VOL. X, NO. X, XXXXXXXX ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

OPTIMIZATION OF ABRASIVE MACHINING OF DUCTILE CAST IRON USING TIO_2 NANOPARTICLES: A MULTILAYER PERCEPTRON APPROACH

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ABSTRACT

This study was carried out to study the effects of using nanofluids as abrasive machining coolants. The objective of this study is to investigate the performance of grinding of ductile iron based on response surface method and to develop optimization model for grinding parameters using artificial neural network technique. The abrasive machining process selected was surface grinding and it was carried out two different coolants which are conventional coolant and titanium dioxide nanocoolant. The selected inputs variables are table speed, depth of cut and type of grinding pattern which are single pass and multiple pass. The selected output parameters are temperature rise, surface roughness and material removal rate. The ANOVA test has been carried out to check the adequacy of the developed mathematical model. The second order mathematical model for MRR, surface roughness and temperature rise are developed based on response surface method. The artificial neural network model has been developed and analysis the performance parameters of grinding processes using two different types of coolant including the conventional as well as TiO_2 nanocoolant. The obtained results shows that nanofluids as grinding coolants produces the better surface finish, good value of material removal rate and acts effectively on minimizing grinding temperature. The developed ANN model can be used as a basis of grinding processes.

Keywords: Grinding · Multilayer perceptron Approach · TiO_2 Nanofluid · Ductile Cast Iron ·

INTRODUCTION

Grinding is a material removal and surface generation process used to shape and finish components made of metals and other materials. The precision and surface finish obtained through grinding can be up to ten times better than with either turning or milling (Krajnik, Kopac and Sluga, 2005; Shen, Shih and Simon, 2008). Grinding employs an abrasive product, usually a rotating wheel brought into controlled contact with a work surface (Kadirgama, Rahman, Ismail and Bakar, 2012; Rahman and Kadirgama, 2014; Rahman, Kadirgama and Ab Aziz, 2014; Walsh, Baliga and Hodgson, 2002). The grinding wheel is composed of abrasive grains held together in a binder. Heat generation is an important factor in the grinding process. It can degrade the integrity of the wheel matrix and/or abrasive, reduce workpiece surface quality by causing thermal cracks or burning of the surface, introduce strength reducing tensile residual stresses, and creates dimensional inaccuracies (Chen and Rowe, 1996; Malkin and Guo, 2007). Temperature may also influence the grinding mechanism either by softening the material or by introducing phase transformations. This is one of the important output parameters that will be observed where it will be influenced widely on the usage of nano-coolants. A large volume of grinding fluid is most commonly used to flood the grinding zone, hoping to achieve tangible productivity targets while often neglecting the seemingly fewer tangible environmental safety hazards. In addition, the inherent high cost of disposal or recycling of the grinding fluid becomes another major concern, especially as the environmental regulations get stricter. Minimizing the quantity of cutting fluid is desirable in grinding.

The conventional grinding wheels are low performance and contain lower-cost abrasives such as aluminum oxide (Al_2O_3) and silicon carbide (SiC). The super-abrasive wheels are higher performance and contain high-cost abrasives consisting of diamond or cubic boron nitride (CBN)(Lee, Nam, Li and Lee, 2010; Prabhu and Vinayagam, 2010). In many applications, manufacturing industries cannot achieve their productivity goals with conventional grinding wheels. The use of a super abrasive grinding wheel is prohibitively expensive and complex for many machine shops. Therefore, a limited number of manufacturing companies are using super-abrasive wheels in their grinding operations (Krueger et al., 2000). Most abrasives used in industry are synthetic. Aluminum oxide is used in three quarters of all grinding operations, and is primarily used to grind ferrous metals. Next is silicon carbide, which is used for grinding softer, non-ferrous metals and high density materials, such as cemented carbide or ceramics. Super abrasives, namely cubic boron nitride or "CBN" and diamond, are used in about five percent of grinding. Hard ferrous materials are ground with "CBN" while non-ferrous materials and non-metals are best ground with diamond. The grain size of abrasive materials is important to the process.

Nanofluids are solid-liquid composite materials consisting of solid nanoparticles with sizes typically of 1-100 nm suspended in liquid. Nanofluids have attracted great interest recently because of reports of greatly enhanced thermal properties (Hussein, Sharma, Bakar and Kadirgama, 2013; Mahendran, Lee, Sharma and Shahrani, 2012; Syam Sundar and Sharma, 2011a). Conventional particle-liquid suspensions require high concentrations (>10%) of particles to achieve such enhancement (Das, Choi, Wenhua and Pradeep, 2008; Das, Putra, Thiesen and Roetzel, 2003). Key features of nanofluids that reported to so far include thermal conductivities exceeding those of traditional solid/liquid suspensions; a nonlinear relationship between thermal conductivity and concentration in the case of nanofluids containing carbon nanotubes; strongly temperature-dependent thermal conductivity; and a significant increase in critical heat flux in boiling heat transfer(Azmi, Sharma, Mamat and Anuar, 2013; Hussein, Bakar, Kadirgama and Sharma, 2013; Rao et al., 2011; Ravisankar and Tara Chand, 2013; Syam Sundar and Sharma, 2011b). Each of these features is highly desirable for thermal systems; a stable and easily synthesized fluid with these attributes and acceptable viscosity would be a strong candidate for the next generation of liquid coolants (Fadhillahanafi, Leong and Risby, 2013; Ravisankar and Tara Chand, 2013). There is increasing interest in using artificial neural networks (ANNs) for modelling and optimization of machining process (Kadirgama et al., 2012; Madic and Radovanovic, 2011; Rahman and Kadirgama, 2014). Analytical models are developed based on many simplified assumptions. It is sometimes difficult to adjust the parameters of the above mentioned models according to the actual situation of the machining process. Therefore, an artificial neural networks can map the input/output relationships and possess massive parallel computing capability, have attracted much attention in research on machining processes. ANN provides significant advantages in solving processing problems that require real-time encoding and interpretation of relationships among variables of high-dimensional space (Khan, Rahman, Kadirgama and Bakar, 2012; Rahman, 2012; Rahman, Mohyaldeen, Noor, Kadirgama and Bakar, 2011). ANN has been extensively applied in modeling many metal-cutting operations such as turning, milling and drilling. The general ability of the network is actually dependent on three factors. These factors are the selection of the appropriate input/output parameters of the system, the distribution of the dataset, and the format of the presentation of the dataset to the network. The selection of the neuron number, hidden layers, activation function and training algorithm are very important to obtain the best results. The objectives of this study are to investigate the effect of titanium dioxide (TiO_2) nanocoolant on precision surface grinding and to develop optimization model for grinding parameters using multilayer perceptron technique..

METHODS AND MATERIALS

The grinding process was undertaken using a Supertec precision grinding machine, model STP-102ADCII. A vitrified bond aluminum oxide grinding wheel (PSA-60JBV) with an average abrasive size of 60 grains was used. The workpiece material was block ductile iron with a carbon content of 3.5–3.9% and average hardness of 110-Rockwell C. The width and length of the workpiece surface for grinding were 35 mm and 80 mm, respectively. First, the workpiece was clamped onto a clamper jaw since cast iron is not attracted to the magnet field. Then the zero point of the Z-axis was found by grinding the disc slowly until there were some sparks. After that, the coolant was sprayed directly onto the workpiece to ensure the temperature of the workpiece was equivalent to the temperature of the coolant and as a precaution to achieve an exact value of rising temperature. Then the workpiece speed was calibrated using a tachometer. The model STP-102ADCII can be controlled and uses a hydraulic system to move left and right. The speed is controlled by a control valve; however, there is no speed display. So, in this research, calibration of the table speed using a tachometer had to be undertaken and the speed was set at 20 mm/min, 30 mm/min and 40 mm/min. The design of experiments techniques enables designers to determine simultaneously the individual and interactive effects of many factors that could affect the output results. The central composite design (CCD) is the most popular. There is good commercial software available to help with designing and analyzing response-surface experiments. Table 1 shows the DOE table generated using Minitab software.

Table 1: Design of experiment.

Specimen	Table speed (m/min)	Depth of cut (μm)
A	20	20
B	20	40
C	20	60
D	30	20
E	30	40
F	30	60
G	40	20
H	40	40
I	40	60

An experiment was conducted based on the DOE table and different types of coolant: titanium oxide (TiO_2) nanocoolant with a 0.10% volume concentration and a 20% volume concentration conventional soluble oil water-based coolant. Constant grinding wheels, of vitrified bond aluminum oxide (PSA-60JBV) were used. Two types of grinding were considered: single pass and multiple pass set to ten passes.

Nanofluid Preparation

Titanium oxide nanoparticle materials were selected. A two-step method was used to prepare the nanofluid. The dispersed nanoparticles which come in liquid form with a volume of one liter have 20% weight concentration with a 30–40 nm particle size, an 8.9 pH level and density equal to 5600 kg/m³. It is diluted to a 0.10% volume concentration. The conversion of the weight percent concentration to volume concentration is expressed as equation (1). It shows the dilution formula to determine how much distilled water is required to dilute the initial nanofluid.

$$\varphi_1 = \frac{\omega \rho_w}{\frac{\omega}{100}\rho_w + \left(1 - \frac{\omega}{100}\right)\rho_{TiO_2}} \quad (1)$$

where

φ_1 is the initial volume concentration, ω is the weight percent of nanoparticles, ρ_w is the density of water, and ρ_{TiO_2} is the density of the nanoparticles,

For a two-phase system, some important issues have to be faced. One of the most important issues is the stability of the nanofluids, and it remains a considerable challenge to achieve the desired stability of the nanofluids. The stability of the mixture is ensured by maintaining the pH of the aqueous solution of nano-particles and ultra-sonication for about two hours resulting in no settling of particles observed for the machining period. To achieve stability in the dilution, the solution needs to be stirred continuously for two hours with the mixture set to 1000 rpm. Nanoparticles have a tendency to aggregate. The use of surfactants is an important technique in enhancing the stability of nanoparticles in fluids. However, the functionality of the surfactants under high temperature is also a major concern, especially for high-temperature applications. Therefore, no surfactant is applied in this study.

Multilayer Perceptron Approach

Multilayer perceptron (MLP) approach is an analysis method under Artificial Neural Networks. In this study, the analysis is performed using the Neuro Solutions 6 software. It is done by keying the sets of the experimental data obtained from the experiments done in the lab. The columns of depth of cut and table speed are tagged as input while the columns of temperature rise, MRR and surface roughness are tagged as desired. The tagged input parameters to develop the MLP model. The hidden layer for the optimization process is set to 1. The processing elements are set to 4 while SigmoidAxon is selected for transfer function. Momentum is selected for learning rule at 1.00000 value of step size and 0.7 for momentum value. Maximum epochs is set 30000 and Termination is set at MSE, minimum with Threshold of 0.000001.the data are then tested for regression for each training, cross validation and testing options. From then, the optimization model is obtained.

RESULTS AND DISCUSSION

Figure 1 represents the comparison between desired output value and actual network. Figure 2 represents the sensitivity about the mean for single pass grinding pattern. The increment of both input variables which are table speed and depth of cut highly affects the temperature rise of the workpiece followed by MRR while the surface roughness is the least affected. Table 1 shows the comparison between the output parameters of desired value (predicted) and actual value (experimental) for single pass grinding pattern. Figure 3 indicates the effect of varied input value towards all three output parameters for single pass grinding pattern. It is observed that as the table speed increases, temperature rise and MRR value increases steadily while the surface roughness value also increases but in small increment. As the depth of cut increases, the temperature rise increases a lot while MRR and surface roughness increases steadily in small portions.

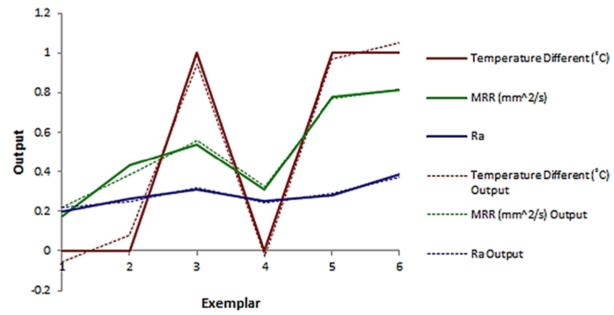

Figure 1: Desired output and actual network output for single pass grinding.

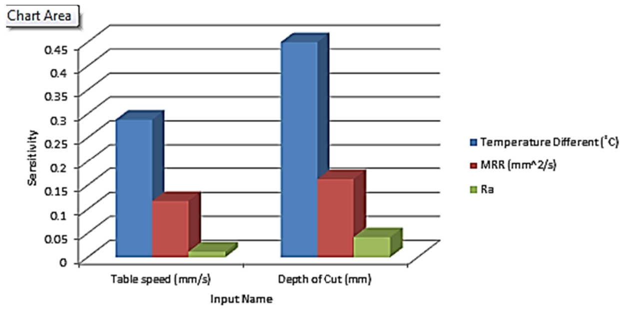

Figure 2: Sensitivity analysis for single pass.

Figure 4 represents the comparison between desired output value and actual network output for TiO_2nanocoolant with multiple pass grinding pattern. Figure 5 represents the sensitivity about the mean for multiple pass grinding pattern. As shown in the figure, the increment of both input variables which are table speed and depth of cut highly affects the temperature rise of the workpiece. After that it differs where after temperature rise, MRR is the second followed by surface roughness as table speed increases. But for the increment of depth of cut, it is the other way around where surface roughness is the second most affected and the least affected is MRR.

VOL. X, NO. X, XXXXXXXX ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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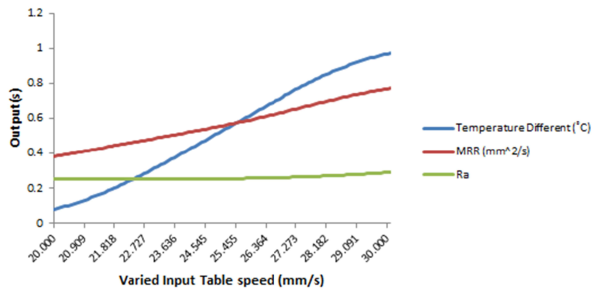
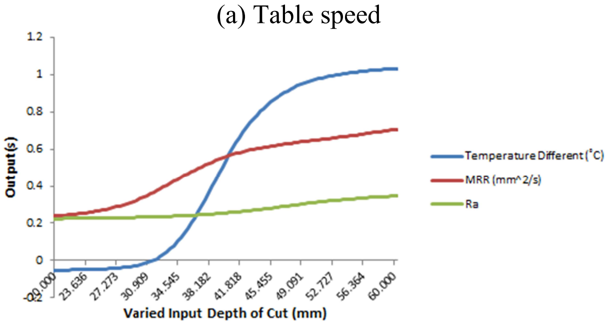
Table 1: Comparison between experimental value and predicted value (0.1% TiO_2) for single pass grinding pattern.

Table Speed (m/min)	Depth of Cut (µm)	Temperature rise (°C)		MRR (g/sec)		Surface Roughness (µm)	
		Experimental	Predicted	Experimental	Predicted	Experimental	Predicted
20	20	0	-0.054	0.178	0.219	0.201	0.218
20	40	0	0.079	0.435	0.383	0.264	0.251
20	60	1	0.946	0.541	0.562	0.310	0.317
30	20	0	-0.028	0.312	0.326	0.251	0.242
30	40	1	0.969	0.781	0.769	0.281	0.289
30	60	1	1.052	0.813	0.815	0.385	0.372
40	20	0	0.952	0.714	0.802	0.237	0.320
40	40	1	1.041	0.952	0.830	0.303	0.324
40	60	1	1.051	1.310	0.827	0.489	0.364



(a) Table speed



(b) Depth of cut

Figure 3: Effect of network outputs for single pass grinding.

Table 2 shows the comparison of output value between desired value (predicted) and actual value (experimental) for multiple pass grinding patterns.Figure-6 indicates the effect of varied input value towards all three output parameters for multiple pass grinding patterns. It is observed that as the table speed and depth of cut increases, temperature rise increases steadily while the MRR and surface roughness values increases but in small increment.

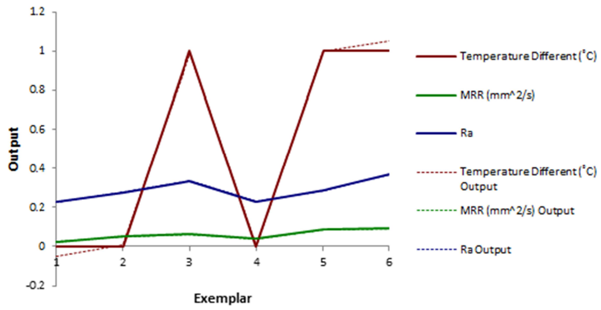


Figure 4: Desired output and actual network output for multiple pass grinding pattern.

Table 2: Comparison between experimental value and predicted value (0.1% TiO_2) for multiple pass grinding.

Table Speed (m/min)	DOC (µm)	Temperature rise (°C)		MRR (g/sec)		Surface Roughness (µm)	
		Experimental	Predicted	Experimental	Predicted	Experimental	Predicted
20	20	0	-0.050	0.023	0.023	0.226	0.226
20	40	0	0.011	0.052	0.052	0.276	0.276
20	60	1	0.988	0.063	0.063	0.336	0.336
30	20	0	0.003	0.038	0.038	0.229	0.228
30	40	1	0.998	0.085	0.085	0.284	0.284
30	60	1	1.055	0.091	0.090	0.369	0.367
40	20	1	0.869	0.107	0.086	0.233	0.263
40	40	1	1.052	0.190	0.087	0.316	0.299
40	60	1	1.055	0.214	0.087	0.401	0.325

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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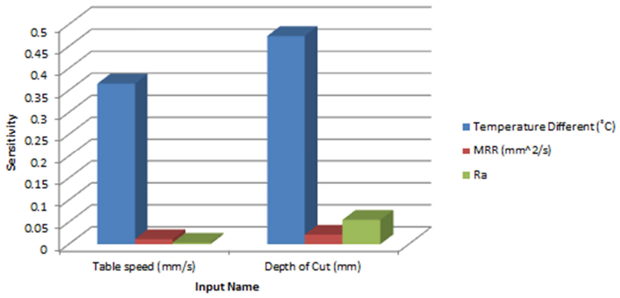
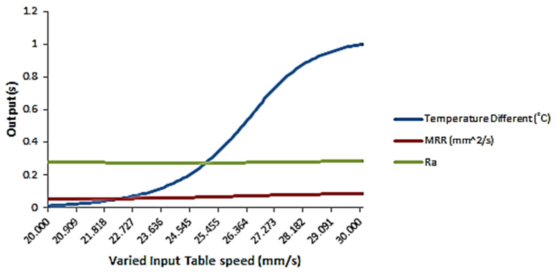
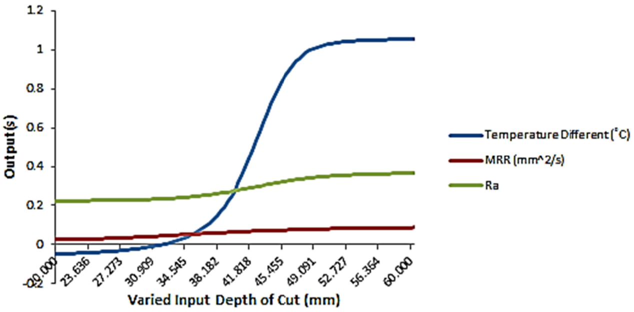


Figure 5: Sensitivity about the mean for multiple pass grinding pattern.



(a) Table speed



(b) Depth of cut

Figure 6: Network outputs for varied input depth of cut for multiple pass grinding.

CONCLUSIONS

The effects of selected of input parameters including the grinding pattern, depth of cut and table speed have been studied towards the output parameters including the temperature rise, surface roughness and material removal rate for both conventional coolant and titanium dioxide nanocoolant. The selection is based on desired minimize the temperature rise, minimum surface roughness and maximum material removal rate. For single pass grinding patterns, all three output parameters are more affected by depth of cut followed by the table speed. As table speed increases, grinding temperature and MRR increases steadily while surface roughness is nearly constant. However, as the depth of cut increases, grinding temperature increases the most followed by MRR and lastly is surface roughness. For multiple pass grinding patterns, the grinding temperature and surface roughness are more influenced by the depth of cut compared to table speed while MRR is more affected by varying table speed compared to depth of cut. The increase in table speed causes the grinding temperature to increase dramatically while MRR and surface roughness are significantly affected. On the other hand, the increase of depth of cut also highly affects temperature difference, MRR also increases by a small amount while surface roughness is nearly constant.

ACKNOWLEDGMENTS

The authors would like to thank Universiti Malaysia Pahang for financial support under university research project no. RDU120310.

REFERENCE

Azmi, W.H., Sharma, K.V., Mamat, R. and Anuar, S. (2013). Nanofluid properties for forced convection heat transfer: An overview. *Journal of Mechanical Engineering and Sciences,* 4, pp.397-408.

Chen, X. and Rowe, W.B. (1996). Analysis and simulation of the grinding process. Part i: Generation of the grinding wheel surface. *International Journal of Machine Tools and Manufacture,* 36(8), pp.871-882.

Das, S.K., Choi, S.U.S., Wenhua, Y.W. and Pradeep, T. (2008). *Nanofluids: Science and technology*. USA: John Wiley & Sons, Inc.

Das, S.K., Putra, N., Thiesen, P. and Roetzel, W. (2003). Temperature dependence of thermal conductivity enhancement for nanofluids. *Journal of Heat Transfer,* 125(4), pp.567-574.

Fadhillahanafi, N.M., Leong, K.Y. and Risby, M.S. (2013). Stability and thermal conductivity characteristics of carbon nanotube based nanofluids. *International Journal of Automotive and Mechanical Engineering,* 8, pp. 1376-1384.

Hussein, A.M., Bakar, R.A., Kadirgama, K. and Sharma, K.V. (2013). Experimental measurements of nanofluids thermal properties. *International Journal of Automotive and Mechanical Engineering,* 7, pp.850-863.

Hussein, A.M., Sharma, K.V., Bakar, R.A. and Kadirgama, K. (2013). Heat transfer enhancement with nanofluids – a review. *Journal of Mechanical Engineering and Sciences,* 4, pp.452-461.

Kadirgama, K., Rahman, M.M., Ismail, A.R. and Bakar, R.A. (2012). A surrogate modelling to predict surface roughness and surface texture when grinding aisi 1042 carbon steel. *Scientific Research and Essays,* 7(5), pp.598-608.

Khan, M.A.R., Rahman, M.M., Kadirgama, K. and Bakar, R.A. (2012). Artificial neural network model for material removal rate of ti-15-3 in electrical discharge machining. *Energy Education Science and Technology Part A: Energy Science and Research,* 29(2), pp.1025-1038.

Krajnik, P., Kopac, J. and Sluga, A. (2005). Design of grinding factors based on response surface methodology. *Journal of Materials Processing Technology,* 162-163, pp.629-636.

Krueger, M.K., Yoon, S.C., Gong, D., McSpadden, J.S.B., O'Rourke, L.J.O. and Parten, R.J. (2000). New technology in metalworking fluids and grinding wheels achieves tenfold improvement in grinding performance. *Technical Report*: NASA STI.

Lee, P.H., Nam, T.S., Li, C. andLee, S.W. (2010). *Environmentally-friendly nano-fluid minimum quantity lubrication (MQL) meso-scale grinding process using nano-diamond particles.* Paper presented at the International Conference on Manufacturing Automation.

Madic, M.J. and Radovanovic, M.R. (2011). Optimal selection of ann training and architectural paramaters using taguchi method: A case study. *FME Transactions,* 39, pp.79-86.

Mahendran, M., Lee, G.C., Sharma, K.V. and Shahrani, A. (2012). Performance of evacuated tube solar collector using water-based titanium oxide nanofluid. *Journal of Mechanical Engineering and Sciences,* 3, pp. 301-310.

Malkin, S. and Guo, C. (2007). Thermal analysis of grinding. *CIRP Annals - Manufacturing Technology,* 56, pp.760-761.

Prabhu, S. and Vinayagam, B.K. (2010). Nano surface generation of grinding process using carbon nano tubes. *Sadhana,* 35(6), pp.747-760.

Rahman, M.M. (2012). Modeling of machining parameters of ti-6al-4v for electric discharge machining: A neural network approach. *Scientific Research and Essays,* 7(8), pp.881-890.

Rahman, M.M. and Kadirgama, K. (2014). Performance of water-based zinc oxide nanoparticle coolant during abrasive grinding of ductile cast iron. *Journal of Nanoparticles, Article ID 175896*, pp.1-7.

Rahman, M.M., Kadirgama, K. Ab Aziz, A.S. (2014). Artificial neural network modeling of grinding of ductile cast iron using water based sio2 nanocoolant. *International Journal of Automotive and Mechanical Engineering,* 9, 1649-1661.

Rahman, M.M., Mohyaldeen, H.M., Noor, M.M., Kadirgama, K. and Bakar, R.A. (2011). Linear static response of suspension arm based on artificial neural network technique. *Advanced Materials Research,* 213, pp.419-426.

Rao, G.S., Sharma, K.V., Chary, S.P., Bakar, R.A., Rahman, M.M., Kadirgama, K. and Noor, M.M. (2011). Experimental study on heat transfer coefficient and friction factor of AL_2O_3 nanofluid in a packed bed column. *Journal of Mechanical Engineering and Sciences,* 1, pp.1-15.

Ravisankar, B. and Tara Chand, V. (2013). Influence of nanoparticle volume fraction, particle size and temperature on thermal conductivity and viscosity of nanofluids- a review. *International Journal of Automotive and Mechanical Engineering,* 8, pp.1316-1338.

Shen, B., Shih, A.J. and Simon, C.T. (2008). Application of nanofluids in minimum quantity lubrication grinding. *Tribology Transactions,* 51, 730-737.

Syam Sundar, L. and Sharma, K.V. (2011a). An experimental study on heat transfer and friction factor of al2o3 nanofluid. *Journal of Mechanical Engineering and Sciences,* 1, pp.99-112.

Syam Sundar, L. and Sharma, K.V. (2011b). Laminar convective heat transfer and friction factor of al2o3 nanofluid in circular tube fitted with twisted tape inserts. *International Journal of Automotive and Mechanical Engineering,* 3, pp.265-278.

Walsh, A.P., Baliga, B. and Hodgson, P.D. (2002). A novel technique to optimize grinding process. *International Manufacturing Leaders Forum*, pp.101-106.

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