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

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DEDICATION

I specially dedicate to my beloved parents

And those who have guided

and motivated me for this project

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I would like to express my sincerest gratitude to Allah the Almighty for the blessing and giving me the strength to complete my project. I would also like to thank and show my greatest appreciation towards my supervisor, Associate Professor Dr. Md. Mustafizur Rahman for her constant guidance, consideration and constructive ideas in leading me in completing this project.

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ABSTRACT

This project was carried out to study the effects of using nanofluids as abrasive machining coolants. The objective of this project is to study the effect of nanocoolant on precision surface grinding, 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_2nanocoolant. 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.

ABSTRAK

Tujuan kajian ini dijalankan adalah untuk mengkaji kesan penggunaan cecair nano sebagai cecair penyejuk dalam proses abrasive machining. Objektif kajian ini adalah untuk mengkaji kesan penggunaan cecair nano dalam proses precision surface grinding, membuat kajian dalam prestasi grinding menggunakan ductile cast iron berpandukan response surface method dan untuk membina modal optimum bagi parameter yang telah dipilih menggunakan artificial neural network. Proses abrasive machining yang dipilih ialah precision surface grinding yang dilakukan menggunakan dua jenis cecair penyejuk yang berbeza iaitu cecair penyejuk konvensional dan cecair penyejuk nano titanium dioxide. Parameter input yang telah dipilih adalah kelajuan meja, kedalaman potongan dan corak grinding iaitu single pass dan multiple pass. Parameter yang dikaji pula adalah kenaikan suhu, kekasaran permukaan dan kadar pembuangan bahan. Analisa ANOVA juga dilakukan untuk membuat pengesahan ke atas model matematik yang dibina. Model matematik tahap dua yang dibina bagi setiap pembolehubah yang dikaji adalah dengan menggunakan RSM. Model ANN pula dibina untuk kedua-dua jenis cecair penyejuk yang berbeza bagi mengkaji kesan parameter yang berbeza. Daripada keputusan yang diperoleh, ia menunjukkan bahawa dengan menggunakan cecair penyejuk nano menghasilkan produk akhir yang baik dari segi surface finish, nilai yang memberangsangkan bagi MRR dan berkesan dalam meminimakan kenaikan suhu semasa proses grinding.

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LIST OF SYMBOLS

R_a	Surface Roughness

LIST OF ABBREVIATIONS

Al_2O_3	Aluminum Oxide
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
CBN	Cubic Boron Nitride
DOC	Depth of Cut
DOE	Design of Experiment
HTF	Heat Transfer Fluids
ID	Internal Diameter
MLP	Multilayer Perceptron
MRR	Material Removal Rate
RSM	Response Surface Methodology
SEM	Scanning Electron Microscopy
SiC	Silicon Carbide
TiO_2	Titanium Dioxide
TS	Table speed

CHAPTER 1

INTRODUCTION

1.1 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. Grinding employs an abrasive product, usually a rotating wheel brought into controlled contact with a work surface. 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. 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 nanocoolants. 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 disposalor 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.

Cooling is one of the most important technical challenges facing many diverse industries. Technological developments such as microelectronic devices with smaller (sub-100 nm) features and faster (multi-gigahertz) operating speeds, higher-power engines and brighter optical devices are driving increased thermal loads, requiring advances in cooling. The conventional method for increasing heat dissipation is to increase the area available for exchanging heat with a heat transfer fluid. However, this approach requires an undesirable increase in the thermal management system's size. There is an urgent need for new and innovative coolants with improved performance. The novel concept of 'nanofluids' – heat transfer fluids containing suspensions of nanoparticles – has been proposed as a means of meeting these challenges (Keblinski et al., 2005). Heattransfer fluids have many industrial and civil applications, including in transport, energy supply, air-conditioning and electronic cooling, etc. Research and development activities are being carried out to improve the heat transport properties of fluids. Solid metallic materials, such as silver, copper and iron, and non-metallic materials, such as alumina, CuO, SiC and carbon nanotubes, have much higher thermal conductivity's than HTFs (Maxwell, 1873). At the very beginning, solid particles of micrometer, even millimeter magnitudes were blended into the base fluids to make suspensions or slurries. However, large solid particles cause troublesome problems, such as abrasion of the surface, clogging the microchannels, eroding the pipeline and increasing the pressure drop, which substantially limits the practical applications. Actually, liquid suspension was primarily a theoretical treatment only of some theoretical interest, and subsequent studies by other researchers achieved minor success. The large size of the particles and the difficulty in production of small particles were limiting factors (Han, 2008).

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. Conventional particle-liquid suspensions require high concentrations (>10%) of particles to achieve such enhancement (Das et al., 2008). Key features of nanofluids that have been 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. 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 (Das et al., 2008).

In recent years, there is increasing interest in using artificial neural networks (ANNs) for modelling and optimization of machining process (Madic et al., 2011). 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. 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 (Razak et al., 2010).

1.2 PROBLEM STATEMENT

Nowadays, nanotechnology is becoming a fast paced development in the science and engineering world. Cooling is one of the most important technical challenges facing many diverse industries. Technological developments suchas microelectronic devices with smaller (sub-100 nm) features and faster (multi-gigahertz) operating speeds, higher-power engines, and brighter optical devices are driving increased thermal loads, requiring advances in cooling. The same goes to the grinding process where it also requires the use of coolant to provide quality work. The conventional method for increasing heat dissipation is to increase the area available for exchanging heat with a heat transfer fluid. However, this approach requires an undesirable increase in the thermal management system’s size. There is an urgent need for new and innovative coolants with improved performance. The grinding method used in this experiment is surface grinding. Surface grinding produces flat, angular, or contoured surfaces by feeding work in a horizontal plane beneath a rotating grinding wheel. Work is most often magnetically attached to the table, and may be ground by either a traversing or rotating movement of the table. Most surface grinding machines use a horizontal spindle which adjusts up and down allowing either the edge or the face of the wheel to contact the work. The novel concept of ‘nanofluids’ – heat transfer fluids containing suspensions of nanoparticles – has been proposed as a means of meeting these challenges. Nanofluids have the potential to be the next generation of coolants due to their higher thermal conductivities. The selection of appropriate base fluid is very critical in the application of nanoparticle based lubricants in grinding. A proper selection of the cutting parameters for machining to obtain performances similar to flood lubricated conditions is studied. The reason this title is chosen is because of the interest in the nanotechnology fields where it has been fast developing in the engineering field.

1.3 OBJECTIVES OF THE PROJECT

The objectives of the project are as follows:

(i) To study the effect of titanium dioxide (TiO_2) nanocoolant on precision surface grinding.
(ii) To investigate the performance of grinding of ductile iron based on response surface method.
(iii) To develop optimization model for grinding parameters using multilayer perceptron technique.

1.4 SCOPE OF PROJECT

The artificial neural network technique is used to prepare the design of experiments and find the optimum parameters. In the experiment, the material used is cast iron where it is grinded based on certain input parameters and the desired output parameters are observed. The input parameters of the experiment consist of four parameters includinggrinding pattern, table speed,depth of cut and type of coolant. The output parameters consist of three parameters including the surface roughness of the workpiece, temperature and material removal rate. For this experiment, the grinding process using conventional coolant is carried out. After the data is collected, the grinding process is carried out using TiO_2 nanocoolant. The both data collected, the surface roughness and material removal rate analysis is performed. Then, the data will be analyzed using response surface method and multilayer perceptron approach.

1.5 ORGANIZATION OF REPORT

Chapter 1 contains the introduction, problem statement, project objectives, scope of project and organization of report. Chapter 2 contains the literature review of the report based on studies of published papers and books that are related to the project. Chapter 3 is the methodology of the report which contains the methods used in completing the project. Chapter 4 contains the results and analysis obtained from the project. Chapter 5 is summarized the finding and recommended for future work.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter is briefly explained about the basic grinding process, the input parameters including the grinding patterns, table speed, depth of cut and type of coolant, the output parameters, including the surface roughness, grinding temperature and material removal rate and also the difference between conventional coolants and nanocoolants. 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. Grinding employs an abrasive product, usually a rotating wheel brought into controlled contact with a work surface. The grinding wheel is composed of abrasive grains held together in a binder. These abrasive grains act as cutting tools, removing tiny chips of material from the work. As these abrasive grains wear and become dull, the added resistance leads to fracture of the grains or weakening of their bond. The dull pieces break away, revealing sharp new grains that continue cutting.

2.2 GRINDING WHEELS

Figure 2.1 shows schematic illustration of surface grinding process (Shen et al., 2008). Grinding wheels are categorized by the type of abrasive they contain. The grinding process utilizes these abrasive particles as cutting edges in random contact with the material to be worked. The two major categories of grinding wheels are conventional and super-abrasive. 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). 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).

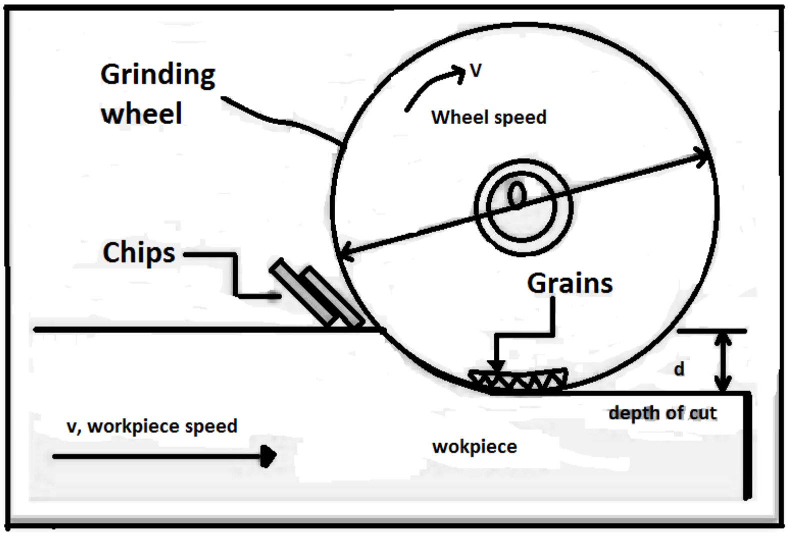


Figure 2.1: Schematic illustration of surface grinding process (Shen et al., 2008)

Most abrasives used in industry are synthetic. Aluminum oxide is used in three quarters of all grinding operations, and is primarily used to grind ferrousmetals. Next is silicon carbide, which is used for grinding softer, non-ferrousmetals and high density materials, such as cemented carbide or ceramics. Super abrasives, namely cubic boron nitride or "CBN" and diamond, are used inabout 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. Large coarsegrains remove material faster, while smaller grains produce a finer finish.Wheels are graded according their strength and wear resistance. A "hard" wheelis one that resists the separation of its individual grains. One that is toohard will wear slowly and present dulled grains to the work and overheat,affecting the final finish. Another aspect of grinding wheels is their pore structure or density, which refers to the porosity between individual grains. This pore structure creates spaces between the grains that provide coolant retention and areas for the chips to form. Dense wheels are best for harder materials, while more open densities are better for the softer metals.The three factors of grain size, bond type, and pore structure are closely related, and together determine how well a wheel will perform. Damaged wheels or even wheels suspected of being damaged should not be used.

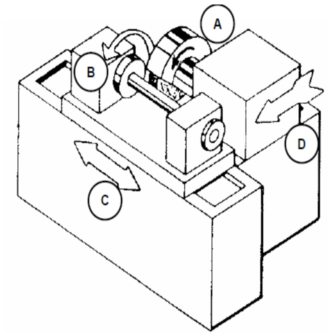
Wheel dressing and truing is done with special tools designed for that purpose. Although wheel dressing is often done manually between work cycles, some grinding machines perform the dressing task automatically.The application of coolants to the grinding process is important. Coolants reduce grinding machine power requirements, maintain work quality, stabilize part dimensions, and insure longer wheel life. Coolants are either emulsions, synthetic lubricants or special grinding oils. Coolants are applied by either flooding the work area or by high pressure jet streams.

2.3 TYPES OF GRINDING

There are many forms of grinding, but the four major industrial grinding processes are as follows:

- Cylindrical grinding
- Internal grinding
- Centerless grinding
- Surface grinding

These types of grinding are shown in Figure 2.2. In cylindrical grinding, the workpiece rotates about a fixed axis and the surfaces machined are concentric to that axis of rotation. Cylindrical grinding produces an external surface that may be either straight, tapered, or contoured. The basic components of a cylindrical grinder include a wheelhead, which incorporate the spindle and drive motor; a cross-slide, that moves the wheelhead to and from the workpiece; a headstock, which locates, holds, and drives the workpiece; and a tailstock, which holds the other end of the work.



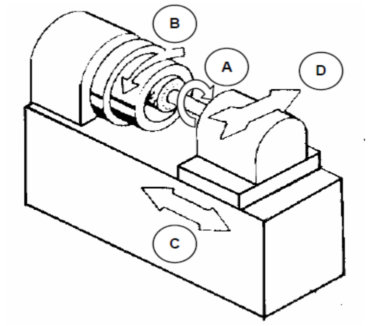
A: rotation of grinding wheel

B: work table rotation

C: reciprocation of worktable

D: Infeed

(a) Cylindrical grinding



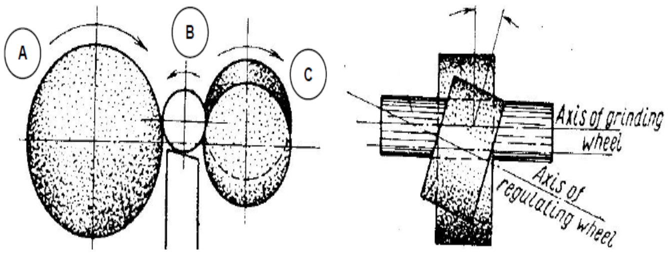
A: rotation of grinding wheel

B: workpiece rotation

C: reciprocation of worktable

D: infeed

(b) Internal Diameter Grinding

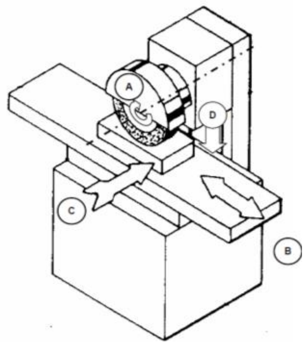


A: rotation of grinding wheel

B: workpiece rotation

C: reciprocation of worktable

(c) Centerless Grinding



A: rotation of grinding wheel

B: reciprocation of worktable

C: transverse feed

D: downfeed

(d) Surface grinding

Figure 2.2: Types of grinding

Internal diameter grinders (Figure 2.2(b)) finish the inside of a previously drilled, reamed, or bored hole, using small grinding wheels at high RPM. The principle elements of an internal grinding machine are the workhead, which holds the work and has its own drive, and the wheelhead, which is the internal grinding spindle. In addition to the rotary motions of work and wheel, an internal grinder has a traverse movement to bring the wheel to and from the work zone, and a reciprocating spindle movement for both the wheel's approach to the work surface and for the feed movement of the wheel during grinding. Several different internal contours can be produced within a workpiece using I.D.grinding.

In centerless grinding (Figure 2.2(c)), the workpiece rotates between a grinding wheel and aregulating drive wheel. The work is supported from below by a fixed work-rest blade. The two basic modes of centerless grinding are "thru-feed" and "in-feed". In the thru-feed mode, the work proceeds in the axialdirection through the slowly narrowing gap between the grinding wheel and the regulating wheel. Work is advanced by the axial force exerted on it by therotating surface of the regulating wheel. This is a highly productive form ofgrinding in that a number of workpieces can be ground simultaneously and in a continuous stream. The "infeed" mode is used for work with projecting heads that would prohibit "thru-feeding," the work is placed on the work-rest blade whileone wheel is retracted and fed to an end stop. The wheel is then brought back, reducing the gap between the wheels, grinding the work.

Surface grinding (Figure 2.2 (d)) produces flat, angular, or contoured surfaces by feeding workin a horizontal plane beneath a rotating grinding wheel. Work is most often magnetically attached to the table, and may be ground by either a traversing or rotating movement of the table. Most surface grinding machines use a horizontal spindle which adjusts up and down allowing either the edge or the face of the wheel to contact the work. Workpiece surfaces produced by grinding are influenced by the following factors:

- Workpiece material - harder materials allow finer finishes
- Type of wheel - fine grains yield finer finishes
- Dressing procedure - improperly dressed wheels will mar the work surface
- Feed rate - finer finishes are obtained with slower feed rates

- Machine rigidity - older, worn machines yield a poor quality finish
- Wheel condition - clogged wheels cannot produce a good finish
- Lubricant cleanliness - coolant filtration removes waste that could damage workpiece surface

2.4 GRINDING VARIABLES

The grinding process consists of several variables or parameters that affect the results of the experiment. The parameters were selected based on their availability through equipments and machinery capability available.

Grinding Pattern: There are two types of grinding pattern which are single pass and multiple pass. Single pass is defined when the grinding wheel passes along the grinding surface of the workpiece at a certain depth of cut only once. On the other hand, multiple pass is defined when the grinding wheel passes along the grinding surface of the workpiece ten times at a certain depth of cut.

Depth of Cut: Depth of cut is the determination of the depth of the grinding wheel into the workpiece at y-axis or vertically. It is done at depths of 20 µm, 40 µm and 60 µm.

Workpiecespeed: The workpiece speed is considered as a variable. There are three workpiece speed selected for this experiment which are 20, 30 and 40 m/s.

Types of Coolant: Most grinding machines are equipped with coolant systems. The coolant is directed over the point of contact between the grinding wheel and the work. This prevents distortion of the workpiece due to uneven temperatures caused by the cutting action. In addition, coolant keeps the chips washed away from the grinding wheel and point of contact, thus permitting free cutting. In this project, two types of coolants are used which are 5% soluble oil water-based conventional coolant and 0.1% titanium dioxide nanocoolant. The grinding results using these two different coolants will then be compared to see the effect of using nanocoolants instead of conventional coolants.

2.5 GRINDING PARAMETERS

From the manipulated parameters, the selected response parameters are surface roughness, grinding temperature and material removal rate (MRR) are discussed in the following section.

2.5.1 Surface Roughness

Characterization of surface topography is important in applications involving friction, lubrication, and wear (Thomas, 1999). In general, it has been found that friction increases with average roughness. The effect of roughness on lubrication has been studied to determine its impact on issues regarding lubrication of sliding surfaces, compliant surfaces, and roller bearing fatigue. Another area where surface roughness plays a critical role is contact resistance (Thomas, 1999). Thermal or electrical conduction between two surfaces in contact occurs only through certain regions. In the case of thermal conduction, the heat flow lines are squeezed together at the areas of contact, which results in a distortion of the isothermal lines, as illustrated in Figure 2.3.

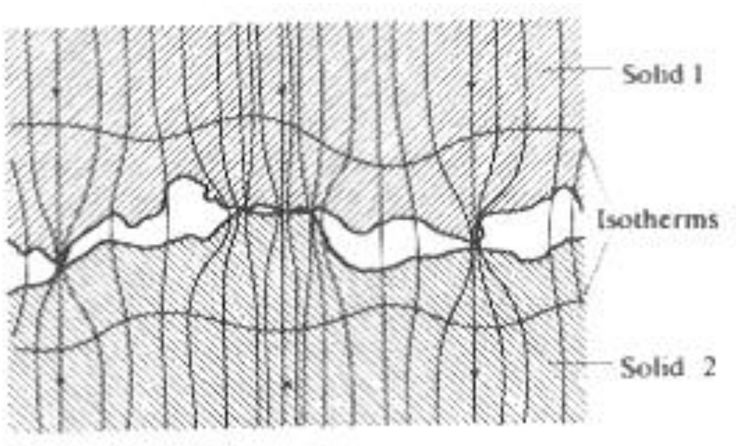


Figure 2.3: Contact resistance due to constriction of flow lines (Thomas, 1999)

2.5.2 Grinding Temperature

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 strengthreducing tensile residual stresses, and creates dimensional inaccuracies. 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 in this project where it will be influenced widely on the usage of nanocoolants.

When a grinding grit engages the workpiece, it first causes deformation. This stage is known as plowing. The stress level becomes great enough, chip formation begins. Finally, the chip breaks loose and is carried out of the grinding zone by grinding fluid. The fluid serves both to remove chips, collectively known as swarf, and to cool the workpiece. Cooling is often critical in grinding because a significant amount of heat is typically generated in the process. Heat is generated primarily by three actions. First is shearing or fracture of the workpiece during chip formation. Second is the friction of the chip sliding at the grit's rake face. Lastly, heat is generated along the portion of the grit worn flat either by truing or by previous passes through the workpiece. Heat generated by any of these means, when it is localized near the grit or in the chip, is known as hot-spot (flash) temperature. Each grit acts as an asperity heat source, with conduction serving to distribute the heat from individual grits and raise the overall temperature of the grinding surface.

2.5.3 Material Removal Rate

Material removal rate is one the most important response parameter for abrasive machining. It is often desired to have maximum value of MRR. It is defined as the amount of mass removed from the workpiece over a period of time. In this experiment, MRR is calculated as Eq. (2.1)

$$MRR = \frac{\text{Initial mass - Final mass}}{\text{Grinding time}} \tag{2.1}$$

2.6 NANOFLUIDS

Heat transfer fluids (HTFs) have many industrial and civil applications, including in transport, energy supply, air-conditioning and electronic cooling, etc. Traditional HTFs, such as water, oils, glycols and fluorocarbons, however, have inherently poor heat transfer performance due to their low thermal conductivities. Research and development activities are being carried out to improve the heat transport properties of fluids. Solid metallic materials, such as silver, copper and iron, and non-metallic materials, such as alumina, CuO, SiC and carbon nanotubes, have much higher thermal conductivities than HTFs. It is thus an innovative idea trying to enhance the thermal conductivity by adding solid particles into HTFs since Maxwell initiated it in 1881 (Maxwell, 1873). At the very beginning, solid particles of micrometer, even millimeter magnitudes were blended into the base fluids to make suspensions or slurries. However, large solid particles cause troublesome problems, such as abrasion of the surface, clogging the microchannels, eroding the pipeline and increasing the pressure drop, which substantially limits the practical applications. Actually, liquid suspension was primarily a theoretical treatment only of some theoretical interest, and subsequent studies by other researchers achieved minor success. The large size of the particles and the difficulty in production of small particles were limiting factors (Han, 2008). The situation changed when National Laboratory revisited this field with their nanoscale metallic particle and carbon nanotube suspensions (Choi and Eastman 1995; Eastman et al., 1997). They have tried to suspend various metals and metal oxides nanoparticles in several different fluids and the results are promising, however, many things remain elusive about these suspensions of nano-structured materials, which have been termed “nanofluids” (Das et al., 2008).

Nanofluids are solid-liquid composite materials consisting of solid nanoparticles or nanofibers with sizes typically of 1-100 nm suspended in liquid. Nanofluids have attracted great interest recently because of reports of greatly enhanced thermal properties. For example, a small amount (<1% volume fraction) of Cu nanoparticles or carbon nanotubes dispersed in ethylene glycol or oil is reported to increase the inherently poor thermal conductivity of the liquid by 40% and 150%, respectively. Conventional particle-liquid suspensions require high concentrations (>10%) of particles to achieve such enhancement (Das et al., 2008). However, problems of rheology and stability are amplified at high concentrations, precluding the widespread use of conventional slurries as heat transfer fluids. In some cases, the observed enhancement in thermal conductivity of nanofluids is orders of magnitude larger than predicted by well-established theories. Other perplexing results in this rapidly evolving field include a surprisingly strong temperature dependence of the thermal conductivity and a three-fold higher critical heat flux compared with the base fluids. These enhanced thermal properties are not merely of academic interest. When confirmed and found consistent, they would make nanofluids promising for applications in thermal management. Furthermore, suspensions of metal nanoparticles are also being developed for other purposes, such as medical applications, including cancer therapy. The interdisciplinary nature of nanofluid research presents a great opportunity for exploration and discovery at the frontiers of nanotechnology.

2.6.1 Cooling Challenge

Cooling is indispensable for maintaining the desired performance and reliability of a wide variety of products, such as computers, power electronics, car engines, and high-powered lasers or x-rays. With the unprecedented increase in heat loads (in some cases exceeding 25 kW) and heat fluxes (in some cases exceeding 2000 W/cm2) caused by more power and/or smaller feature sizes for these products, cooling is one of the top technical challenges facing high-tech industries such as microelectronics, transportation, manufacturing, metrology, and defense. The electronics industry has provided computers with faster speeds, smaller sizes, and expanded features, leading to ever-increasing heat loads, heat fluxes, and localized hot spots at the chip and package levels. These thermal problems are also found in power electronics or optoelectronic devices. Air cooling is the most basic method for cooling electronic systems. However, heat fluxes over 100 W/cm^2 in electronic devices and systems will necessitate the use of liquid cooling. Recently, single-phase liquid cooling technologies such as the microchannel heat sink, and two-phase liquid-cooling technologies such as heat pipes, thermosyphons, direct immersion cooling, and spray cooling for chip- or package-level cooling have emerged. Nanofluid technology offers a great potential for further development of high-performance, compact, cost-effective liquid cooling systems (Das et al., 2008). In the transportation industry, cooling is a crucial issue because the trend toward higher engine power and exhaust-gas regulation or hybrid vehicles inevitably leads to larger radiators and increased frontal areas, resulting in additional aerodynamic drag and increased fuel consumption. A pressing need for cooling also exists in ultrahigh–heat-flux optical devices with brighter beams, such as high-powered x-rays (Das et al., 2008).

2.6.2 Nanofluids as Coolant

Cooling is one of the most important technical challenges facing many diverse industries, including microelectronics, transportation, solid-state lighting, and manufacturing. Technological developments such as microelectronic devices with smaller (sub-100 nm) features and faster (multi-gigahertz) operating speeds, higher-power engines, and brighter optical devices are driving increased thermal loads, requiring advances in cooling. The conventional method forincreasing heat dissipation is to increase the areaavailable for exchanging heat with a heat transferfluid. However, this approach requires an undesirableincrease in the thermal management system's size. There is therefore an urgent need for new andinnovative coolants with improved performance. The novel concept of 'nanofluids' – heat transfer fluidscontaining suspensions of nanoparticles – has beenproposed as a means of meeting these challenges (Keblinski et al., 2005). The emergence of nanofluids as a new field of nanoscale heat transfer in liquids is related directly to miniaturization trends and nanotechnology. Modern nanotechnology can produce metallic or nonmetallic particles of nanometer dimensions. Nanomaterials have unique mechanical, optical, electrical, magnetic, and thermal properties. Nanofluids are engineered by suspending nanoparticles with average sizes below 100 nm in traditional heat transfer fluids such as water, oil, and ethylene glycol. A very small amount of guest nanoparticles, when dispersed uniformly and suspended stably in host fluids, can provide dramatic improvements in the thermal properties of host fluids. Table 2.1 shows the thermal conductivity of various materials (Wang et al., 2006).

Table 2.1: Thermal conductivity of various materials (Wang et al., 2006)

Type	Material	Thermal conductivity (W/m.K)at 300k
Metallic solids	Silver	429
	Copper	401
	Aluminum	237
Nonmetallic solids	Diamond	3300
	Carbon nanotubes	3000
	Silicon	148
	Alumina (Al_2O_3)	40
Metallic liquids	Sodium at 644K	72.3
Nonmetallic liquids	Water	0.613
	Ethylene glycol	0.253
	Engine oil	0.145

It is well known that at room temperature, metals in solid form have orders-of magnitude higher thermal conductivities than those of fluids (Touloukian et al., 1970). For example, the thermal conductivity of copper at room temperature is about 700 times greater than that of water and about 3000 times greater than that of engine oil as shown in Table 2.1. The thermal conductivity of metallic liquids is much greater than that of nonmetallic liquids. Therefore, the thermal conductivities of fluids that contain suspended solid metallic particles could be expected to be significantly higher than those of conventional heat transfer fluids.The basic concept of dispersing solids in fluids to enhance thermal conductivity is not new. Solid particles are added because they conduct heat much better than do liquids. The major problem with the use of large particles is the rapid settling of these particles in fluids. Other problems are abrasion and clogging. These problems are highly undesirable for many practical cooling applications. Nanofluids have pioneered in overcoming these problems by stably suspending in fluids nanometer-sized particles instead of millimeter- or micrometer-sized particles. Compared with microparticles, nanoparticles stay suspended much longer and possess a much higher surface area. The surface/volume ratio of nanoparticles is 1000 times larger than that of microparticles. The high surface area of nanoparticles enhances the heat conduction of nanofluids since heat transfer occurs on the surface of the particle. The number of atoms present on the surface of nanoparticles, as opposed to the interior, is very large. Therefore, these unique properties of nanoparticles can be exploited to develop nanofluids with an unprecedented combination of the two features most highly desired for heat transfer systems: extreme stability and ultrahigh thermal conductivity. Furthermore, because nanoparticles are so small, they may reduce erosion and clogging dramatically. Other benefits envisioned for nanofluids include decreased demand for pumping power, reduced inventory of heat transfer fluid, and significant energy savings.Because the key building block of nanofluids is nanoparticles (1000 times smaller than microparticles), the development of nanofluids became possible simply because of the advent of nanotechnology in general and the availability of nanoparticles in particular. Researchers in nanofluids exploit the unique properties of these tiny nanoparticles to develop stable and high-thermal-conductivity heat transfer fluids. Stable suspension of small quantities of tiny particles makes conventional heat transfer fluids cool faster and thermal management systems smaller and lighter.Size is also an important physical variable in nanofluids because it can be used to tailor nanofluid thermal properties as well as the suspension stability of nanoparticles. Nanotechnogy offers excellent prospects for producing a new type of heat transfer fluid that has excellent thermal properties and cooling capacity, due primarily to novel nanoscale phenomena. Table 2.2 contrasts suspensions of microparticles and nanoparticles and shows the benefits of nanofluids containing nanoparticles.

Table 2.2: Comparison between microparticles and nanoparticles

Characteristic	Microparticles	Nanoparticles
Stability	Settle	Stable (remain in suspension almost indefinitely)
Surface/volume ratio	1	1000 times larger than that of microparticles
Conductivity	Low	High
Clog in microchannel?	Yes	No
Erosion?	Yes	No
Pumping power	Large	Small
Nanoscale phenomena?	No	Yes

2.6.3 Titanium Dioxide

Titanium Dioxide (TiO_2) has a wide range of applications. Since its commercial production in the early twentieth century, it is used as a pigment in paints, coatings, sunscreens, ointments and toothpaste. $TiO_2$is considered a “quality–of–life” product with demand affected by gross domestic product in various regions of the world. Titanium dioxide pigments are inorganic chemical products used for imparting whiteness, brightness and opacity to a diverse range of applications and end–use markets. TiO_2as a pigment derives value from its whitening properties and opacifying ability (commonly referred to as hiding power). As a result of TiO_2's high refractive index rating, it can provide more hiding power than any other commercially available white pigment. Titanium dioxide is obtained from a variety of ores that contain ilmenite, rutile, anatase and leucoxene, which are mined from deposits located throughout the world.

2.7 PREPARATION OF NANOFLUIDS

Several studies, including the earliest investigations of nanofluids, used a two-step method in which nanoparticles or nanotubes are first produced as a dry powder and then dispersed into a fluid in a second processing step. In contrast, the one-step method entails the synthesis of nanoparticles directly in the heat transfer fluid.

2.7.1 Two step process

Several studies, including the earliest investigations of nanofluids, used a two-step process (Lee et al., 1999) in which nanoparticles or nanotubes are first produced as a dry powder, often by inert gas condensation. Chemical vapor deposition has also been used to produce materials for use in nanofluids, particularly multiwalled carbon nanotubes. The nanoparticles or nanotubes are then dispersed into a fluid in a second processing step. Simple techniques such as ultrasonic agitation or the addition of surfactants to the fluids are sometimes used to minimize particle aggregation and improve dispersion behavior. Such a two-step process works well in some cases, such as nanofluids consisting of oxide nanoparticles dispersed in deionized water (Lee et al., 1999). Less success has been found when producing nanofluids containing heavier metallic nanoparticles (Eastman et al., 1997). Since nanopowder synthesis techniques have already been scaled up to industrial production levels by several companies (Romano et al., 1997), there are potential economic advantages in using two-step synthesis methods that rely on the use of such powders.

2.7.2 One step process

Single-step nanofluid processing methods have also been developed. For example, nanofluids containing dispersed metal nanoparticles (Eastman et al., 2001) have been produced by a ‘directevaporation’ technique (Yatsuya et al., 1978). As with the inert gas condensation technique, this involves the vaporization of a source material under vacuum conditions. An advantage of this technique is that nanoparticle agglomeration is minimized, while a disadvantage is that only low vapor pressure fluids are compatible with the process. Various single-step chemical synthesis techniques can also be employed to produce nanofluids.

2.8 ARTIFICIAL NEURAL NETWORK TECHNIQUE

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neuronsas illustrated in Figure 2.4 (Sydenham and Thorn, 2005).The complexity of real neurons is highly abstracted when modelling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependance of a certain threshold). ANNs combine artificial neurons in order to process information.

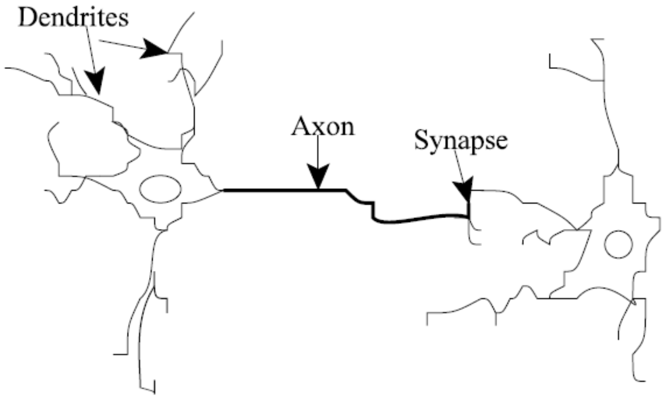


Figure 2.4: Natural neurons (artist's conception).

The higher a weight of an artificial neuron is, the stronger the input which is multiplied by it will be. Weights can also be negative, so we can say that the signal is inhibited by the negative weight. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron we can obtain the output we want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. But we can find algorithms which can adjust the weights of the ANN in order to obtain the desired output from the network. This process of adjusting the weights is called learning or training. The number of types of ANNs and their uses is very high. Since the first neural model there have been developed hundreds of different models considered as ANNs. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc. Also, there are many hybrid models where each neuron has more properties than the ones we are reviewing here. Because of matters of space, we will present only an ANN which learns using the backpropagation algorithm for learning the appropriate weights, since it is one of the most common models used in ANNs, and many others are based on it(Sydenham et al., 2005).Since the function of ANNs is to process information, they are used mainly in fields related with it. There are a wide variety of ANNs that are used to model real neural networks, and study behaviour and control in animals and machines, but also there are ANNs which are used for engineering purposes, such as pattern recognition, forecasting, and data compression (Sydenham and Thorn, 2005).

A typical artificial neuron and the modeling of a multilayered neural network are illustrated in Figure 2.5. Referring to Figure 2.5, the signal flow from inputs $x_1 \ldots x_n$ is considered to be unidirectional, which are indicated by arrows, as is a neuron's output signal flow (O). The neuron output signal O is given by Eq. (2.11):

$$O = f(net) = f\left(\sum_{j=1}^{n} w_j x_j\right) \qquad (2.11)$$

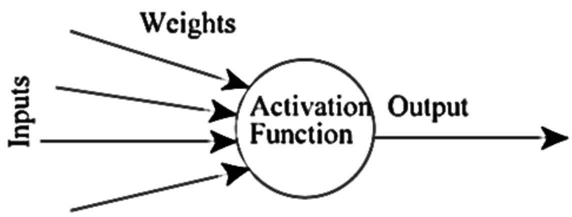


Figure 2.5: An artificial neuron

Where w_j is the weight vector, and the function f (net) is referred to as an activation (transfer) function. The variable net is defined as a scalar product of the weight and input vectors,

$$net = w^T x = w_1 x_1 + \ldots + w_n x_n \qquad (2.12)$$

Where T is the transpose of a matrix, and, in the simplest case, the output value O is computed as Eq. (2.13).

$$O = f(\text{net}) = \begin{cases} 1 & \text{if } w^T x \geq \theta \\ 0 & \text{Otherwise} \end{cases} \qquad (2.13)$$

Where θ is called the threshold level; and this type of node is called a linear threshold unit.

Environmental modeling involves using a variety of approaches, possibly in combination. Choosing the most suitable approach depends on the complexity of the problem being addressed and the degree to which the problem is understood. Assuming adequate data and computing resources and if a strong theoretical understanding of the problem is available then a full numerical model is perhaps the most desirable solution. However, in general, as the complexity of a problem increases the theoretical understanding decreases (due to ill-defined interactions between systems) and statistical approaches are required(Gardner et al., 1998). Recently, the multilayer perceptron has been shown to be effective alternatives to more traditional statistical techniques (Schalkoff, 1992).Primarily, it has been shown that the multilayer perceptron can be trained to approximate virtually any smooth, measurable function (Horniket al., 1989). Unlike other statistical techniques the multilayer perceptron makes no prior assumptions concerning the data distribution. It can model highly non-linear functions and can be trained to accurately generalise when presented with new, unseen data. These features of the multilayer perceptron make it an attractive alternative to developing numerical models, and also when choosing between statistical approaches. As will be seen the multilayer perceptron has many applications in the atmospheric sciences. The multilayer perceptron consists of a system of simple interconnected neurons, or nodes, as illustrated in Figure 2.6, which is representing a nonlinear mapping between an input vector and an output vector. The nodes are connected by weights and output signals which are a function of the sum of the inputs to the node modiÞed by a simple nonlinear transfer, or activation, function. It is the superposition of many simple nonlinear transfer functions that are described as being fully connected, with each nodeconnected to every node in the next and previous layer (Gardner et al., 1998).

By selecting a suitable set of connecting weights and transfer functions, it has been shown that a multilayer perceptron can approximate any smooth, measurable function between the input and output vectors (Hornik et al., 1989). Multilayer perceptrons have the ability to learn through training. Figure 2.7 shows a multilayer perceptron with two hidden layers.Training requires a set of training data, which consists of a series of input and associated output vectors. During training the multilayer perceptron is repeatedly presented with the training data and the weights in the network are adjusted until the desired input-output mapping occurs. Multilayer perceptrons learn in a supervised manner. During training the output from the multilayer perceptron, for a given input vector, may not equal the desired output. An error signal is defined as the difference between the desired and actual output. Training uses the magnitude of this error signal to determine to what degree the weights in the network should be adjusted so that the overall error of the multilayer perceptron is reduced. There are many algorithms that can be used to train a multilayer perceptron. Once trained with suitably representative training data the multilayer perceptron can generalise to new, unseen input data (Gardner et al., 1998).

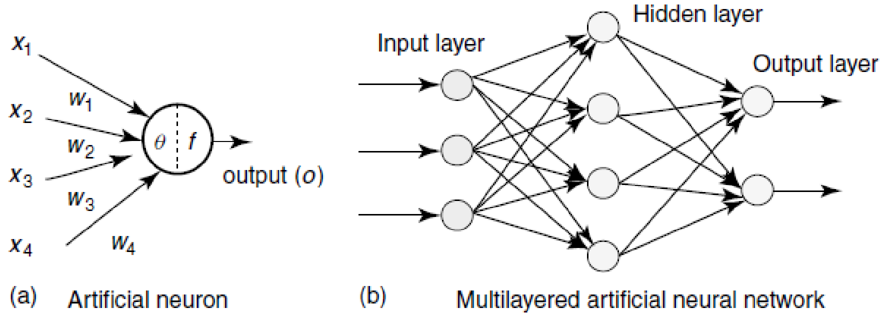


Figure 2.6: Architecture of an artificial neuron and a multilayered neural network.

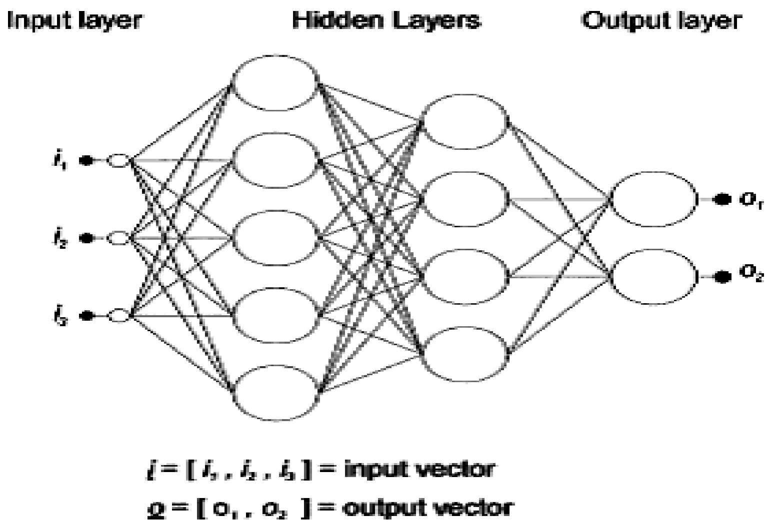


Figure 2.7: A multilayer perceptron with two hidden layers.

Source: Gardner et al.(1998)

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

This project is mainly about analyzing the effect of nanofluids as coolant on cast iron in grinding process. It is carried out based on several parameters which are type of grinding wheel, depth of cut and grinding pattern where we observe the output parameters which are surface roughness, grinding temperature and MRR. The experiment is designed using design of experiment method (DOE). DOE is a technique that enables designers to determine simultaneously the individual and interactive effects of many factors that could affect the output results in any design. DOE also provides a full insight of interaction between design elements; therefore, it helps turn any standard design into a robust one. In addition, the DOE tool comes with full supporting plots that enable designers to determine simultaneously the individual and interactive effects of many factors that could affect the output results in any design. Pareto plots, main effects and Interactions plots can be automatically displayed from the data display tool for study and investigation. However, DOE is illustrated using a manual calculations approach in order to allow you to observe how the analysis and results are calculated, and what these results mean. After generating several combinations of grinding parameters such as depth of cut, type of grinding wheel and grinding pattern, the experiment is conducted and run according to various combination. Data is then collected and lastly, the data will be analyzed using response surface method (RSM) and artificial neural network method (ANN) to determine the best optimum response on the output parameters.

3.2 WORKPIECE PREPARATION

Firstly, the sample of ductile cast iron obtained from the foundry lab was in the condition as shown in Figure 3.1. It was machined using carbide cutting tool in dry end milling condition. Milling is the most common form of machining, a material removal process, which can create a variety of features on a part by cutting away the unwanted material. The milling process requires a milling machine, workpiece, fixture, and cutter. The workpiece is a piece of pre-shaped material that is secured to the fixture, which itself is attached to a platform inside the milling machine. The cutter is a cutting tool with sharp teeth that is also secured in the milling machine and rotates at high speeds. By feeding the workpiece into the rotating cutter, unwanted material is cut away from the workpiece in the form of small chips to create the desiredshape in Figure 3.2.

Figure 3.1: Initial form of workpiece

Milling is typically used to produce parts that are not axially symmetric and have many features, such as holes, slots, pockets, and even three-dimensional surface contours. Parts that are fabricated completely through milling often include components that are used in limited quantities, perhaps for prototypes, such as custom designed fasteners or brackets. Another application of milling is the fabrication of tooling for other processes. For example, three-dimensional molds are typically milled. It is also commonly used as a secondary process to add or refine features on parts that manufactured using a different process.

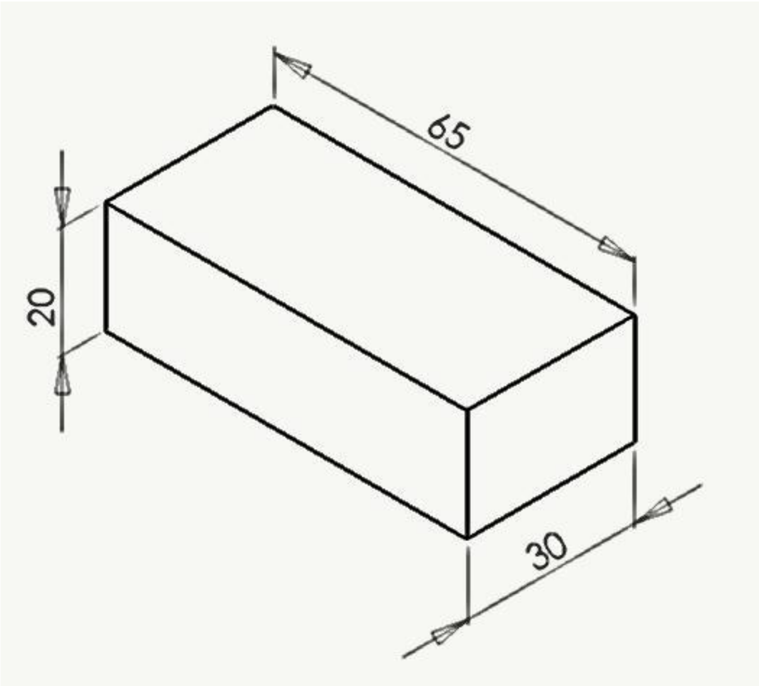


Figure 3.2: Desired form of workpiece

Due to the high tolerances and surface finishes that milling can offer, it is ideal for adding precision features to a part whose basic shape already was formed. In milling, the speed and motion of the cutting tool were specified through several parameters. These parameters are selected for each operation based upon the workpiece material, tool material, tool size, and more. The spindle speed isdetermined using Eq. (3.1):

$$Spindle\ speed = \frac{c.s\ X\ 1000}{\pi d} \tag{3.1}$$

Where*c.s*is cutting speed and *d*is tool or cutter diameter.

Squaring process has been done to obtain workpiece with dimensions illustrated in figure 3.2. Machining problems associated with cast iron were drilling, milling, turning and other machining processes. Most of the problems were due to the microstructure formation/changes during the machining process itself. As during the high pressure drilling operation, the matrix structure of the cast iron was changed actually due to stress transformation of the high carbon-retained austenite in the matrix into martensite (Griffin et al., 2007). Milling process is done using Partner milling machine with the guidance of a digital panel that indicates the distance for the *x*, *y* and *z* axis. The spindle speed is calculated and set constant and the feed rate is set automatically. As a result, a long square block of cast iron is obtained.

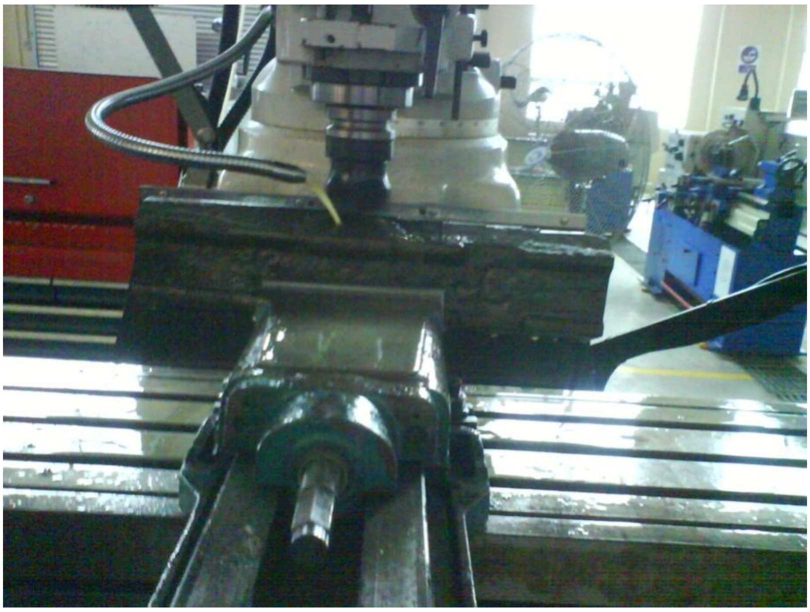


Figure 3.3: Milling process

3.3 WORKPIECE COMPOSITION

The determination of the composition of the workpiece is done using a spectrometer. The importance of the spectrometer as a scientific instrument is based on a simple but crucial fact. Light is emitted or absorbed when an electron changes its orbit within an individual atom. Because of this, the spectrometer is a powerful tool for investigating the structure of atoms. It is also a powerful tool for determining which atoms are present in a substance.

3.4 SURFACE GRINDING

The grinding process is performed using a precision surface grinder machine. Figure 3.4 shows the precision surface grinder. The grinding wheel used is aluminum oxide grinding wheel. Figure 3.5 presents aluminum oxide grinding wheel. The grinding process is done using two types of coolants which are conventional coolant and nanocoolant in order to study the different effects in grinding process of the two coolants.

Figure 3.4: Precision surface grinder

Figure 3.5: Aluminum oxide grinding wheel.

3.5 NANOCOOLANT PREPARATION

The nanocoolant is prepared for the experiment is 0.1% titanium dioxide, TiO_2 nanocoolant. Figure 3.6 shows the preparation of nanocoolant. Preparation is carried out using the one step process. In this process the dispersion of nanoparticles is obtained by direct evaporation of the nanoparticle metal and condensation of the nanoparticles in the base liquid and is the best technique for metallic nanofluids. It is prepared by using distilled water as the base fluid and is mixed with 0.1% TiO_2 in liquid form.

(a)Bottle of TiO_2 nanoparticle (b) Mixing process

Figure 3.6: Preparation of Nanocoolant

3.6 SURFACE ROUGHNESS

The roughness of the grinded surface is measured using a perthometer as shown is Figure 3.7. It is measured in two directions which are along the grinded surface and across the grinded surface. It is measured in micrometer (µm). Figure 3.8 shows the scanning electron microscope (SEM). Itis carried out in order to study the surface topography of the workpiece in result to the grinding process using two different coolants.

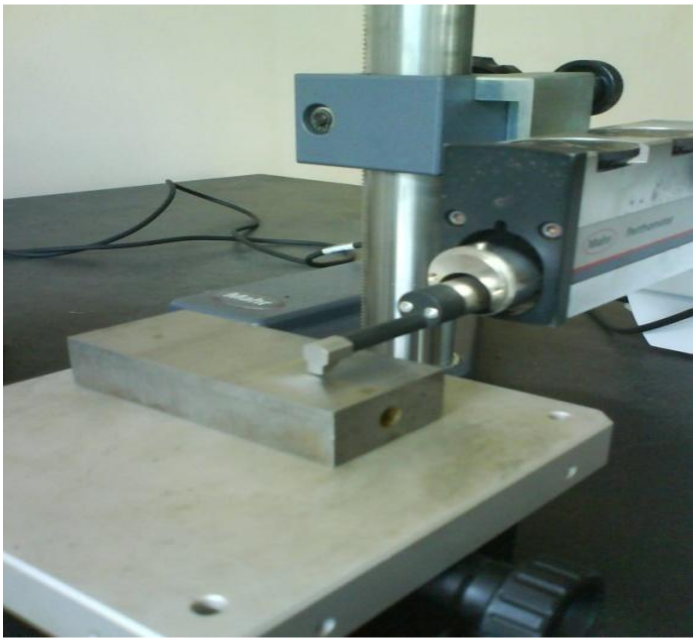


Figure 3.7: Measuring surface roughness using a Perthometer

Figure 3.8: Scanning electron microscope

3.7 GRINDING TEMPERATURE

The grinding temperature is determined by comparing the difference between the initial temperature of the workpiece which is before grinding and the final temperature of the workpiece which is after grinding. The temperature is measured using a thermocouple which is located in a hole grinded at the side surface of the workpiece.

3.8 DESIGN OF EXPERIMENT

Any scientific investigation involves formulation of certain hypotheses whose validity is examined through the data generated from an experiment conducted for the purpose. Thus, experimentation becomes indispensable part of every scientific endeavor and designing an experiment is integrated component. Experimental design is the process of planning a study to meet specified objectives. Planning an experiment properly is very important in order to ensure that the right type of data and a sufficient sample size and power are available to answer the research questions of interest as clearly and efficiently as possible.For this study, the DOE is designed using the JMP software. The steps of creating the DOE are described as Table 3.1.

Table 3.1: Design of Experiment (DOE)

Run	DOC	TS	Temperature rise	MRR	Ra
1	20	20	-	-	-
2	20	30	-	-	-
3	20	40	-	-	-
4	40	20	-	-	-
5	40	30	-	-	-
6	40	40	-	-	-
7	60	20	-	-	-
8	60	30	-	-	-
9	60	40	-	-	-

3.9 RESPONSE SURFACE METHOD

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes. The most extensive applications of RSM are in the particular situations where several input variables potentially influence some performance measure or quality characteristic of the process. Thus performance measure or quality characteristic is called the response. The input variables are sometimes called independent variables. The field of response surface methodology consists of the experimental strategy for exploring the space of the process or independent variables, empirical statistical modeling to develop an appropriate approximating relationship between the yield and the process variables, and optimization methods for finding the values of the process variables that produce desirable values of the response. In this report we will concentrate on the second strategy: statistical modeling to develop an appropriate approximating model between the response y and independent variables $\xi_1,\xi_2,...,\xi_k$ (Carley et al., 2004).

In general, the relationship is expressed as Eq. (3.2):

$$y = f\left(\xi_1, \xi_2, \ldots, \xi_k\right) + \varepsilon \tag{3.2}$$

where the form of the true response function $f$is unknown and perhaps very complicated, and $\varepsilon$is a term that represents other sources of variability not accounted for in f. Usually ε includes effects such as measurement error on the response, background noise, the effect of other variables, and so on. Usually $\varepsilon$is treated as a statistical error, often assuming it to have a normal distribution with mean zero and variance σ^2. Then

$$E(y) = \eta = E\left[f\left(\xi_1, \xi_2, \ldots, \xi_k\right)\right] + E(\varepsilon) = f\left(\xi_1, \xi_2, \ldots, \xi_k\right) \tag{3.3}$$

The variables ξ_1, ξ_2, ...,ξ_k in Eq.(3.3) are usually called the natural variables, because they are expressed in the natural units of measurement, such as degrees Celsius, pounds per square inch, etc. In much RSM work it is convenient to transform the natural variables to codedvariablesx_1, x_2,...,x_k, which are usually defined to be dimensionless with mean zero and the same standard deviation. In terms of the coded variables, the response function will be written as Eq. (3.4).

$$\eta = f\left(x_1, x_2, \ldots, x_k\right) \quad (3.4)$$

Because the form of the true response function f is unknown, we must approximate it. In fact, successful use of RSM is critically dependent upon the experimenter’s ability to develop a suitable approximation for *f*. Usually, a low-order polynomial in some relatively small region of the independent variable space is appropriate. In many cases, either a first-order or a second order model is used (Carley et al., 2004). The first-order model is likely to be appropriate when the experimenter is interested in approximating the true response surface over a relatively small region of the independentvariable space in a location where there is little curvature in *f*(Carley et al, 2004). For the case of two independent variables, the first-order model in terms of the coded variables is in Eq. (3.5).

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \quad (3.5)$$

The form of the first-order model in Eq. (3.5) is sometimes called a main effects model, because it includes only the main effects of the two variables x_1 and x_2. There is an interaction between these variables; it can be added to the model easily as follows:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_{12} x_1 x_2 \quad (3.6)$$

This is the first-order model with interaction. Adding the interaction term introduces curvature into the response function(Carley et al., 2004). Often the curvature in the true response surface is strong enough that the first-order model (even with the interaction term included) is inadequate. A second-order model will likely be required in these situations. For the case of two variables, the second-order model is expressed as Eq. (3.7).

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1{}^2 + \beta_{22} x_2{}^2 + \beta_{12} x_1 x_2 \quad (3.7)$$

This model would likely be useful as an approximation to the true response surface in a relatively small region. The second-order model is widely used in response surface methodology for several reasons:

1. The second-order model is very flexible. It can take on a wide variety of functional forms, so it will often work well as an approximation to the true response surface.
2. It is easy to estimate the parameters (the β's) in the second-order model. The method of least squares can be used for this purpose.
3. There is considerable practical experience indicating that second-order models work well in solving real response surface problems.

In general, the first-order model is in Eq. (3.8).

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \quad (3.8)$$

and the second-order model is in Eq. (3.9).

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i<} \sum_{j=2}^{k} \beta_{ij} x_i x_j \quad (3.9)$$

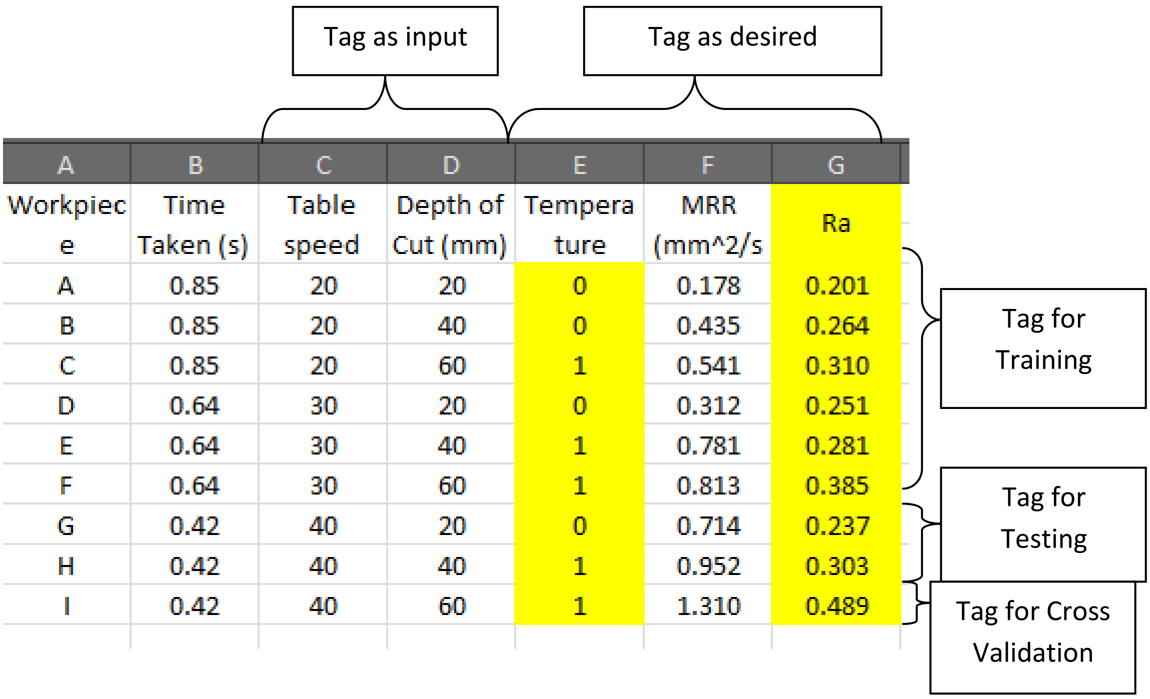
In some infrequent situations, approximating polynomials of order greater than two are used. The general motivation for a polynomial approximation for the true response function *f* is based on the Taylor series expansion around the point x_{10}, x_{20}, ...,x_{k0}. Finally, let's note that there is a close connection between RSM and linear regression analysis. For example, consider the model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \quad (3.10)$$

The β's are a set of unknown parameters. To estimate the values of these parameters, we must collect data on the system we are studying. Because, in general, polynomial models are linear functions of the unknown β's, we refer to the technique as linear regression analysis (Carley et al., 2004).

3.10 MULTILAYER PERCEPTRON APPROACH

Multilayer perceptron (MLP) approach is an analysis method under Artificial Neural Networks. In this project, the analysis is done using the NeuroSolutions6 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. Figure 3.9 shows the tagged input parameters to develop the MLP model.



A	B	C	D	E	F	G
Workpiece	Time Taken (s)	Table speed	Depth of Cut (mm)	Temperature	MRR (mm^2/s	Ra
A	0.85	20	20	0	0.178	0.201
B	0.85	20	40	0	0.435	0.264
C	0.85	20	60	1	0.541	0.310
D	0.64	30	20	0	0.312	0.251
E	0.64	30	40	1	0.781	0.281
F	0.64	30	60	1	0.813	0.385
G	0.42	40	20	0	0.714	0.237
H	0.42	40	40	1	0.952	0.303
I	0.42	40	60	1	1.310	0.489

Figure 3.9: Tagged input parameters and output data

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.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter presents the results obtained from the grinding process using two different types of coolants including the conventional coolant and nanocoolant for single pass and multiple pass grinding patterns. The selected parameters for this study are surface roughness, grinding temperature and material removal rate (MRR). The experimental data are analysed using response surface method and artificial neural network using a multilayer perceptron approach. Microstructure analysis using scanning electron microscope (SEM) is also included to observe the effects of different coolants of the material.

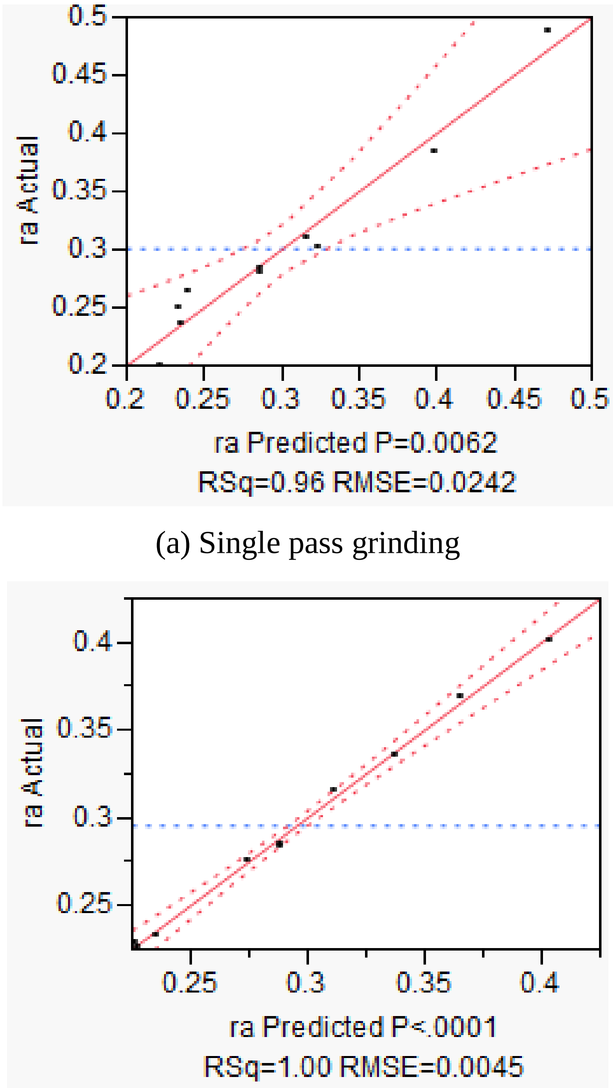
4.2 REPONSE SURFACE METHOD

Equations(4.1)and (4.2) show the prediction equation that are obtained from performing RSM for surface roughness for single pass and multiple pass grinding using nanocoolant. Theseequations are used to calculate the prediction value that is to be compared with experimental value.

$$\begin{aligned} Ra = {} & 0.5087142857 + 0.09616667 \times \left(\frac{(TS-30)}{10}\right) + 0.0751667 \times \left(\frac{DOC-40}{20}\right) \\ & + \left(\frac{TS-30}{10} \times \frac{DOC-40}{20} \times 0.02625\right) \\ & + \left(\frac{TS-30}{10} \times \frac{TS-30}{10} \times -0.02792857\right) \\ & + \left(\frac{DOC-40}{20} \times \frac{DOC-40}{20} \times -0.1479285714\right) \end{aligned} \tag{4.1}$$

$$Ra = 0.2752857 + 0.00561667 \times \left(\frac{(TS-30)}{10}\right) + 0.051833 \times \left(\frac{DOC-40}{20}\right) + \left(\frac{TS-30}{10} \times \frac{DOC-40}{20} \times 0.00675\right) + \left(\frac{TS-30}{10} \times \frac{TS-30}{10} \times -0.01107142857\right) + \left(\frac{DOC-40}{20} \times \frac{DOC-40}{20} \times 0.05192857\right) \quad (4.2)$$

Figure 4.1 shows the prediction profile plot for surface roughness for single pass and multiple pass using 0.1% titanium dioxide as grinding coolant. The desired value for Rsq is above 0.90 where it proves the validity of mathematical models.



(a) Single pass grinding

(b) Multiple pass grinding

Figure 4.1: Surface roughness prediction plot

From Table 4.1, it is observed that only the P-value of ANOVA for Temperature Rise exceeds 0.05 while the values for MRR and surface roughness is less than 0.05. For this to matter, the P-value for Lack of Fit is then observed. For the lack of fit, all the values are more than 0.05, whichis desired. Therefore, all the prediction equations for output response are valid. Table 4.2 shows the comparison between the actual and predicted results of grinding output parameters for TiO_2nanocoolant with single pass grinding pattern.

Table 4.1: ANOVA resultsVariance analysis for second order surface roughness in single pass and multiple pass using 0.1% titanium dioxide water based nanocoolant

Source	Degree of freedom	Sum of sq.	F-static	P-value
		Single pass grinding		
Model	5	0.1498406	11.966	0.0161
Error	4	0.0100169		
C.Total	9	0.1598576		
Interaction	10			
Lack-of-Fit	3	0.00990449	29.3466	0.1347
Pure Error	1	0.00011250		
Total	4	0.01001699		
		Multi-pass grinding		
Model	5	0.04153661	24.0272	0.0044
Error	4	0.00138299		
C.Total	9	0.04291960		
Interaction	10			
Lack-of-Fit	3	0.00137049	36.5463	0.1209
Pure Error	1	0.00001250		
Total	4	0.00138299		

From Table 4.1, it is observed that only the P-value of ANOVA for Temperature Rise exceeds 0.05 while the values for MRR and surface roughness is less than 0.05. For this to matter, the P-value for lack of fit is then observed. For the lack of fit, all the values are more than 0.05 which desired. Therefore all the prediction equations for output response are valid. Table 4.3 shows the comparison results between the experimental and predicted value for TiO_2 nanocoolant with multiple pass grinding pattern.

Table 4.2: Comparison between experimental value and predicted value for 0.1% TiO_2 nanocoolant with multiple pass grinding pattern

Table Speed (m/min)	Depth of Cut (μm)	Temperature rise (°C)		MRR (g/sec)		Surface Roughness (μm)	
		Exp.	Predicted	Exp.	Predicted	Exp.	Predicted
20	20	0	-0.22381	0.178	0.166107	0.201	0.221488
20	40	0	0.114286	0.435	0.380952	0.264	0.232857
20	60	1	0.109524	0.541	0.65694	0.310	0.234655
30	20	0	0.447619	0.312	0.451619	0.251	0.238524
30	40	1	0.785714	0.781	0.724714	0.281	0.285643
30	60	1	0.780952	0.813	1.058952	0.385	0.32319
40	20	0	0.77619	0.714	0.536274	0.237	0.314988
40	40	1	1.114286	0.952	0.867619	0.303	0.397857
40	60	1	1.109524	1.310	1.260107	0.489	0.471155

Table 4.3: Comparison between experimental value and predicted value (0.1% TiO_2)

Table Speed (m/min)	Depth of Cut (μm)	Temperature rise (°C)		MRR (g/sec)		Surface Roughness (μm)	
		Exp.	Predicted	Exp.	Predicted	Exp.	Predicted
20	20	0	-0.25952	0.02299	0.02284	0.226	0.22681
20	40	0	0.352381	0.05172	0.031709	0.276	0.226048
20	60	1	0.90714	0.06322	0.11404	0.336	0.235143
30	20	0	0.352384	0.03846	0.059146	0.229	0.274048
30	40	1	0.714286	0.08462	0.084744	0.284	0.287786
30	60	1	1.019044	0.09077	0.183806	0.369	0.311381
40	20	1	0.907146	0.10714	0.055944	0.233	0.337143
40	40	1	1.019048	0.19048	0.098272	0.316	0.365381
40	60	1	1.073806	0.21429	0.214064	0.401	0.403476

4.3 MULTILAYER PERCEPTRON APPROACH

4.3.1 Single Pass Grinding Pattern

Figure 4.2 represents the comparison between desired output value and actual network. Figure 4.3 represents the sensitivity about the mean for single 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 followed by MRR while the surface roughness is the least affected.Table 4.4 shows the comparison between the output parameters of desired value (predicted) and actual value (experimental) for single pass grinding pattern.Figure 4.4 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.

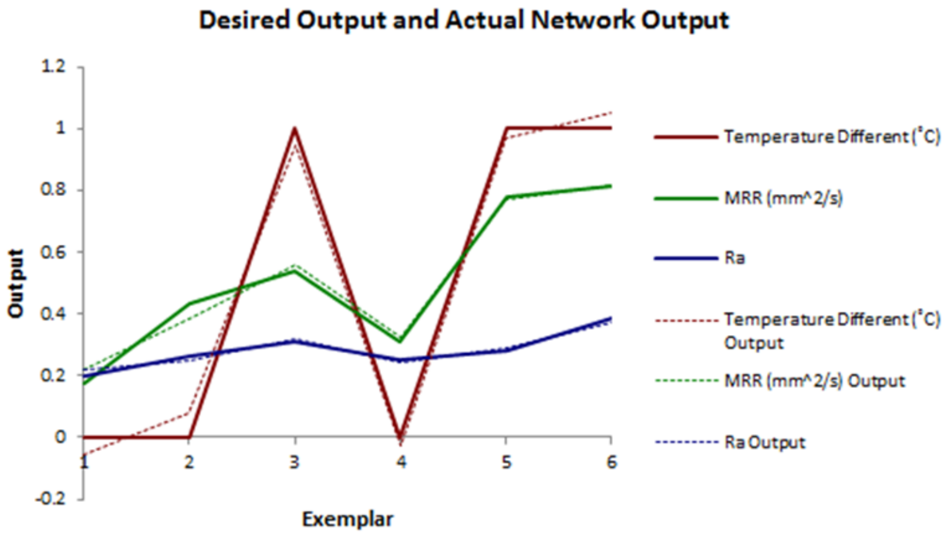


Figure 4.2: Desired output and actual network output for single pass grinding

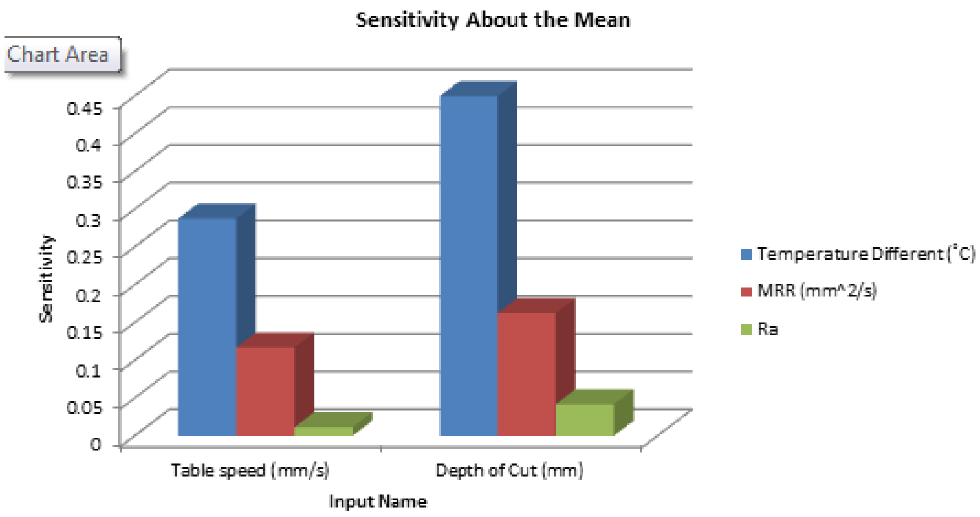
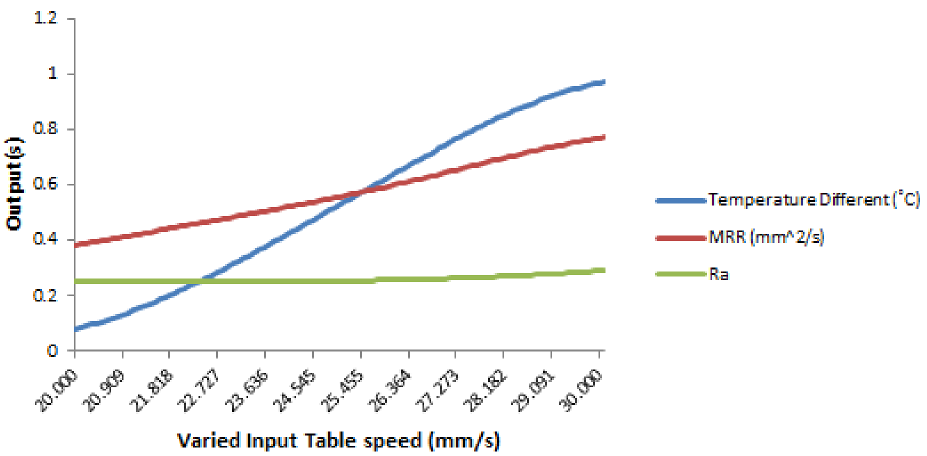


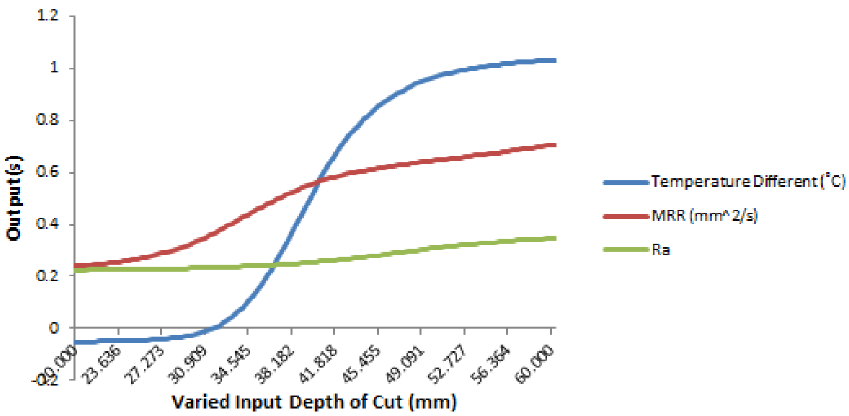
Figure 4.3: Sensitivity analysis for single pass

Table 4.4: 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)	
		Exp.	Predicted	Exp.	Predicted	Exp.	Predicted
20	20	0	-0.0540739	0.178	0.21932251	0.201	0.21788301
20	40	0	0.07946455	0.435	0.3830495	0.264	0.25120899
20	60	1	0.9463876	0.541	0.5621653	0.310	0.31710736
30	20	0	-0.028191	0.312	0.32618009	0.251	0.24245339
30	40	1	0.96933321	0.781	0.76872709	0.281	0.28908126
30	60	1	1.05191041	0.813	0.81456429	0.385	0.37242817
40	20	0	0.95158659	0.714	0.8018772	0.237	0.320733
40	40	1	1.04126467	0.952	0.83014882	0.303	0.32380495
40	60	1	1.05119844	1.310	0.82710682	0.489	0.36369481



(a) Table speed



(b) Depth of cut

Figure 4.4: Effect of network outputs for single pass grinding

4.3.2 Multiple Pass Grinding Pattern

Figure 4.5 represents the comparison between desired output value and actual network output for TiO_2nanocoolant with multiple pass grinding pattern. Figure 4.6 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. Table 4.5 shows the comparison of output value between desired value (predicted) and actual value (experimental) for multiple pass grinding patterns. Figure 4.7 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.

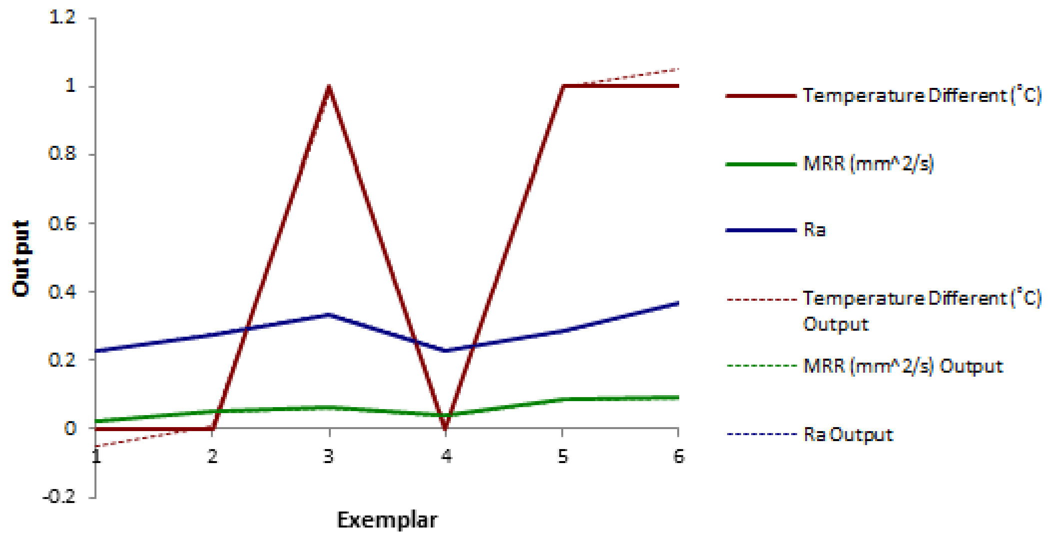


Figure 4.5: Desired output and actual network output for multiple pass grinding pattern

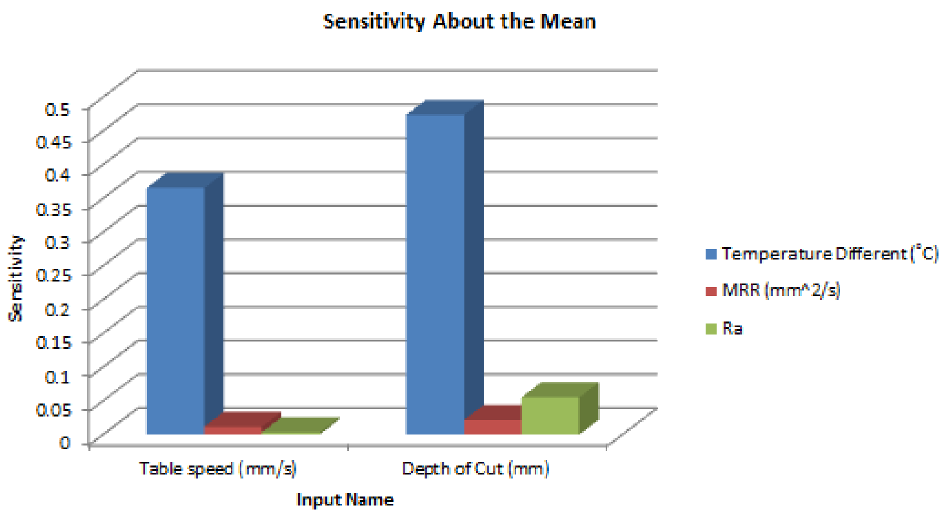
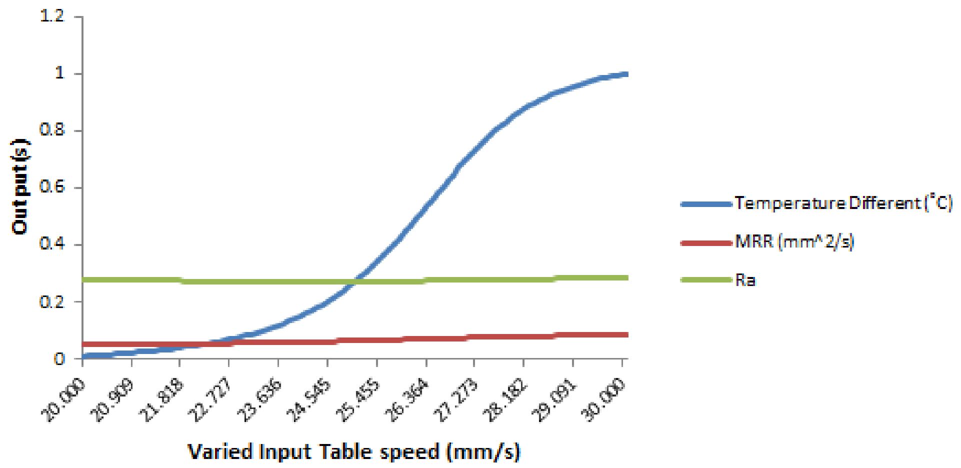
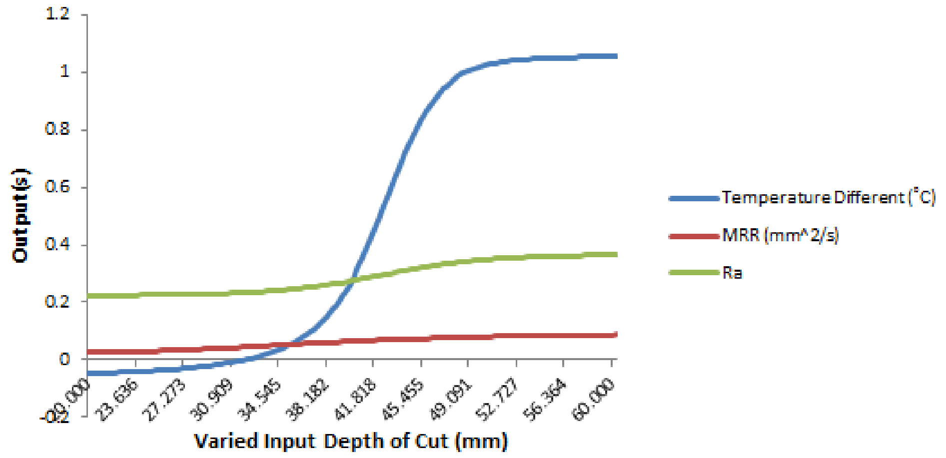


Figure 4.6: Sensitivity about the mean for multiple pass grinding pattern



(a) Table speed



(b) Depth of cut

Figure 4.7: Network outputs for varied input depth of cut for multiple pass grinding

Table 4.5: 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)	
		Exp.	Predicted	Exp.	Predicted	Exp.	Predicted
20	20	0	-0.0502149	0.02299	0.0231965	0.226	0.22598616
20	40	0	0.01064569	0.05172	0.0516446	0.276	0.27594046
20	60	1	0.98785565	0.06322	0.06337769	0.336	0.33647348
30	20	0	0.00254025	0.03846	0.03840697	0.229	0.22843209
30	40	1	0.99805915	0.08462	0.08476135	0.284	0.28421489
30	60	1	1.05458394	0.09077	0.09013633	0.369	0.36746414
40	20	1	0.86939214	0.10714	0.08620159	0.233	0.26333428
40	40	1	1.05205992	0.19048	0.0871913	0.316	0.29940688
40	60	1	1.05458241	0.21429	0.08740265	0.401	0.32547883

4.4 COMPARISON BETWEEN CONVENTIONALCOOLANT AND TiO_2 NANOCOOLANT

4.4.1 Single Pass Grinding Pattern

Tables 4.6 shows the difference of all output responses between using 0.1% TiO_2 nanocoolant and conventional coolant for single pass grinding pattern. For the temperature rise of the workpiece indicates the effectiveness of nanocoolant in absorbing heat. This is shown where the maximum temperature rise for nanocoolant is only 1°C while the maximum temperature rise for conventional coolant is 3°C. As observed in Table 4.6, the comparison of MRR value which is desired to be high does not really go to nanocoolant. Moreover, there is no significant difference for MRR value between the two coolants. Lastly,the surface roughness which is desired to be minimum, TiO_2nanocoolant indicates better surface finish compared to conventional coolant.

It indicates the difference of using TiO_2 nanocoolant compared with conventional coolant. The output responses studied, which are grinding temperature, MRR and surface roughness all have been compared and analysed. The results show that TiO_2 nanocoolant dominates in terms of grinding temperature where TiO_2 nanocoolant effectively conducts temperature with its high thermal conductivity property. By combining nano-sized particles with base fluids, results in fluids with improved thermal coonductivity which is effective as a coolant in abrasive machining such as grinding. In terms of material removal rate (MRR) which is desired to be maximum, TiO_2 nanocoolant achieves a slightly higher value compared to conventional coolant. Because of the nanosized particles, they are so small that they fill in the gaps in the grinding wheel which results in less friction and may affect the MRR of the process. This indicates there is not much difference in MRR value.

Table 4.6: Comparison of temperature rise, MRR and surface roughnessbetween conventional coolant and 0.1% TiO_2 nanocoolant for single pass grinding

Workpiece	Table Speed	Depth of Cut	0.1% TiO_2 Nanocoolant	Conv. Coolant
		Temperature Rise		
A	20	20	0	1
B	20	40	0	1
C	20	60	1	1
D	30	20	0	1
E	30	40	1	1
F	30	60	1	1
G	40	20	0	2
H	40	40	1	2
I	40	60	1	3
		Material removal rate		
A	20	20	0.178	0.179
B	20	40	0.435	0.362
C	20	60	0.541	0.533
D	30	20	0.312	0.230
E	30	40	0.781	0.472
F	30	60	0.813	0.698
G	40	20	0.714	0.329
H	40	40	0.952	0.698
I	40	60	1.310	1.131
		Surface Roughness		
A	20	20	0.201	0.205
B	20	40	0.264	0.280
C	20	60	0.310	0.316
D	30	20	0.251	0.327
E	30	40	0.281	0.445
F	30	60	0.385	0.537
G	40	20	0.237	0.326
H	40	40	0.303	0.384
I	40	60	0.489	0.542

4.4.2 Multiple Pass Grinding Pattern

Tables 4.7 shows the difference of all output responses between using 0.1% TiO_2 nanocoolant and conventional coolant for multiple pass grinding pattern. For the temperature rise of the workpiece indicates the effectiveness of nanocoolant in absorbing heat. This is shown where the maximum temperature rise for nanocoolant is only 1°C while the maximum temperature rise for conventional coolant is 4°C.

Table 4.7: Comparison of temperature rise, MRR and surface roughnessbetween conventional coolant and 0.1% TiO_2 nanocoolant for multiple pass grinding

Workpiece	Table Speed	Depth of Cut	0.1% TiO_2 Nanocoolant	Conv. Coolant
		Temperature Rise		
A	20	20	0	1
B	20	40	0	1
C	20	60	1	1
D	30	20	0	2
E	30	40	1	2
F	30	60	1	3
G	40	20	1	3
H	40	40	1	3
I	40	60	1	4
		MRR		
A	20	20	0.02299	0.0234
B	20	40	0.05172	0.0407
C	20	60	0.06322	0.0589
D	30	20	0.03846	0.0302
E	30	40	0.08462	0.0534
F	30	60	0.09077	0.0766
G	40	20	0.10714	0.0457
H	40	40	0.19048	0.0814
I	40	60	0.21429	0.1160
		Surface Roughness		
A	20	20	0.226	0.238
B	20	40	0.276	0.288
C	20	60	0.336	0.344
D	30	20	0.229	0.231
E	30	40	0.284	0.272
F	30	60	0.369	0.309
G	40	20	0.233	0.289
H	40	40	0.316	0.494
I	40	60	0.401	0.572

As observed in Table 4.7, the comparison of MRR value, which is desired to be high goes to nanocoolant. It can be seen that the MRR value for multiple pass grinding is much effective compared to single pass grinding in comparison to respected conventional coolant for respected grinding pattern. Lastly, it can be observed that the surface roughness is desired to be minimum, TiO_2nanocoolant also indicates better surface finish compared to conventional coolant.

Lastly, for surface roughness which is to minimize, TiO_2 nanocoolant produces products with better surface finish and low value of surface roughness compared to conventional coolant. This is due to nanosized particles, which fill in the tiny gaps and voids which make the surface to be flatter and therefore, produces the good surface finish of products. Furthermore, because of the effective thermal conductance of the TiO_2 nanocoolant which minimses the grinding temperature and results in no aggressive change in the microstructure that causes the low-quality surface finish.

4.5 MICROSTRUCTURE ANALYSIS

Figure 4.8 shows the workpiece grinded using 0.1% TiO_2 nanocoolant surface microstructure at 200x magnification. It is observed that using nanocoolant produces much clean flat surfaces. Eventhough there is a void defect, but as a whole, the figure shows the potential of producing high quality surface finish products.

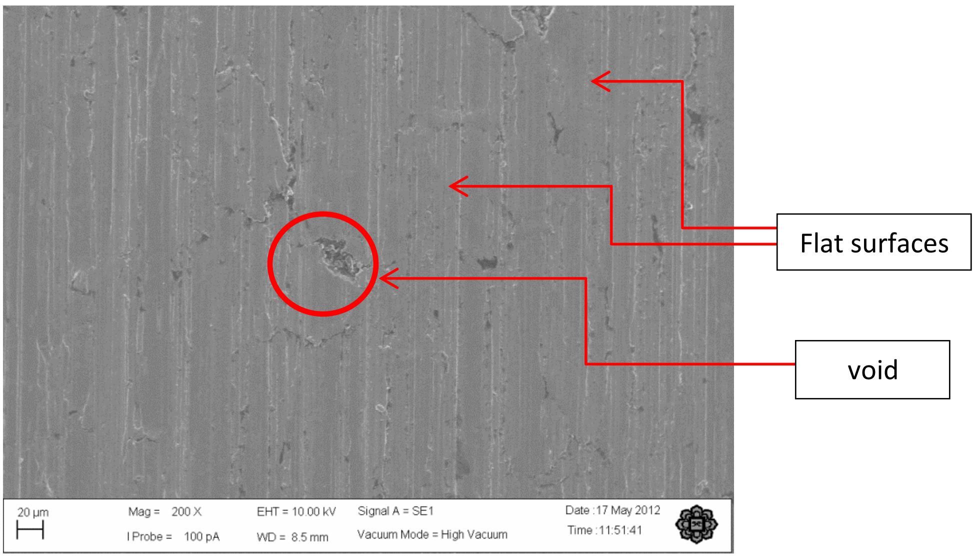


Figure 4.8: 0.1% TiO_2 nanocoolant(200x magnification)

Figure 4.9 shows the workpiece grinded using conventional coolant surface microstructure at 200x magnification. it is observed that using conventional coolant produces many grinding marks on the surface of the specimen. Figure 4.10 shows the surface microstructure of workpiece grinded using 0.1% TiO_2 nanocoolant while Figure 4.11 shows the surface microstructure of workpiece grinded using conventional coolant at magnification of 700x. The difference between the two images are significant where Figure 4.10 shows better surface finish while Figure 4.11 shows a surface with many grinding marks and also some cracks on the surface.

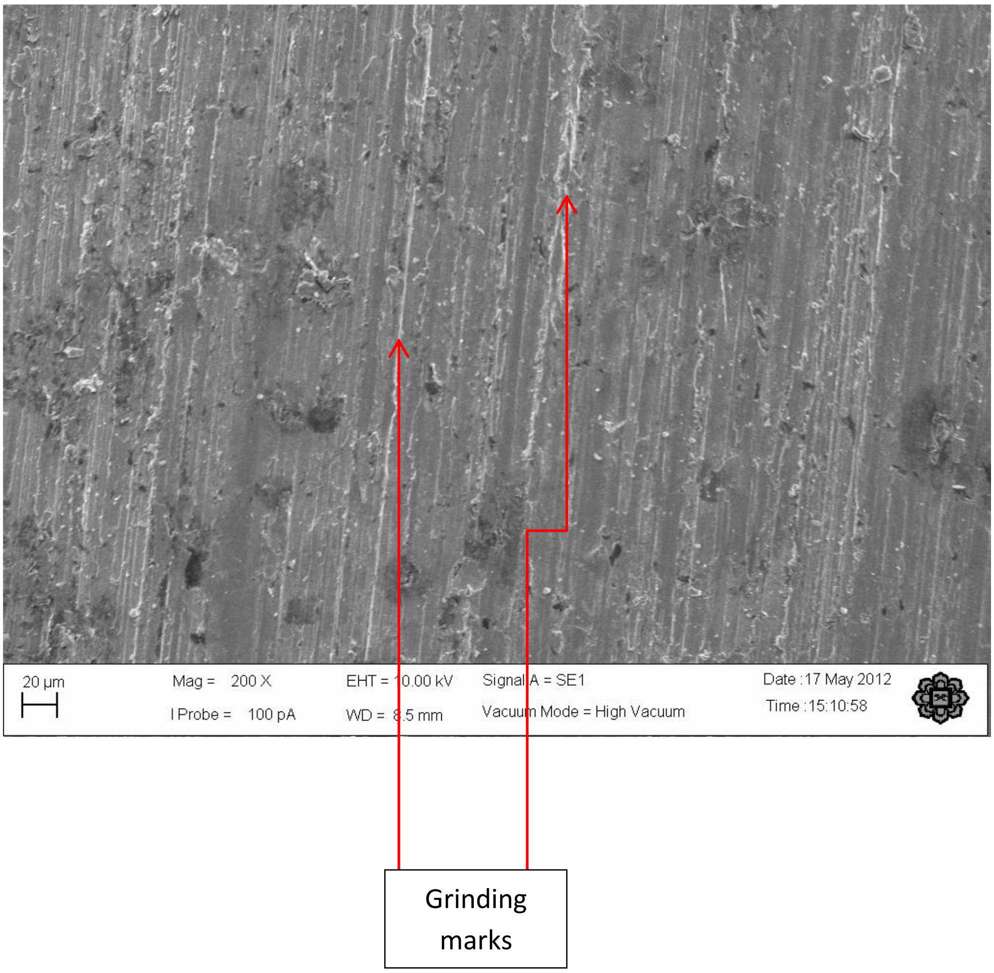


Figure 4.9: Conventional Coolant (200x magnification)

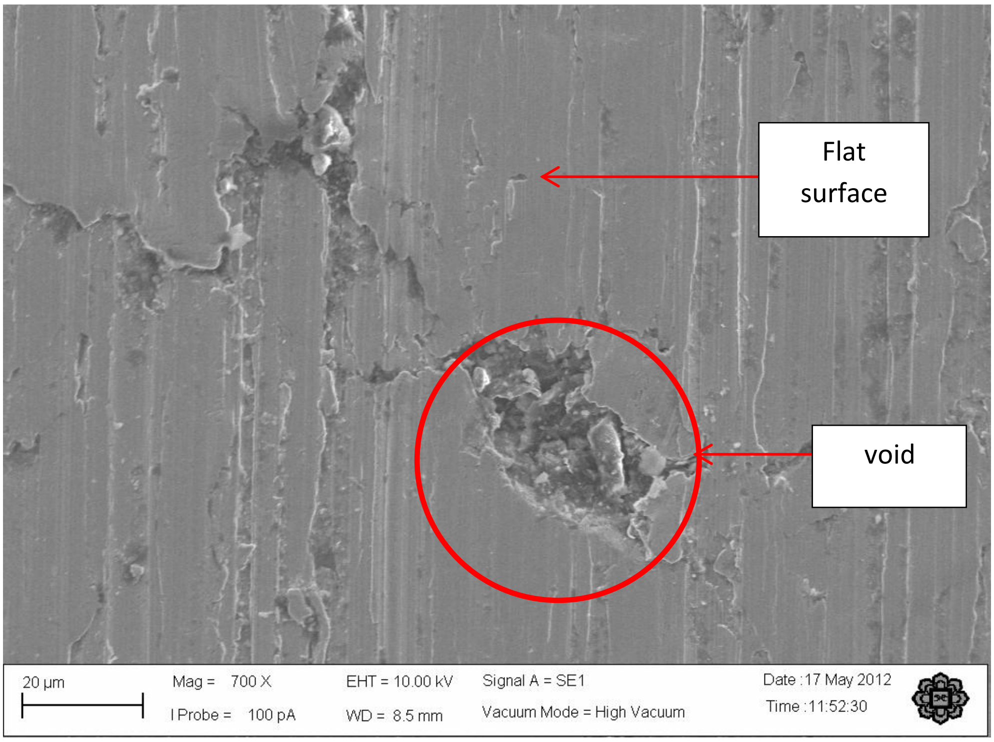


Figure 4.10: 0.1% TiO_2 nanocoolant (700x magnification)

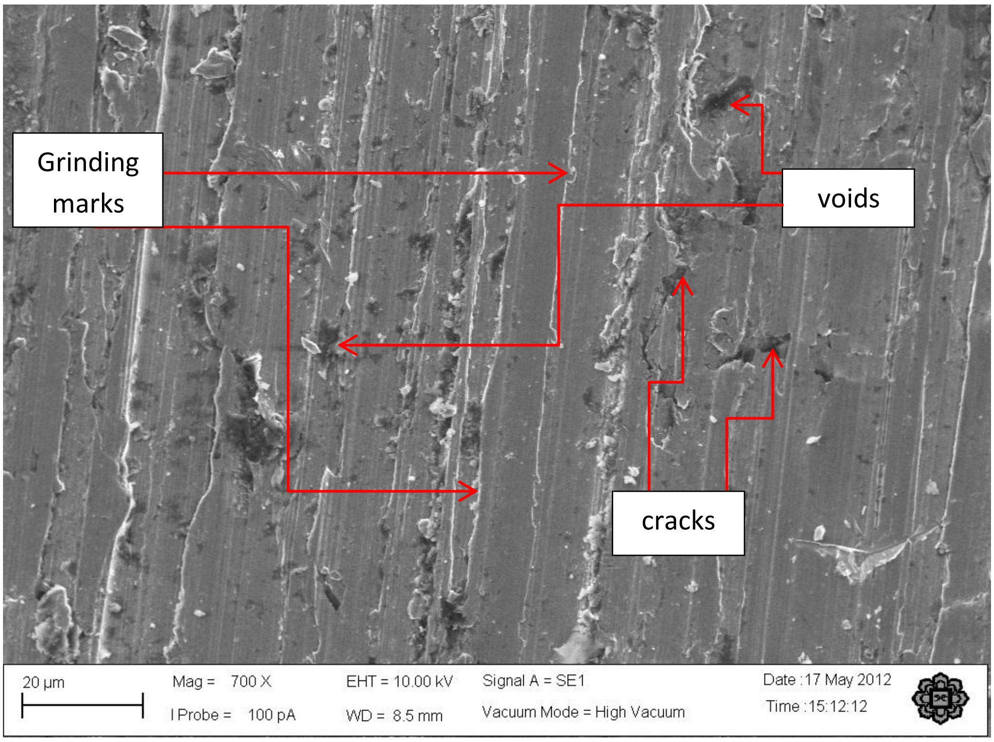


Figure 4.11: Conventional Coolant (700x magnification)

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

From this experiment, the effects of selected of input parameters which are 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. According to the output parameters, it is desired that in order to select the optimum input parameter value. The selection is based on desired minimize the temperature rise, minimum surface roughness and maximum material removal rate.

For single passgrinding 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 not affected by the increment. 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.

From the SEM images, it is concluded that nanocoolant produces better surface finish compared to use conventional fluid as the coolant. This study has shown that nanofluids are in a superior way in acting as grinding coolants compared to conventional coolants. This is shown in the data obtained from experiments on selected output parameters of temperature rise and surface roughness. This proves that by using nanofluids as coolants, the quality of the product in terms of surface finish increases while performs better in removing heat from the grinding process.

5.2 RECOMMENDATIONS

From the study that has been done, a few recommendations have been made for potential future study:

- Make comparison between different nanoparticles to obtainthe better performance.
- Develop ways to ensure better stability for nanoparticles
- Develop new synthesis methods necessary to make nanofluids more affordable.

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