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Investigating the influence of cutting fluid on tool life and power usage during AISI-4130 steel turning

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Abstract

Purpose – This study evaluates the impact of cutting fluids on energy consumption and tool life in machining, focusing on sustainable practices to reduce environmental impact and improve efficiency. By comparing vegetable-based soyabean oil with mineral-based blasocut oil, the study assesses their effects on power usage and tool life.

Design/methodology/approach – This study introduces a novel approach by applying both response surface methodology (RSM) and artificial neural network (ANN) models to validate the performance of vegetable-based cutting fluids, specifically soyabean oil, in machining operations.

Findings – Results indicate that soyabean oil reduces energy use by 9% and extends tool life by 29% compared to blasocut oil, with strong alignment between model predictions and actual results.

Research limitations/implications – The findings, though specific to certain fluids and conditions, suggest that soyabean oil offers a viable eco-friendly alternative for machining processes.

Practical implications – Adoption of such fluids could lower greenhouse gas emissions, reduce dependency on mineral oils and benefit farmers by creating additional demand for vegetable oils.

Originality/value – This dual-model validation of cutting fluid performance marks an innovative contribution to sustainable machining, supporting the adoption of greener, resource-efficient manufacturing practices. This study underscores the potential of vegetable-based cutting fluids to enhance sustainability in manufacturing.

Keywords Minimum quantity lubrication, Soyabean oil, Power consumption, Tool life, Response surface methodology (RSM), Artificial neural network (ANN)

Paper type Research paper

1. Introduction

Cutting fluids are extensively employed in a variety of machining activities across the manufacturing sector. The coolant removes the heat in the cutting zone by absorbing the heat from the workpiece, tool and chip. The reduced temperature of the cutting tool also results in an increase in tool life. Cutting fluids lower friction by wetting the tool's cutting edge and the surface of the chip. Reduction in friction results in decrease in cutting forces and that results in

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reduced power consumption. When turning, it's crucial to take into account the power that a single point cutting tool consumes. The tool's power consumption analysis is useful in both determining the machine's minimum motor power requirement and in the component design process. Mineral based cutting fluids are not environmentally friendly and results in health hazards to workers. These negative effects are minimized by using minimum quantity lubrication (MQL) and vegetable-based cutting fluid (Ghuge and Palande, 2022).

According to Sen *et al.* (2021), cutting fluids are regarded as an essential support for high-volume, high-quality machining processes. However, the cutting fluids used in industry are harmful to the operator.

In order to reduce cutting fluid exposure and health risks from overexposure, the Iowa Waste Reduction Centre (2003) reported that a metalwork fluid management program needed to be established. This report also includes information on the expenses of waste management in the industrial chain.

In their work, Musavi and Davoodi (2021) proposed an ecologically sound technique for cutting fluid. For the analysis, they used mineral-based and vegetable-based lubricants. The causes of their vulnerabilities were explored. The presence of phosphorus, chlorine and zinc dialkyl dithiophosphate has been identified to contribute to several respiratory ailments. Lubricants derived from vegetables have been recognized as safe lubricant.

Tools, power, manpower and cutting fluid expenses all affect the total production cost. Watts (2012) published a pie chart that depicts the capital and operational costs of a typical machining machine for automobile using water-soluble coolant. The percentage share of the cost associated with cutting fluid is shown in Figure 1.

As part of their endeavor to reduce the consumption of cutting fluid, Dhar *et al.* (2006) presented a new technology, MQL. Cutting fluid is conserved when the quantity of cutting fluid used is minimized. In addition, it limits the possibility of the machinist coming into contact with the cutting fluid.

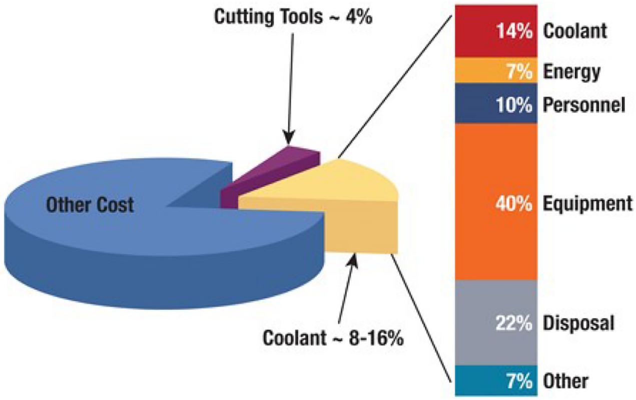
According to Walker (2013), using the negligible quantity of oil is a new methodology, which has now emerged as an alternative to existing machining techniques. In the MQL method, coolant is used at low flow rates, typically just under 250 mL/h, and liquid vapors are pushed to the cutting area by pressurized air.

Korkmaz *et al.*'s (2021) investigation focused on Nimonic 80 A's machining characteristics under various cooling environments. As per the findings, the positioning of MQL nozzles is crucial in enhancing the Nimonic-80 alloy's machining efficiency. The total tool wear for nano-MQL (mixed direction) was approximately 60% lower than that for dry circumstances. The findings also revealed that abrasion and adhesion are driving tool wear mechanisms in dry cutting.

Kuram *et al.* (2011) concentrated on the development of vegetable-based cutting fluids and machining using these cutting fluids. Vegetable oils are referred to as an agricultural product that originates from plants. They are harmless, sustainable and biodegradable due to their ability to be grown and biologically transformed. Vegetable oil molecules give a strong and homogeneous film. They are suitable for high-temperature applications owing to the high flash point. This even lowers the risk of fire and smoke development. Evaporation loss is significantly reduced only when the boiling point and molecular weight are both high. Vegetable oils have therefore arisen as a feasible substitute for mineral oil.

Sankaranarayanan *et al.* (2021) considered the impact of bio-based fluids in machining applications. The mineral-based fluid was to blame for the operators' poor health. Vegetable-based cutting fluid developed as a promising eco-friendly cutting fluid with better performance. The authors examined and analyzed the appropriateness of a number of vegetable oils for various metal cutting applications.

Musavi *et al.* (2018) described an environmentally sustainable technique for cutting fluid in their work. For the analysis, they employed mineral-based and vegetable-based lubricants. The causes of their vulnerabilities have been researched. The presence of phosphorus, chlorine



Source(s): Figure courtesy of Watts (2012)

Figure 1. Cutting fluid cost

and zinc dialkyl dithiophosphate resulted in a higher risk of respiratory disease. Vegetable lubricants have been recognized as safe lubricants.

Awale *et al.* (2021) compared the lubricating characteristics of plant-based oils such as castor, peanut, sunflower and soyabean in order to determine which lubricant would be ideal for a given type of work material. The force ratio, surface roughness, surface topography, microchip morphology and wettability were examined in relation to the lubricating characteristics. According to the experimental findings, castor oil demonstrated exceptional lubricating properties.

Shah *et al.* (2021) examined flood and cryogenic coolants such LCO_2 and LN2 for drilling Ti-6Al-4V with respect to surface roughness (Ra), Active Cutting Energy (ACE), Active Energy Consumed by Machine Tool (AECMT) and Energy Efficiency (EE). They used life cycle assessment to determine how drilling Ti-6Al-4V under three different cutting circumstances will affect the environment, natural resources and public health.

Awale *et al.* (2020) utilized grey relational analysis to fine-tune the MQL mist parameters – air pressure (P), flow rate (Q) and stand-off distance (ds) – with the aim of reducing the impact of MQL-based plunge grinding on hardened AISI H13 tool steel. Their goal was to minimize grinding force, specific energy consumption, grinding temperature and surface roughness. According to their findings, optimizing the MQL mist settings to P: 4 bar, Q: 200 mL/h and ds: 50 mm resulted in the highest Grey Relational Grade (GRG) value (0.972).

Awale *et al.* (2019) conducted a study comparing various grinding conditions on hardened H13 hot die steel, including dry, flood, MQL with deionized water (DIW) and MQL using liquid paraffin oil and castor oil. Their findings indicated that employing MQL-castor grinding resulted in the lowest specific grinding force, specific grinding energy and grinding force ratio. Furthermore, this method significantly reduced surface roughness, measuring Rɑ at 0.245 μm and Rz at 1.846 μm.

Awale *et al.* (2022) investigated various lubricants – such as vegetable oil, a mixture of vegetable oil and DIW and Al_2O_3 NFs – as foundational lubricants for MQL grinding. Their objective was to investigate how these lubricants affected technological parameters, including energy consumption, carbon emissions, production costs, apparent friction coefficient, surface roughness, Bearing Ratio (BC) ratio, surface texture and microchip structure when applied to AISI H13 tool steel.

Musavi *et al.* (2019) conducted experiments on A286, examining the effects of three cutting fluid modes: traditional cutting fluid, nanofluid without a surfactant (comprising copper-oxide and silicon-oxide nanoparticles) and nanofluid with a surfactant, on the surface quality of machined components and chip formation shapes. Results showed that the surface roughness value (Ra) achieved through the MQL technique surpassed that obtained using flood lubrication.

Musavi *et al.* (2022) explored enhancing the lifespan of tungsten carbide inserts by introducing micro-textured grooves on their surfaces. These distinct textures were created using laser technology. Comparative analysis between textured and non-textured inserts revealed that the introduction of micro-textures influenced surface quality and tool wear under both MQL and dry conditions.

The manufacturing industries aim to achieve either a high output rate or an affordable cost of production. The cutting parameters that users choose, such as feed, depth of cut and velocity, are associated with these two measures. Carefully selecting the input parameters is necessary to achieve the desired result. Montgomery (1997) addressed many statistical techniques along with the fundamentals of experiment design and analysis. Artificial neural networks, Taguchi analysis, response surface techniques and other analytical software are utilized for experimental analysis and prediction.

In accordance to the literature, power consumption and the associated expenses of tools and cutting fluids are key challenges for local enterprises. The mineral-based oil is being phased out because of environmental and health risks. Few studies have examined the simultaneous interactions between energy-aware decisions for shop-floor control, process planning and machine parameter settings. Despite previous research efforts focusing on studying machining energy consumption individually from the angles of machinery, process planning and shop floor considerations, the impact of different cutting fluids on machining effectiveness remains unexplored. This study aims to evaluate the machining performance, specifically tool wear, tool longevity and power usage, when employing Blassocut oil and vegetable-based soyabean oil in MQL.

Specifically, while previous studies have explored the influence of cutting fluids in machining processes, our study is unique in its focus on AISI-4130 steel turning under specific experimental conditions. Moreover, our work integrates an analysis of both tool life and power usage in a single experimental framework, which has not been extensively covered in the literature. This dual analysis allows for a more comprehensive evaluation of cutting fluid performance and its practical implications for industrial machining processes. To validate the experiment's outcomes, both the response surface statistical method and neural networks are utilized.

2. Methodology

The experimental setup, depicted in Figure 2, incorporates a medium-duty lathe machine along with the MQL system. The experiment employed a full-factor design involving three parameters, each at three different levels (3^3 levels). The dependent variables were tool wear (*VB*) and power consumption (*P*), while cutting speed (*v*), feed (*f*) and depth of cut (*dp*) served as independent parameters. The experiments involved turning a 60 mm diameter and 120 mm length AISI 4130 steel bar. In selecting the cutting tool, the focus was on choosing one commonly used in small-scale industries. For the study, an uncoated carbide-brazed tool (P-30, Make-Miranda, ISO-6 and R1616) was utilized. These tools are easily available and less costly. A medium-duty lathe machine of Dhara make, manufactured by Tirupati Hydraulics, is used for experimentation. Cutting speed is estimated using the workpiece diameter and machine spindle speed. The feed is varied from 0.35 mm/rev to 0.45 mm/rev. The depth of cut is varied from 0.5 mm to 1.5 mm. Trials are conducted for MQL cutting. The flow rate is adjusted to 60 ml per hour for MQL. The parameter selection is based on the machine capacity and limitation (Ghuge and Mahalle, 2016).

Source(s): Authors' work

Figure 2. Experimental setup

2.1 Power consumption measurement

One goal for manufacturers to maintain their competitiveness in the global market has been to become "energy efficient." The ability to efficiently model and regulate the energy consumption of machining, a significant manufacturing activity, becomes essential. Minimizing power usage in machining operations can help to save money and improve productivity. Manufacturers are increasingly concerned about the escalating electricity expenses. There are two approaches to gauge power consumption. One involves using a wattmeter linked to the lathe tool's motor. However, this method overlooks mechanical and transmission losses. Alternatively, the second method derives power consumption by considering cutting force and velocity (Li *et al.*, 2022).

Nur *et al.* (2021) give a comprehensive set of mathematical formulas required for estimating power requirements and show how they may be used to the turning of austenitic stainless steel with coated and uncoated carbide.

$$P = Fc * V \ldots \text{ is the power equation.} \tag{1}$$

Where Fc is the principal cutting force, P is the power in watt and V is the cutting speed (m/min).

2.2 Tool wear (VB) and tool life measurement

ISO 3685 (1993) provided a standard tool-life investigation approach for single-point cutting tools used for turning steel. It also offers tool-life testing criteria for different aspects. The size of the flank wear "VB" is commonly used to assess how much wear has occurred. Tool wear is measured using a toolmaker's microscope. Tool wear is evaluated with respect to machining time. Table 1 shows the power consumption for Soyabean oil and Blassocut oil.

To estimate tool life, tool wear was monitored at fixed feed, 0.45 mm/rev and 1.5 mm depth of cut at intervals of 5 min at cutting speeds of 34.27 m/min, 53 m/min and 79.73 m/min. After 5 min of machining for each test, the flank width VB was recorded. The tool life was computed using the 0.4 mm flank wear criteria (International Organization for Standardization (ISO), 1977).

3. Response surface modeling

As revealed by the observation data, the performance of soyabean oil appears to be superior to that of Blassocut with respect to power consumption, tool wear and tool life. Second-order quadratic models were developed for each response for each cutting condition using response surface methodology (RSM). An ANOVA test is performed to ensure that the model is reliable. Residual plots are plotted. Minitab-17 software application is used for statistical analysis.

3.1 Power consumption model for MQL-soyabean oil

Equation (2) illustrates the mathematical models formulated utilizing Minitab-17 while utilizing soyabean oil as the cutting fluid.

$$\begin{aligned} P_{\text{Soyabean}} &= 0.421 + 0.00255\,v - 2.31\,f + 0.1632\,dp + 0.000001\,v*v + 2.98\,f*f \\ &\quad - 0.0412\,dp*dp + 0.00314\,v*f + 0.001574\,v*dp - 0.1872\,f*dp \end{aligned} \tag{2}$$

3.2 Tool wear model for MQL-soyabean oil

Tool wear progressively increases over machining time, emphasizing the need to quantify wear concerning time to determine tool longevity. The higher wear occurs notably at maximum feed and depth of cut. In this study, trial investigations consider the maximum

Table 1. Power consumption observation

Total runs	Speed V m/min	Feed *f* mm/rev	Depth of cut dp mm	Power consumption expt Soyabean Oil Kilowatt (KW)	Power consumption expt Blassocut Oil Kilowatt (KW)
1	34.27	0.35	0.5	0.1699	0.1887
2	34.27	0.35	1	0.2006	0.2206
3	34.27	0.35	1.5	0.2381	0.2562
4	34.27	0.4	0.5	0.1681	0.1877
5	34.27	0.4	1	0.2151	0.2350
6	34.27	0.4	1.5	0.2306	0.2501
7	34.27	0.45	0.5	0.1730	0.1925
8	34.27	0.45	1	0.2104	0.2284
9	34.27	0.45	1.5	0.225	0.2460
10	53	0.35	0.5	0.253	0.2817
11	53	0.35	1	0.318	0.3394
12	53	0.35	1.5	0.352	0.3816
13	53	0.4	0.5	0.260	0.2877
14	53	0.4	1	0.298	0.3261
15	53	0.4	1.5	0.342	0.3638
16	53	0.45	0.5	0.264	0.2958
17	53	0.45	1	0.322	0.3533
18	53	0.45	1.5	0.344	0.4065
19	79.73	0.35	0.5	0.370	0.4219
20	79.73	0.35	1	0.464	0.5047
21	79.73	0.35	1.5	0.517	0.5695
22	79.73	0.4	0.5	0.382	0.4246
23	79.73	0.4	1	0.4380	0.4978
24	79.73	0.4	1.5	0.5044	0.5456
25	79.73	0.45	0.5	0.391	0.4429
26	79.73	0.45	1	0.484	0.5286
27	79.73	0.45	1.5	0.5184	0.6081

Source(s): Authors' work

values for depth of cut (1.5 mm) and feed (0.45 mm). As cutting parameters remained constant during wear measurement, tool wear becomes a function reliant on machining time (t) and speed (V). Equation (3) embodies a mathematical model for tool wear established using Minitab-17 when employing soyabean oil as the cutting fluid.

$$\begin{aligned} VB_{\mathrm{Soyabean}} = {} & 0.0415 + 0.000644\,V + 0.000318\,t - 0.000001\,V*V + 0.000034\,t*t \\ & + 0.000001\,V*t \end{aligned} \tag{3}$$

3.3 Inferences from residual plot of MQL-soyabean oil

Figures 3 and 4 display the residual diagrams depicting tool wear and power consumption throughout MQL machining with soyabean oil as the cutting fluid.

The data from the histogram indicate that the normal distribution is almost symmetrical. The normal distribution of errors from the mean and variance is illustrated by the normal probability plot. All of the residuals lie on a straight line, indicating that the errors are regularly distributed. Graphs showing residual versus fitted values show that the points are dispersed inside the boundaries. There is no pattern formation on the residual vs observation graph. It denotes the independence of the variables. This demonstrates that the sampled populations' normal distribution and the independence of the observations, which are prerequisites for the ANOVA test, are met. The predicted vs residual plot shows that residual deviates slightly from the mean position, which is typically a positive indication that the model fits the data reasonably well. There is no pattern in the relationship between residual and observation. This suggests that the tool wear model that was built is reliable and faithfully captures the results of the experiments.

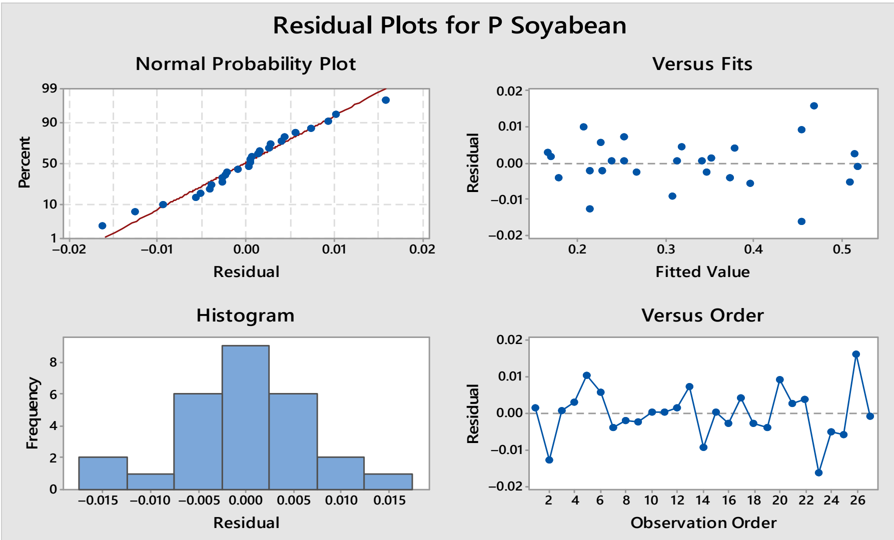


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Figure 3. Residual plot for power consumption (P)

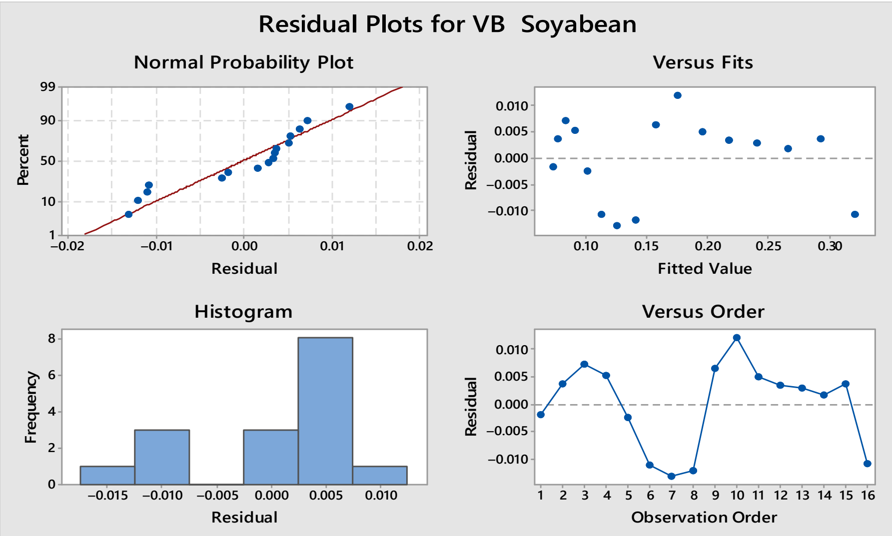

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Figure 4. Residual plot for tool wear (VB)

Anova's summary of the soyabean oil for power consumption and tool wear is represented in Tables 2 and 3, respectively. The R^2-values for power consumption and tool wear are 99.63 and 97.99%. The error is due to machine vibration, measurement error, etc. *Pre.*R^2 is 99.18% for power consumption and 97.75% for tool wear, respectively. Both values are in good concordance with each other. This signifies that the model has been fitted and is able to accurately predict the response. The model values are 510 and 760.85, which shows that both the models are substantial. As compared to Fcritical, the model's *F*-value is significant. The model's *p*-value is 0.000. It specifies that input parameters have an influence on the power consumption and tool wear (Ghuge and Mahalle, 2017).

Power consumption is mostly affected by speed (85.73%) and depth of cut (12.59%). There is negligible effect of feed on power consumption. The most significance terms in the regression equation are v, dp. Other terms are less significant, as *p*-values for these terms are more than 0.05.

Table 2. ANOVA for MQL-soyabean oil

Factor	Power	Tool wear
R^2 (%)	99.63	97.99
Adj.R^2 (%)	99.44	97.75
Pre.R^2 (%)	99.18	97.34
p-value	0.000	0.00
F(model)	510	760.85

Source(s): Authors' work

Table 3. *F*-value and % contribution

Factor	Power Soyabean oil *F*	% C
Model	510.1	–
V	3924.3	*85.73*
f	2.67	0.06
dp	576.3	*12.59*

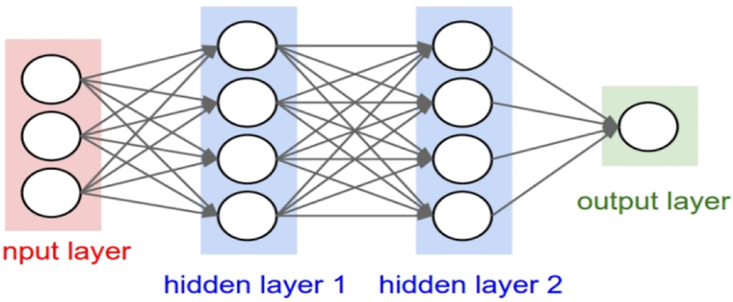
Source(s): Authors' work

4. Artificial neural network

A technique for data processing that performs tasks akin to those of biological neural networks is called an ANN. According to Azouzi and Guillot (1997), an ANN simulation can verify the experimental results. To determine how well the network could forecast intricate occurrences involving non-linear functions, correlation analysis was employed.

Rangwala and Dornfield (1989) utilized process variables to identify the most effective operational conditions, maximizing return on investment by constructing an ANN for future predictive purposes. A standard neural network consists of input, hidden and output layers, with the quantity of input and output neurons determined by the nature of the problem at hand, as illustrated in Figure 5. The objective of a neural network is to compute output values based on provided input values. Multiple configurations were explored to identify the optimal number of hidden neurons. The assessment of the network's predictive abilities relied on the correlation coefficient.

In this study, RSM was employed to create mathematical models predicting tool wear and power consumption during MQL-based turning operations with soyabean oil. To confirm the accuracy of these models, an ANN prediction model was applied. A multi-layer feed-forward topology was adopted for this neural network. Based on experimental observations, soyabean oil exhibited the most favorable performance. Consequently, to authenticate the response surface model, ANN analysis specifically focused on soyabean oil. The development of ANN simulation programs was facilitated through MATLAB software.



Source(s): Figure Credit Fei-Fei Li *et al*., Stanford University

Figure 5. Typical neural network

4.1 Development of ANN model for power consumption and tool wear (soyabean oil)
Through multiple trials, it was determined that a network featuring 27 hidden neurons yielded the most optimal outcomes. Figure 6 illustrates the structure of an ANN model specifically designed for power consumption. This configuration involves a hidden layer ANN utilizing a tangent sigmoid transfer function (tansig) and an output layer ANN employing a linear transfer function (purelin). Data training stands as the initial phase in the process of training an ANN.

Figure 7(a) and (b) display the neural network's training process aimed at forecasting power consumption and tool wear when employing soyabean oil. The graphical representation illustrates errors across various training epochs. The term "tr.best epoch" signifies the iteration where the validation performance achieved its minimum error. Subsequently, the network's validity is assessed by plotting the correlation between the network's outputs and the intended targets using a regression plot. In an ideal training scenario, the network outputs and the targets would align perfectly. The regression values indicate the manner in which the data is trained, validated, and tested.

Figure 8(a) and (b) showcase two scenarios: the dashed line portrays the ideal outcome where outputs perfectly match targets, while the solid line indicates the best-fit linear regression line between outputs and targets. The *R*-value signifies the correlation between outcomes and targets; a value of 1 suggests a flawless linear relationship between outputs and targets. Conversely, an *R*-value close to 0 implies an absence of a linear association between the output and the desired target (Pimenov *et al.*, 2023).

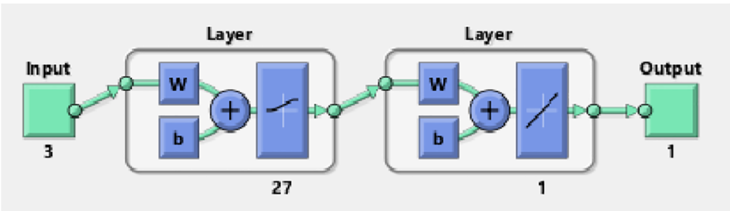


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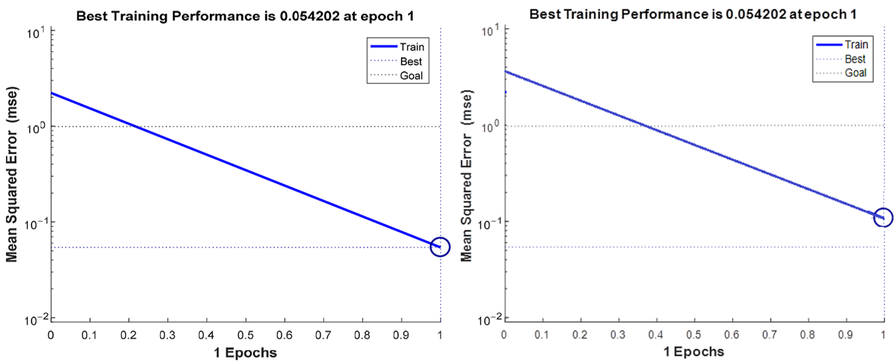
Figure 6. Architecture of ANN model for power consumption



(a) (b)

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Figure 7. Training performance of the ANN for (a) power consumption (b) tool wear

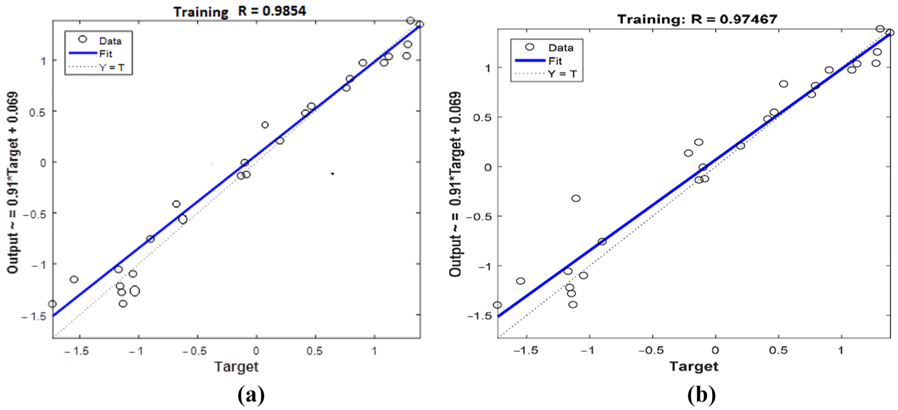

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Figure 8. Regression plot for the ANN for (a) power consumption (b) tool wear

5. Results and discussions

5.1 Variation of power consumption at different machining environment

Radar diagrams are used to characterize the variation of responses as shown in Figure 9. Points 1 to 27 in the figure show the observation number of experiments.

Power consumption is an essential aspect in any sector, and attempts have been made to limit power usage throughout any machining operation. Cutting force and speed can be used to calculate power usage. The amount of power consumed is related to the speed. As speed rises, so does power consumption. More driving force is necessary to enhance speed, resulting in maximum power usage. More power was consumed when the feed and cut depth were increased. This is owing to the greater frictional resistance offered at the tool-workpiece interface. Figure 9 illustrates the varying energy consumption rates at different cutting speeds. At cutting speeds of 34.28 m/min and 53 m/min, energy consumption remains relatively low, whereas a significant increase is observed at the higher speed of 79.27 m/min. Across all

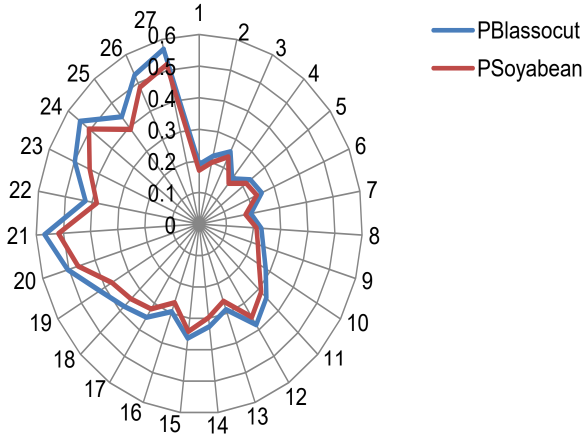

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Figure 9. Power consumption for different cutting fluid

cutting configurations tested, the highest power consumption is recorded at the combination of a cutting speed of 79.27 m/min, a feed rate of 0.35 mm/rev and a depth of cut (dp) of 1.5 mm. This highlights the direct influence of cutting speed and other process parameters on power demand in machining operations.

The study further demonstrates that the application of MQL leads to a notable 10% reduction in power consumption. This efficiency gain is primarily attributed to the superior lubricating properties of soyabean oil, which forms a more effective lubricant film on the tool–workpiece interface. This results in reduced friction and cutting forces, lowering the mechanical resistance during machining and thus reducing energy consumption. Specifically, when comparing soyabean oil-based MQL to conventional mineral oil-based lubricants like Blassocut, soyabean oil exhibits a 9% decrease in power consumption. This superior performance is due to soyabean oil's natural polarity and better boundary lubrication capabilities, which enhance its ability to adhere to metal surfaces, providing better lubrication.

5.2 Variation of tool wear at different cutting conditions

Measuring tool wear poses challenges due to its destructive nature. Increased tool failure rates occur at higher speeds, depths of cut and feed rates. To streamline experiments and manage time constraints, tool wear was assessed under constant feed (0.45 mm/rev) and a fixed depth of cut (1.5 mm), as depicted in Figure 10. Observations were logged at 5-min intervals. The forceful friction interaction between contacting surfaces triggers adhesive and abrasive wear. Initially, wear accelerates, then stabilizes before reaching a consistent state and finally accelerates again towards the end of the tool's life cycle. As cutting speeds rise, the tool gradually loses its cutting edge, impacting its sharpness. Additionally, heightened cutting speeds, feeds and depths of cut elevate cutting temperatures, consequently predisposing the tool to premature fracturing.

Figure 10 demonstrates that the tool wear rate escalates as cutting speeds increase, which is typical in machining operations due to the higher frictional forces and heat generated at elevated speeds. However, the application of MQL, specifically with the use of an air-oil mixture spray, helps mitigate these effects. At high velocities, the air-oil mist in MQL systems effectively reduces the temperature at the cutting zone and lowers cutting forces by forming a lubricating film between the tool and the workpiece. This film minimizes metal-to-metal contact, which would otherwise accelerate wear through friction and adhesion.

Additionally, the air-oil spray facilitates chip evacuation, preventing chips from interfering with the cutting edge or causing further wear due to secondary cutting or rubbing. By keeping

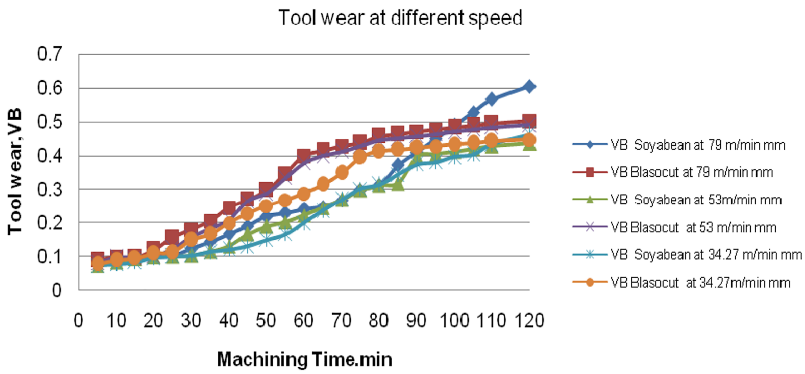

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Figure 10. Variations of tool wear with machining time

the cutting area clean and reducing heat buildup, MQL prolongs tool life, even under higher-speed machining conditions.

One of the critical reasons for the reduced tool wear observed with vegetable oils, such as soyabean oil, lies in their enhanced lubrication properties. This results in significantly lower wear, with soyabean oil showing approximately 19% less wear compared to Blassocut in this study. In summary, the combination of effective heat dissipation, improved chip evacuation and superior lubricating properties of soyabean oil significantly reduces tool wear rates in MQL applications, providing a clear advantage over mineral-based cutting fluids like Blassocut.

5.3 Tool life variation under different cutting conditions

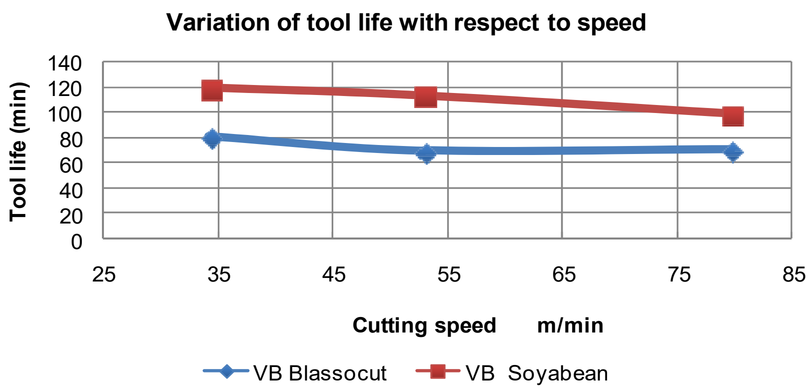
Cutting speed has the utmost influence on tool life. Tool life decreases as speed increases. Tool life is significantly reduced in MQL-soyabean oil, as shown in Figure 11. The average tool life calculated for soyabean oil is 94 min. Soyabean oil shows a 29% increase in tool life as compared to blassocut (67 min of machining time). The intense rubbing action of the two surfaces in contact results in adhesive and abrasive wear. At the beginning, the rate of wear is rapid, settling down to a steady state during the process and accelerating again at the end of tool life. At low cutting speeds, the tool wears by removing the cutting point and then loses sharpness. Increasing cutting speed, feed and depth of cut increases cutting temperature, which leads to rapid failure of the tool.

5.4 Validation of experimental results

Using the regression equation, predicted values of different performance parameters like power and tool wear were computed. The experimental results were compared to the corresponding predicted values. The experimental results and predicted results are in close agreement, which shows that the regression equations developed are true and accurate.

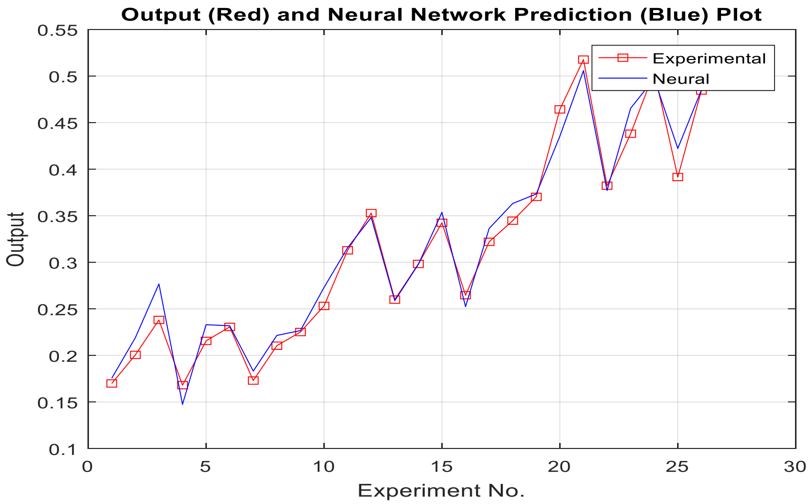
Figures 12 and 13 display comparisons of experimental and neural network-predicted outcomes for power consumption and tool wear, respectively. The blue line representing the neural predictions closely aligns with the red line of the experimental results, suggesting a strong match between them. This alignment signifies the model's accuracy, showcasing a high level of agreement between predicted values and actual measurements with minimal error.

5.4.1 Validation of RSM and ANN results for soyabean oil. RSM and ANN techniques are commonly employed in tandem for modeling. The comparison involves evaluating the experimental results against the predictions derived from RSM and ANN analyses. This



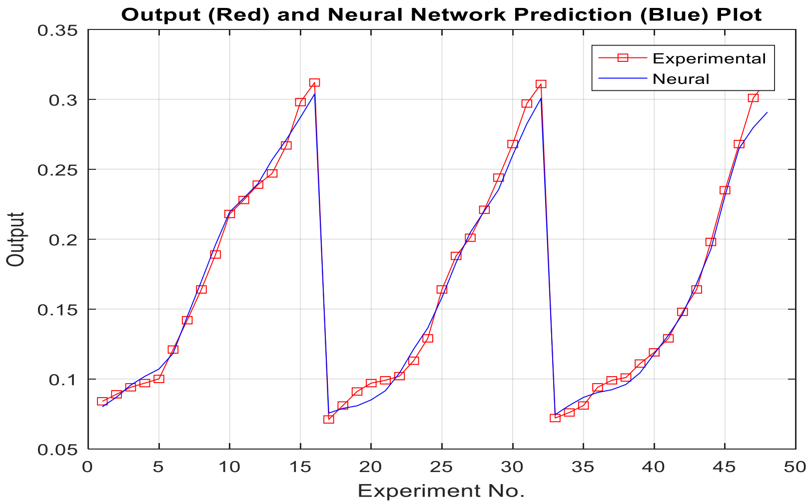
Source(s): Authors' work

Figure 11. Variation of tool life at different cutting speed



Source(s): Authors' work

Figure 12. Comparison of power consumption (Expt. Vs. ANN)



Source(s): Authors' work

Figure 13. Comparisons of tool wear (Expt. Vs ANN)

assessment aims to gauge and compare the predictive capabilities of both the ANN and RSM techniques.

In contrast to experimentation, the comparison of the RSM and ANN methods is reliant on the *R*-squared value and error.

Figures 14 and 15 depict the comparison of errors between the response surface and ANN concerning various cutting parameters. The blue line represents the percentage error for the RSM results, while the red line illustrates the percentage error for the ANN.

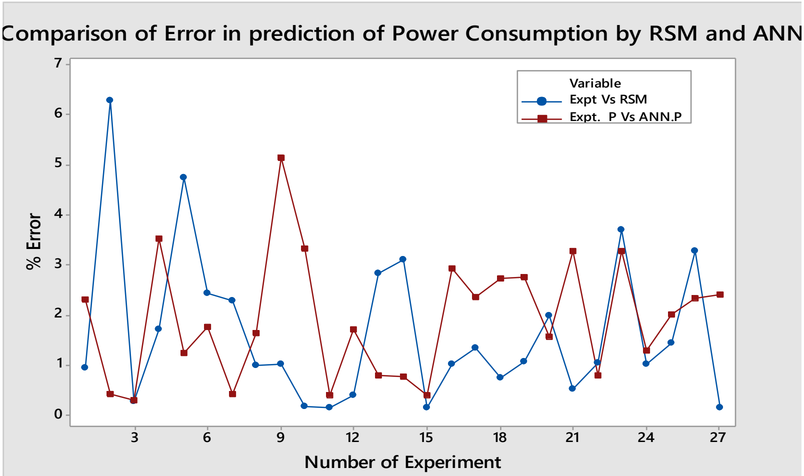


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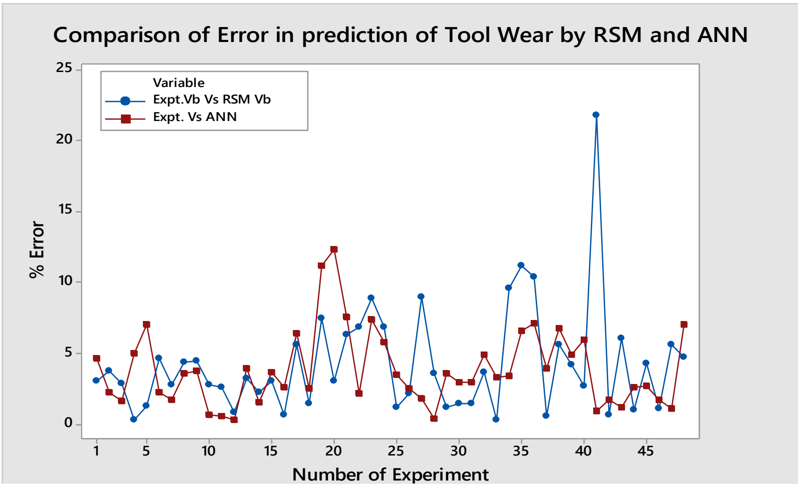
Figure 14. Validation of power consumption by RSM and ANN



Source(s): Authors' work

Figure 15. Validation of tool wear by RSM and ANN

The mean errors between experimental outcomes and predicted values of the RSM model stand at 1.66% for power consumption and 4.23% for tool wear. Meanwhile, using the ANN model, the mean percentage errors for power consumption and tool wear are 1.9 and 3.66%, respectively. These findings exhibit a noteworthy agreement between the actual experimental results and the forecasts generated by both the RSM and ANN models.

The outcomes affirm the efficient applicability of these models in forecasting machining performance during turning processes. Notably, both RSM and ANN models exhibit errors below 5%, signifying their reliability in predicting machining performance accurately.

6. Conclusions

The basic purpose of this research is to determine how well MQL with vegetable oil performs with respect to power consumption, tool wear and tool life. The experimental findings undergo validation through both an RSM and an ANN. These results are then comprehensively examined, employing various numerical and statistical techniques to derive remarks and draw conclusive insights. Power consumed during machining is very less when soyabean oil is used as a cutting fluid. Soyabean oil consumes 9% less power compared to blassocut. Soyabean shows an average of 19% reductions in tool wear compared to blassocut. In respect to Blassocut oil, Soyabean oil improves tool life by 29% on average.

An ANN is employed to predict responses, enabling an assessment of the RSM through its regression model. This analysis involves scrutinizing the predictive capabilities of different approaches' outcomes. It's worth noting that the ANN model's output closely resembles the RSM model's output and the experimental findings. The findings obtained from the developed modeling equation have been quantitatively proven to be congruent with the experimental data.

Across industries, there's heightened exposure to mineral-based cutting fluids during diverse operations, posing significant health risks to operators. The developed MQL system offers economic advantages, even catering to small-scale domestic units. MQL demands minimal cutting fluid, enabling savings in each operation and consequent cost reductions. Adopting vegetable oil as a cutting fluid mitigates health issues for operators. The combined MQL and vegetable oil system emerge as an economically viable, benign and eco-friendly alternative without compromising performance.

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