges of the tool degrade, the definition of this shape deteriorates. The number of locations at which the peak magnitude is observed increases, indicating higher contact between the tool and the workpiece. This also results in reduced standard deviation of the signal for the worn tool compared to a new tool. The graph's rotation was due to the movement of the contact points between the cutting tool and the workpiece in the cutting tool's coordinate system, as the wear progresses. This indicates the impact of wear on the tool-workpiece engagement and the consequent shift in the signal frequency in the time domain.

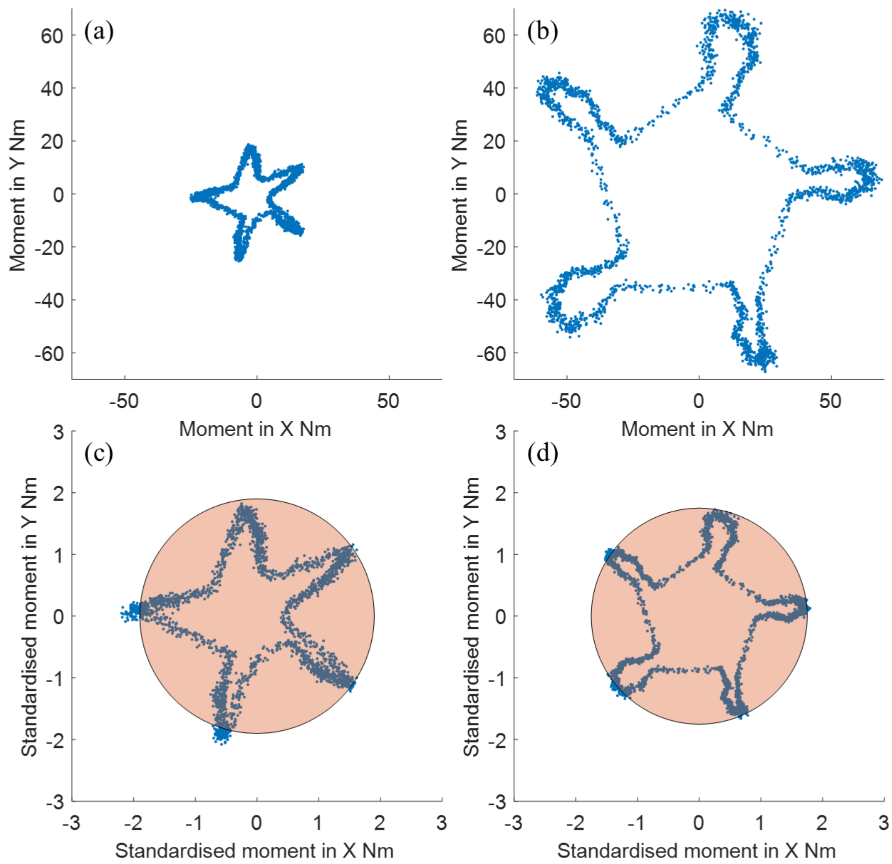


Fig. 9. Cutting tool bending moment in X versus Y direction for a (a, c) new and (b, d) worn tool

Whilst analysing the signal magnitude can distinguish between a new and worn tool by assigning a threshold, it does not offer a monitoring approach that is independent of milling parameters, as the signal can be influenced by factors unrelated to tool wear conditions. To establish a direct relationship between the signal and tool condition, features from the time domain, frequency domain or time-frequency domain can be utilised into a machine learning algorithm. A convolutional neural network (CNN) through the continuous wavelet transform of the bending moment for TCM is considered. The overall framework for the TCM is shown in Fig. 10.

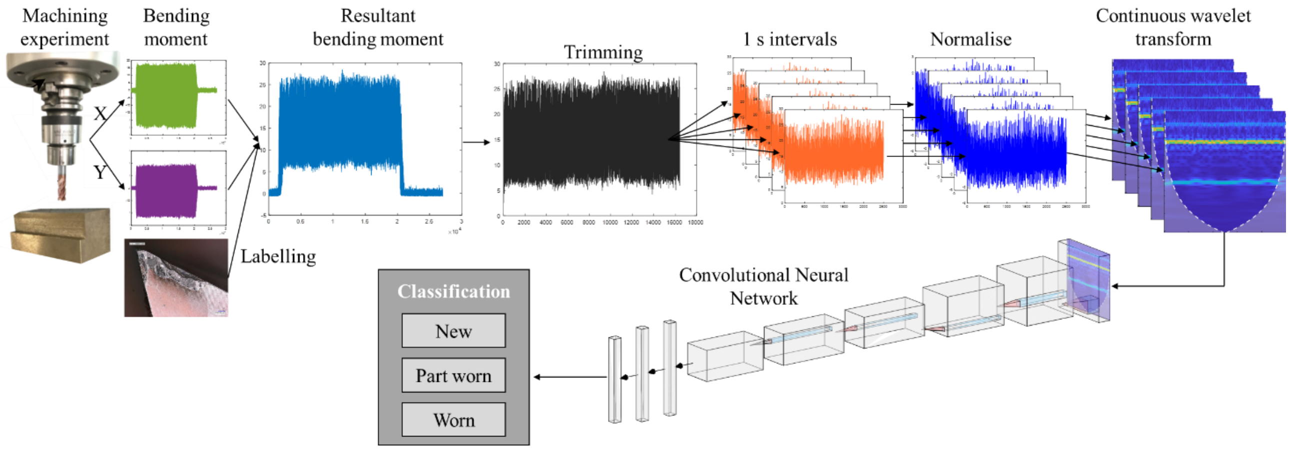


Fig. 10. Overall framework for TCM incorporating tool bending moment signal from a sensory tool holder, CWT feature extraction, and CNN classifier

#### 4.1. DATA PREPARATION FOR TRAINING AND TESTING OF THE MODEL

As shown in Fig. 7, the bending moment signals also contain non-cutting data before the cutting tool engages with the workpiece, and after. Thresholding was used to detect when the cutting tool engages with the workpiece and the bending moment increases. The sensitivity of the detection can be adjusted depending on the load on the cutting tool. For this study, engagement is detected when the bending moment reaches 10 Nm and the signal is trimmed. The signal is divided into packets of 1 s length for further analysis. In order to eliminate the impact of signal magnitude on the analysis, the signal was normalised locally for each 1 s packet.

Using the continuous wavelet transform, both frequency and time domain properties of a signal are preserved. It also has the benefit of representing the signal as an image, which can be used as input to deep learning models such as convolutional neural networks (CNN) which are predominantly developed for classifying images. As shown in Fig. 11, there are distinct differences between scalograms of the transformed normalised signals for new and worn tools. By normalising the data across each scalogram interval, the frequency shift with wear became apparent. It ensured that the most active frequency during each interval was a distinct yellow/orange band, while the least active frequency appeared deep blue. The following figure demonstrates that with wear, the magnitude of high frequency oscillations increased at an accelerated rate relative to low frequency oscillations. Therefore, the active band lower in the image effectively faded, capturing the frequency shift. This method of representing the signal for tool wear captures each 1 s interval independently.

Therefore, each scalogram is autonomous of the behaviour that preceded it, meaning that if a partially worn tool is installed within the system, then the expected scalograms would be similar to those of a tool used from new.

In total, nearly 9.5k samples were prepared and used for training and validation. Of these, over 7.3k were from machining at 150 m/min cutting speed and 2.1k samples were from machining at 200 m/min cutting speed. The bending moment signals were categorised into three classes of (0) new, (1) partially worn, and (2) worn depending on the state of the tool wear. The first 70% of the tool life is classified as new until the end of the tool wear plateau state, the following 15% is classified as partially worn, and the final 15% of the signal is classed as worn. The average flank wear in the worn stage ranges from 280 µm and more. The scalograms of the signal packets were generated with a frequency range of 50–1000 Hz. The scalograms were prepared for each machining experiment and labelled for the training and validation datasets.

### 4.2. CONVOLUTIONAL NEURAL NETWORK TRAINING

Convolutional neural networks (CNNs) are a type of deep learning architecture which have powerful capabilities in classifying images [51]. There are many different pretrained CNN models with different architectures and number of layers such as ResNet, SqueezeNet and GoogLeNet. The present study employed AlexNet, a well-known CNN architecture developed by Krizhevsky [52], comprising 8 layers and a total of 62.3 million parameters.

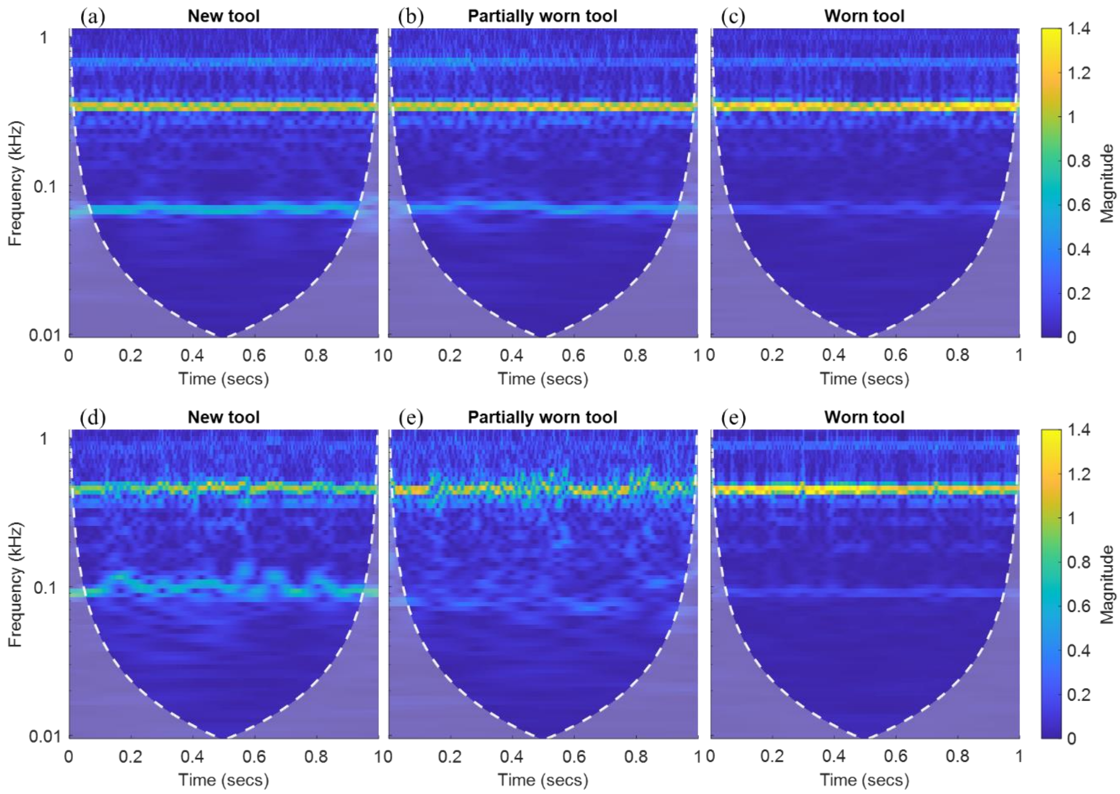


Fig. 11. Scalogram of normalised bending moment signal for a new, partially worn and worn tool at 150 m/min cutting speed (a, b, c) and 200 m/min cutting speed (d, e, f)

Transfer learning was used to train AlexNet on the scalograms of the bending moment signals. Transfer learning is a technique that involves taking a pre-trained neural network (that has already been trained on a large dataset), and then fine-tuning it for a new task using a smaller, more specific dataset. This reduces the time needed to determine specific parameters and layers within the network structure. It can often lead to faster and more accurate training since the pre-trained network has already learned to recognise a wide range of visual features that can be used for the new dataset. The data was randomly split into 70% for training and 30% for validation. The network was trained with a minimum batch size of 10 for 10 epochs and an initial learning rate of 1e-4. Compared to ResNet and GoogLeNet, AlexNet has less depth and can be trained faster, making it the ideal architecture for this investigation. It also focuses on macroscopic features and is less likely to be affected by the noise present in the signals. Given the variability of the data in terms of cutting speed and cooling/lubrication conditions, two approaches for training were chosen based on: i) cooling/lubrication method and ii) cutting speed.

### 4.3. TESTING AND VALIDATION RESULTS FOR TOOL CONDITION MONITORING

In the first method, the network was trained and validated independently for each cooling/lubrication method using the data from 150 m/min and 200 m/min. The location of the dominant frequencies arising from the spindle speed and cutting edges differ in scalograms depending on the cutting speed. As such, the network should be robust to the location of the dominant frequencies and their potential shifts. The performance of the network was assessed using “recall” or true positive rate for each class. That is the ratio between the number of samples that were correctly assigned to a class (true positive) and the total number of samples in that class. The performance of the network for training and validation data is shown in Table 4 and 5, respectively. The network performed well in detecting both new and worn tools achieving about 93% average overall accuracy on the training data and nearly 90% for unseen validation data. Its performance varied across different cooling/lubrication conditions achieving the best performance for CMQL and commercial MQL and the worst performance for OD. This reflects the impact of data availability for training on the performance of the network in correctly classifying the tool condition. The number of data samples for training the network on OD was negatively affected by the short tool life during the experiments. In addition, the performance of the network was limited in detecting partially worn tools, as shown in Fig. 12 and 13. In essence, the partially worn class acts as a buffer for ambiguous signals near the worn or new categories.

The confusion matrices for training and validation data for the signals from flood cooling condition are shown in Fig. 12 (a) and (b), respectively. Although the accuracy of the partially worn category was erratic, it has proved its benefits in providing a buffer for ambiguous images, reflected in low false positive and false negative rates, as shown in Fig. 12. Effectively, the worn and unworn categories, which were of primary interest suffered little misclassification.

From above, it might be argued that false negatives dominated over false positives; marginally, but even so, misclassification rates remained below 10% in most cases. The results did not otherwise exhibit any significant bias across different lubricants or speeds, extinguishing concern that high accuracies were a result of bias toward the dominant 150 m/min datasets.

Table 4. True positive classification rate of speed-independent classifier for training data

| Lubricant | Training (All values quoted as percentages) | | | |
|---|---|---|---|---|
| | Overall Accuracy | Correct New | Correct Partially Worn | Correct Worn |
| Air | 93.68 | 98.06 | 74.84 | 92.16 |
| Flood | 92.38 | 94.01 | 94.16 | 82.89 |
| Commercial MQL | 95.67 | 96.78 | 88.21 | 97.96 |
| OA | 93.66 | 100.00 | 58.82 | 99.09 |
| OD | 92.18 | 99.38 | 74.79 | 75.93 |
| Oil | 96.11 | 99.44 | 90.67 | 86.00 |

Table 5. True positive classification rate of speed-independent classifier for unseen validation data

| Lubricant | Validation (All values quoted as percentages) | | | |
|---|---|---|---|---|
| | Overall Accuracy | Correct New | Correct Partially Worn | Correct Worn |
| Air | 87.47 | 95.78 | 56.06 | 80.00 |
| Flood | 86.53 | 88.60 | 89.39 | 73.85 |
| Commercial MQL | 90.60 | 94.11 | 71.43 | 93.33 |
| OA | 92.37 | 99.77 | 54.26 | 95.74 |
| OD | 85.98 | 98.14 | 57.69 | 57.69 |
| CMQL | 93.77 | 98.68 | 81.60 | 83.02 |

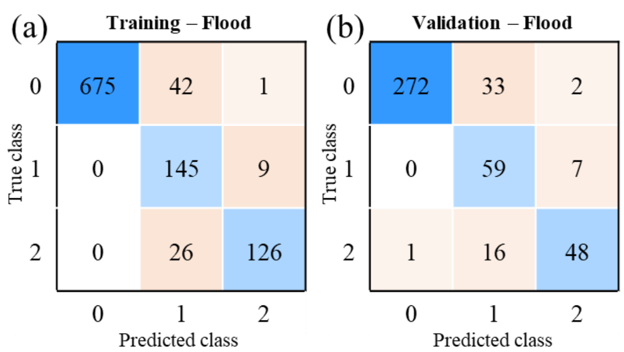


Fig. 12. Confusion matrices for speed-independent training and validation data for flood cooling

The lubricant-independent investigation focused on batching the data based on their cutting speed (150 m/min or 200 m/min) and training the networks irrespective of the cooling/lubrication method. The network achieved 95% and 92% accuracy on training and validation data, respectively, for 150 m/min cutting speed as shown in Fig. 13. For the experiments at 200 m/min, the accuracy was lower at 88% and 85% for training and validation data. The lower accuracy of the network in classifying the cutting tool state at 200 m/min cutting speed is potentially due to the lower number of training data at this speed compared with 150 m/min. Apart from the partially worn class, minimal accuracy reduction was suffered between training and validation demonstrating that the classifier had identified general patterns rather than training data specifics.

## 5. DISCUSSION

There is an increasing concern on the impacts of manufacturing processes on the environment and the workers' health. Within the published literature on machining, the latter is mostly focused on the adverse health impacts of conventional water-based cutting fluids. Water-based cutting fluids are designed to recirculate in the machine tool for a prolonged length of time and they are susceptible to contamination and fungi and bacterial growth [8]. Exposure to the water-based cutting fluids has been linked to many occupational health diseases such as asthma and dermatitis. There are many regulations and advice for minimising the exposure to the cutting fluids and eliminating their adverse health impacts on workers.

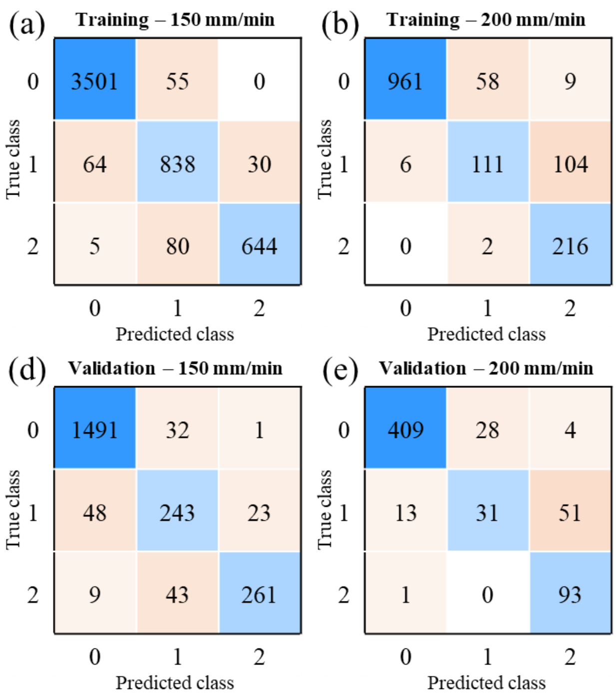


Fig. 13. Confusion matrices for lubricant-independent training and validation data at 150 m/min and 200 m/min cutting speed

Energy consumption and the associated carbon emissions is one of the main environmental impacts of machining processes. It also affects the costs of producing parts. The majority of the studies concerning energy consumption, only consider the direct energy consumption by the machine tool. These studies have led to the development of a number of predictive models which are further employed for minimising energy consumption during machining. However, these studies fail to consider the energy embodied in the consumables for machining i.e. cutting tools and cutting fluids. The investigations in this paper highlighted that despite high energy consumption for producing and disposal of water-based cutting fluids, their share in the overall machining energy footprint is marginal. Mainly due to the fact that they have a long service life and recirculate within the machine tool. The main contributor to the energy footprint of water-based cutting fluids is the coolant pump used for circulating the cutting fluids during machining. Unlike flood cooling, the coolant/lubricant in MQL is consumed. This significantly increases the impact of coolant/lubricant on the overall energy consumption of MQL methods. Nevertheless, the embodied energy in cutting tools dominate the overall energy footprint of machining processes. This highlights the impact of alternative cooling/lubrication methods in extending tool life and reducing the overall machining energy consumption. Even though MQL with $WS_2$ suspended in oil has a higher energy footprint, the overall machining energy is 6.8 times lower than that of flood cooling primarily due to the extended tool life.

Data availability is a major constraint in performing a detailed analysis for energy consumption and environmental impact of machining, specifically for cutting tools and cutting fluids. Whilst there are increasing numbers of investigations for both cutting tools and cutting fluids, many of these studies rely on outdated data and/or assumptions. The exact composition of the cutting fluids is a proprietary material of producers which are not disclosed. Additionally, the embodied energy and environmental impacts of some additives are still not known. Similarly, there are still many unknowns regarding the production of cutting tools and their energy demand and environmental impacts. There are many different grades of tungsten carbides of different origins with varying performances. The overall energy requirement for coatings is still not well understood and the best estimates are limited to the coating machines' direct energy consumption, often based on lab apparati. End users do not necessarily have the resources for performing detailed analysis and make decisions based on the environmental impacts of their processes taking Scope 2 and 3 impacts into consideration. Therefore, suppliers of parts and consumables should provide the data regarding the energy and carbon footprint of their products. The complexity of energy and carbon accounting and its impact on decision making for manufacturing processes also highlights the need for intelligent systems capable of comprehending information and performing optimisation.

As mentioned in the introduction, only 50%-80% of cutting tool's useful life is used to prevent tool wear induced damage to the workpiece. Given the high embodied energy in cutting tools, this can have a significant impact on the overall energy consumption of machining. For instance, replacing the tool in OWS 20% earlier will result in 25% increased specific energy footprint. Replacing the tool when only 50% of its useful life is used will double the specific energy footprint to 242 J/mm$^3$. TCM using sensor-based intelligent systems can ensure that a higher percentage of a tool's useful life is utilised in machining. In this paper, an indirect TCM system is proposed by utilising a sensory tool holder and using CNN with the continuous wavelet transfer features. This has the additional benefit of ease of use and limited impact of environmental noise on the TCM system's performance compared to acoustic emission and vibration sensor-based systems. The proposed method achieved over 90% accuracy in correctly detecting the state of the cutting tool for 150 m/min cutting speed. The accuracy was 85% for tools at 200 m/min cutting speed. This is potentially due to the shorter tool life at 200 m/min cutting speed and lower number of training data (630 data sets). Nevertheless, it still misclassifies a considerable portion of the tools, and its performance can be further enhanced. Potentially, more complex deep learning architectures can be tested and utilised at the expense of training data and time. Additionally, the network is only trained on varying cutting speeds and cooling/lubrication methods. Nevertheless, it demonstrated robustness in dealing with data from varying conditions i.e. cutting speed and cooling/lubrication method. Further investigations and training will extend its capability to a range of cutting parameters including feed rate and depth of cut. Beyond progressive wear, chatter can result in unexpected tool failure [53]. Stavropulos et al. [54] demonstrated that machine learning methods can be used to detect chatter using an accelerometer. The sensory tool holder used in this study is incapable of detecting chatter [55]. By using higher sampling rates or incorporating vibration/accelerometer sensors, the proposed method can be trained to detect chatter and avoid chatter induced tool wear/failure. Successful implementation of such systems requires integration into the machine tool controllers where the machine tool ultimately makes the decision of adjusting cutting parameters or replacing the tool, rather than prescribed by the CAM engineers or the user operating the machine tool.

Whilst the focus of this paper was on energy footprint of machining, there are many other sustainability aspects such as material footprint, impact on soil and aquatic life, economic and societal impacts which were not considered. The implementation of digital technologies to incorporate these aspects, as proposed by Mourtzis et al. [56], can allow for decision making that takes various sustainability parameters into account.

## 6. CONCLUSION

In this paper, the energy footprint for end milling Ti-6Al-4V titanium alloy extensively used in aerospace industry was investigated using dry machining with compressed air, flood cooling and minimum quantity lubrication (MQL) with pure rapeseed oil, and tungsten disulphide ($WS_2$) microparticles suspended in rapeseed oil. The embodied energy in cutting fluids and coolant/lubricants were also considered. The analysis indicated that excluding the workpiece material, the embodied energy of cutting tools dominates the energy footprint of machining with 69% to 97% of the machining energy footprint associated with cutting tools. Extending the tool life by using alternative cooling/lubrication methods such as $WS_2$-rapeseed oil suspension can reduce the overall energy footprint of machining despite the increased energy requirements for the cooling/lubrication. In this study, MQL machining with $WS_2$-rapeseed oil suspension had 6.3 times lower energy footprint than that of flood cooling with water-based emulsion. The reduction in energy footprint was attributed to the extended tool life rather than lower energy requirements for producing and operating the MQL methods. Hence, if MQL does not deliver improved tool life, conventional flood cooling remains the ideal cooling/lubrication method when energy footprint is of concern. However, biodegradability and renewability should also be taken into account. The energy requirement for producing compressed air for operating the machine tool was quantified. The analysis showed for the first time that the energy consumption for generating compressed air is comparable to the electrical energy consumption of the machine tool itself.

The investigations clearly demonstrated that the embodied energy of cutting tools dominates the energy footprint of machining. Replacing the cutting tools early can significantly increase the energy footprint of machining. Therefore, utilising the entirety of the useful life of cutting tools is vital in reducing the energy footprint of machining. A method for tool condition monitoring has been tested and validated by using the cutting tool bending moment signal obtained from a wireless sensory tool holder, continuous wavelet transform signal processing and convolutional neural network deep learning classifiers. The proposed method is capable of correctly classifying the tool condition with nearly 90% accuracy. This method can help with detecting when a cutting tool needs replacing to ensure that the maximum useful life of a cutting tool is utilised.

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