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3 authors:

M. Sayuti
University of Malaya

Ahmed A. D. Sarhan
King Fahd University of Petroleum and Minerals

Salem Faheem
University of Malaya

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Novel uses of SiO_2 nano-lubrication system in hard turning process of hardened steel AISI4140 for less tool wear, surface roughness and oil consumption

Mohd Sayuti [a,1], Ahmed A.D. Sarhan [a,b,*,1,2], Faheem Salem [a]

[a] Centre of Advanced Manufacturing and Materials Processing, Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia
[b] Department of Mechanical Engineering, Faculty of Engineering, Assiut University, Assiut 71516, Egypt

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ABSTRACT

Hardened steel AISI 4140 material is commonly used to produce automotive parts such as shafts, gears and bearings. Machining this material significantly increases the temperature in the cutting zone and is critical in deciding workpiece quality. Though cutting fluids are widely employed to dissipate the heat in machining, they threaten the ecology and health of workers. Hence, there arises a need to identify eco-friendly and user-friendly alternatives to conventional cutting fluids. Modern tribology has facilitated the use of a nano-lubrication system. For this purpose, a novel uses of nano-lubricants in minimum quantity lubrication (MQL) system were studied. In the present work, a mist of SiO_2 nano-lubrication was used and applied by air pressure in turning of hardened steel AISI4140. In this research work, the optimum SiO_2 nano-lubrication parameters to achieve correct lubrication conditions for the lowest tool wear and best surface quality were investigated. These parameters include nano-lubricant concentration, nozzle angle and air carrier pressure. The Taguchi optimization method is used with standard orthogonal array $L_{16}(4)3$. This research is investigating on the new and novel uses of SiO_2 nano-lubricant by conducting analysis on tool wear and surface roughness using fuzzy logic and response analysis to determine which process parameters are statistically significant. Besides, these analyses were conducted in order to prove the effectiveness of nano-lubricant. Finally, confirmation tests were carried out to investigate optimization improvements.

1. Introduction

Hardened steel material is generally used to produce critical parts in the automotive industry due to its mechanical properties of hardness, toughness and weldability. For example, hardened steel AISI 4140 is used to produce automotive parts such as shafts, gears and bearings. Machining of hardened steel, particularly in hard turning, experiences high temperatures due to high friction between the tool and workpiece, thus affecting product quality (Li et al., 2009). Machining temperatures can be controlled by introducing an effective lubrication system to reduce the friction at the tool–chip interfaces (Kuram et al., 2013). A common lubrication system employed in machining is conventional flooding techniques to act as both lubricant and coolant (Sayuti et al., 2013a, b, c). However, the application of conventional flooding techniques has become a huge liability since it can cause several adverse effects such as environmental pollution, dermatitis to operators, water pollution, and soil contamination during disposal (Shaji and Radhakrishnan, 2003). In economic terms, it has been reported that the cost related to lubrication and cutting fluid is 17% of the total production cost is normally higher than that of cutting tool equipment, which incurs only 7.5% of the total cost (Klocke and Eisenblätter, 1997).

At present, many efforts are being undertaken to develop advanced machining processes using less lubricant. Researchers are striving to achieve eco-friendly, sustainable manufacturing due to tight regulations and environmental aspects set by governmental pollution-preventing initiatives (Tai et al., 2011). Hence, as an alternative to cutting fluids, researchers are investigating dry machining, coated tools, cryogenic cooling, minimum quantity

* Corresponding author. Centre of Advanced Manufacturing and Materials Processing, Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia. Tel.: +60 603 79674593; fax: +60 603 79677669.

E-mail addresses: mdsayuti@siswa.um.edu.my (M. Sayuti), ah_sarhan@yahoo.com, ah_sarhan@um.edu.my (A.A.D. Sarhan), salemfaheem@yahoo.com (F. Salem).

[1] Tel.: +60 603 79674489; fax: +60 603 79677633.
[2] Tel./fax: +20 882335572.

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Table 1
Control factors and experimental condition levels.

Factor	A	B	C
Level (i)	Nanoparticles concentration (wt%)	Air pressure (Bar)	Nozzle orientation (Degree °)
Level 1 ($i = 1$)	0%	1	15
Level 2 ($i = 2$)	0.2%	2	30
Level 3 ($i = 3$)	0.5%	3	45
Level 4 ($i = 4$)	1.0%	4	60

Table 3
Mechanical properties of AISI4140 steel.

Properties		Conditions	
		T (°C)	Treatment
Density (× 1000 kg/m^3)	7.7–8.03	25	
Poisson's ratio	0.27–0.30	25	
Elastic modulus (GPa)	190–210	25	
Tensile strength (MPa)	655.0	25	Annealed at 815 °C more
Yield strength (MPa)	417.1		
Elongation (%)	25.7		
Reduction in area (%)	56.9		

lubrication (MQL), and solid lubricants. MQL is one of the promising techniques adopted by researchers (Sayuti etal., 2013a, b, c). The encouraging results include significant reduction in tool wear and surface roughness by MQL obtained as a result of lowered temperature in the cutting zone and favorable changes in the chip–tool and work–tool interactions (Díaz et al., 2010).

The reduction of tool wear, surface roughness and improving dimensional accuracy was successfully conducted using clean machining processes with minimum quantity lubricant (MQL). MQL shows superior performance compared to dry and wet turning. However, the usage of MQL in conjunction with a nano-lubrication system would be a noteworthy advantage to the manufacturing process due to its effect on product quality (Itoigawa et al., 2007). Nowadays, several nano-lubricants have been identified by the advancement in modern technology, making it possible to sustain and provide lubricity over a wide range of temperatures (Nakamura et al., 2000). Nano-lubricant is a novel type of engineering system consisting of nanometer-sized particles dispersed in base oil. It could be an effective method to reduce friction between two contact surfaces depending on working conditions. Lubrication effectiveness depends on the morphology and crystal structure of solid lubricants, as well as the way particles are introduced to the tool–workpiece interface (Sayuti et al., 2013a, b, c).

Beside the nano based lubricants high performance, labor and materials associated with preserving lubricant and equipment integrity will soon be minimized. Health and environmental concerns need to be addressed when dealing with lubricant materials. In addition, productivity in the machining industry could be increased through cost reduction by abandoning cutting fluid, saving the environment and at the same time machining performance would be improved. Physical analysis of nano-lubricants (Peng et al., 2009) shows that dispersed nanoparticles can easily penetrate into the rubbing surfaces and have a great elasto-hydrodynamic lubrication effect. Under a single-thrust bearing tester, researchers reported that the nano-lubricant's coefficient of friction is less than that of pure oil, and the extreme pressure of a nano-lubricant is two times higher than that of pure oil; hence, it can be concluded that nano-lubricant improves lubrication performance by preventing contact between the metal surfaces. Moreover, thermal conductivity of the nano-lubricant increases linearly with concentration, interacting hydro-dynamically to enhance thermal transport capability (Murshed et al., 2009).

Various nanoparticle types have been used as lubricant by researchers in order to investigate its effects on machining performance. It is well documented that silicon dioxide (SiO_2) nanoparticles are hard, cheap and available on the market. This nanoparticle has very good mechanical properties especially in terms of hardness (Vickers hardness – 1000 kgf/mm^{-2}) and is available in very small sizes, ranging from 5 nm up to 100 nm. Accordingly, the SiO_2 solid nanoparticles in mineral oil would act as a combination of rolling and sliding bearings at the tool chip interface. These, in turn, could reduce the coefficient of friction and improve machining performance significantly.

In line with previous research works reviewed above, an investigation of optimum SiO_2 nano-lubrication parameters in hard turning of AISI4140 is needed to effectively improve the machined surface quality by minimizing tool wear. Parameters include nanolubricant concentration, air carrier pressure and nozzle angle (hereafter called control factors). The conventional method to determine the optimal values of these parameters is the "trial and error" approach. However, due to the large number of experiments, the "trial and error" approach is very time consuming. Hence, a reliable systematic approach for parameter optimization is required. The optimization method presented in this study is an experimental process called the Taguchi optimization method.

Taguchi optimization, developed by Dr. Genichi Taguchi, is a set of methodologies in which the inherent variability of materials and manufacturing processes is taken into account at the design stage (Kuram and Ozcelik, 2013). In Taguchi optimization, multiple

Table 2
Standard L16(4)3 Orthogonal array, the sixteen experiments with detail of the combination levels.

Exp. no.	Control factors and levels (i)		
	A	B	C
1	$i = 1$	1	1
2	$i = 1$	2	2
3	$i = 1$	3	3
4	$i = 1$	4	4
5	$i = 2$	1	2
6	$i = 2$	2	1
7	$i = 2$	3	4
8	$i = 2$	4	3
9	$i = 3$	1	3
10	$i = 3$	2	4
11	$i = 3$	3	1
12	$i = 3$	4	2
13	$i = 4$	1	4
14	$i = 4$	2	3
15	$i = 4$	3	2
16	$i = 4$	4	1

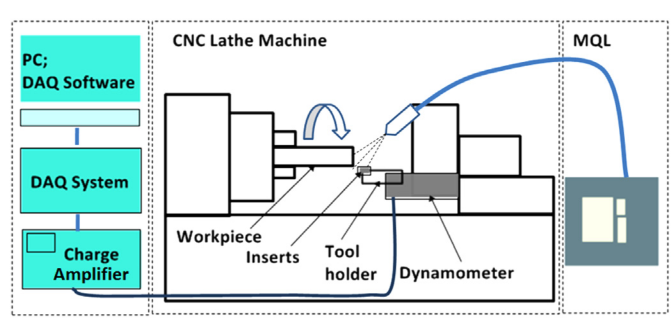


Fig. 1. Experimental set up.

Table 4
Experimental conditions.

Machine tool	OKUMA LB15 Lathe machine, 15 hp
Instrumentation	
Surface profilometer	Mitutoyo SJ-201, range (0–12.5 mm)
Tool wear microscope	Dino-Lite AM-4013ZT4 range (400X ∼ 470X)
Work material and cutting condition	
Work specimens	AISI 4140 steel
Hardness	52 HRC
Size	D 30 × 200 mm
Cutting insert	Coated carbide, Sandvik DNMG 150608 PM
Cutting velocity	120 m/min
Feed rate	0.15 mm/rev
Depth of cut	0.5 mm
Cutting fluid	MQL condition at 0.75 L/hr, FuchsECOCUT oil HSG 905 S,
Nanoparticles	Silicon dioxide, 5–15 nm particle size, 99.5% trace metals basis

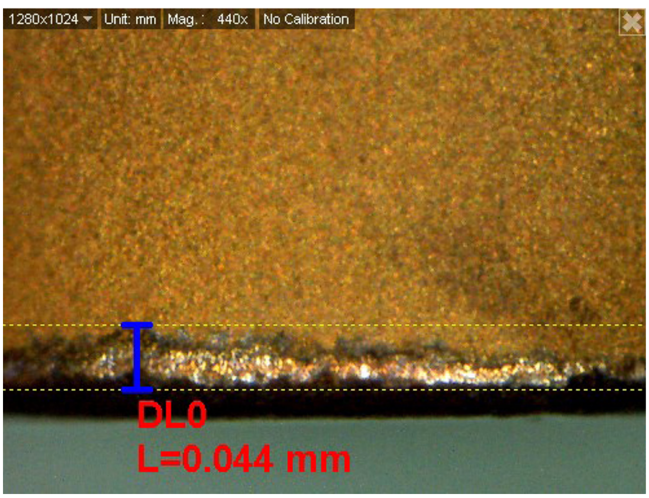


Fig. 2. An example of measured tool wear at 120 m/min cutting speed, 0.15 mm/rev feed and 0.5 mm depth of cut, nanoparticle concentration: 0.0 wt%, air pressure: 1 bar and nozzle angle 15°.

factors can be considered at once. Moreover, it seeks nominal design points that are insensitive to variations in production and user environments to improve the yield in manufacturing and a product's performance reliability. By using Taguchi optimization techniques, industries are able to greatly reduce product development cycle time for design and production, therefore reducing costs and increasing profit (Cetin et al., 2011). Due to the complexity and uncertainty of machining processes, additional analysis via soft computing techniques are preferred to physics-based models for predicting the performance of machining processes and their optimization (Makadia and Nanavati, 2013). Soft computing techniques are useful when exact mathematical information is not available and they differ from conventional computing in that they are tolerant to imprecision, uncertainty, partial truth, approximation, and met heuristics. Major soft computing tools applied for this purpose are neural networks, fuzzy sets, genetic algorithms, simulated annealing, ant colony optimization, and particle swarm optimization. Fuzzy logic is one of the soft computing techniques that play a significant role in input–output matrix relationship modeling (Hanafi et al., 2012). It is used when subjective knowledge and suggestions by experts are significant in defining objective functions and decision variables. Fuzzy logic is preferred to predicting machining performance based on input variables due to the nonlinear condition in machining processes.

In this research, the Taguchi optimization method is applied to optimize SiO_2 nano-lubricants parameters and to achieve the lowest tool wear and surface roughness in hard turning of hardened steel AISI4140. Further fuzzy logic approach and response analyses were conducted to better understand process performance. To achieve this, the relationship between the controllable factors (nanolubricant concentration, air carrier pressure and nozzle angle) and the response factors (tool wear and surface roughness) was explored to spot the most significant factors affecting machined surface quality.

2. Material and method

In this research work, Taguchi optimization method will be used. The steps in the Taguchi optimization method include: selecting the orthogonal array (OA) according to the number of controllable factors, running experiments based on the OA, analyzing data, identifying the optimum parameters, and conducting confirmation runs with the optimal levels of all the parameters. To point out the non-significant variables, maximum possible factors should be included in the experiment.

As the first step in Taguchi, the orthogonal array of $L_{16}(4^3)$ is identified to optimize machining parameters for minimum tool wear and best surface quality. The standard orthogonal array consists of sixteen experiments with three control factors and four different experimental condition levels for each factor. The factors and levels are specified in Table 1, while Table 2 presents the sixteen experiments with the combination details of the experimental condition levels for each control factor (A–C). The 16 experiments

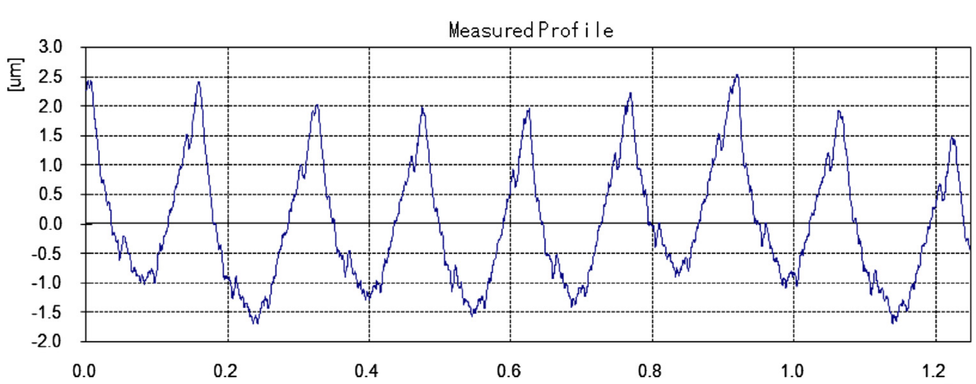


Fig. 3. An example of measured surface roughness at 120 m/min cutting speed, 0.15 mm/rev feed and 0.5 mm depth of cut, nanoparticle concentration: 0.0wt%, air pressure: 1 bar and nozzle angle 15°.

Table 5
Measured response for the selected array of experiments.

Exp. no.	Control factors and levels (i)			Measured parameters							
	SiO_2 concentration (A)	Air pressure (B)	Nozzle orientation (C)	Tool wear (μm)				Surface roughness (μm)			
				Reading			Average	Reading			Average
				1	2	3		1	2	3	
1	$i = 1$	1	1	43.50	45.60	43.80	44.30	0.755	0.701	0.834	0.763
2	$i = 1$	2	2	27.20	26.50	24.30	26.00	0.652	0.672	0.656	0.660
3	$i = 1$	3	3	40.80	38.50	38.60	39.30	0.752	0.763	0.816	0.777
4	$i = 1$	4	4	27.60	26.80	26.00	26.80	0.853	0.886	0.881	0.873
5	$i = 2$	1	2	36.30	35.90	33.70	35.30	0.701	0.741	0.748	0.730
6	$i = 2$	2	1	24.10	23.80	22.00	23.30	0.890	0.924	0.926	0.913
7	$i = 2$	3	4	24.01	23.52	23.57	23.70	0.711	0.691	0.718	0.707
8	$i = 2$	4	3	25.80	24.4	25.70	25.30	0.773	0.790	0.787	0.783
9	$i = 3$	1	3	26.30	26.80	24.90	26.00	0.568	0.612	0.590	0.590
10	$i = 3$	2	4	19.90	19.40	19.50	19.60	0.699	0.660	0.691	0.683
11	$i = 3$	3	1	23.50	24.00	24.80	24.10	0.763	0.756	0.700	0.740
12	$i = 3$	4	2	23.70	24.80	24.40	24.30	0.620	0.642	0.698	0.653
13	$i = 4$	1	4	24.10	23.30	22.50	23.30	0.832	0.856	0.921	0.870
14	$i = 4$	2	3	30.40	30.80	31.80	31.00	0.838	0.802	0.841	0.827
15	$i = 4$	3	2	31.90	31.50	30.50	31.30	0.812	0.798	0.810	0.807
16	$i = 4$	4	1	27.70	29.20	29.20	28.70	0.744	0.757	0.759	0.753

were carried out in a random sequence to eliminate any other invisible factors, which might also contribute to tool wear and surface roughness. For the fuzzy logic approach, the twelve experiments' data from a similar combination of experimental levels for each parameter was utilized.

The second step in the Taguchi optimization method entailed running the experiments based on the selected OA. The 16 experiments were carried out in random sequence to eliminate any invisible factors that might also contribute to tool wear and surface roughness. To study how SiO_2 nano-lubrication system affects tool wear and surface roughness in the hard turning process, the hardened steel AISI4140 and coated carbide inserts were selected as workpiece and tools. For each experimental set, new cutting inserts were put in. The cutting process of a cylindrical AISI4140 steel workpiece of 20 × 200 mm^2 was selected as a case study. The workpiece material was heat treated (through-hardened) to get 52 ± 02HRC. This material is normally used for manufacturing roller bearings and automotive components. The mechanical properties of hardened steel AISI4140 are shown in Table 3 and the experimental set up can be seen in Fig. 1. The machine employed in this study is an OKUMA LB15 Lathe Machine, 15hp. To measure the average machined workpiece's surface roughness, a calibrated portable surface meter (Mitutoyo SJ-201P) was applied with a cut off distance and sampling length of 1.2 mm and 4 mm. The roughness data obtained from measurements can be manipulated to determine the roughness parameters (Vakondios et al., 2012). There are many different roughness parameters, which include average variation from mean line (R_a), the highest peak to the deepest valley (R_t) and average R_t over a given length (R_z). R_a is universally recognized and the most used international parameter for roughness, as it can be easily measured by graphical processes (Esteves Correia and Paulo Davim, 2011). Besides, R_a values were more accurate than the R_t and R_z values because its consider the averages of peaks and valleys on the surface. Hence, R_a was selected as measuring parameter for surface roughness and an average of three measurements served as a response value.

In machining of hardened steel, the surface roughness is critically affected by tool wear (Hessainia et al., 2013). Tool wear in hard turning involves serious flank wear due to the friction from the hardened workpiece. Therefore, reduction of tool wear in hard turning is considered as a necessary requirement (Smithey et al., 2001). Tool wear was measured off-line at the end of each cut under 450× magnification of an optical microscope model Dinolite. In addition, the polished granite surface for more stable and accurate surface roughness measurements was used.

The nano-lubricants was prepared by adding SiO_2 nanoparticles with an average size of 5–15 nm to the mineral oil, followed by sonification (Ultrasonic Power 240W, Ultrasonic frequency 40 kHz, Heating power 500W) for 48 h in order to suspend the particles homogeneously in the mixture. To deliver the oil to the tool chip interface area, the MQL system equipped with a thin-pulsed jet nozzle developed in the laboratory and controlled by a variable speed control drive was used. With regards to the nano-lubrication system, the MQL nozzle was provided with an additional air nozzle to accelerate the lubricant entering the cutting zone and to reduce oil consumption. The nozzle system was attached to a flexible portable fixture set on the machining spindle. The flexible design allows the injection nozzle to be located at any desired position without interfering with the tool or workpiece during machining. The diameter of the nozzle orifice was 1 mm and MQL oil pressure was set to 20 MPa with a delivery rate of 2 ml/min Table 4 presents the overall research experimental conditions.

Table 6
Fuzzy linguistic and abbreviation of variables for each parameter.

Inputs		Range
Parameters	Linguistic variables	
A – Nanoparticle concentration (wt %)	Low (L), medium (M), high (H), very high (VH)	0.0–1.0 wt%
B – Air pressure (bar)		1–4 bar
C – Nozzle orientation (degree °)		15°–60°
Output		
Tool wear (μm)	Best, good, average, bad	19.6 μm–44.3 μm
Surface roughness (μm)	Best, good, average, bad	0.590 μm–0.913 μm

3. Results and analysis

The hard turning test was carried out to investigate tool wear reduction and surface quality improvement of machined hardened steel AISI4140 when using SiO_2 nano-lubrication. Figs. 2 and 3 provide the examples of measured tool wear and surface roughness at 120 m/min cutting speed, 15 mm/rev feed and 0.5 mm depth of cut, 0.2% nanoparticle concentration, 1 bar air pressure and

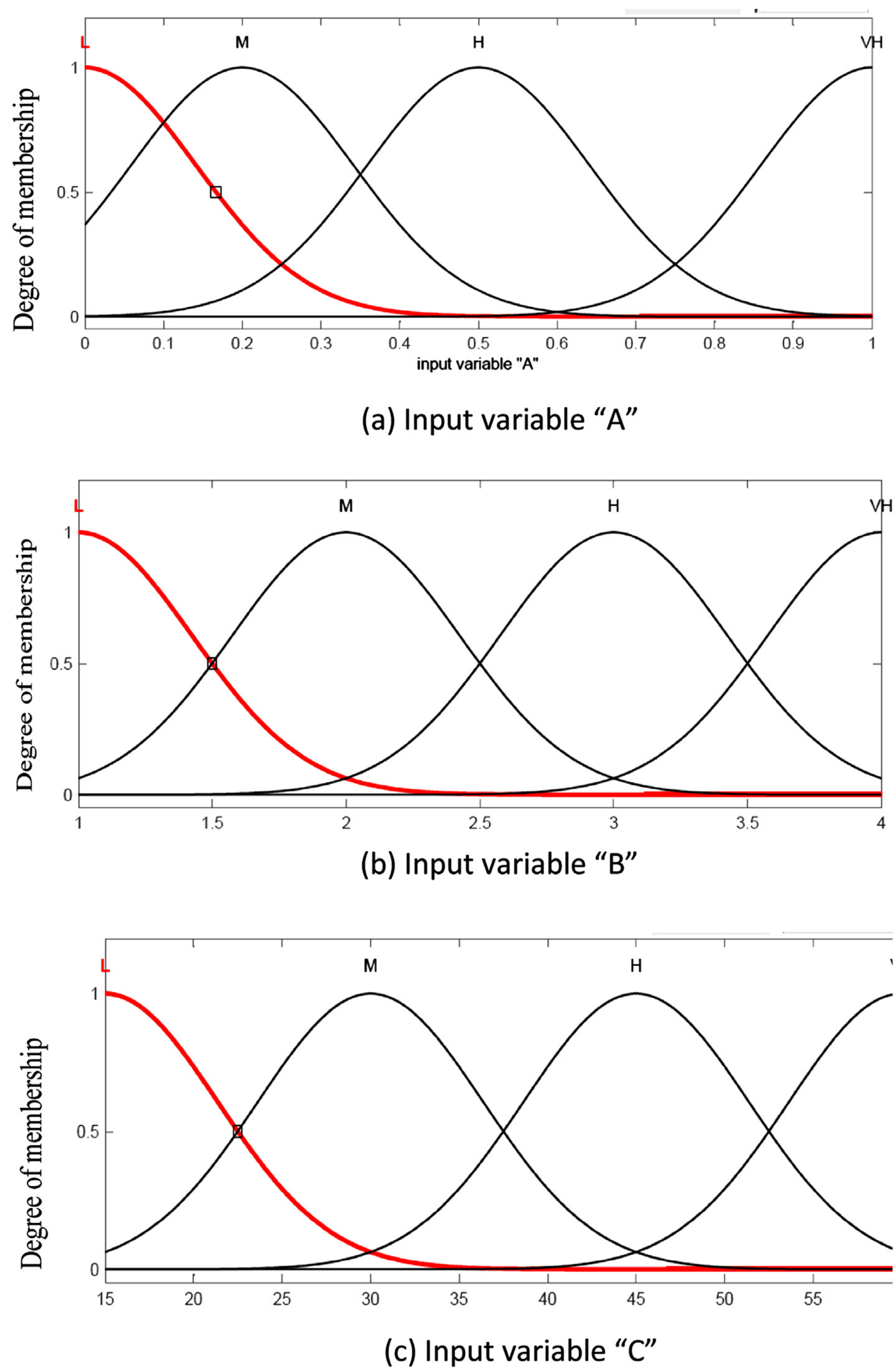


Fig. 4. Membership function for variables of inputs.

a nozzle angle of 30º. Table 5 presents the measured responses for the selected array of experiments. The subsequent step in the optimization process was to analyze the data, optimize the parameters and identify which process parameters are statistically significant using fuzzy logic analysis and signal to noise (*S*/*N*) response analysis.

3.1. Fuzzy logic to predict tool wear and surface roughness

The relationship between input parameters, namely nano-lubrication concentration, air pressure and nozzle orientation, with the output parameters tool wear and surface roughness of a machined surface in AISI4140 hard turning operation, were referred to for constructing the rules. The twelve experiments used were randomly selected from Taguchi experiment for the purposes of training data to build the fuzzy model. Fuzzy linguistic variables and fuzzy expression for input and output parameters are shown in Table 6. For each input variable, four membership functions were used: Low, Medium, High, and Very High. The output variables (tool wear and surface roughness) also had four membership functions: Best, Good, Average and Bad. The characteristics of the input and output variables are given in Table 6.

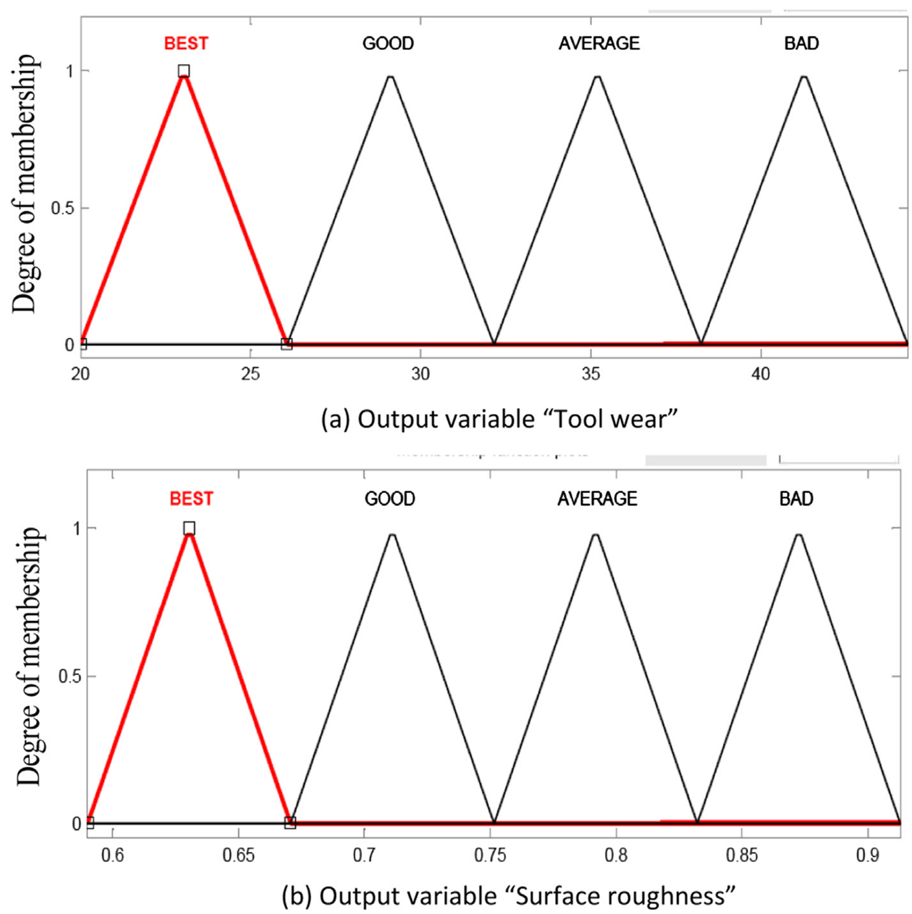


Fig. 5. Membership function for the output variable tool wear and surface roughness.

3.1.1. *Membership functions for input and output fuzzy variables*

In choosing the membership functions for fuzzification, the event and type of membership functions are mainly dependent upon the relevant event. In this model, each input and output parameter has four membership functions. The Gauss shape of membership function is employed to describe the fuzzy sets for input variables. In the output variables fuzzy set, the triangular shape of membership functions is considered. Triangular membership function is generally used and possesses gradually increasing and decreasing characteristics with only one definite value. The input variables have been partitioned according to the experiment's parameter ranges. Membership functions for fuzzy set input variables are shown in Fig. 4 *a*, *b*, and *c*. Moreover, Fig. 5 illustrates the membership functions for the output tool wear and surface roughness fuzzy set.

3.1.2. *Structure of fuzzy rules*

A set of 12 rules was constructed based on the actual experiment for tool wear and surface roughness of AISI4140 hard turning operation using SiO_2 nano-lubricants. Experimental results were simulated in Matlab software on the basis of Mamdani Fuzzy Logic (Table 7).

3.1.3. *Defuzzification*

In this model, the centroid of area (COA) defuzzification method was called for due to its wide acceptance and capability in giving

Table 7
The basis of mamdani Fuzzy logic.

Tool wear	Surface roughness
1. If (A is LOW) and (B is L) and (C is L) then (Tool wear is BAD)	1. If (A is LOW) and (B is L) and (C is L) then (Surface roughness is AVERAGE)
2. If (A is LOW) and (B is M) and (C is M) then (Tool wear is BEST)	2. If (A is LOW) and (B is M) and (C is M) then (Surface roughness is BEST)
3. If (A is LOW) and (B is H) and (C is H) then (Tool wear is BAD)	3. If (A is LOW) and (B is H) and (C is H) then (Surface roughness is AVERAGE)
4. If (A is MEDIUM) and (B is L) and (C is M) then (Tool wear is AVERAGE)	4. If (A is MEDIUM) and (B is L) and (C is M) then (Surface roughness is GOOD)
5. If (A is MEDIUM) and (B is M) and (C is L) then (Tool wear is BEST)	5. If (A is MEDIUM) and (B is M) and (C is L) then (Surface roughness is BAD)
6. If (A is MEDIUM) and (B is H) and (C is VH) then (Tool wear is BEST)	6. If (A is MEDIUM) and (B is H) and (C is VH) then (Surface roughness is GOOD)
7. If (A is HIGH) and (B is L) and (C is H) then (Tool wear is BEST)	7. If (A is HIGH) and (B is L) and (C is H) then (Surface roughness is BEST)
8. If (A is HIGH) and (B is M) and (C is VH) then (Tool wear is BEST)	8. If (A is HIGH) and (B is M) and (C is VH) then (Surface roughness is GOOD)
9. If (A is HIGH) and (B is H) and (C is L) then (Tool wear is BEST)	9. If (A is HIGH) and (B is H) and (C is L) then (Surface roughness is GOOD)
10. If (A is VERY_HIGH) and (B is L) and (C is VH) then (Tool wear is BEST)	10. If (A is VERY_HIGH) and (B is L) and (C is VH) then (Surface roughness is BAD)
11. If (A is VERY_HIGH) and (B is M) and (C is H) then (Tool wear is GOOD)	11. If (A is VERY_HIGH) and (B is M) and (C is H) then (Surface roughness is AVERAGE)
12. If (A is VERY_HIGH) and (B is H) and (C is M) then (Tool wear is GOOD)	12. If (A is VERY_HIGH) and (B is H) and (C is M) then (Surface roughness is AVERAGE)

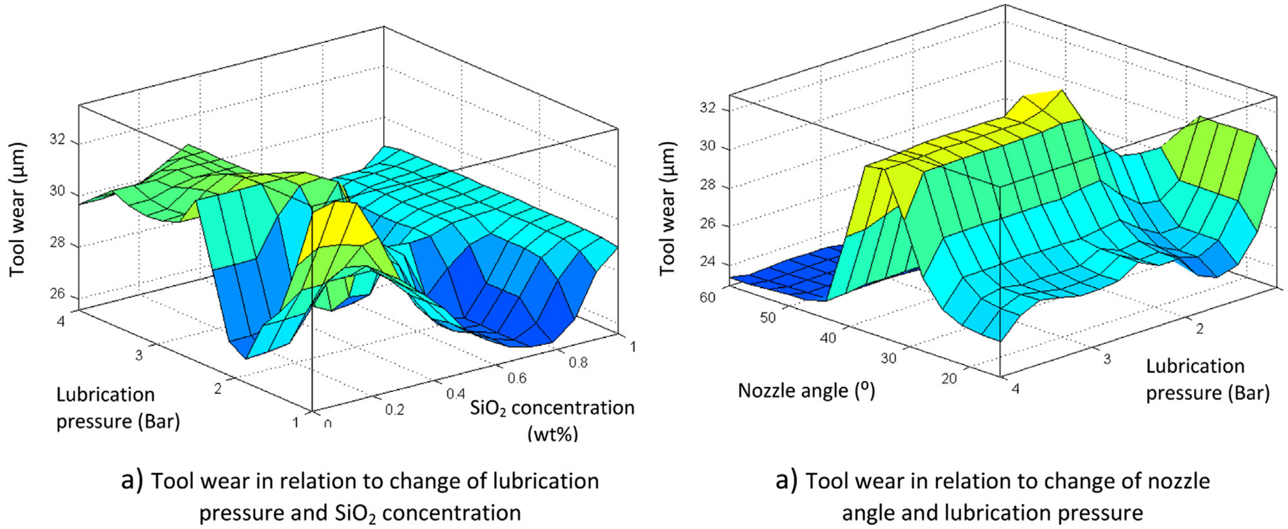


Fig. 6. The predicted tool wears by fuzzy logic in relation to lubrication parameters.

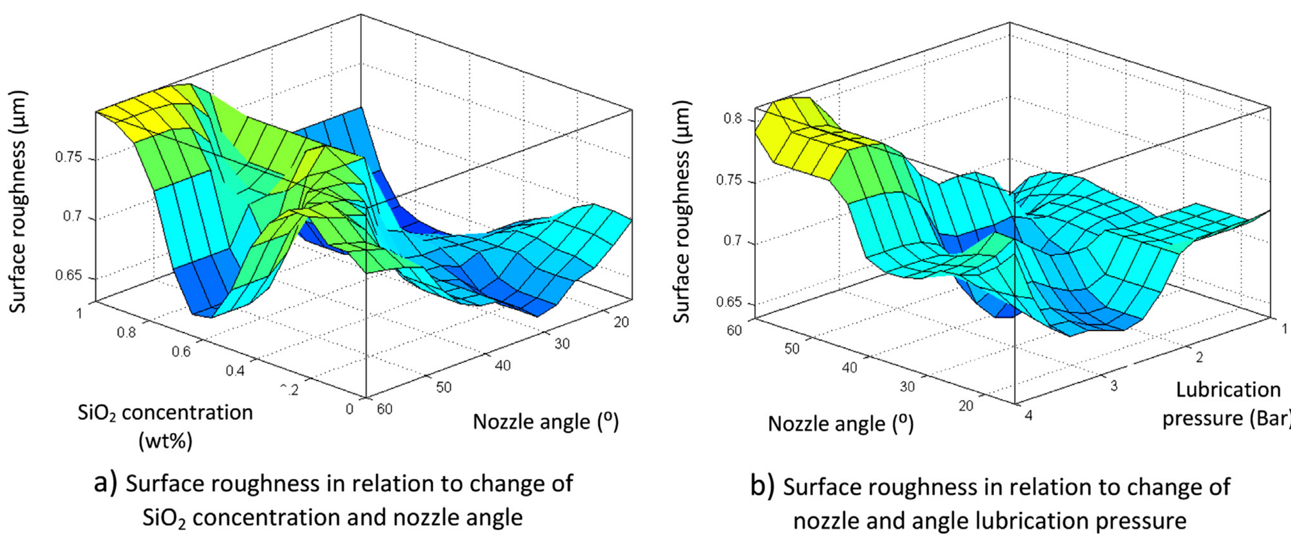


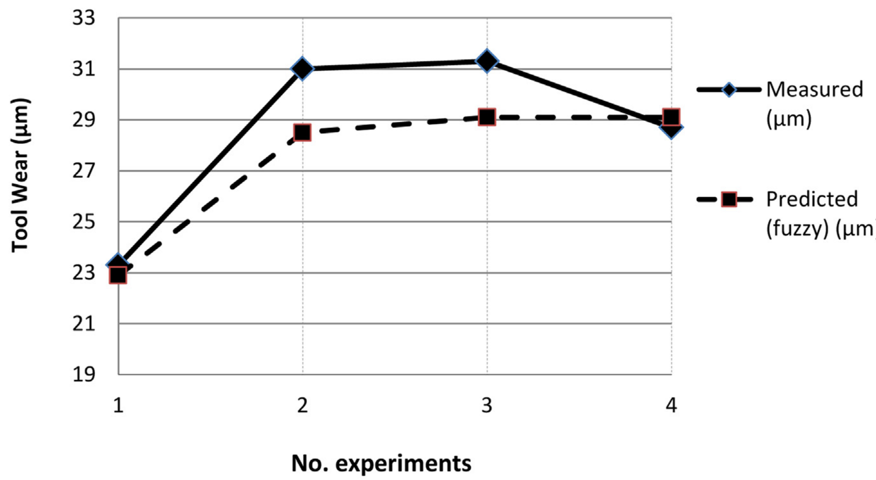
Fig. 7. The predicted surface roughness by fuzzy logic in relation to lubrication parameters.

more accurate results compared to other methods (Leung et al., 2003). In this method, the resultant membership functions are developed by uniting the output of each rule, in other words the overlapping area of the fuzzy output set is counted as one, providing more results (Hashmi et al., 2003).

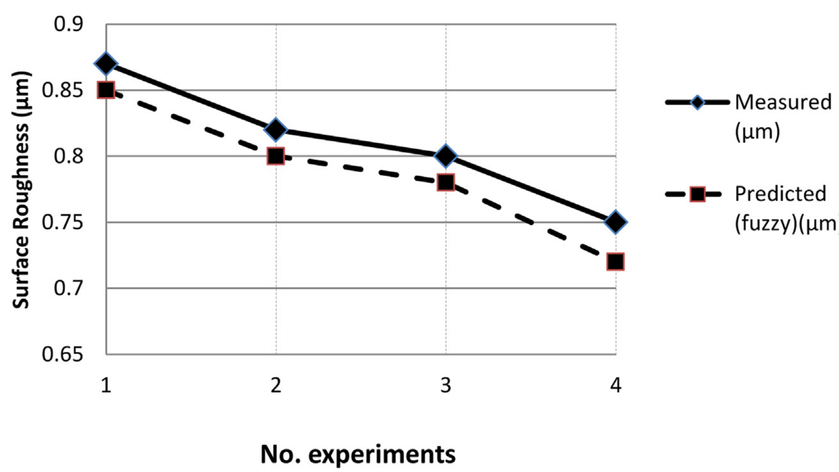
The graph of the tool wear and surface roughness from the fuzzy logic model were constructed as shown in Figs. 6 and 7. Fig. 6(a) and (b) are examples of the relation between input parameters change and tool wear of a machined surface in an AISI4140 hard turning operation predicted by a fuzzy-based model. As per Fig. 6(a), tool wear is at a minimum at 0.5%wt of SiO_2 concentration and significantly rises with increasing SiO_2 concentration. Meanwhile, at 2 bar lubricant pressure, tool wear is minimal and increases at 3 bar lubrication pressure. From Fig. 6(b) it is clearly seen that nozzle angle reduces tool wear at 60° orientations. In Fig. 7(a), surface roughness is minimal at 0.5%wt of SiO_2 concentration and significantly goes up with increasing SiO_2 concentration. At a 30° nozzle angle, surface roughness is found to be at a minimum. Obviously, in Fig. 7(b), the increment of lubrication pressure increases machined surface roughness.

Table 8
The accuracy and error of the fuzzy logic model prediction.

No.	Exp. condition			Tool wear (output)				Surface roughness (output)			
				Measured	Predicted (fuzzy)	Error, %	Accuracy %	Measured	Predicted (fuzzy)	Error, %	Accuracy, %
1	4	1	4	23.3	22.9	1.71	98.29	0.87	0.85	2.29	97.71
2	4	2	3	31.0	28.5	8.06	91.93	0.82	0.80	2.50	97.50
3	4	3	2	31.3	29.1	7.02	92.8	0.80	0.78	2.56	97.44
4	4	4	1	28.7	29.1	1.37	98.63	0.75	0.72	4.00	96.00



(a) Measured and predicted tool wear



(b) Measured and predicted surface roughness

Fig. 8. Comparison of the predicted and measured of a tool wear and surface roughness in hard turning of hardened steel AISI4140.

Table 9
The calculated of *S*/*N* and TPM response for tool wear.

Response table for signal to noise (*S*/*N*) ratios				Response table for means (TPM)			
Level	SiO_2 concentration (wt%)	Air pressure (bar)	Nozzle orientation (°)	Level	SiO_2 concentration (wt%)	Air pressure (bar)	Nozzle orientation (°)
1	−30.42	−29.88	−29.26	1	34.10	32.23	30.08
2	−28.46	−27.83	−29.22	2	26.90	24.98	29.23
3	−27.37	−29.22	−29.52	3	23.48	29.58	30.40
4	−29.06	−28.37	−27.31	4	28.58	26.28	23.35
Delta	3.05	2.05	2.21	Delta	10.62	7.25	7.05
Rank	1	3	2	Rank	1	2	3

Table 10
The calculated of *S*/*N* and TPM response for surface roughness.

Response table for signal to noise (*S*/*N*) ratios				Response table for means (TPM)			
Level	SiO_2 concentration (wt%)	Air pressure (bar)	Nozzle orientation (°)	Level	SiO_2 concentration (wt%)	Air pressure (bar)	Nozzle orientation (°)
1	2.332	2.718	2.052	1	0.7683	0.7383	0.7925
2	2.165	2.339	2.977	2	0.7833	0.7708	0.7125
3	3.551	2.423	2.638	3	0.6666	0.7575	0.7442
4	1.797	2.364	2.177	4	0.8142	0.7658	0.7833
Delta	1.754	0.379	0.924	Delta	0.1475	0.0325	0.08
Rank	1	3	2	Rank	1	3	2

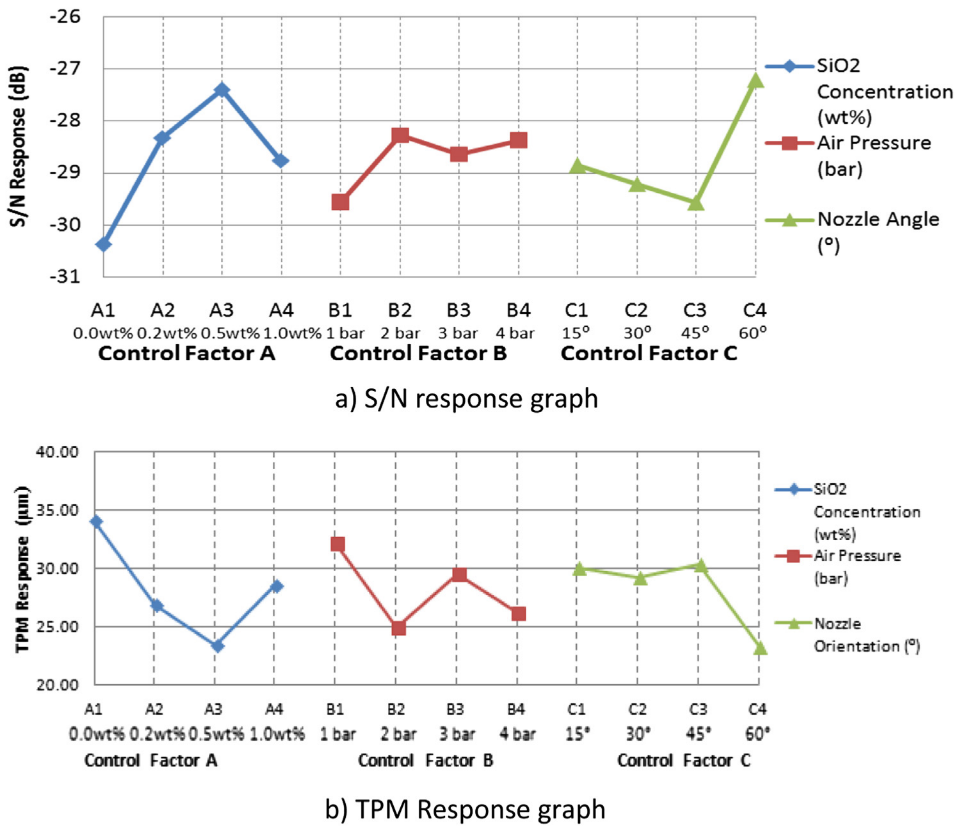


Fig. 9. *S*/*N* and TPM response graphs of tool wear at different control factors.

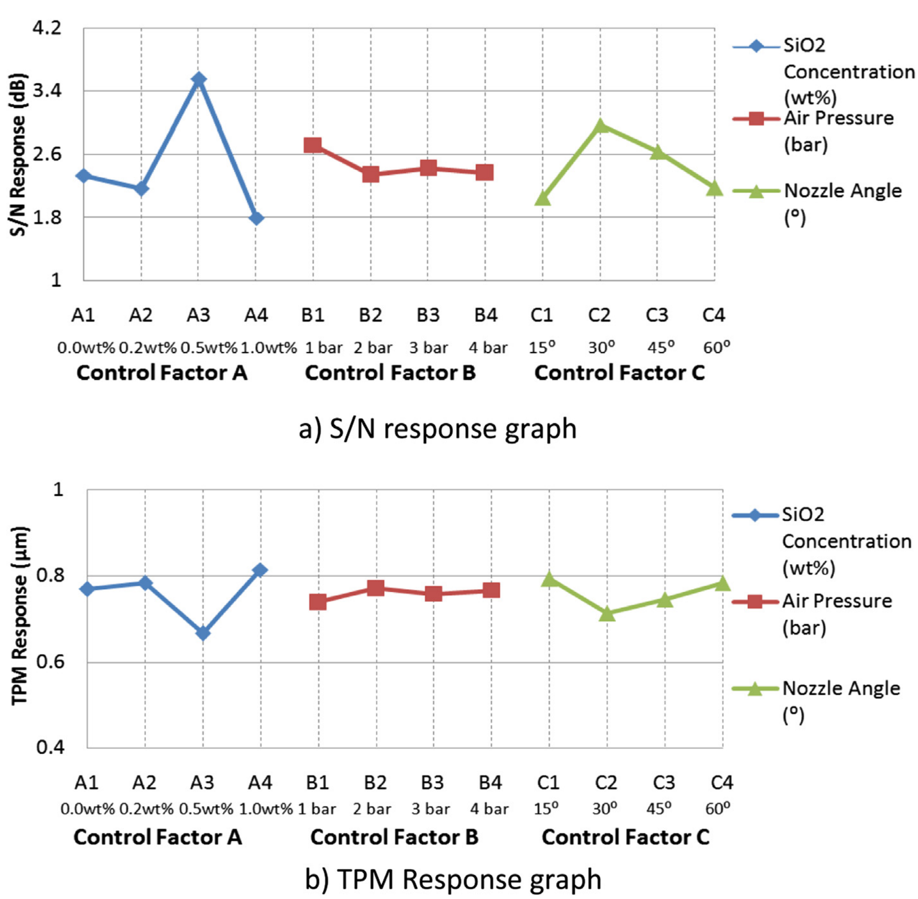


Fig. 10. *S*/*N* and TPM response graphs of surface roughness at different control factors.

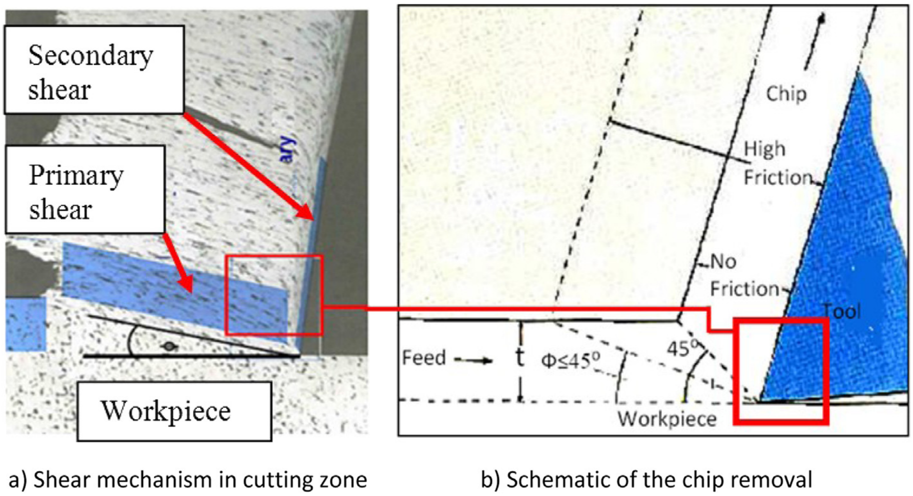


Fig. 11. Schematic of the chip removal and shear mechanism in cutting zone.

3.1.4. Investigating fuzzy model accuracy and error

Four new experimental tests were carried out while the proposed fuzzy model predicted the tool wear and surface roughness at the same conditions to investigate fuzzy model accuracy. Tool wear and surface roughness results, along with fuzzy model predicted values are provided in Table 8. Fig. 8 is presenting the corresponding graph for comparison of the predicted and measured tool wear and surface roughness in hard turning of hardened steel AISI4140. For tool wear and surface roughness, the highest error percentages for fuzzy model prediction are 8.06% and 4.35%. The low error level signifies that the fuzzy prediction for tool wear and surface roughness results were very close to the actual experimental values. Accuracy value indicates that the proposed model can satisfactorily predict the tool wear and surface roughness of a machined surface in AISI4140 hard turning operation using SiO_2 nano-lubricants. Thus, the proposed fuzzy logic model provides a promising solution for predicting roughness and tool wear values in a specific range of parameters.

3.2. Signal to noise (S/N) response analysis

With respect to the methods for calculating the S/N ratio for tool wear and surface roughness, smaller values are always preferred. The equation for calculating the S/N ratio for smaller-the-better characteristics (in dB) is as follows:

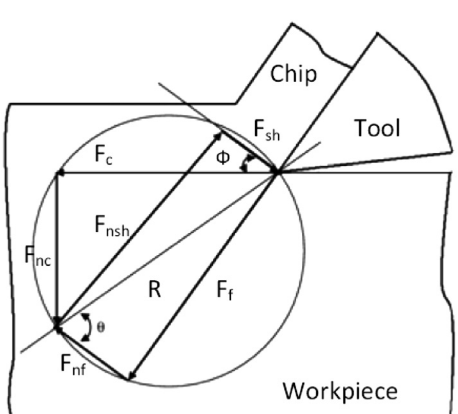


Fig. 12. Cutting mechanism.

$$S/N = -10\log\left(\frac{1}{n}\sum y_i^2\right)_j \quad (1)$$

where (j) is the test number from 1 to 16; y_i is the individual measured tool wear and surface roughness in the first, second and third columns in Table 5; and n is the number of individually measured response, in this case $n = 1$. The S/N values function shown in Equation (1) is a performance measurement parameter for developing processes insensitive to noise factors. The degree of predictable performance of a process in the presence of noise factors could be defined from the S/N ratios in which, for each factor, the higher the S/N ratio the better the result. TPM represents the target performance measurement, which is equal to the average of the measured tool wear at the same level of input parameters (i) in Table 5.

The calculated S/N ratio and TPM response values are presented in Tables 9 and 10 for tool wear and surface roughness characteristics. As for an example of TPM and S/N response calculation, A_i is the average of all TPM and S/N values corresponding to the same level of input parameters (i) under A. In this case, (i) is equal to 1, 2, 3, or 4. The difference under column A_i is equal to the maximum minus the minimum of the S/N or TPM response values. Similarly, the S/N, TPM response values and differences are calculated for B_i and C_i. The rank is given in order from the highest to the lowest difference values. The significance of each factor is determined based on the value of the difference for both S/N and TPM.

Figs. 9 and 10 show both TPM and S/N responses for tool wear and surface roughness. From Fig. 9(a) and (b) and based on the criteria of smaller TPM and larger S/N response, the nanoparticle concentration (A3, 0.5 wt%), air pressure (B2, 2 bar) and nozzle angle (C4, 60°) are determined to be the best choices for obtaining the lowest tool wear. While from Fig. 10(a) and (b), nanoparticle concentration (A3, 0.5 wt%) with air pressure (B1, 1 bar), and nozzle angle (C2, 30°) are deemed the best choices for attaining the lowest surface roughness. In conclusion, the optimal parameter combinations for lower tool wear and best surface roughness are A3B2C4 and A3B1C2.

4. Discussion

In this study, SiO_2 serves as the nanoparticle and is mixed with ordinary mineral oil at different concentrations to investigate tool wear reduction and surface quality improvement in CNC hard

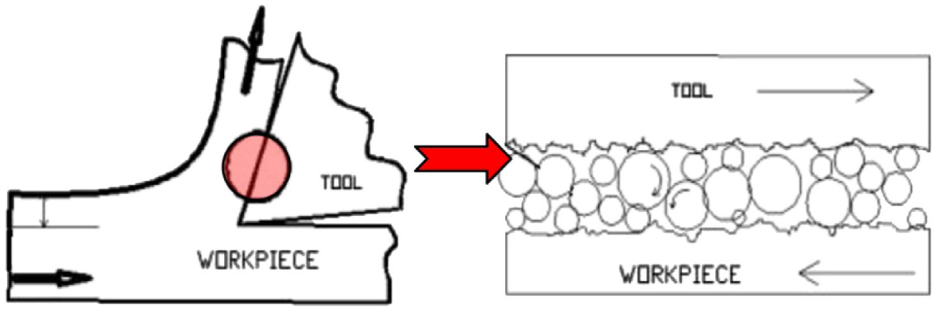


Fig. 13. Rolling elements in the tool–chip interface.

turning machined steel AISI4140. From the results, fuzzy logic approach and response analyses lead to similar conclusions. Clearly, mode 3 with 0.5% concentration produces the lowest tool wear and best surface quality. As depicted in Figs. 11 and 12, the explanation could be that the chip deformation flowing over the tool leads to localized regions of intense shear occurring due to the friction at the rake face, which is known as secondary shear (Senff et al., 2012). If the coefficient of friction is greater than 0.5, a higher frictional force component (F_f) will result, leading to sticky friction, after which chip flow would occur only within the workpiece but not at the tool–workpiece interface. Consequently, the deformed chip thickness would increase, thus decreasing the cutting ratio and shear angle Φ and increasing the shear length. Hence, the cutting force (F_c) component required to remove the chip would increase significantly, as shown in Fig. 12 (Smithey et al., 2001). Furthermore, at higher plastic deformation, a chip is welded to the tool face, effectively changing tool geometry and rake steepness. This would result in poor surface finish since the bits of the welded chip would eventually break off and stick to the workpiece. These bits tend to be problematic due to the very hard and abrasive work-hardening they undergo.

Applying the lubrication system to the tool–chip interface will reduce the coefficient of friction (Emami et al., 2013), achieving less tool wear and better surface quality. However, introducing the SiO_2 nano-lubrication system would provide much less friction and superior surface quality, something mainly attributed to the tribological properties of SiO_2 which reduce the coefficient of friction at the tool–chip interface during machining, acting as billions of nano-scale quasi-spherical structure rolling elements (Fig. 13). Additionally, it is believed that cutting zone temperature will be diminished as well, resulting in lower tool wear, and consequently in improved surface quality. A higher SiO_2 concentration will lead to disadvantage effects because more and more nanoparticles will transfer additional kinetic energy to the workpiece surface and dissipate more heat. The low friction behavior in the nature of nanoparticles is effective in minimizing the frictional effects at the tool–workpiece interface (Rahmati et al., 2013) and reducing cutting force (Fig. 10). For large amounts of nanoparticles present in cutting oil, they will collide with, and be impeded by, the asperities on the work surface and generate higher cutting force (Rapoport et al., 2002). Besides, by using MQL system in this research, the effective cutting manufacture which is economically and environmentally could be obtained (Fratila, 2009) due to less usage of lubricant oil.

After the optimal levels of all control factors were identified, the last step in the Taguchi optimization method was to conduct a verification test using the following optimal parameter combinations: A3 B2 C4 for tool wear and A3 B1 C2 for surface roughness, to validate the recommendation. This test was repeated six times and the average TPM values of the measured tool wear and surface roughness were calculated. The confirmation test results for tool wear and surface roughness values are 19.50 μm and 0.44 μm. This confirmation test verify the best combination parameters for tool wear as per in the Table 5. While, the confirmation test indicates the improvement of 23% in surface roughness compared to the smallest values obtained from the experiments shown in Table 5.

5. Conclusions

In this research work, the optimum novel uses of SiO_2 nano-lubrication parameters in hard turning AISI4140 steel to improve machining performance were investigated. Nano-lubricant was prepared by adding silicon dioxide nanoparticles (SiO_2) with an average size of 5–10 nm to the mineral oil, followed by sonification (240 W, 40 kHz, 500 W) for 48 h in order to suspend the particles homogeneously in the mixture. The oil was delivered to the tool chip interface area via an MQL system with a thin-pulsed jet nozzle. In the case of the nano-lubrication system, the nozzle was equipped with an additional air nozzle to accelerate the lubricant entering the cutting zone. Based on fuzzy logic and response analysis obtained from the Taguchi optimization, the following conclusions can be made:

1. The minimum tool wear is obtained with a 0.5%wt nanoparticle concentration in the mineral oil, 2 bar air stream pressure and a 60° nozzle orientation angle.
2. Surface roughness can be enhanced with a 0.5 wt% concentration in the mineral oil, less air stream pressure and a 30° nozzle orientation angle.

The excellent performance over pure oil and drastic reduction in cutting oil consumption has led to the conclusion that minimal quantity lubrication oil mixed with a nanoparticle additive is feasible for augmenting the machining process. With the low cost and outstanding properties of SiO_2 nanoparticles, it might be an innovative, effective alternative to flood lubrication due to environmental issues as well.

Acknowledgments

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