

**PARAMETRIC OPTIMIZATION OF MAGNETIC ASSISTED FINISHING
OF TITANIUM (GRADE 5) USING ARTIFICIAL NEURAL NETWORKS &
GENETIC ALGORITHMS**

A PROJECT REPORT

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FOR THE AWARD OF THE DEGREE**

**MASTER OF TECHNOLOGY
IN
PRODUCTION ENGINEERING**

Submitted by:

MOHD TAYYAB

2K16/PIE/012

Under the supervision of

Prof. RANGANATH M.S.
Prof. RAJIV CHAUDHARY



**DEPARTMENT OF MECHANICAL, PRODUCTION
& INDUSTRIAL ENGINEERING**

**DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)**

Bawana Road, Delhi – 110042

JULY, 2018

CANDIDATE’S DECLARATION

I, Mohd Tayyab, Roll No. 2K16/PIE/012, students of M.Tech. (Production Engineering), hereby declare that the project dissertation titled “PARAMETRIC OPTIMIZATION OF MAGNETIC ASSISTED FINISHING OF TITANIUM (GRADE 5) USING ARTIFICIAL NEURAL NETWORKS & GENETIC ALGORITHMS”, which is submitted to the Department of Mechanical, Production and Industrial Engineering, Delhi Technological University in partial fulfillment for the award of the degree of Master of Technology, is first and not replicate from any source without true citation. This work is not formerly being formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title.

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MOHD TAYYAB

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Prof. RANGANATH M.S.
SUPERVISOR

Prof. RAJIV CHAUDHARY
CO SUPERVISOR

Department of Mechanical, Production &
Industrial Engineering

Delhi Technological University
Bawana Road Delhi - 110042

Place: Delhi

Date:

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Place: Delhi

MOHD TAYYAB

Date:

2K16/PIE/012

ABSTRACT

This work is an experimental study of parametric optimization of the Magnetic Abrasive Finishing (MAF) process, during finishing of Titanium Grade 5 using unbonded MAF process. Magnetic Abrasive Finishing (MAF) is a non-traditional finishing process which is initially controlled by magnetic field and by which a high degree of surface finish with very close tolerances can be obtained. The principal idea behind this finishing process bank on using a large number of arbitrarily cutting edges with unfixed alignment and geometry, called the abrasive particles, for potent exclusion of material with chip smaller compared to that come by in machining process using definite edges cutting tools. The abrasive particles don't have any innate magnetic properties, for this reason magnetic iron ore is mixed, so that they can be glide in air using a magnetic field for brush formation, by which the material surface is grinded. As the particles are loosely held at their positions by the effect of the magnetic field applied, their weight, friction and mechanical boundations caused by the adjoining particles, MAF allows better surface finish, close tolerances, creation of unclear surface features and machining of harder and strenuous to machine materials. In this study, the potential of the process is strived to be capitalize by studying the outcome of input parameters such as coil's current, abrasive percentage, machining gap, total machining time, and the RPM of spindle, using an L16 orthogonal design of experiments.

Artificial Neural Networks was then employ to optimise the MAF process, by growing a relation in the input and the output parameters, that is the change in surface roughness R_a , and MRR values of the jobbed surface. The optimizing using ANN are very sturdy and productive in determining the relation in the input and output values. For the existing appraisal, the highest error possesss in the actual machining outputs and the ANN foresee values was 3.25 % and 7 % for ΔR_a and M.R.R respectively.

Keywords: Magnetic Abrasive finishing, Design of Experiments, Artificial Neural Network, Genetic Algorithm, Optimization, Modelling, Titanium Grade 5.

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LIST OF SYMBOLS & ABBREVIATIONS

Artificial Neural Networks	A.N.N
Genetic Algorithms	G.A.
Magnetic Field Strength	H
Material Removal Rate	M.R.R.
Average Surface Roughness	Ra
Surface Roughness	S.R.
Time	T
Volume	V
Horizontal direction	χ
Vertical Direction	y
Volume	V

CHAPTER 1

INTRODUCTION

Finishing of a part or more appropriately termed as the surface finishing process is the final operation through which a part undergoes during its manufacturing process. Finishing operations are an inherent part of the manufacturing processes which includes conversion of raw material into final part through processes such as casting, forging, forming, welding, machining etc., resulting in varying surface profiles that contains uneven surfaces, surface micro cracks, burrs, etc. Surface finishing processes include all the methods and technologies used for processing the parts to enhance their surface quality after the required geometric and dimensional accuracy is achieved. The surface finish and dimensional accuracy achieved through the processes involved is crucial for the performance of the part not only in terms of its appearance, but also the functional parameters such as resistance to Wear, hardness, corrosion resistance, electrical conductivity, fatigue strength etc., which directly affect the performance in terms of its quality, usability, accuracy of assembly (fitting) with other parts, vibration, noise and heat produced during operation, mechanical efficiency, working life etc. Through these mechanical processes the surface layer of the part gets modified, which can be expressed in 2 ways [1]: -

- Geometric characteristics: Roughness, texture and the defects produced during the process.
- Physical-Mechanical Characteristics: Residual stresses in the surface layer, plastic deformation, and changes in the microstructure of the layer.

The finishing processes can thus be coupled on the basis of the surface characteristic which they tend to improve out of the abovesaid two, for e.g. the traditional finishing techniques such as grinding, superfinishing (lapping, honing), polishing etc. focusses on improving the geometrical characteristics, while other

methods such as peening and rolling tends to improve the physical-mechanical properties. In the manufacturing of precision parts, where the required surface finish value falls down below the 1-micron mark, the cost of this highly labor-intensive process starts escalating at profoundly steep rates [2]. Therefore, a number of different methods have been developed to achieve the desired finish of parts, depending upon their shapes, sizes and the degree of finish required, some of which are explained below.

1.1 TRADITIONAL FINISHING PROCESSES

Finishing operations are a crucial part of the whole machining process, as it directly affects the final appearance, performance and life of the product. Therefore, a number of different types of processes have been developed to achieve the desired surface finish. In the following section, the most commonly used finishing techniques, are defined, such as grinding, honing and lapping. As all these 3 types of finishing processes are abrasive based, one first needs to understand what an abrasive based finishing process is. Surfaces with desired features with low rate of surface generation are produced by exploiting abrasive finishing process. Generally, abrasives with high Wear resistance are used for surface induction. These processes are elaborated as the finishing methods with random cutting edges, to differentiate them from traditional methods which finishes with defined cutting edges. An appropriate process is required to be used for brittle workpieces, in order to achieve a durable and enhanced surface. Application of abrasive processes for creating component which includes precise dimensions and excellent surface finish is an evidence of its merit. Moreover, these processes depend on numerous parameters which can be regulated for the better surface finish and for the optimization of cost as well. This dependency enables abrasive processes to achieve a wide gamut of surface roughness.

Doan D. Marinescu [3] in his work, categorized finishing processes involving fixed and loose abrasives among three main groups, the basis of which come from the abrasive tool and shape of the workpiece, which are:

- Bonded or fixed Abrasive processes

- Dressing process
- Loose or unfixed Abrasive processes

1.1.1 BONDED ABRASIVE PROCESS

In this process, an abrasive tool is utilized for following finishing processes, grinding, honing, and polishing. The crucial feature in the abrasive tool is the integration of composite structure with a layer of abrasive on it. Composite structure consists abrasive grits in a matrix, and a tool holder is used to support the abrasive layer. Abrasive grits with sufficient hardness along with the bonding agent are constituents of the layer. Application of abrasive processes for creating component which includes precise dimensions and excellent surface finish is an evidence of its merit. Moreover, these processes depend on numerous parameters which can be regulated for the better surface finish and for the optimization of the cost as III.

The physical and mechanical properties vary with the size of the grit and with the type of the bonding agent. The grit's hardness should be sufficient to deform the material of the workpiece in plastic manner, which is a necessity for the material removal from the surface of the workpiece. The surface of the tool interacts with the workpiece on the sharp and hard edges and the abrasive particle's deformation is insignificant as compared to the diversion of the bonding agent [4]. The super-finishing behavior of the tool is enhanced by its elastic properties which is achieved by selecting the hardness, and shape of the bonding agent.

1.1.2 DRESSING PROCESS

Dressing technology can be distinguished from the other types of groups. The abrasive tool itself is a workpiece with crumbled and composite structure consisting abrasives. In this process, the abrasive tool or wheel is profiled. The abrasive tool is profiled to follow the necessary shape and texture for the grinding process. The shape of the tool is made to

conform by removing the abrasive from the tool through cutting and crushing. To enhance the dressing of the abrasive, tool the process is carried out in the existence of a machining fluid which decreases the Wear of the tool by lubricating it and carrying away the heat produced during the process.

1.1.3 LOOSE ABRASIVE PROCESS

Polishing processes utilize loosely bonded abrasives and become a part of fine finishing processes. Loosely bonded abrasives are extensively used for finishing numerous types of jobs, Farago [4] differentiated them among three categories. Most of the area of the workpiece is covered by the loose abrasives and supported on a solid such as face of the rotating shaft. The supporting solid is kept in motion in very close proximity of the workpiece, avoiding physical contact between tool and worksurface. The material removal will be in control of the abrasive particles but less amount of material will be removed and maintaining the chirality between the solid backing and workpiece. The job of the abrasive is to act as a medium which increase the cutting efficacy of the tool.

Random allocation of the abrasives supports their free motion by the virtue of inertia, which is relayed by the rotating solid backing, that provides support for the abrasive. Each abrasive particle has its own specific Weight which results in each abrasive rotating at a different velocity and rubs the surface of the workpiece differently. The method which discussed here, involves loosely bonded abrasives which are moving freely, can be executed by rotating hollow bodies such as cylinder and trembling containers.

1.2 GRINDING

Grinding is one of the most commonly used abrasive based finishing process among all the traditional surface finishing methods. In the grinding process the material removal takes place in the form of tiny chips, with the help of relative motion between the workpiece and an irregular shaped hard grit particle known as “abrasive”. Because a very low amount of material is removed by a single abrasive particle, grinding wheel is

employed to obtain a satisfactory MRR, which is a porous cylindrical wheel made out of a multitude of randomly oriented abrasive grains, held together with the help of a bonding material. The typical abrasives used for the grinding process are Aluminum Oxide (Al_2O_3), Silicon Carbide (SiC), Cubic Boron Nitride (CBN) and Diamond, which are held together with the help of either a vitrified bond, shellac bond, electroplated bond, oxychloride bond, resin bond, or brazed bond etc. The porosity is a crucial feature of the grinding wheel as it ensures clearance for the chips produced during the finishing process, which will otherwise be impossible to form with a solid abrasive wheel, as the chips produced will interact and interfere in the grinding process, and also it helps keep the temperature of the wheel down during machining [5]. The grinding process can be inherently discerned into two different regimes: -

- Stock Removal Grinding (SRG): - In stock removal grinding the prime concern is to remove the excessive material from the part being grinded, and hence the materials removal rate is very high.
- Form Finish Grinding (FFG): - In form finish grinding focus is given on the surface finish being produced during the process and hence the material removal rate is kept low enough to ensure high surface roughness.

The grinding operation is performed on a grinding machine (as shown in Fig. 1), which consists of a fixture installed on a bed to hold the workpiece during the machining process, and a grinding wheel powered by an electric motor. During the grinding process either the workpiece can be moved with respect to a steady grinding wheel or vice versa depending upon the type of machine being used and the application. The surface speed of the grinding wheel is kept between 20 m/s – 45 m/s during the traditional grinding process, but it can go as high as 140 m/s in high speed applications [3].

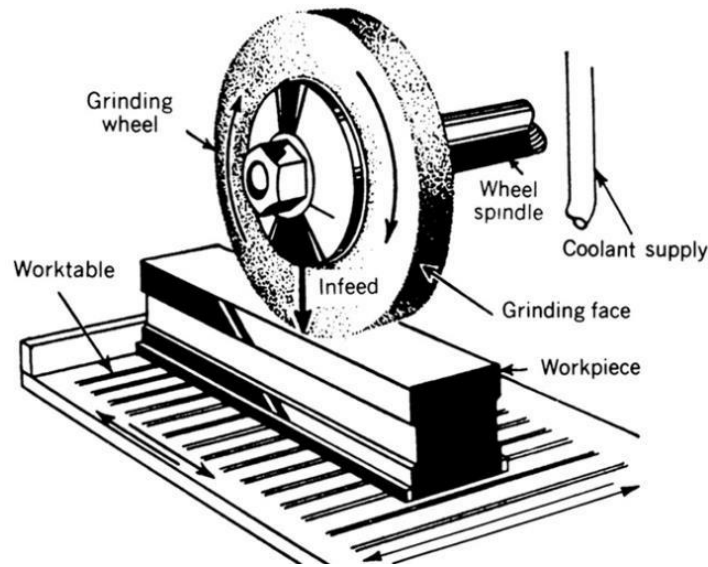


Fig. 1 Surface Grinding Process [5]

1.3 LAPPING

Lapping is a loose abrasive-based surface finishing technique that works on the 3-body abrasive Wear mechanism. An abrasive particle (5-20 μm) slurry that is formed by combining the loose abrasive particles with a fluid (mineral oil, grease) serving as an aqueous medium, is filled between the workpiece surface (as shown in fig. 2) to be finished and the lap plate. A normal force is applied on the lap plate which is given a relative motion with respect to the worksurface, resulting in penetration of the abrasive particle within the surface and removal of workpiece material in the form of microchips. Thus, very low material removal rate is a characteristic of the lapping process. The depth of indentation of the particles is dependent on the amount of normal force being applied and the size of the grit particles. As the particles become coarser the surface finish obtained through lapping deteriorates and the finer they are the better finish will be obtained. The hardness of the lap plate also affects the surface texture obtained through the lapping process. When hardness of the lap plate is high, it resists penetration of the particles within itself resulting in a rotatory motion of the abrasive particles and material removal from the workpiece due to

microfracture from the induced surface stresses. When the hardness of the plate is less which is the most

commonly used setup, the normal force results in partial deformation of the plate causing a sliding motion of the particles and hence material removal takes place due to ploughing of the workpiece material. The lap plate can be made out of wood, lead, cast iron, copper etc. [6]. The surface roughness obtained with a softer plate is better (finer) compared to the hard plate, but the planarity of the surface is deteriorated due to the uneven deformation of the lap plate depending on the size and shape of the abrasive particle.

The lapping process produces a semi-glossy surface with close tolerances ($< 2.5 \mu\text{m}$) and a non-directional processing pattern. The lapping process is mainly preferred for producing super-finished planar and cylindrical surfaces over other methods such as honing and ultra-fine grinding process, but it can also be used for free form surfaces with a few modifications. The lapping process is characterized form the following features: -

- The slow rotational speed of the lap ($< 80 \text{ RPM}$) and the micro level indentation resulting in a very low M.R.R value.
- Very low damage to the workpiece surface as the amount of heat generated during the process is negligible.
- Essentially residual stress-free workpiece surface is obtained.

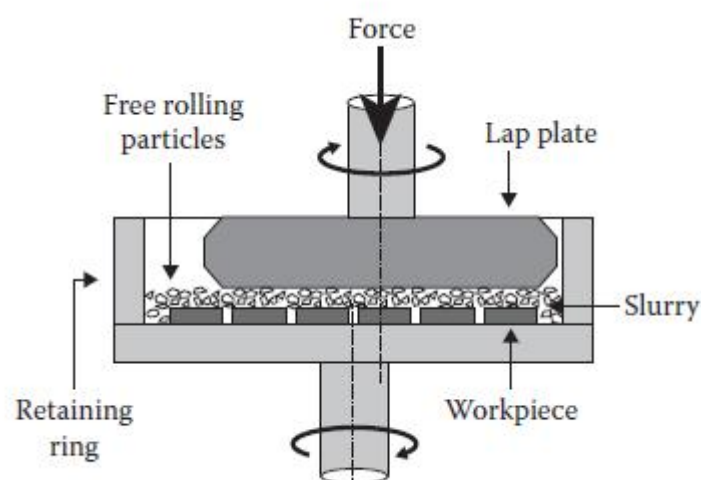


Fig. 2 Schematic diagram of Lapping Process [6]

1.4 HONING

Honing is a bonded abrasive based finishing process that is mainly employed to improve the surface finish of a part along with very close dimensional and geometrical tolerances. The honing process can be divided into 2 different types: a) Internal honing: - It is used to remove fine geometrical errors produced during preceding machining operation because of the mechanical forces or thermal damage in inside cylindrical surfaces, such as waviness, mis-alignment, taper structure, bellmouthness, out-of-roundness etc. in engine cylinders, engine valves and seat, hydraulic cylinders, gears, brake drums, guide valves etc. b) External honing :- This process is used to remove feed marks out of external surfaces such as crankshafts, pistons, cam shafts, piston pins, taper and roller bearings etc. The honing is carried out at a slow speed (0.2 – 2 m/s) with an abrasive tool called the hone, through 2 body abrasion method. A very low radial pressure is applied on the hone as it continuously slides over the workpiece surface, also according to which the abrasive tool aligns itself during its motion, because of the design of the machine as shown in fig. 3. Honing process not only produces a very low surface finish (0.13 - 1.25 μm), with close tolerances but it also improves the resistance to Wear and corrosion, and the fatigue strength of the part.

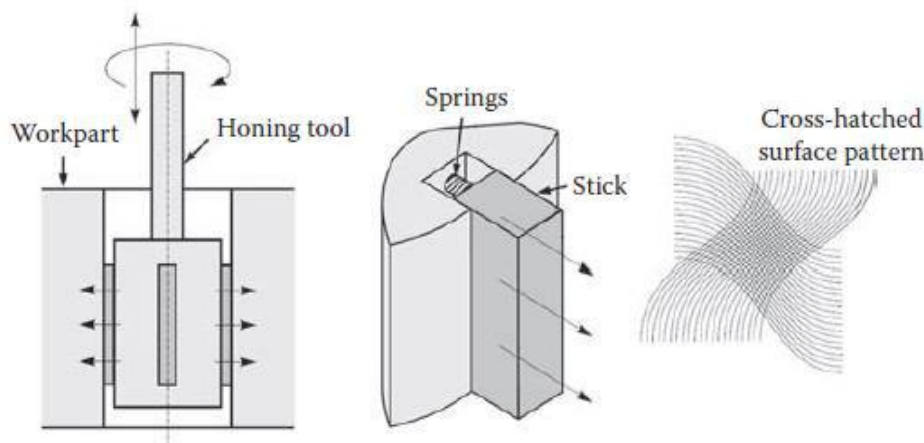


Fig. 3 Schematic diagram of Honing Process [2]

Honing process is highly employed to produce the cross-hatch pattern inside the engine cylinders, used to improve their oil holding capacity on the surface, for reducing the friction produced during motion of the piston. The honing stone is given a continuous

longitudinal motion along with its circular rotation resulting in the specific cross- hatched after surface (as shown in fig.3)

1.5 MAGNETIC ABRASIVE FINISHING (MAF)

Magnetic Abrasive Finishing (MAF) is a magnetic field assisted abrasive-based finishing technique that was developed to process hard surfaces with ease compared to other traditional methods. The process was initially developed in United States in 1930s, but most of the developments in the process is attributed to Bulgaria and USSR [2]. The process is based on the idea of using multitude of randomly oriented cutting surfaces of the abrasive particles to remove micro-chips from the working surface to improve its surface finish. The particles are suspended in the gap between the tool surface and workpiece with the help of magnetic field, though abrasive particles being non-magnetic in nature requires other ferromagnetic particles, for e.g. iron powder to be influenced by the applied magnetic field. The two particles can be either bonded with each other through sintering or some other method or can directly be used in the unbonded state with a lubricant in between to act as a glue to keep the two particles together. The workpiece is placed inside the magnetic field lines produced by an electromagnet, due to which the magnetic abrasive particles present in between the gap arrange themselves along the magnetic field lines forming a flexible mechanical brush (as shown in fig. 4).

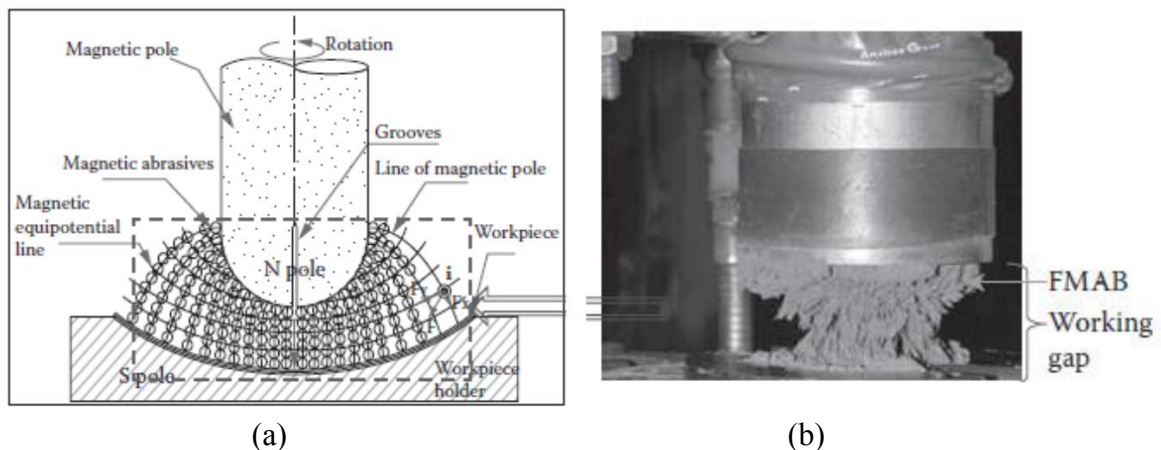


Fig. 4 The MAF process (a) Schematic diagram of MAF process. (b) Actual photograph of a flexible magnetic abrasive brush (FMAB) at large gap between the tool and the workpiece [6].

The magnetic field provides the necessary force required for removing the material from the workpiece, and the relative motion between the tool, hence the magnetic field lines and the workpiece initiates this process. The magnetic abrasive particles orient along the magnetic field lines by juxtaposing each other because of the dipolar interaction between the particles, resulting in a strand of particles behaving like a brush thread. Numerous such strands form the whole magnetic brush, strength of which can be easily controlled by varying the magnetic field strength. The flexible magnetic brush which contains randomly oriented and geometrically varying particles, when rotated over the working surface causes removal of material from the outer surface resulting in a superior finish with close tolerances [7].

1.5.1 WORKING PRINCIPLE

MAF is a process which has caught attention of industrialists and researchers as a prime finishing method for processing hard materials to achieve nano-level of surface finish, which is otherwise very difficult and inefficient with the traditional or other advanced finishing methods. The major advantage of MAF process lies in its flexibility to machine flat, (internal or external) curved or even free form surfaces, to achieve the desired surface finish by simply varying the strength of the magnetic field and the size or type of the magnetic abrasive particles (MAP), without damaging the surface by excessive mechanical or thermal stresses. Magnetic field is used in magnetic abrasive finishing method to suspend abrasive particles within the gap between the workpiece and the tool surface which acts as a magnetic pole, to form a brush. The brush is given a relative motion with respect to the workpiece by imparting rotary motion to either the tool or the workpiece along with the path following during machining process. The resulting force on the particles due to magnetic field as well as the relative motion causes removal of material from the worksurface in the form of small chips, thus enhancing the finish and integrity of the surface [1]. Since the brush which acts as the cutting tool in MAF process is made up of abrasive particles held at their place with the help of magnetic field, which is not distributed uniformly throughout the whole face of the flexible magnetic brush, the

particles continuously change their location and orientation, resulting in a very random and intermittent cutting process. The amount of material removed by each of the abrasive particles is very less ($< 1 \mu\text{m}$ depth of cut), hence the amount of heat produced during machining is less, resulting in a surface which has very less residual stress and thermal damage. The main features of a typical MAF process are explained below: -

1.5.2 BRUSH COMPOSITION

The flexible magnetic brush used in the magnetic abrasive finishing process is composed of hybrid magnetic particles that have abrasion ability as well. When a magnetic field is applied across these ferromagnetic particles they orient themselves along the field lines, due to the dipolar interaction (as shown in fig. 4), forming a flexible brush that can abrade material from the workpiece surface having hardness less than particle.

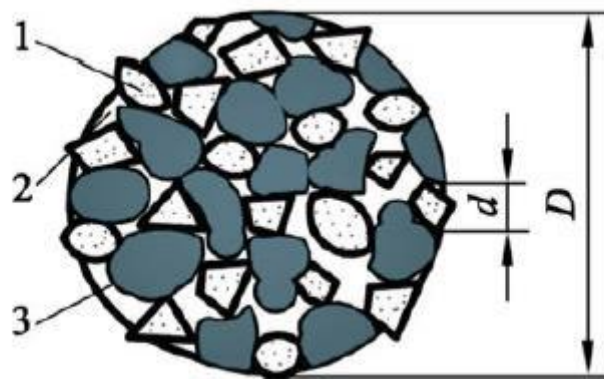


Fig. 5 Bonded Magnetic Abrasive Particle (MAP), where d = dia. of abrasive particle, & D = dia. of MAP

The size of the magnetic abrasive particles ranges from $60 \mu\text{m}$ to $200 \mu\text{m}$. As clearly visible in the fig. 5, there are 2 different phases in a magnetic abrasive particle, i.e.

- Magnetic medium: - The magnetic medium in an MAP is very crucial for the machining performance as the amount of force that holds the particle in its place and successively the shearing force responsible for material removal depends on it. To obtain a brush that has stable and controllable strength, particles of materials having high magnetization property is used such as iron, nickel-iron based alloys, alloys of magnesium barium etc.
- Abrasive Medium: - For the abrasive medium a compound having high hardness (at least 1.2 – 1.5 times of Vickers's hardness than the workpiece), good strength, and thermally stable mechanical and chemical properties is selected. The hardness ensures that the particles will be able to shear off the workpiece material. Wear of the abrasives will be low if they have high strength values and they will not be chipped off easily during operation, and if the mechanical properties of the particle deteriorate as it gets heated during operation, the efficiency of the brush
- will be less, as the particles will get blunt early. Common abrasive particles are Aluminium Oxide Powder (Al_2O_3), Carbon Boro-Nitride (CBN), Tungsten Carbide (WC), Silicon Carbide (SiC), synthetic diamonds etc.

There are two different types of magnetic abrasive particles that are commonly used in the MAF process, depending upon the type of bond between the abrasive and the magnetic phase, i.e. Bonded and Unbonded MAPs. The bonded MAPs (such as the one shown in fig. 5) are produced by the help of sintering method (as the one shown in fig. 6), that includes mixing the 2 phases with each other in a desired ratio, along with an adhesive such as Polyvinyl Acetate (PVA), epoxy resins, poly-amide resins etc. These components are then compacted (with or without application of heat, depending upon the type of method being used) in a mold by high pressure application. The compound so formed is then sintered in a furnace at the sintering temperature for 2-3 hms and is allowed to cool down. The sintered compound is then ground into fine particles which are then sieved as per requirement [8].

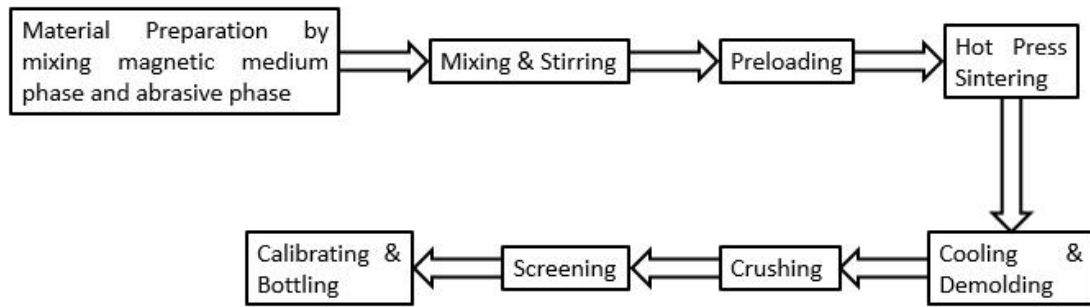


Fig. 6 Preparation method of Bonded MAPs using hot-press sintering

In the unbonded type of abrasives the two medias are not joined physically with each other, rather they are mixed in a desired ratio and then a lubricant is added in the mixture to provide holding strength to the mix. The lubricant keeps the two types of particles together so that a magnetic abrasive particle can be formed. The lubricant used needs to be dilatant fluid, e.g. lubricant oils, vegetable oils, mineral oils etc.

1.5.3 BRUSH FORMATION

The magnetic brush is formed when a magnetic field is applied across the gap between the tool and the workpiece, through aggregation of the magnetic abrasive particles in bundles which align along the magnetic field lines, the shape of which is shown in fig. 7. The formation of the brush can be attributed as a stable system which occurs when the its total energy becomes stable, i.e. when the sum of energies that balances the whole flexible magnetic brush and energies which try to disrupt the whole brush cancels each other's effect and becomes stagnant. When examined with due care, 3 different types of energies come into picture during the formation of the magnetic brush, which are: -

- Energy of Magnetization, E_M : This is the amount of energy required to form the aggregate of the ferromagnetic magnetic particles, due to dipoles formed

inside them which attracts the adjoining particles whose opposite pole is in contact.

- Energy of Repulsion, E_R : The repulsion energy is generated due to repulsion of similar poles formed within the particles, which tries to break the whole brush into constituent particles.
- Energy of Tension, E_T : The shape of the aggregate bundle of particles is spherical, which induces a tension within it. Just as the molecules within a water bubble are have an excess energy due to its shape, same phenomenon occurs for the abrasive particles [9].

A stable abrasive brush will be formed when the sum of all the above said 3 energies becomes stable, i.e. the net change in the sum of energies becomes zero, i.e.

$$\frac{d}{dt} (E_M + E_R + E_T) = 0$$

A remarkable relation exists between these 3 types of energies and the size of the bundles formed within the magnetic field. When the amount of abrasives filled within the gap is less, the diameter of the aggregated particles is of the order of several hundred μm , but when it is increased the size of these aggregates increases along with a reduction in the separation between them, which remains constant with the addition of more particles but the average size of the agglomeration increases.

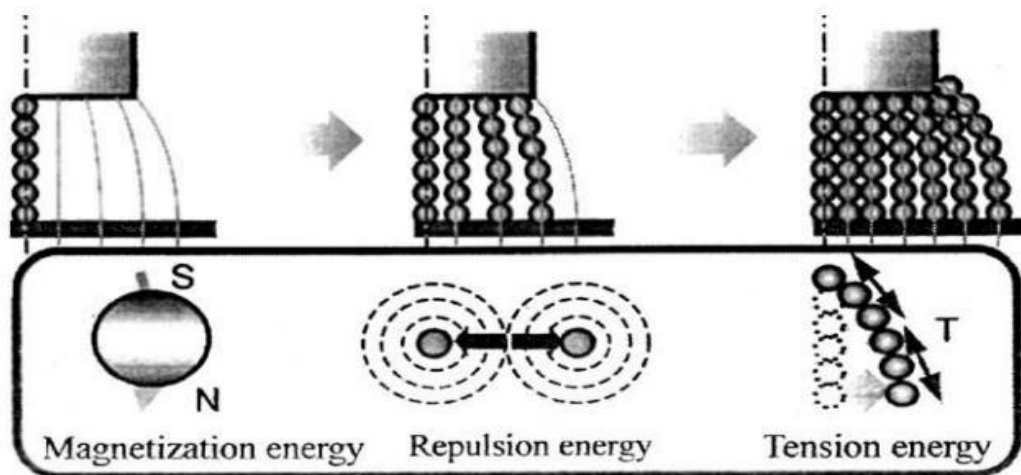


Fig.7 Formation of magnetic abrasive brush [9]

1.5.4 CUTTING FORCES IN MAF PROCESS

The magnetic abrasive particles that exist between the working gap experience two different types of forces, which account for the removal of material from the workpiece surface, which are as follows: -

- Normal Force, F_N : This is the force which is responsible for the indentation of the abrasive particle inside the work surface resulting in removal of material in the form of small chips. The normal force also helps to pack the magnetic particles inside the flexible magnetic brush.
- Tangential Force, F_T : The actual chipping of the workpiece material takes place due to the presence of the tangential force acting on the abrasive particle. As the abrasive particles indent into the workpiece a resistance is offered by it on the particle due to the mechanical interaction that is taking place. The tangential force acts opposite to this resistive force, thus shearing off the material from the workpiece.

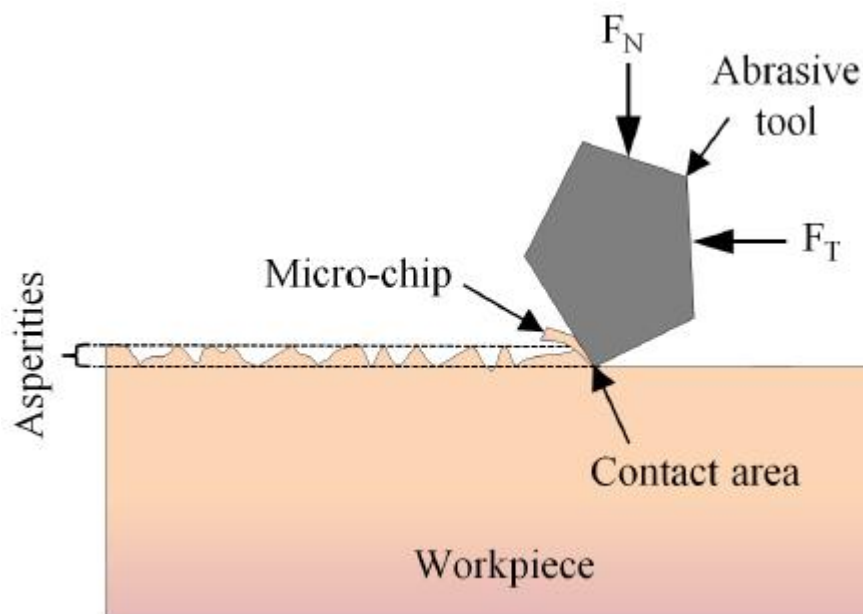


Fig. 8 Forces acting on an abrasive particle during the MAF process [10]

The net magnetic force acting on the magnetic abrasive particles is due to the two components of forces acting on it, i.e. force F_X which acts along the magnetic field line, and the force F_Y , which acts along the equipotential magnetic line, which is given by the following mathematical relations [11],

$$F_X = \chi^{FP} * \mu_0 * V * H * \left(\frac{dH}{dX} \right)$$

$$F_Y = \chi^{FP} * \mu_0 * V * H * \left(\frac{dH}{dY} \right)$$

Where μ_0 = Permeability of the vacuum

V = Volume of the particles

H = Strength of the magnetic field at a point

χ^{FP} = Susceptibility of the particles

As shown in the fig. 9, the F_N and F_T values can be easily calculated through the and values given above, i.e.

$$F_N = F_X * \cos(\theta) + F_Y * \sin(\theta)$$

$$F_T = -F_X * \sin(\theta) + F_Y * \cos(\theta)$$

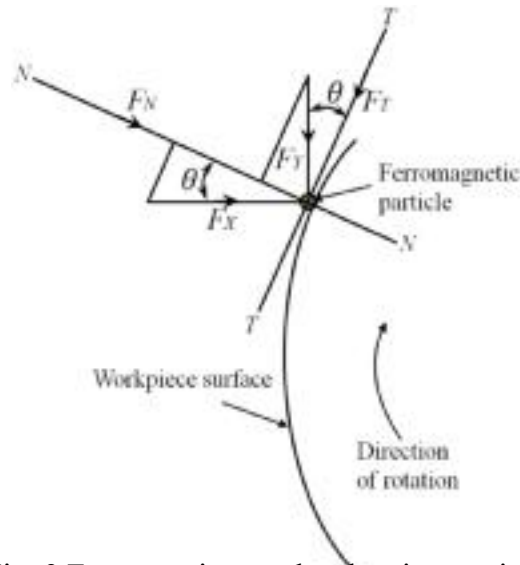


Fig. 9 Forces acting on the abrasive particle

1.5 APPLICATIONS OF MAF PROCESS

1.5.1 POLISHING OF BALLS AND ROLLERS

Traditional finishing of ceramic balls, for bearing applications, uses low polishing speeds and diamond abrasives as a polishing medium. The long processing time and the use of expensive diamond abrasives result in high processing costs. Diamond abrasives at high loads can result in deep pits, scratches, and micro cracks. Consequently, the high processing cost and the lack of the machining system reliability form possible limitations. To minimize the surface damage, placid polishing conditions are required, namely, low levels of restricted force and abrasives not much harder than the work material.

A recent development in MAF involves the use of a magnetic field to support abrasive slurries in polishing ceramic balls and bearing rollers (fig.10). A magnetic field, containing abrasive grains and extremely fine ferromagnetic particles in a certain fluid such as water or kerosene, fills the chamber within a guide ring. The ceramic balls are between a drift shaft and a float. The abrasive grains, ceramic balls, and the float (made from nonmagnetic material) are suspended by the magnetic forces. The balls are present against the rotating drive shaft and are polished by the mechanical abrasion action.

Since the forces applied by the abrasive grains are enormously small and controllable, the polishing action is very fine. The process is economical, and the surfaces produced have little or no defects.

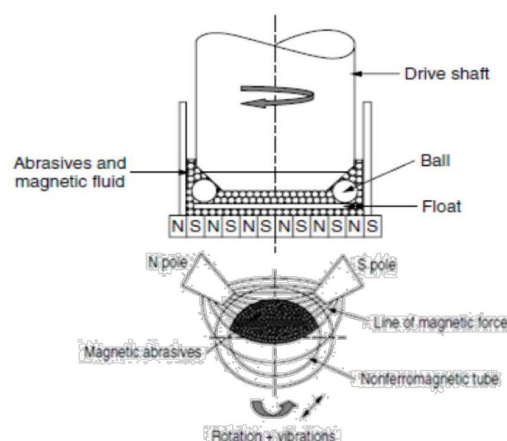


Fig. 10 Polishing of ceramic balls and bearing rollers by MAF process

1.5.2 FINISHING OF INNER TUBE SURFACE

Clean gas and liquid piping systems need to have highly finished inner surfaces that prevent contaminant from accumulating. When the pipe is slender, it is hard to produce smooth inner surfaces in a lucrative way. Electrolytic finishing has numerous problems associated with the high cost of controlling the process conditions and disposing of electrolyte without environmental pollution. Fig. 11 shows the two-dimensional schematic view of the internal finishing of a non-ferromagnetic tube using MAF [16]. The magnetic abrasives, inside the tubes, are converged toward the finishing region by the magnetic field, generating the magnetic force needed for finishing. By rotating the tube at a higher speed, the magnetic abrasives make the inner surface smoother. Fig. 11 shows the case of ferromagnetic tube finishing where the magnetic fluxes generally flow into the tube (instead of through the inside of the tube) due to their high magnetic permeability. Under such conditions, the abrasives scarcely remain in the finishing zone when the tube is rotated. [17] achieved mirror finishing and removed burrs without loosing the accuracy of the shape.

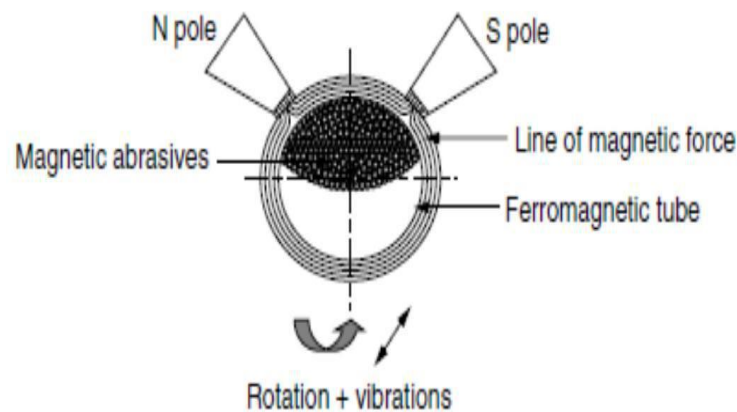


Fig. 11 Internal finishing of a non-ferromagnetic tube

1.5.3 OTHER MAF APPLICATIONS

The process can be applied in many other fields

- Polishing of fine components such as printed circuit boards (PCB)
- The removal of oxide layers and curing coatings
- Automatic polishing of intricate shapes
- Cutting tools
- Turbine Blades
- Optics
- Prosthetics
- Polishing of flat surfaces.
- Chamfering and deburring of gears and cams.

1.5.4 ADVANTAGES OF MAF PROCESS

- Flexibility of the magnetic brush makes MAF process effective symmetric as well as odd hard to reach shapes, such as holes easily.
- A wide range of surface characteristics can be obtained by varying the machining parameters.
- The process is independent of the workpiece material, i.e. it can finish ceramics, steel, brass, carbides etc.
- The finishing tool has self-adaptability, self-sharpening, and self-compensation.
- The method can be used to finish non-ferromagnetic and ferromagnetic materials both.

- Using this process, the surface can be modified without affecting the shape and form of the workpiece.
- The surface produced has low thermal and mechanical damage, and hence is defect free.

1.5.5 DISADVANTAGES OF MAF PROCESS

- It is difficult to implement Magnetic Abrasive finishing in mass production operation.
- Not application for any ordinary finishing task where traditional finishing technique can be easily implemented.
- Process is highly time consuming.
- The cost of process is high.

CHAPTER 2

LITERATURE REVIEW

The advancements in the field of technology and sciences have embarked the requirement of high surface finish of products along with very tight tolerances and surface integrity. The parts now-a-days are subjected to conditions which have never been so harsh along with being efficient in terms of energy and Weight. Thus, the requirement of a process that can produce very high finish surfaces without affecting its integrity due to thermo-mechanical damage, has made Magnetic Abrasive Finishing, a highly sought-after surface finishing technique. As my present study focusses on development of machinery for exploiting and characteristics of the limitations of MAF process. The following chapter thus presents a detailed analysis of the development, variations and different applications of the MAF process, available in previous literature.

2.1 MAGNETIC ABRASIVE FINISHING

V.K. Jain et al. [12] in 2001 studied the effect of working gap and circumferential speed on the performance of magnetic abrasive finishing process. In which they designed an experimental setup for finishing cylindrical workpiece and used loosely bounded powder as the abrasive mixture which consists magnetic powder, abrasive powder (Al_2O_3 600 mesh size), current and lubricant. Parameters selected by them are abrasive particle size, amplitude of vibration, Applied Voltage, Ferromagnetic Particles, Finishing Time, Frequency of vibration. Based upon the results, in general material removal decreases by increasing working gap or decreasing circumferential speed of the workpiece and change in surface roughness increases by increasing circumferential speed of the workpiece. **K. Saraswathamma et al. [13]** in 2015 predicted the effect of parameters such as rotational speed, working gap, and magnetizing current on the percentage reduction in surface roughness of silicon wafer in BEMRF

process. In their study, working gap was found to be the critical process parameter for finishing silicon workpiece in BEMRF. The percentage reduction in surface roughness of the silicon workpiece reduced with increase in working gap and increases with increase in magnetizing current.

Mishra et al. [14] in 2014 analyzed the work brush interface temperature in magnetic abrasive finishing process. In the study, they performed transient analysis of workpiece to predict temperature rise due to magnetic flux. During the transient analysis current in the coil was in between 0.45 to 0.91 Ampere, Number of turns 480, and volume ratio of iron was 43-70. The results of the transient study stated that magnetic flux density was 0.10-0.223 T for the coil current in range of 0.45-0.91 A and the maximum rise in temperature occurred at 450 rpm and 0.23 T magnetic flux. **V.K. Jain et al. [15]** studied the effect of pulsating Direct current in the magnetic abrasive finishing process. Parameters considered for the study are Duty Cycle, On time, Off time, and Pulse Time. They observed that, there is an enhancement in the surface finish by utilizing pulsating DC supply, which due to the formation and destruction of FMAB during on-time and off-time of the pulsating power supply, respectively.

2.2 MODIFICATION IN THE MAF PROCESS:

2.2.1 VIBRATION ASSISTED MAF

The traditional MAF process has major advantage that the brush used to machine workpiece may become blunt after some time of operation, as the cutting edges of all the abrasive particles present in the region of brush that is in contact with the workpiece and actually carrying out the cutting, fades down. To overcome this shortcoming a number of different approaches are employed by researchers. One such commendable technique is to impart vibrations to either the workpiece or the tool. The vibrations help to replenish the cutting edges by moving the abrasive particles in contact with the workpieces to the non-cutting zone and vice versa.

K. B. Judal et. al. [16] developed a novel approach to improve the efficiency of magnetic abrasive finishing process of cylindrical workpieces by applying longitudinal vibrations to magnetic poles. A U-shaped electromagnet setup having 1,000 turns of copper wire having 1 mm diameter was wound per coil, around a 40 mm diameter core. A 0-5A DC supply was used as the power source, and the workpiece material was selected as aluminum. 60:40 ratio of steel grit and Al_2O_3 powder was used as the abrasive material and the finishing operation was performed for 300 seconds. The change in Ra values was studied and it was found that the frequency of vibrations applied to the electromagnet and the size of abrasive particles are crucial for the change in S.R. and the MRR, because the vibrations helps to resharpen the magnetic brush by removing the worn-out abrasives and supplying fresh abrasives from the magnetic brush. He also concluded that the rotational speed of the workpiece has profound effects on the output characteristics and as the size of abrasives reduces the resulting surface finish improves.

Shaohui Yin et. al. [17] in their paper titled “Vertical vibration-assisted magnetic abrasive finishing and deburring for magnesium alloy”, explored the use of vertical vibration assisted MAF process for finishing and deburring of Mg alloy-based materials. Vertical vibrations of 1 mm magnitude were imparted to the workpiece in order to enhance the efficiency of the process, by replenishing the working surface of the flexible abrasive brush with new cutting surfaces. Therefore, the time required for deburring the holes to a desired value decreased heavily by employing vibrations during the MAF process. An increase in Ry value was obtained when using vibrations with the process, due to the increased normal pressure on the surface. The vibrations occurring in the workpiece produces a pulsating effect of the pressure due to which the peak and mean pressure rises heavily, resulting in an increased MRR but with rougher finish obtained

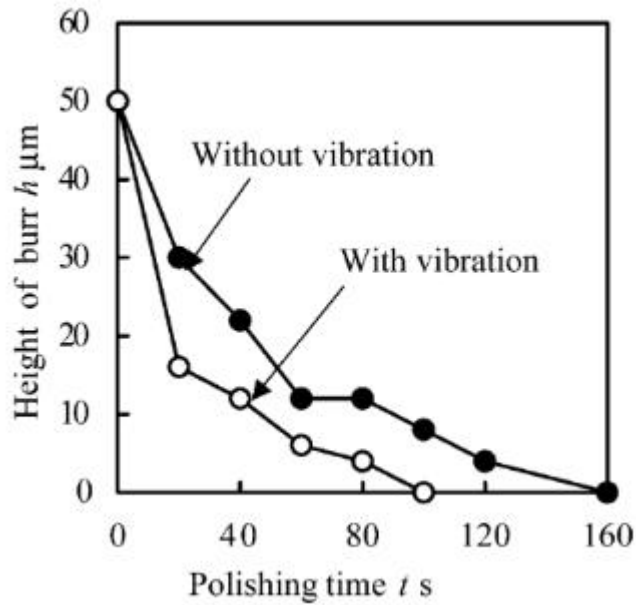


Fig. 12 Effect of vibrations on deburring of holes [17]

2.2.2 ULTRASONIC ASSISTED MAF

Rahul S. Mulik et. al. [18] [19] in his paper titled “Experimental Investigations and Modeling of Temperature in the Work-Brush Interface during Ultrasonic Assisted Magnetic Abrasive Finishing Process” developed a numerical model using Buckingham Pi theorem to develop a relationship between the worksurface temperature and the various parameters present in an ultrasonic assisted MAF process. The vibrations imparted during the finishing process are of the range between $5\ \mu\text{m}$ - $12\ \mu\text{m}$, 20 KHz frequency. Unbonded magnetic abrasive particles consisting of 300 mesh size iron particles and 800 mesh size SiC particles are used to finish the surface with 1.5 mm working gap, for 5-minute-long machine runs. Because of the ultrasonic vibrations a net increase in the maximum working temperature of the work-brush surface was observed, as it changed to 46°C from 41°C , which was measured with the help of K-type temperature sensors, installed below the workpiece surface. It was also concluded that a net increase in the temperature during the finishing process takes place with increase in the applied voltage, Weight of abrasives, and the pulse on time duration. The model thus formed was in good agreement with the experimental results.

Magnetic Abrasive Finishing is a process that is primarily used to finish ferrous alloys, because the low value of magnetic permeability of non-ferrous materials makes the process highly inefficient with no appreciable results being achieved using typical MAF process, hence a number of researchers have tried to overcome this shortcoming by the use of double electromagnets, employing a permanent magnet along with an electromagnet [20] [21] etc. One such noticeable attempt was successfully made by **P. Kala et. al. [22]**. In his paper “Polishing of Copper Alloys using Double Disk Ultrasonic Assisted Magnetic Abrasive Polishing”, he placed a disk made out of perpex, so that the workpiece rests between it and the electromagnet, to increase the intensity of magnetic field through the workpiece. The electromagnet used was made of 4 sets of coils, designed such that each pole produces a maximum of 0.25 T magnetic field at peak operation. In order to study the effects of imparting ultrasonic vibrations to the workpiece, he carried out 2 sets of experiments, one without vibrations and other with it. Voltage, rotational speed, pulse on time of the vibration horn and mesh number of the MAPs were selected as the input parameters and each workpiece was machined for 5 minutes. A 16 point % change was obtained by using the ultrasonic assisted MAF compared to the typical MAF process.

2.2.3 OTHER MODIFICATIONS

J. Wu et. al. [23] proposed an ultraprecision MAF process using low frequency alternating magnetic field which promotes the dispersion of micro magnetic particles and enhance the stability of tool used for grinding. In this study, the investigation of impact of alternating magnetic field on magnetic field distribution, force of finishing and abrasive behavior was carried out. A design of experiment was developed for finishing the SUS304 stainless steel plate. The effect of different process parameters namely grinding fluid, rotational speed of pole and current frequency on the surface geometry and material removal was studied. The surface roughness of SUS304 stainless steel plate was improved from 240.24 nm to 4.38 nm, with the increase of magnetic particle diameter, the

size and variation of amplitude of force I_{re} increased. The surface geometry and the material removal enhance with increase in rotational speed.

Kima et. al. [24] proposed a new finishing process called magneto-electrolytic abrasive polishing. By combining the Lorentz force effect to the traditional electrolytic finishing process, the process was developed to notice the high efficiency and enhance the surface geometry. This work provides a theoretical explanation behind the modification of motion of electrolytic ion caused by magnetic field, the effect of magnetic field was studied by analyzing the results of model test. The magnetic field affects the movement of electrolytic ion and changes the linear path to curved path by accelerating the ions. It enhances the finishing efficiency. For the higher efficiency, the optimum magnetic flux density exists and it was 0.6 T for gap of 1mm. The correlation between the flux density, the working electrode gap and potential determines the optimal value for optimal value for optimum efficiency of surface finish. K. B. Judal et. al. [25] presented the performance of machining on cylindrical electrochemical MAF to get the enhanced efficiency of machining. A list of experiments was conducted on AISI 304 stainless steel workpiece based on rotational design technique of response surface methodology. The effect of different process parameters (viz. workpiece rotational speed, current to electromagnet, electrolytic current and frequency of vibration) is studied on processed variables i.e. surface roughness and material removal. After conducting analysis of model it was found that rotational speed and electrolytic current have a noticeable influence on the output variable i.e. MR and Ra. Increase in these variables results in increasing material removal and lowering Ra due to synergic working effect of abrasive assisted passivation and passivation assisted abrasive. After carrying out multiple response optimization for maximizing MR and minimizing Ra, the optimal input processing variables are working rpm, electrolytic current and 6Hz frequency of vibration.

T.A El-Taieb [26] proposed a hybrid process of Electrochemical Turning and MAF that enhances the material removal rate and lowers down the surface roughness of 6021 Al/Al₂O₃. This study focuses on the characteristics of development of

empirical mathematical models based on RSM for comparing the interactive relationships of processing parameters i.e. magnetic flux density, applied voltage, tool feed rate and workpiece rotational speed. The effect of these machining parameters was studied on the MRR and SR. This also highlights on validity and correctness of models developed for in depth analysis of processing parameters on MRR and SR. To maximize MRR and minimize SR, these parameters are optimized. Increasing both voltage and feed rate leads to enhancing the machining efficiency and surface roughness. Assigning ECT with MAF improves surface geometry of material. The formed mathematical model was found to be flexible and it shows the optimized effects of processing parameters. G.Y. Liu et. al. [27] proposed a tangled hybrid model combining electrochemical machining and magnetic abrasive finishing. A suitable tool which is capable enough to work under two different processes of different characteristics was designed and list of experiments was carried out on Al-6061 to investigate the impact of EMAF process. The results obtained after conducting experiments should that EMAF help to obtain the better surface finish and higher metal removal rate compared to traditional MAF process. The surface roughness Ra of material is reduced down to range of 0.2 μm to 1.3 μm by EMAF technology. To obtain the enhanced surface quality in the hybrid process, the ECM must be kept in passivation status. A limit of surface quality exists with spindle type tools due to non-uniform distribution of magnetic and abrasive.

N. Sihag et. al. [28] devised a new process combining the chemical oxidation and magnetic field assisted abrasion for fast processing of material. A list of experiments was conducted on tungsten workpiece and the effect of machining parameters like percentage Weight of abrasive, oxidizing agent cluster, rotational speed of magnet and working gap on the surface geometry are investigated. The planned design of experiment designed by using Taguchi L9 orthogonal array was analyzed by ANOVA to study the contribution of individual parameter on the surface geometry. To study the surface morphology of material SEM micrographs are obtained. A model was developed to study the change in surface roughness of material. It was found that in CMAF process, the surface geometry i.e., Ra was affected by rotational speed of magnetic disk (37.71%), percentage Weight of abrasive (27.74%), working gap (16.12%) and cluster of H₂O₂ which is used to form oxide layer. The maximum peak to valley height in geometry profile is approximately 1/5th of same of unfinished sample.

2.3 PERFORMANCE PREDICTION USING MATHEMATICAL & NUMERICAL TECHNIQUES:

The MAF process is very tangled in nature due to the large number of cutting surfaces present inside the flexible magnetic brush at any time. The interaction of all the MAPs in the brush is also very difficult to study and model using mathematical or numerical techniques but still a number of commendable attempts have been made in the past to perform such herculean task. **S.C. Jayswal et. al. [29]** tried to model the material removal taking place in the MAF process, and the ensuing surface roughness obtained by assuming a uniform surface profile, lacking any variation in its surface. The whole space within the working gap was divided into 2-dimensional mesh around which the governing equations were solved using the Glarekin's method of finite element analysis. Number of different assumptions regarding the constancy of magnetic field with time, homogeneity of working brush, and zero leakage of magnetic flux etc. were made in order to simplify the problem. The shearing model of material removal was used by assuming the MAP to be perfect spherical in shape. An experiment was also carried out on SUS304 using Silicon Carbide based magnetic abrasives, by them to check the accuracy of the model. Appreciable conformity between the experimental and predicted results was obtained at 4 minutes of machining time. The same methodology was extended to non-uniform surface profiles [30], assuming a statistical distribution of surface topology in order to improve the accuracy of predictions, and a reduction in % error between the predicted and experimental results was achieved. A finite element model of a rotating magnetic field was developed by **J. D. Kim et. al. [31]** in his paper "Development and finite element analysis of the finishing system using rotating magnetic field"

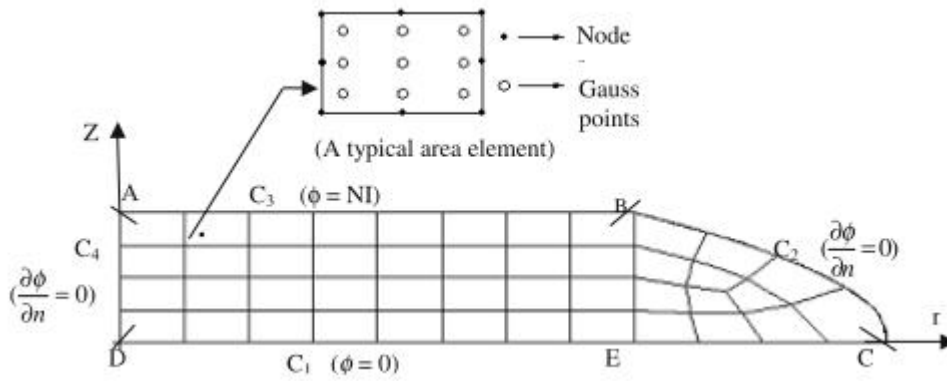


Fig. 13 Mesh of working gap

2.4 PERFORMANCE PREDICTION USING AI BASED METHODS:

Artificial intelligence is the new hype in the technological world that is going to change the landscape in each and every paradigm of life, and production engineering is none the less spared at all. Surprisingly though the focus of scientists, engineers and programmers have shifted heavily on this method of programming, in the last few years but still I can find a number of different applications of Artificial Intelligence in the field of my focus in the present study.

F. Djavanroodi [32] discussed the utilization of Artificial Neural Network for predicting the surface roughness during magnetic abrasive finishing process. In his paper on “Artificial Neural Network Modeling of Surface Roughness in Magnetic Abrasive Finishing Process” he performed an experiment to study the effect of various input parameters such as magnetic field intensity, velocity of workpiece surface being machined and the total machining time, on the surface roughness obtained during magnetic abrasive finishing of a CuZn37 brass shaft. He fed the results obtained to a 3 layered back-propagation neural network, with 5 neurons in the middle layer, powered by Levenberg-Marquardt training algorithm. The configuration of the neural net used was 3-5-1, with tangent sigmoid transfer functions. Using this method, he was able to obtain a 99.9% agreement between the experimental values and those predicted by ANN. With

the experiment, he concluded that the current intensity has the most extreme effect on the surface finish out of all the input parameters studied and the most optimum results ($0.52 \mu\text{m Ra}$ value) were obtained with 2.5 A current, 1.15 m/s surface speed and while the machining time was set to be 30 minutes. R.K. Jain et al. [33] developed a back propagation neural network having four inputs, one hidden layer and two outputs to find the optimum machining parameters in abrasive flow machining process. The parameters taken into account for the optimization were abrasive mesh size, abrasive cluster, and piston velocity.

J. H. Oh et. al. [34] used ANN to develop an automated manufacturing system by studying the acoustic signals being continuously reflected by the finished surface during the machining process. Acoustic Emission sensor which was installed within the workpiece to read the low intensity and high frequency elastic waves propagating through the workpiece. Acoustic waves which can be effectively used to study nano-level variation in the surface integrity, were fed to the ANN as the input parameter. An L27 orthogonal array was used to design the 3-leveled set of experiments performed on S136 steel, where rotation velocity of the tool, machining gap, abrasive size, its quantity and the feed rate were used as the input parameter. Two different types of ANN prediction systems were compared, first the data fusion based in which the input data was used to predict the surface roughness and the sensor based fusion ANN in which the Acoustic Emission sensor data was fed directly as the input. The latter gave more reliable results over the whole range of experiment.

Ameer A. Moosa [35] developed an adaptive neuro fuzzy inference system (ANFIS) to evaluate the relative change in surface roughness after MAF process is performed on brass plates. 2.022% error was obtained between the predicted and experimental values, using 4 different input parameters i.e. the working gap, spindle speed, amount of abrasive being used and the magnetic flux density.

2.5 CONCLUSION

From the present literature survey, it was concluded that the MAF process has emerged as a concern of extensive study in the past few years. A number of different applications and modifications in the typical process, was performed. The unbonded MAF process was found to be a robust technique to improve the surface finish. Therefore, in the following study an unbonded MAF process will be used to exploit the performance characteristics of the magnetic abrasive finishing process. TITANIUM GRADE 5 material is selected as the workpiece due to its extensive application in the medical industry, such as in prosthetic implants, which require a nano-level surface finish in order to reduce Wear of muscles in the body. From the literature, it is also observed that artificial intelligence-based techniques are robust modelling methods that can be applied on MAF process with commendable accuracy. Hence in the following study Artificial neural networks & Genetic Algorithms will be used in modelling and optimizing the MAF process

CHAPTER 3

ARTIFICIAL NEURAL NETWORKS (ANN) & GENETIC ALGORITHMS (GA)

In cognitive science and machine swotting, **Artificial-Neural-Networks (ANN)** frequently allude to as Neural-Networks are computational models which stimulate biological neural-networks (bio-neural networks) and acquainted with verge on a function which depends on large number of particulars and customarily unknown. The bio-neural network in a human's brain is an extremely sophisticated, unplanned, and side by side information operating system. The efficacy of a bio-neural network can be evaluated by the fact that it can restructure its structural constituents to carry out a convinced computation many times quicker than the expeditious digital computer today.

For example, consider a bat sonar. It is an active echolocation system. Moreover, it also provides information concerning the target distance, the target's relative velocity and the size. The tangled neural problem needed to extricate all data from the target echo occur within a brain the size of a plum. Undeniably, an echo locating bat can hunt and apprehend its target with a knack and success rate that striving the desire of a radar or sonar engg.

An Artificial Neural Network resembles the brain in two facets:

- A swotting algorithm or process is used to possess information from its environment.
- The possessed knowledge is heaped in the connection strengths of interneuron, known as synaptic Weights and bias.

3.1 HISTORICAL PERSPECTIVE

Like any other field of science, Neural networks also has a long history filled with many ups and downs. In the 1940's history of neural networks begins and meanwhile with the history of programmable computers.

- **Late 1940s:** A hypothesis was developed by D.O. Hebb, which was based on the neural plasticity mechanism. The hypothesis was known as Hebbian Swotting. It is freely swotting.
- **As soon as 1943:** The first elementary computing neuron modeling proposed by McCulloch and Walter Pitts. The model had all the aspect to perform logic operations.
- **1949:** Donald Hebb formulated the Hebbian Swotting Rule, it is a swotting scheme for renovating the connection of neuron's. He stated "the neuron's connection has the capability to store the information and hypothesized a swotting technique that has a massive impact on future development in this field".
- **1950-1958:** Marvin Minsky, a graduate at Princeton built the first neurocomputer Snark. In 1958 at the MIT, Frank Rosenblatt, Charles Wightman and their colleague invented the first successful neurocomputer, perceptron. The perceptron can categorize certain pattern by modifying the connections of the initiation aspect.
- **1960:** ADALINE (Adaptive Linear combiner) and a new robust swotting rule called (the Widrow Hoff swotting rule) was originated by Bernard Widrow and Marcian Hoff. During the training, the rule lessens the summed square error to categorize the pattern.
- **1975-1980:** Paul Irbos in 1975 proposed a backpropagation algorithm, which solved the problem of quickly training multi-layered networks. Kunihiro Fukushima proposed a multilayered artificial neural network that I now refer to as the Neocognitron. It can recognize handwritten

characters.

- **1986:** To pretend neural processes, the employ of connectionism described by Rumelhart and McClelland.
- **1992:** Max-pooling was originated to assist with least shift unchangingness and tolerance to deformation to help in 3D seeing. because the error propagates from layer to layer, they shrink exponentially with the amount of layers, hampering the standardization of vegetative cell Weights that's supported those errors, notably touching deep network, as a result of deep neural network consists quite one hidden layers. to beat this downside, once more in 1992, a man of science, Schmidhuber director of the Dalle Peruvian mastic tree Institute of AI analysis in Manno, used a multi-level hierarchy of networks pre-trained one level at a time by freely swotting and fine-tuned by backpropagation.
- **2010:** Backpropagation coaching through max-pooling was accelerated by GPUs and shown to perform higher than different pooling variants.
- **2012:** Ng and Dean developed a neural network that learned to acknowledge higher-level options, reminiscent of cats, solely from observant unlabeled pictures.

3.2 THE HUMAN BRAIN

The anxious framework of a human being has three-stage framework, as appeared within the fig. 14. Central to the framework is human brain, spoken to by the organic neural arrange, which gets data from the environment ceaselessly, sees it, and at that point make fitting choices. In fig. 14 two sets of arrows are utilized. Those indicating from cleared out to right shows the forward stream of the information carrying signals through the framework. The bolts indicating from right to the cleared out, shows that a criticism framework is consolidated into the apprehensive framework. The receptors change over jolts from the outside environment into electrical motivations that carries data to the neural arrange (Brain). The

effectors change over electrical driving forces produced by the neural arrangement into perceivable reactions as framework yields.

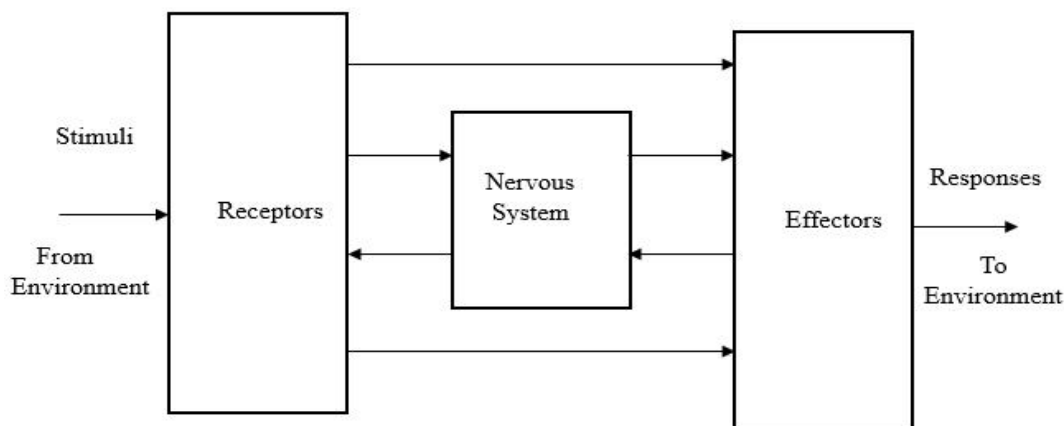


Fig. 14 Block diagram of Nervous System

3.3 BIOLOGICAL NEURON

Neuron is an information cell and it's the elemental building block of the biological neural network. A neuron consists of a cell body known as the Soma, the Axon, and therefore the dendrites as shown in Fig. 15. A neuron communicates with the neighboring neurons through electrical signals. The signal is transferred to neighboring neurons through the nerve fiber, which could be a long slender extension of the soma. The tip of a part of an associated nerve fiber splits into a fine arborization. The tip of every branch includes a bulb-like form that touches the dendrites of the neighboring neurons, and this contact creating organ is known as a conjunction. At conjunction, a neuron introduces its signal to the neighboring neuron. The signal is in the form of electrical impulses; the receiving neuron either generates an associated impulse to its nerve fiber or produces no response. The neuron can manufacture a response if the potential of the neuron's membrane exceeds a definite level or the neuron can fire if it meets the mandatory conditions.

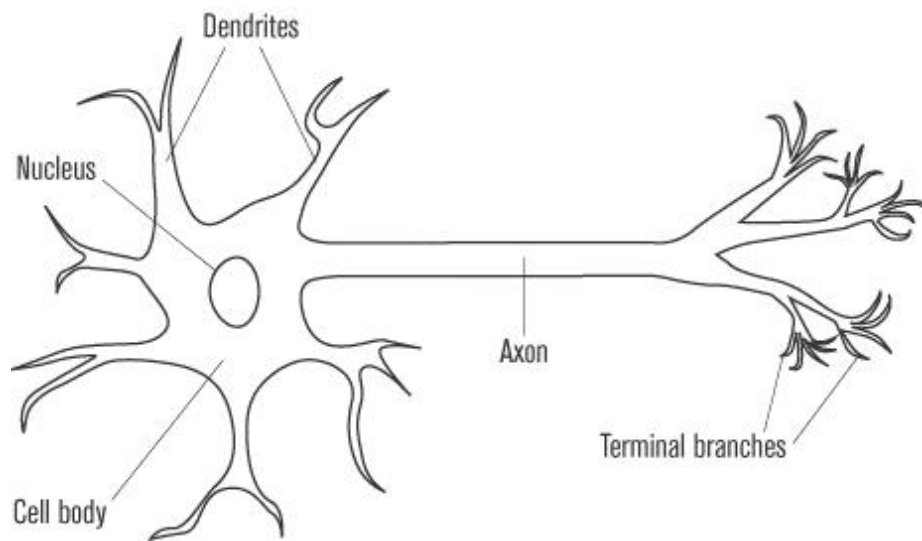


Fig. 15 Biological Neuron

Now let's take into account the required conditions for the firing of a neuron. If the incoming impulses cause the neuron to fire, they're excitatory impulses and if they hinder the neuron from firing they're inhibitory impulses. An additional precise condition for firing is that the excitation ought to exceed the inhibition by the quantity referred to as the threshold of the neuron. Once carrying a pulse, for a few amounts of your time referred to as the biological time, the nerve fiber is in a very state of non-excitability. For this interval of your time the nerve fiber doesn't transfer any signal, in spite of the intensity of the impulse. Thus, I'll divide the continuance into ordered time intervals, every adequate the length of the refractory period. Exploiting this I will specify that neuron can fire at the moment $k+1$ supported the excitation condition at instant k .

3.4 THE RESTING POTENTIAL

To understand the character of the electrical impulse that travels on the neuron, it's necessary to appear at the changes that occur associated exceedingly in a very neuron between once it's at rest and once it's carrying an impulse. Once there's no impulse traveling through a vegetative cell, the cell is at its electric potential and therefore the inside the cell contains a charge in regard to the surface. Maintaining a charge within the cell is a lively

method that needs energy. The plasma membrane of the neuron contains a macromolecule known as Na^+/K^+ nucleotidase that uses the energy provided by one molecule of ATP to pump three charged metallic element atoms (Na^+) out of the cell, whereas at the same time taking into the cell two charged K ions (K^+).

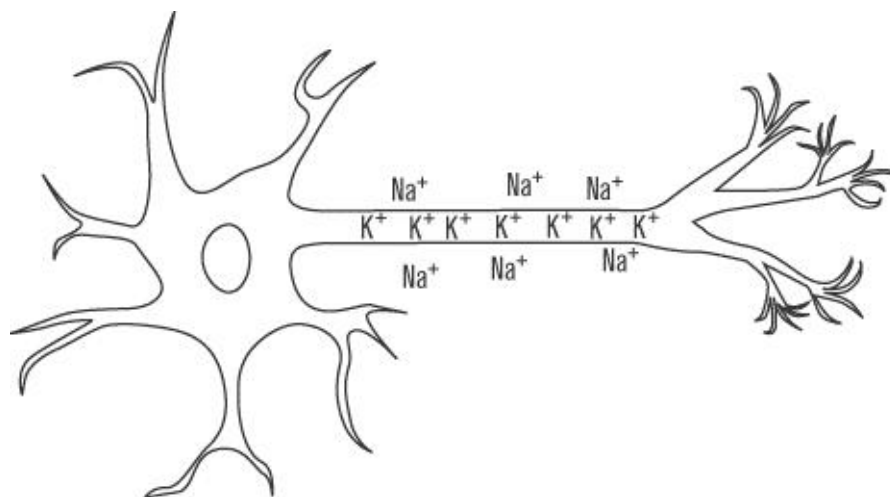


Fig. 16 Biological Neuron consisting ions

The sodium-potassium pump builds up a high cluster of sodium ions outside the cell associate degreeed a way over metallic element ions within the cell. These ions naturally need to diffuse across the membrane to regularize the distribution. However, one in every of the special properties of lipid cell membranes is that they bar passage to particles unless there's a special macromolecule channel that enables a selected ion in or out. No such channel exists for the atomic number 11 that's engineered up outside the cell, though there are unit metallic element leak channels that enable a number of the metallic element ions to emanate of the cell. The distinction in particle clusters creates a internet electrical phenomenon across the cytomembrane of roughly -70 mV (millivolts), that is that the worth of the voltage.

3.5 ARTIFICIAL NEURON

An Artificial neuron is that the basic building block of every and each artificial neural network. Its functionalities square measure analogous to the biological neuron, that is that the basic building block of the biological neural system. the synthetic neuron is way quicker in process associate info than the biological neuron. Fig. seventeen shows that what quantity similar the biological and artificial neuron is, the left aspect has the biological neuron with its cell body referred to as soma, axone and dendrites that forms the nerve fibre tree, wherever the proper aspect represents a man-made neuron with inputs, Weights, bias, activation operate and output. As compared to the biological neuron during which info comes through the dendrites, processed by soma then transmitted by axone, a man-made neuron receives the knowledge via inputs that square measure Weighted, then the neuron sums the Weighted inputs and biases, then processes it victimisation associate activation operate.

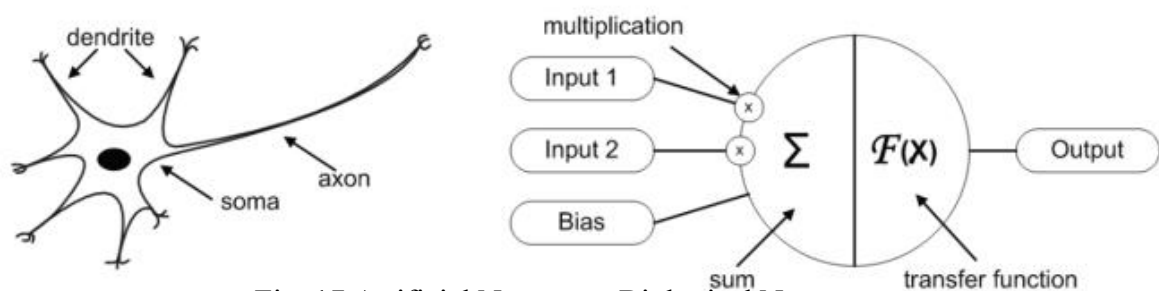


Fig. 17 Artificial Neuron vs Biological Neuron

The mathematical description of an artificial neuron is shown below:

$$Z(k) = F(\sum w_i(k) \cdot x_i(k) + b)$$

- $Z(k)$ is that the output, wherever k is that the separate time
- F is the Activation Function of the artificial neuron
- $w_i(k)$ is the Weight, in discrete time
- $x_i(k)$ is input
- b is the bias value

The major unknown variable within the on top of shown equation is that the activation performs. The activation perform or Transfer perform may be elect in keeping with the matter that the substitute nerve cell needs to solve.

3.6 ACTIVATION FUNCTION

The function $F(X)$ in fig. 18, defines the output of a neuron in terms of the iatrogenic native field X . There are two basic kinds of Activation or Transfer Functions.

3.6.1 THRESHOLD FUNCTION

For this sort of activation function, delineated in fig. 18, I have

$$F(X) = \begin{cases} 1, & X \geq 0 \\ 0, & X \leq 0 \end{cases}$$

This type of function is additionally called Heaviside operate.

Here the X is that the input passed to the neuron once multiplying the inputs with their corresponding Weights then adding biases to them. The X will be calculated as below:

$$F(X) = \sum_{i=0}^n w_i(k).x_i(k) + b$$

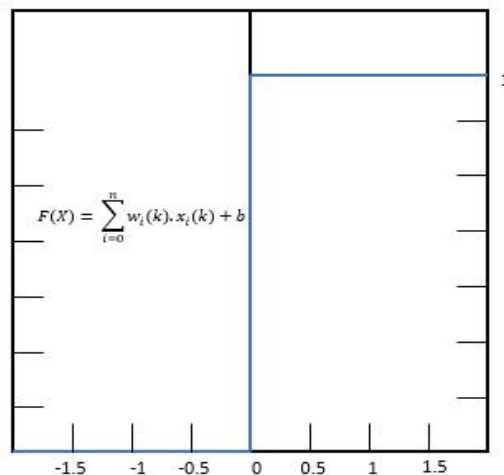


Fig. 18 Threshold Function.

In neural computing, such a neuron is brought up as McCulloch-Pitts model, in recognition of the pioneering work done by McCulloch and Pitts (1943). during this model, the output of a neuron takes on the worth of one if the induced native field of that neuron is plus, and zero otherwise. This statement describes the all-or-none property of the McCulloch-Pitts model.

3.6.2 SIGMOID FUNCTION

The sigmoid operator, whose graph is S-shaped as we can see in fig. 19, is out and away the foremost common type of activation perform employed in the development of neural networks. it's outlined as a strictly increasing perform that exhibits a swish balance between linear and nonsequential behavior. An example of the sigmoid perform is that the logistical perform, defined by:

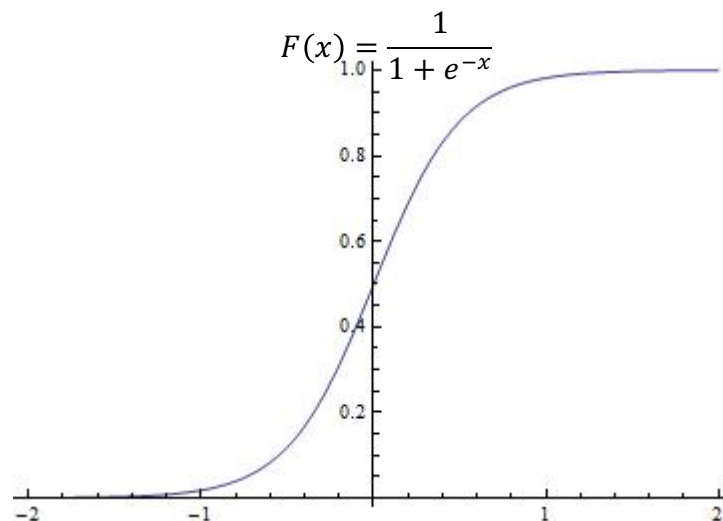


Fig. 19 Sigmoid Function

3.7 FEEDBACK

Feedback is alleged to exist in an exceedingly dynamic system whenever the output of the component within the system depends on the input applied to it explicit

element. Undeniably, feedback happens in virtually each a part of the system of each animal. Moreover, it plays a serious role within the study of a special category of neural networks referred to as repeated networks. one loop feedback system is shown within the fig. 20 below.

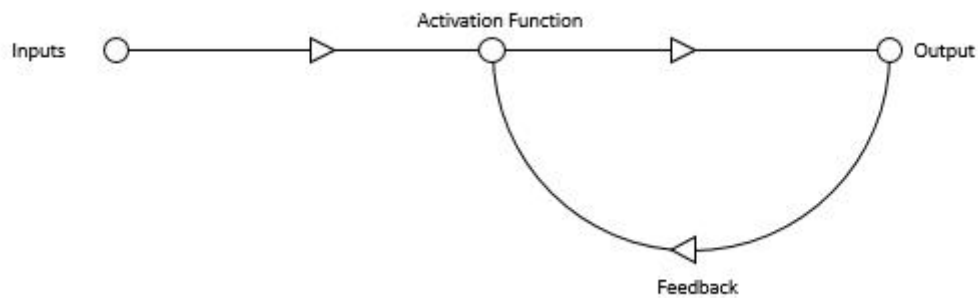


Fig. 20 Feedback System

Through the feedback system a neural network knows by how much amount the Weights and biases of the network need to be changed in order to minimize the error between predicted output and actual output.

3.8 ARTIFICIAL NEURAL NETWORK

On connecting two or additional artificial neurons i will be able to get artificial neural network. Artificial neural networks area unit capable of resolution tangled real-life issues by process data in their basic building blocks (artificial neurons) in a very non-linear, distributed, parallel and native method. Artificial neural networks is employed in modeling tangled machining processes, as a result of these networks have the aptitude to find out the associated pattern between input and output information sets.

3.9 NETWORK ARCHITECTURE

The means within which individual artificial nerve cell is connected is termed topology or design of a man-made neural network. Interconnection will be tired varied ways in

which ends up in varied doable topologies that are divided in three essentially totally different classes:

1. Feedforwarded Single-Layer Networks
2. Feedforwarded Multi-Layer Networks
3. Repeated Neural Networks

3.9.1 FEEDFORWARDED SINGLE LAYER NETWORK

In a stratified neural network, the neurons square measure organized within the type of layers. within the simplest type of a stratified network, I actually have an input layer of nodes that comes onto an output layer of neurons. during this network flow of data is simply in one direction. the everyday design of a feedforward neural network is shown in fig. 21 below:

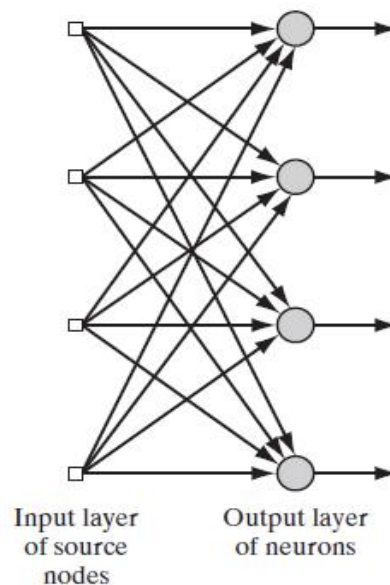


Fig. 21 Feedforward Neural Network with single layer of neurons [32]

Here all the computational work is carried by neurons of the output layers, neurons in input layer do not contribute to the computation work.

3.9.2 FEEDFORWARDED MULTILAYER NETWORK

The second category of feedforward neural network have one layer additionally to the layers gift within the single layer feedforward neural network, this additional layer is understood as Hidden Layer, whose computation neurons area unit correspondingly referred to as hidden neurons. The term hidden refers to the very fact that this layer of the neural network isn't seen directly from either the input or output of the network. The perform of the hidden neurons is to intervene between the external input and also the network output in some helpful manner. By adding one or a lot of hidden layers, the network is enabled to disengage higher-order statistics from its input. in a very rather loose sense, the network possesses a world perspective despite its native property, because of the additional set of conjugation connections and also the extra dimension of neural interactions.

The supply nodes within the input layer of the network offer several facets of the activation pattern, that represent the input signals applied to the neurons within the second layer. The output signals of the second layer area unit used as inputs to the third layer, so on for the remainder of the network. Typically, the neurons in every layer of the network have as their inputs the output signals of the preceding layer solely. The set of output signals of the neurons within the output layer of the network constitutes the response of the network to the activation pattern provided by the supply nodes within the input layer. The design of a typical Multilayer Feedforward Neural Network is shown in fig. 22.

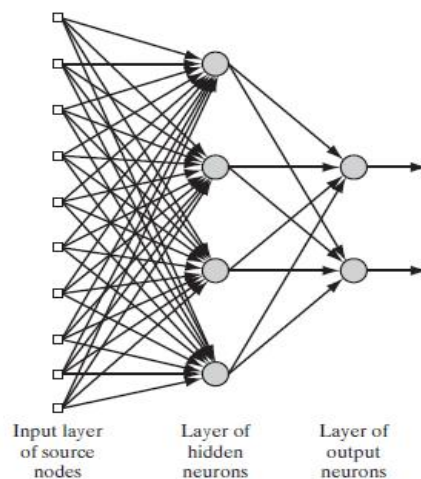


Fig. 22 Feedforwarded Multilayer Neural Network having one hidden and one input layer.

The feedforwarded multilayer neural network as shown in Figure 22 is named as 10-4-2 network as a result of its 10 supply nodes, 4 hidden neurons, and a pair of output neurons.

3.9.3 REPEATED NEURAL NETWORK

A repeated neural network is completely different from the feedforward neural network as a result of it's a minimum of one feedback loop. let's say, a continual network could encompass a layer of neurons with every neuron feeding its signal back to the inputs of all the opposite neurons. A typical repeated neural network is shown in Figure 23.

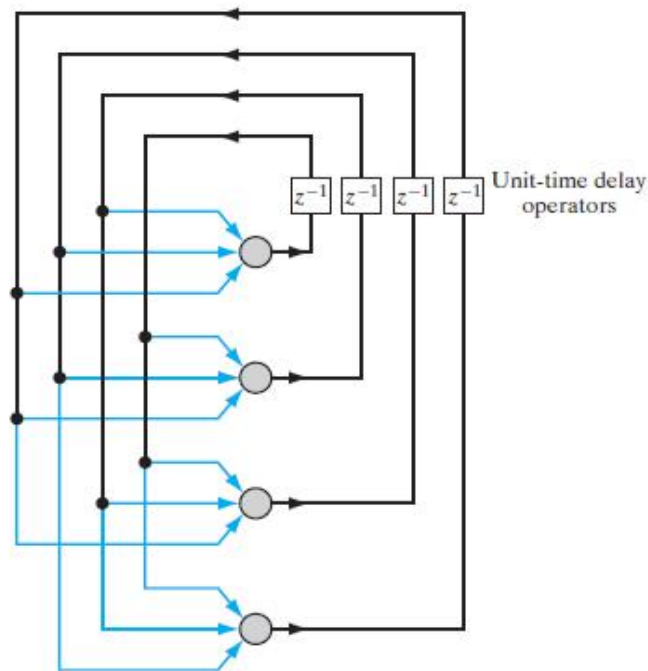


Fig. 23 Repeated Neural Network with no hidden-neurons and with no self-feedback

In the design represented during this figure, there are not any self-feedback loops within the network; self-feedback refers to a scenario wherever the output of a neuron is fed back to its own input. Also, the network has no hidden neurons. The presence of feedback loops, be within the repeated design with no hidden neuron, or in repeated design

with hidden neurons, incorporates a profound impact on the swotting capability of the network and on its performance. Moreover, the feedback loops involve the utilization of specific branches composed of unit-time delay side (denoted by z^{-1}), that lead to a nonsequential dynamic behavior, forward that the neural network contains nonsequential units.

3.10 SWOTTING PROCESSES

Just as there are other ways within which I my selves learn from my very own close environments, thus it's with neural networks. Typically, swotting of a neural network is split in three categories:

1. superintended Swotting
2. Freely Swotting
3. Reinforcement Swotting

3.10.1 SUPERINTENDED SWOTTING

Superintended swotting may be a form of machine swotting algorithmic rule that uses a famed dataset (called the training dataset) to create predictions. The training dataset includes input file and response values. From it, the superintended swotting algorithmic rule seeks create} a model which will make predictions of the response values for a brand new dataset. A take a look at dataset is usually wont to validate the model. exploitation larger training datasets typically yield models with higher prophetical power which will generalize all for brand spanking new datasets. Superintended swotting includes two classes of algorithms:

1. Classification: for categorical response values, wherever the info will be separated into specific “classes”
2. Regression: for continuous-response values
3. Support vector machines (SVM)Neural Networks
4. Naïve Thomas Bayes Classifier
5. Decision Trees
6. Discriminant Analysis

7. Nearest neighbors (kNN) Linear regression
8. Nonsequential regression
9. Generalized linear models
10. Decision hairdo
11. Neural Networks

3.10.2 FREELY SWOTTING

Freely swotting may be a form of machine swotting rule accustomed draw inferences from datasets consisting of computer file while not labelled responses. the foremost common freely swotting technique is cluster analysis, that is employed for preliminary knowledge analysis to seek out hidden patterns or grouping in knowledge. The clusters are shapely employing a measure of similarity that is outlined upon metrics equivalent to euclidian or probabilistic distance.

Common bunch algorithms include:

1. Hierarchical clustering: builds a construction hierarchy of clusters by making a cluster tree
2. k-Means clustering: partitions knowledge into k distinct clusters supported distance to the centre of mass of a cluster
3. Gaussian mixture models: model's clusters as a mix of variable traditional density elements
4. Self-organizing maps: uses neural networks that learn the topology and distribution of the info
5. Hidden mathematician models: uses determined knowledge to recover the sequence of states

3.10.3 REINFORCEMENT SWOTTING

Reinforcement swotting is an important type of Machine Swotting where an agent learns how to behave in an environment by performing actions and seeing the results. The idea behind Reinforcement Swotting is that an agent will learn from the environment by interacting with it and receiving rewards for performing actions.

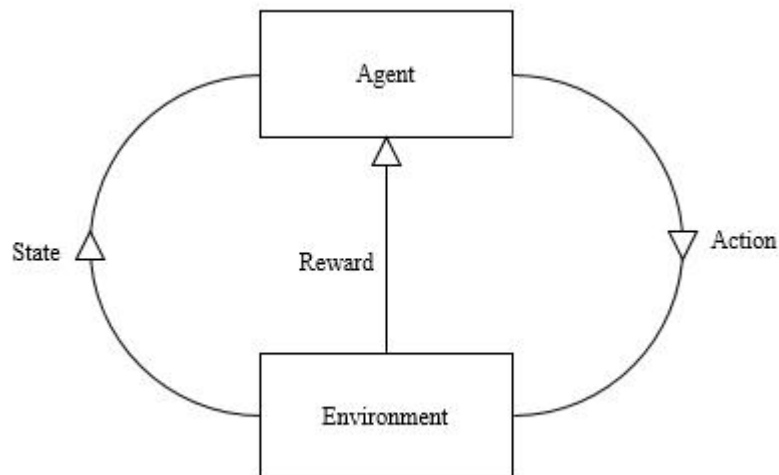


Fig. 24 Reinforcement swotting

In Reinforcement swotting the agent has to be compelled to take actions in associate surroundings thus on maximize some notion of accumulative reward. the matter because of its generality, is studied in several different disciplines, appreciate scientific theory, management Theory, research, scientific theory and Genetic Algorithms.

3.11 GENETIC ALGORITHMS

3.11.1 HISTORY OF GENETIC ALGORITHMS

The history of Genetic formula isn't that abundant massive because the strategy itself is. however, some vital work has been done by researchers within the past. Researchers with success pretendd the concept of natural evolution within the computer systems.

In the 1950s and 1960s many computer scientists studied biological process systems with the concept that evolution will facilitate in determination several optimisation issues in engineering.

In the 1960s, Rechenberg originated “evolution strategies”, associated used this methodology to optimize real-valued variables for an aerofoil. the sector of evolution ways has remained a lively space of analysis, largely developing severally from the sector of genetic algorithms. In 1960s, Genetic formula (GAs) are unreal by John Holland and more developed by Holland and his students at the University of Michigan within the 1960s and therefore the 1970s. Holland’s plan was to check the development of adaptation because it happens within the nature and to import the mechanism of adaption in computer system, instead of determination optimisation drawback exploitation Genetic Algorithms. In 1975 John Holland printed a book *Adaptation in Natural and Artificial Systems*, within which he demonstrates the model’s catholicity by applying it to political economy, neuropsychology, game theory, and AI.

Research in GAs remained mostly theoretical till the mid-1980s, once the primary international conference on Genetic Algorithms was command in metropolis, Pennsylvania.

3.11.2 INTRODUCTION

Genetic Algorithms are metaheuristic and global search algorithms, impressed by the natural evolution. It’s an exploration technique to search out approximate solutions to improvement and search issues. GA handles a population of potential solutions. every population is portrayed through body, that is simply an abstract illustration. secret writing all the potential solutions into a body is that the 1st part. a group of genetic operators are directly applied on the body in a very predefined sequence. once applying the operators, the satisfactoriness of the result is checked, whether or not it's helpful or not, if it’s found to be usable then the algorithmic program terminates and provides the most effective potential resolution, else keep applying the genetic operators in search of the most effective resolution.

3.11.3 WORKING OF GENETIC ALGORITHM

Rather than ranging from one purpose (or guess) at intervals the search area, GAs is associate degree initialized with a population of attainable solutions to a specific drawback [55]. These are typically random and can be unfold throughout the search area. algorithmic program then uses three operators, selection, crossover, and mutation (analogous to the natural world) to direct the population towards convergence at the worldwide optimum [56, 57]. every initial resolution is encoded during a chromosome using one out of diverse coding techniques. this first population then processed by the three main operators.

- Selection pretends the natural selection found within the biological systems. Poorer performing people are welded out and better performing, or fitter, people have a larger probability of promoting the data they contain to consequent population or generation, i.e. people having higher fitness worth have additional probabilities to urge designated for crossover.
- Crossover permits solutions to exchange info in a approach that is analogous to that utilized by a natural organism undergoing reproduction. The people given by the selection method are more experienced this operator. In crossover two solutions that are encoded into a body (called Parents) exchange info with one another and forms a replacement body (called child). a very new generation is generated by activity this operator on the previous generation. There are many ways of performing the crossover, over the population.
- Mutation is employed to indiscriminately modification or flip the worth of single bits among individual chromosomes.

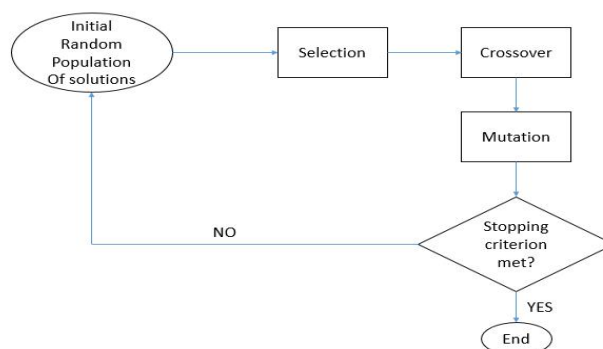


Fig. 25 Flow Chart of Genetic Algorithm.

Fig. 25 shows the overall work flow of a GA program. at the start, a population of chromosomes is developed and therefore the fitness of every competent resolution is evaluated using the Fitness function. These initial generation of solutions forms the initial population pool. The initial population of solutions is chosen indiscriminately to get most genetic diversity among the people. Then a try of those chromosomes is chosen employing a appropriate choice operator for Crossover, later the Crossover operator produces offsprings using that the new Population pool is produced. The offsprings are also mutated with a mutation chance to explore region of the search space which are however not explored through the chosen gene diversity. This second generation of solutions is once more evaluated and the genetic operators are applied on it. throughout successive iterations, the fitness of the solutions usually tends to optimize, and this method continues unless the stopping criterion is met. various stopping criterions are used to terminate the program, particularly maximum number of generation, fitness function criterion, elapsed time, stall generation, stall time limit etc.

3.3 THE HYBRID GA-ANN MODEL

Although artificial neural networks have nice capability to find out, still they're at risk of get stuck in a very local optimum, as a result of in most of the training algorithms used to train a neural network works are gradient based mostly. in a very gradient descent algorithmic rule, one takes steps proportional to the negative of the gradient. due to which after reaching a native minimum the algorithmic rule won't more proceed to following minimum and get stuck within the local minimum.

To overcome this drawback, I have used a Hybrid GA-ANN model, within which Genetic Algorithms are used to train the neural network. due to the random nature of genetic algorithm and its nature to work using a set of attainable solutions, the possibilities of getting stuck during a local minimum is less. The design of the neural network also has to be optimized. because if the quantity of neurons in a neural network isn't adequate enough, then it'll not be ready to learn the tangled non-linear relationships.

- In this model, 1st the design (combination of number of hidden layers, size of the hidden layer and training function) of the neural network is optimized using genetic algorithms and so using it once more, the Weights of the neural network is optimized. To do this, a program in MATLAB v15. is developed that performs the subsequent steps: -
- A neural network is made with random range of neurons, training function, and range of hidden layers.
- Then genetic algorithms been used to notice the simplest design that the potential of the neural network is maximum to learn.
- After optimizing the design of neural network, genetic algorithms are further used to optimize the Weights of the neural network in such a way that the error in training of neural network are going to be minimum.
- If at an iteration the error in training is less than an exact value then the genetic algorithms stops and displays the Weights, bias and error. Else GA once more creates a population of potential Weights and applies genetic operators on that.
- After receiving best solution (Weights and bias values) using genetic algorithm, the network is initialized with these Weights and trained.
- To avoid over fitting of the neural network three validation points has been used with 20 validation checks. Fig. 26 represents this methodology within the kind of a flow chart.

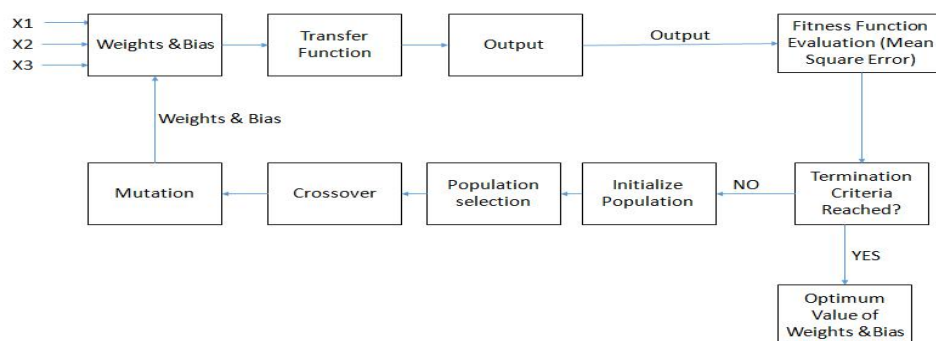


Fig. 26 Flowchart of the Hybrid GA-ANN model

CHAPTER 4

EXPERIMENTAL SETUP & DESIGN OF EXPERIMENT

The following chapter provides a detailed explanation regarding the design, fabrication, assembly and installation of the experimental setup which exploits the performance characteristics of the magnetic assisted abrasive finishing process. It should be noted here that the whole design, assembly and fabrication process was performed in-house, and the final setup developed was the result of numerous design iterations.

4.1 DESIGN OF SETUP

4.1.1 DESIGN OF ELECTROMAGNET

Electromagnet is the heart of the MAF setup that propels the whole finishing operation, by generating the magnetic field in which the magnetic abrasive particles are suspended and provides the normal force required to produce the indentation effect. The main design requirements of the electromagnet are: -

- Its design should be such that it provides flexibility of operation on any desired surface, let it be flat, curved or free form.
- The intensity of magnetic field generated, can be varied sufficiently in order to produce the desired finish.
- The electromagnet should be mechanically and thermally efficient and stable, i.e. heat produced due to the current should be minimized and a system must be provided to remove the excessive heat to prevent damage to electromagnet wires.
- The electromagnet should withstand the mechanical forces generated during operation.

By the extensive literature survey performed in the last chapter it was concluded that the magnetic field strength required at the tool's surface to produce a brush for finishing should be between 0.2 T – 1.5 T. As I know, the magnetic flux strength produced by the electromagnet, depends on variety of factors, such as, the current within the coil, total number of turns within the coil, geometrical parameters, and magnetic properties of the materials used for the fabrication of the electromagnet. Due to the limitations on the availability of the DC power supply the maximum achievable current in the electromagnet is limited to 2 Amperes. But the electromagnet is designed to efficiently operate at 10 Amperes of maximum current.

Table 1: Current-carrying capacity of copper winding

Current-carrying capacity (Amperes)	Area (mm ²)
11	1
13	1.5
18	2.5
24	4
31	6
42	10
56	16
73	25
90	35

From the above table, it can be inferred that for a current value of 11 Amperes the area of the copper wire should be 1 mm², hence the diameter of the copper wire comes out be 0.56 mm. Now in order to make my design robust I take a Factor of Safety value

of 2, which increases the wire diameter to 1.12 mm. The nearest size of copper wire available is 1.14 mm (17 gauge).

For designing the electromagnet following geometrical parameters are found to be influential:

- Diameter of the shaft
- Length of the electromagnet
- Biggest diameter of the electromagnet

The shaft diameter affects the effective machining area, and also the strength of the magnetic field available. The diameter of the shaft cannot be reduced below a certain value due to the bending and tensile stresses produced during the course of machining. Taking into consideration all these factors the shaft diameter was selected to be 35 mm. As the core material of the electromagnet should be ferromagnetic so that it converges and intensifies the magnetic field strength. Therefore, a 35-mm rod of mild steel was chosen as the core material.

Aluminum was chosen as the material for the fabrication of the electromagnet spool, due to its non-interacting property with the magnetic field lines, low density, high thermal conductivity, and moderate cost compared to other diamagnetic materials such as copper, brass, titanium etc.

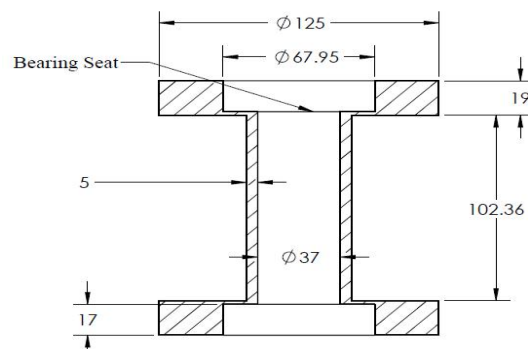


Fig. 27 Schematic drawing of electromagnet spool.

As I can see, in the fig. 27 the inner diameter of the spool is taken to be 37 mm to provide clearance for the shaft to rotate freely. The entire Weight of the

electromagnet is supported on two taper roller bearings installed in the bearing seat of the electromagnet spool and 5 mm wall thickness is provided to withstand the shear stress, bending and torsional moment induced during the machining time. The Webbing of the spool is designed such as to provide adequate strength to the electromagnet, so that the bending of Webbing does not take place due to self-Weight.

4.1.2 FINITE ELEMENT ANALYSIS OF ELECTROMAGNET

Manual calculation of the magnetic field intensity, is a very cumbersome process and can take a lot of time. The results obtained through manual calculations are also not very much dependable due to the simplifying assumption that needs to be made in order to resolve the problem, because of the difficult structure of the electromagnet. An iterative method was developed (as shown in fig. 28) in order to calculate the total number of turns required in the electromagnet using which the desired magnetic field at the tool surface was obtained. For the simulations, ANSYS® (2018) APDL package was used. ANSYS APDL is a very robust interactive finite element analysis software that can be used to pretend a number of different conditions, related to static, dynamic, thermal, magneto analysis or a

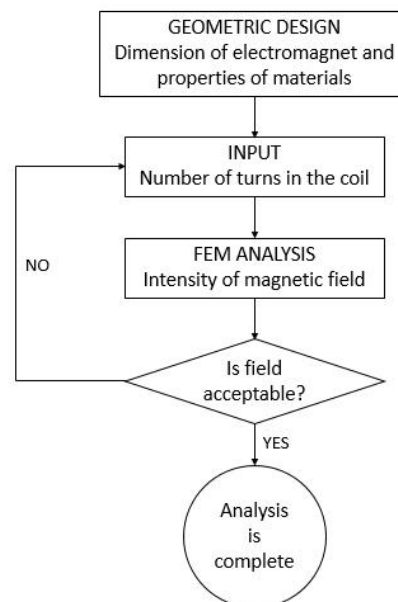


Fig. 28 Flow chart for magnetic field calculation.

From the above flow-chart, the iterative FEA works by selecting the total number of coils in the electromagnet, and then develop a model of the coil corresponding to the number of turns selected. This model was then fed to ANSYS APDL solver which calculates the strength of magnetic field produced. If the strength of this field seems sufficiently acceptable, then the corresponding design was selected as final, or otherwise the whole steps are repeated by varying the number of turns.

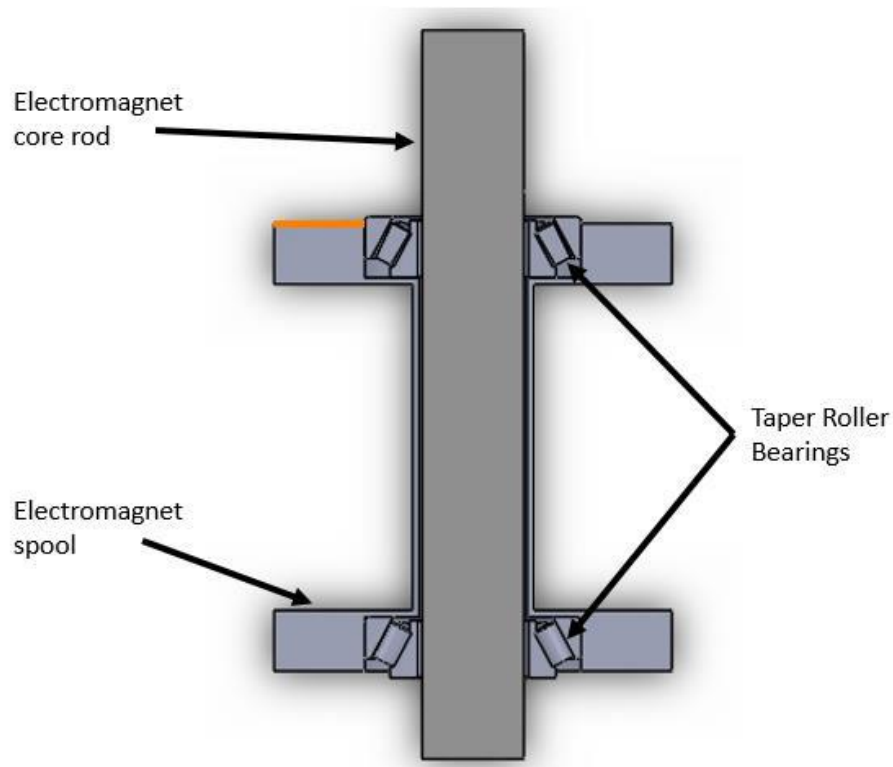


Fig. 29 The electromagnet assembly

A typical finite element analysis process comprises of the following steps: -

- Building the model: Most of the FEA solver packages supports a number of different formats through which CAD models or drawings of the model can be imported in the solver to carry out the analysis, as the common modelling softwares such as SolidWorks®, CATIA®, ProE® etc. have simpler interfaces and are robust enough to make 3D models very effectively and efficiently, compared to the design modelers available in the FEA packages. Though in the

present study a 3D model of the electromagnet supply was developed in SolidWorks® 2017 (shown in fig. 29), but for the analysis of magnetic field, a drawing of the electromagnet was developed in the APDL solver itself.

- Specifying the material properties: In order to carry out the simulation process, the FEA solver requires an input of material properties of the various materials used in the electromagnet, such as copper, aluminum, mild steel and air.
- Running the analysis: The solution of analysis is obtained by defining the parameters related to the mesh size, element type, element size, and the solver type.
- Reviewing results: In the following iterative FEA study, this part is the most crucial, in which the results obtained through the analysis are studied and it was decided whether to reiterate the whole process with different number of turns in the coil or not.

Finally, 2000 turns of copper wire was selected for the final design of the electromagnet. Using the 2000 turns a sufficiently strong magnetic field is obtained in the current setup, without excessive heating of the coil. The results obtained for the corresponding value of turns is shown below.

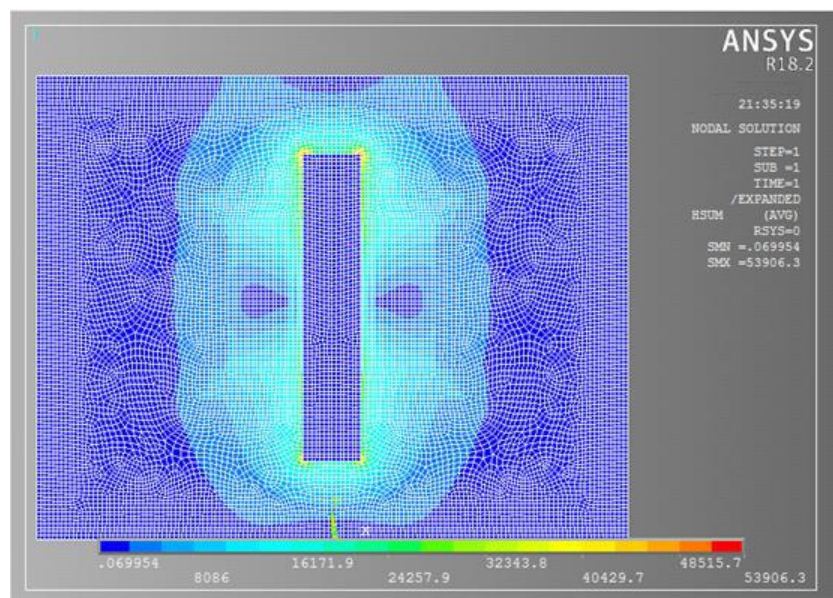


Fig. 30 FEA of electromagnet.

4.2 THE COMPLETE MACHINING SETUP

In this study, the machine setup used to perform magnetic abrasive finishing process of workpieces (Stainless Steel 316L) is illustrated in fig. 31. The MAF setup consists of three main parts/components, i.e. mechanism to rotate the shaft, electromagnet to generate required strength of magnetic field, and a DC supply to regulate the amount of current passed to the electromagnet. To rotate the shaft Radial Drilling Machine (HMT make) is used, to do so one end of the shaft is connected to the Morse Taper through a set of internal and external threads, which is then forced into the spindle of the Radial Drilling Machine.

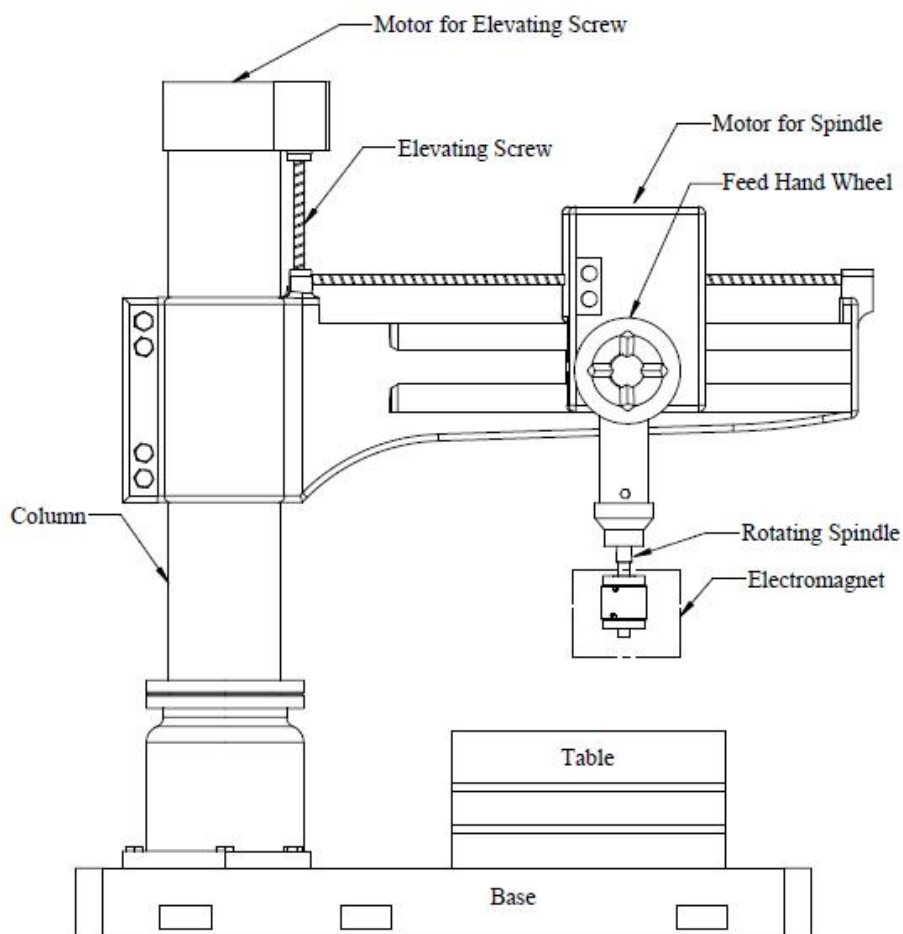


Fig. 31 Machining Setup

The setup after its fabrication is shown in the fig. 32 and 33.



Fig. 32 Assembly of the electromagnet on the radial drill



Fig. 33 The electromagnet

4.3 WORKPIECE MATERIAL

For the current study TITANIUM GRADE 5 is selected as the workpiece material, due to its wide range of utilization in the field of medicinal industry specially in prosthetic implants. Prosthetic implants are artificial bones or joints installed in place of a bone or a natural joint in case the latter is ruptured due to accident or some other reason. Prosthetic implants require a very smooth surface finish to reduce Wear and tear of muscles that are directly in contact with the implant, and MAF is highly used to achieve this superior surface finish.

The TITANIUM GRADE 5 was bought in the form of sheets (as shown in fig. 34) from which, it is cut into pieces of 45 mm * 50 mm size.

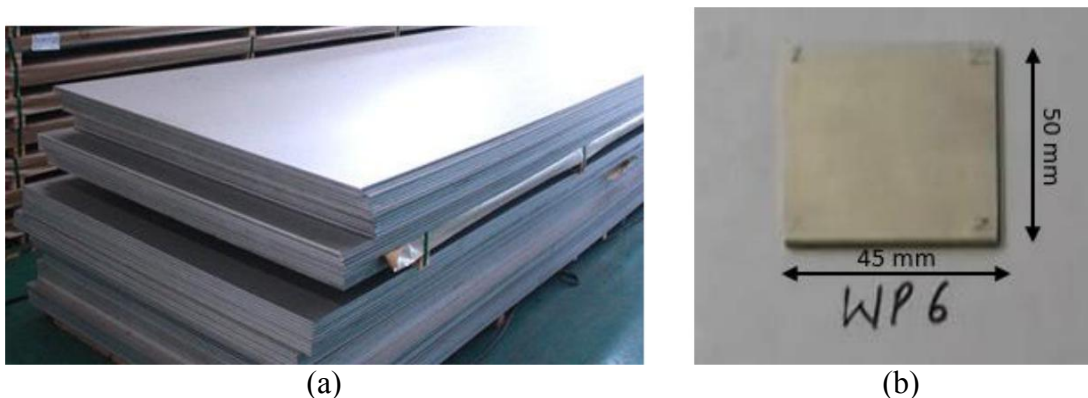


Fig. 34 Workpiece material (a) In the form of sheets (b) Cut in the desired size

The other applications of Titanium Grade 5 are: -

- Food preparation equipment particularly in chloride environments.
- medicinal
- Marine purpose
- Architectural purpose
- Medical implants, including pins, screws and orthopedic implants like, replacements of total hip and knee

- Fasteners

The chemical composition and mechanical properties of TITANIUM GRADE 5: -

Table 2: Composition of TITANIUM GRADE 5 in percentage.

Titanium	Ti	Al	V	C	O	N	H	Fe
Grade 5	90	6	4	<0.10	<0.20	<0.05	<0.0125	<0.3

Table 3: Mechanical Properties of TITANIUM GRADE 5.

PROPERTY	VALUE
Density	4.43 g/cc
Vickers Hardness	396
Tensile Strength(Ultimate)	1170 MPa
Tensile Strength(Yield)	1100 MPa
Modulus of Elasticity	114GPa
Poisson's Ratio	0.33
Thermal Conductivity	6.7 W/m-K
Melting Point	1604-1660 °C
Heat Capacity	0.5263 J/g-°C
Magnetic Permeability	1.00005

4.4 MAGNETIC ABRASIVE PARTICLES

For the following study unbonded type of magnetic abrasive particles are selected for finishing TITANIUM GRADE 5, due to their ease in procurement, flexibility in usage and good performance usage during the MAF process. For the abrasive particles, chemical grade Silicon Carbide (200-300 μm size) is selected due to its low cost, aggressive-fast cutting action and its friability. Iron powder (500 μm size) is used as the ferromagnetic material to carry the abrasive particles in the flexible magnetic brush. 15W50 lubricant is used to act as a binding agent that holds the iron and Silicon Carbide particles

together in the magnetic brush. In all the mixtures that are produced for experimentation henceforth, lubricant equal to 30% of the abrasive weight is mixed to the iron Silicon Carbide mixture.



Fig. 35 Iron and Silicon Carbide powder

4.5 MACHINING PARAMETERS

For the current study, the effect of 5 different types of parameters was selected to be studied by performing an experiment using unbonded magnetic abrasives on TITANIUM GRADE 5. These are the parameters which have the maximum effect on the performance of the MAF process, as observed through the literature survey. The parameters that are selected for study and their values are given in table

Table 4: Machining Parameters

PARAMETER	VALUE
Current (in Amps)	0.4, 0.8, 1.2, 1.6
Working Gap (in mm)	1, 1.5, 2, 2.5
Spindle RPM	112, 150, 220, 300
Abrasive %	40, 50, 60, 70
Time (in mins.)	10, 15, 20, 25

4.6 DESIGN OF EXPERIMENTS

In order to reduce the effort, time and resources required in performing the experimental runs required to study the effect of the 5 input parameters, Taguchi's orthogonal arrays are used to perform the design of experiments. A 5 factor 4 level L16 array was used to as the experiment design, shown in table 5.

Table 5: Design of experiments

S. NO.	CURRENT	GAP	RPM	% ABRASIVE	TIME
1	0.4	1	112	40	10
2	0.4	1.5	150	50	15
3	0.4	2	220	60	20
4	0.4	2.5	300	70	25
5	0.8	1	150	60	25
6	0.8	1.5	112	70	20
7	0.8	2	300	40	15
8	0.8	2.5	220	50	10
9	1.2	1	220	70	15
10	1.2	1.5	300	60	10
11	1.2	2	112	50	25
12	1.2	2.5	150	40	20
13	1.6	1	300	50	20
14	1.6	1.5	220	40	25
15	1.6	2	150	70	10
16	1.6	2.5	112	60	15

4.7 GATHERING THE OUTPUT DATA

As I know that for a finishing operation the change in surface roughness and Weight of the workpiece prior and after carrying out the operation, is very useful to

quantify the efficiency of the finishing technique. In order to reduce the variation in initial surface roughness of the workpieces and obtain a uniform surface with little out of planarity, so that these factors do not hinder the actual performance of the MAF process, all the workpieces are grinded with the help of a surface grinding machine. Hence for my study I will calculate the both initial as well as final surface roughness and Weight of a workpiece. For measuring the surface roughness, a Talysor Hobson Surfotronic 3+ roughness tester was used (shown in fig. 36), whose specifications are given in table . The cutoff length selected was equal to 8 mm. For measuring the Weight, a 1 mg lab precision Weight balance was used.



Fig. 36 Taylorhobson Surfotronic 3+

Table 6: Specification of Talysurf Surfotronic 3+

Gauge Range	$\pm 150 \mu\text{m}$
Resolution	$0.01 \mu\text{m}$
Traverse length	0.25 mm - 25.4 mm
Traverse speed	1 mm/s
Stylus	Diamond tip radius $10 \mu\text{m}/5 \mu\text{m}$
Pickup Type	Variable reluctance

CHAPTER 5

ANALYSIS AND MODELLING OF RESULTS

This chapter gives the results of the experimental runs conducted during the investigation, which will then be used to develop a model of the MAF process using artificial neural-networks and genetic-algorithm. The values of the output parameters obtained after carrying out each experiment in the design of experiments table is given in table. The finished workpieces are shown in fig. 37.

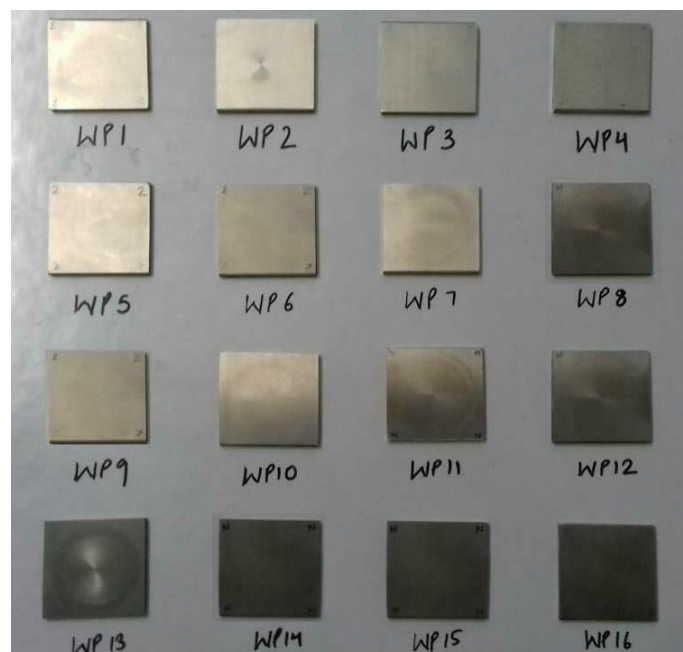


Fig. 37 Finished workpieces

5.1 MODELLING OF RESULT

5.1.1 SURFACE ROUGHNESS

The change in Ra values between the initial and final surfaces is modelled with the help of neural network, and the training plots are shown below.

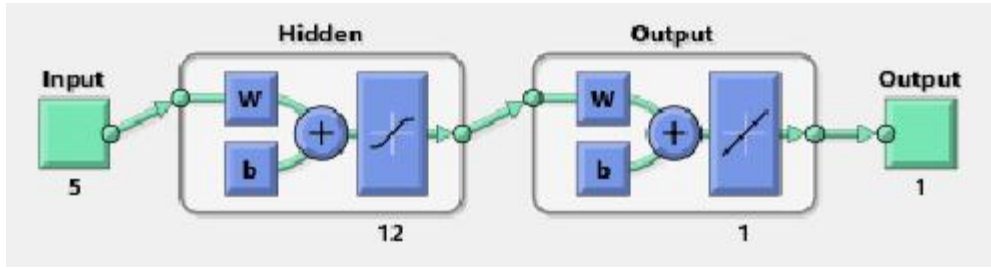


Fig. 38 Neural network for S.R. modelling

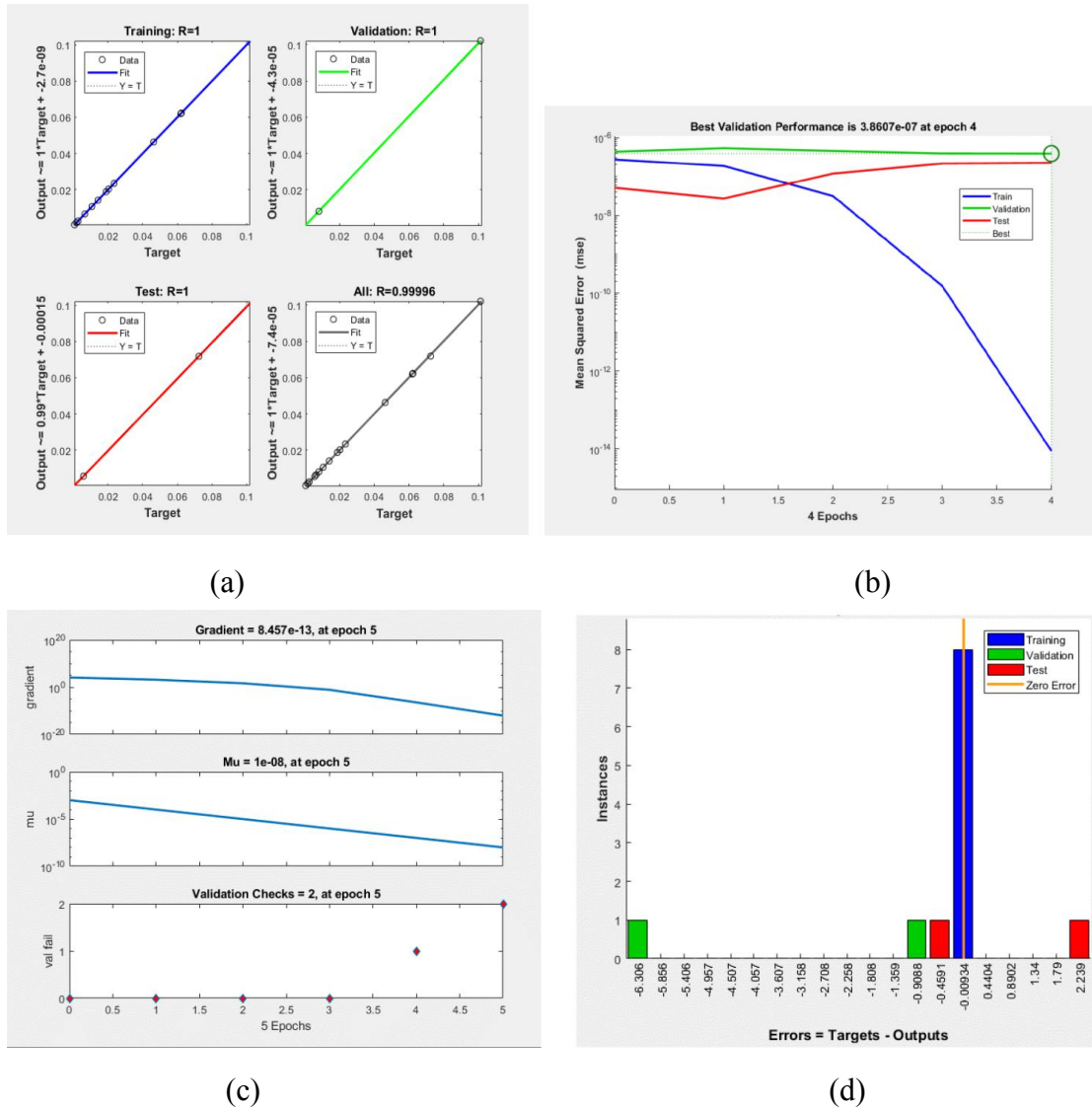


Fig. 39 Training plots of neural network for Ra: (a) Training curve of surface roughness (b) Variation of error with epochs (c) Performance curve of Surface roughness (d) Error histogram plot of surface roughness model

Table 7: Experimental & ANN predicted ΔRa values

S. N0.	CURRENT (Amps)	GAP (mm)	RPM	% ABRASIVE	TIME (min.)	Experimental ΔRa (A)	ANN Predicted ΔRa (B)	% Error $(A-B /A)*100$
1	0.4	1	112	40	10	0.02027	0.020270037	0.000185
2	0.4	1.5	150	50	15	0.0026	0.002599903	0.003745
3	0.4	2	220	60	20	0.0106	0.01060025	0.002358
4	0.4	2.5	300	70	25	0.0141	0.01409996	0.000282
5	0.8	1	150	60	25	0.0016	0.001599862	0.008648
6	0.8	1.5	112	70	20	0.0188	0.018799994	3.08E-05
7	0.8	2	300	40	15	0.0725	0.071856295	0.887869
8	0.8	2.5	220	50	10	0.0463	0.046299921	0.00017
9	1.2	1	220	70	15	0.0065	0.006500041	0.000628
10	1.2	1.5	300	60	10	0.0081	0.008131086	0.383777
11	1.2	2	112	50	25	0.0057	0.005514563	3.25328
12	1.2	2.5	150	40	20	0.0234	0.023400017	7.07E-05
13	1.6	1	300	50	20	0.0005	0.000499994	0.001224
14	1.6	1.5	220	40	25	0.1012	0.102078166	0.867753
15	1.6	2	150	70	10	0.0623	0.062299965	5.6E-05
16	1.6	2.5	112	60	15	0.062	0.06200006	9.7E-05

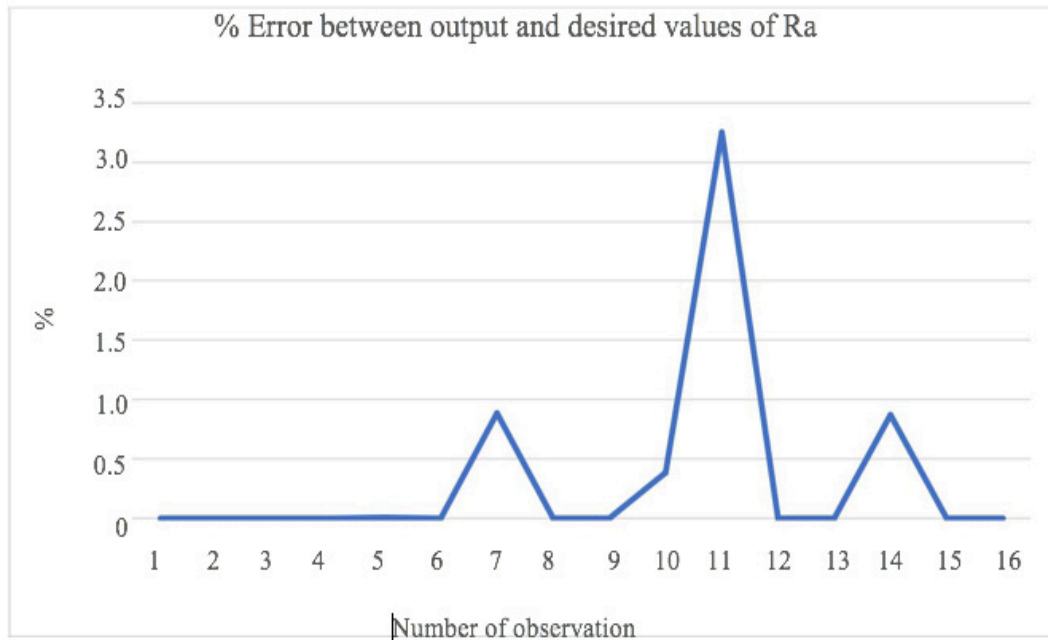


Fig .40 % error between predicted and desired Ra values

The feed-forward ANN model developed for modelling the change in Ra values of the surface roughness contains 3 different layers of neurons. The 1st layer being the input layer contains 5 neurons corresponding to each of the input variable, the 2nd layer contains 12 neurons and is called the hidden layer. The 3rd layer has 1 neuron corresponding to the single output value. For the present data of MRR, Levenberg-Marquardt training method was used, and the transfer function selected for hidden-layer and output-layer was Log-sigmoid and Tan-sigmoid respectively.

As clearly visible from the above diagrams the predicted and desired values of change in Ra between initial and final states conforms with each other to a very high degree, with the maximum error equal to 3.25 %, hence it is assured that the developed ANN model has effectively learned the relationship between the input values and the change in Ra values, and thus can be used for maximizing the change in surface roughness.

5.1.2 MATERIAL REMOVAL RATE

Table 8: Experimental & ANN predicted MRR values

S. NO.	CURRENT (Amps)	GAP (mm)	RPM	% ABRASIVE	TIME (min.)	W (initial)	w (final)	Δw
1	0.4	1	112	40	10	102.855	102.85	0.005
2	0.4	1.5	150	50	15	106.556	106.554	0.002
3	0.4	2	220	60	20	107.313	107.315	0.002
4	0.4	2.5	300	70	25	103.964	103.961	0.003
5	0.8	1	150	60	25	107.392	107.387	0.005
6	0.8	1.5	112	70	20	104.261	103.899	0.362
7	0.8	2	300	40	15	104.594	104.591	0.003
8	0.8	2.5	220	50	10	104.575	104.539	0.036
9	1.2	1	220	70	15	106.897	106.801	0.096
10	1.2	1.5	300	60	10	101.489	101.01	0.479
11	1.2	2	112	50	25	98.6	98.601	0.001
12	1.2	2.5	150	40	20	102.385	101.961	0.424
13	1.6	1	300	50	20	105.729	104.68	1.049
14	1.6	1.5	220	40	25	101.896	101.25	0.646
15	1.6	2	150	70	10	104.835	104.837	0.002
16	1.6	2.5	112	60	15	105.365	105.023	0.342

The feed-forward ANN model developed for predicting the material removal rate composed of 3 layers of neuron, first being the input-layer consisting 5 neurons corresponding to each of the input variable, the 2nd layer consist 10 neurons and is called the hidden-layer. The total neurons in this layer is selected on the basis of quantity as well as quality of data. As the relation between the input and output variables becomes more tangled, and the number of data sets available increases, the total hidden neurons needed to be used also increases. The 3rd layer has 1 neuron corresponding to the single output value. For the current data of MRR, Levenberg-Marquardt training method was used, and the transfer function selected for hidden-layer and output-layer was Log-sigmoid and Tan-sigmoid respectively. The output curves are shown below.

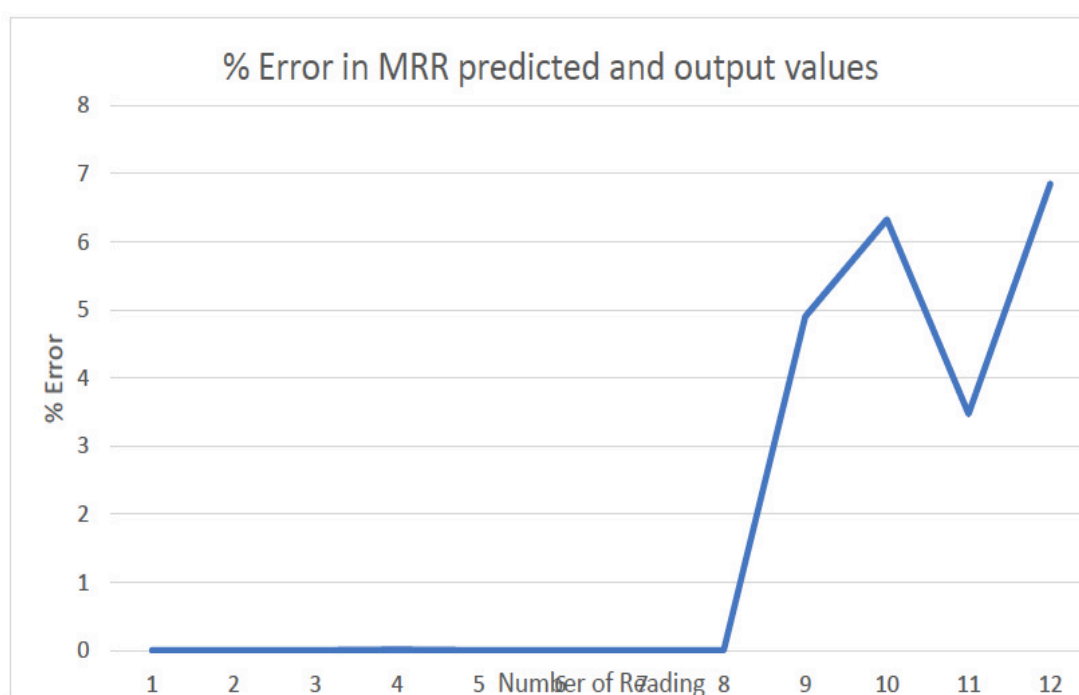
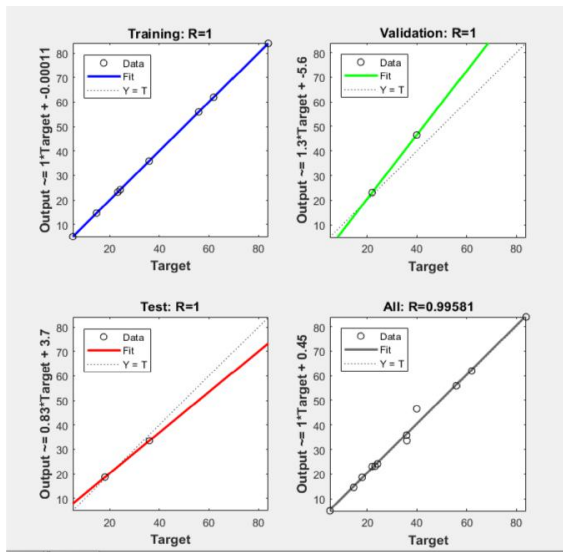
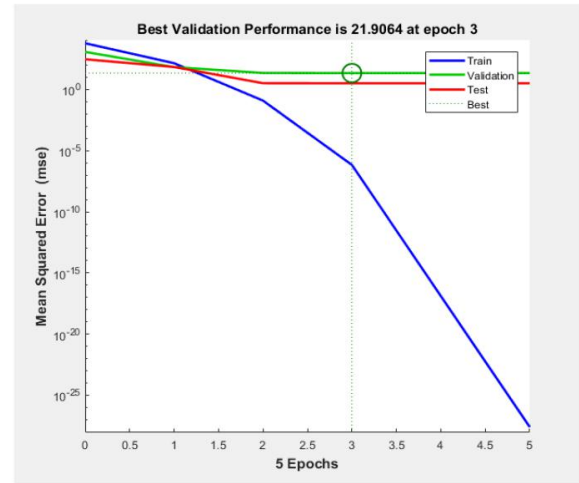


Fig. 41 % error between predicted and desired MRR values

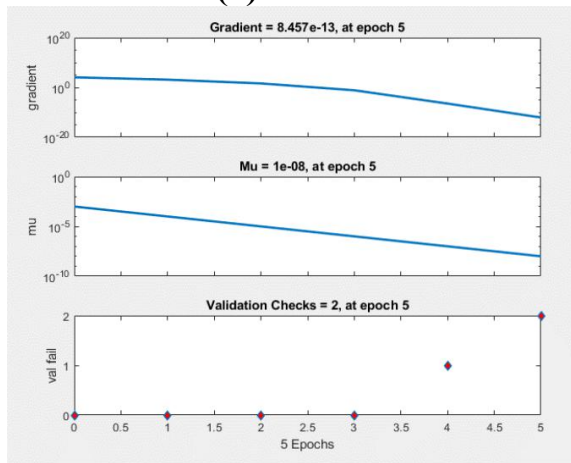
The developed ANN model can adequately have used to predict the MRR as output experimental conforms highly to the values predicted by the ANN model, and a maximum of 7% error is obtained between the two. Hence, I can use this model to calculate the operating variables that will optimize the material removal rate.



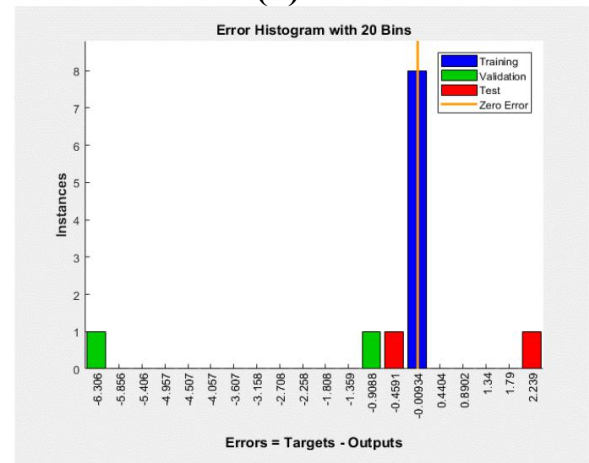
(a)



(b)



(c)



(d)

Fig. 42 Training plots of neural network for MRR: (a) Training curve of surface roughness (b) Variation of error with epochs (c) Performance curve of Surface roughness (d) Error histogram plot of surface roughness mod

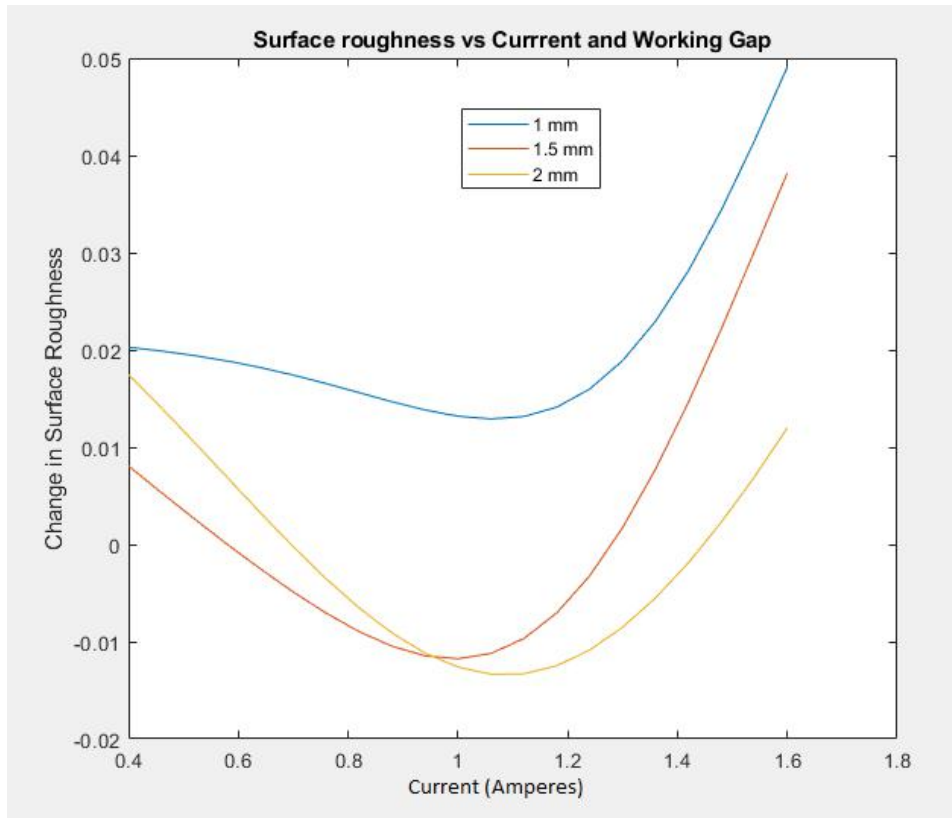


Fig. 43: Plot of Surface Roughness with Current and Working Gap

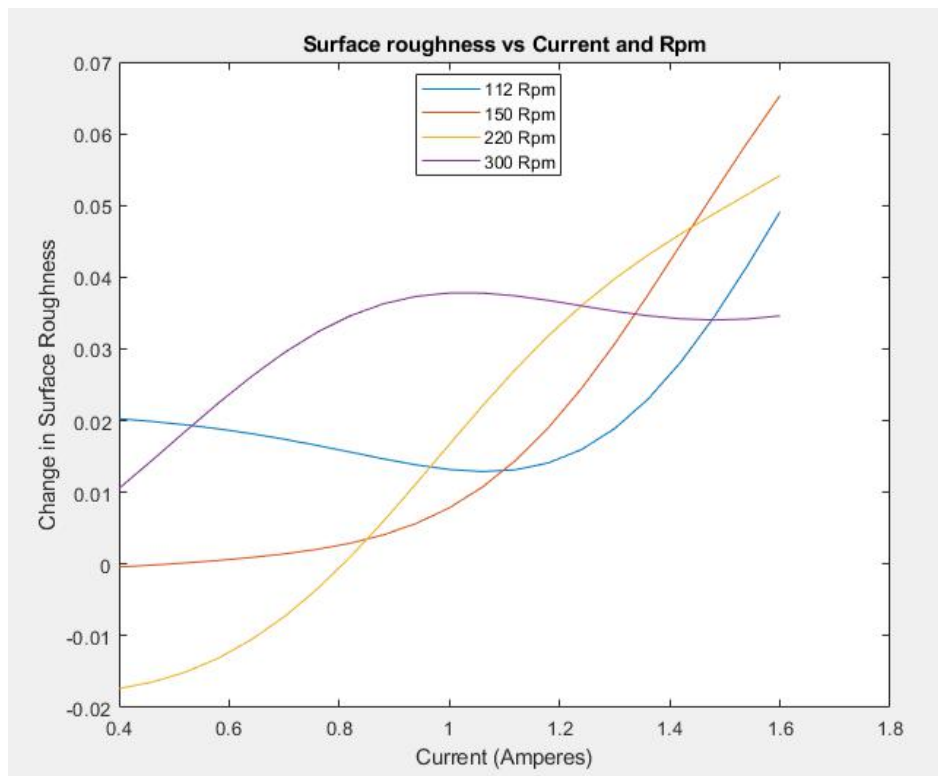


Fig. 44: Plot of Surface Roughness with Current and Rpm.

5.2 OPTIMIZED OUTPUT VALUES

In order to optimize (maximize) the shift in surface roughness and the material removal rate, the developed ANN models are fed to a genetic algorithm program which calculates the value of each input parameter corresponding to the maximum output value achievable. When the program is running for maximizing the ΔRa and M.R.R. values, the following results are obtained (refer to appendix):

- Optimized ΔRa value: 0.1474

Table 9: Optimum parameters for ΔRa

CURRENT	GAP	RPM	% ABRASIVE	TIME
1.5996	2.4986	299.9995	40.11	19.96

- Optimized M.R.R value: 140.4097

Table 10: Optimum parameters for MRR

CURRENT	GAP	RPM	% ABRASIVE	TIME
0.400	1.4576	300	70	20.9809

The plots of genetic algorithm used to optimize the MRR & ΔRa value are shown below.

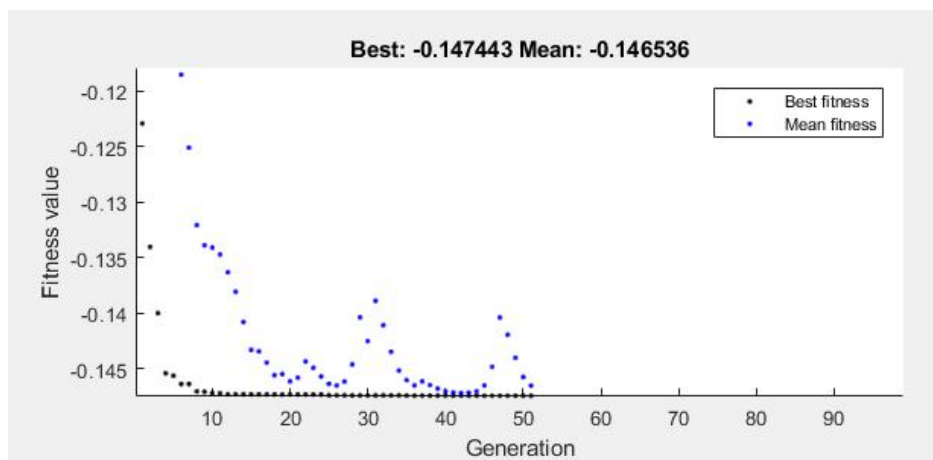
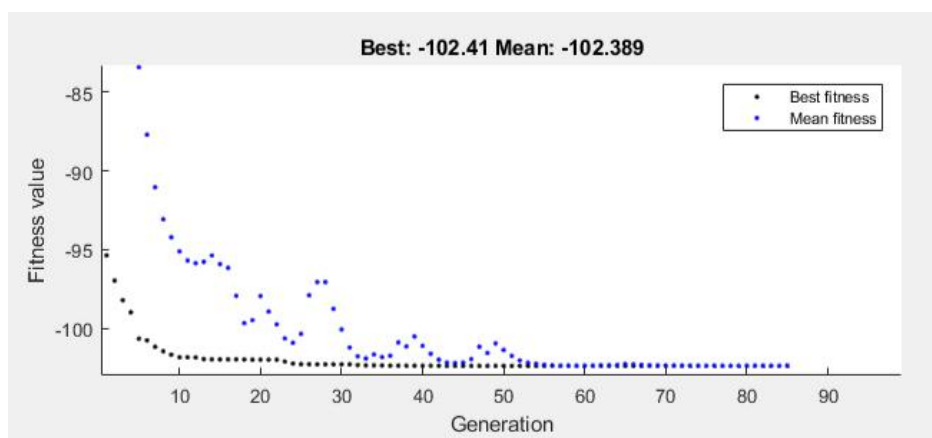
Fig. 44 GA plot of ΔR_a optimization

Fig. 45 GA plot of MRR optimization

CHAPTER 6

CONCLUSION & SCOPE OF RESEARCH

In the present study, through the extensive review of various research papers and by analyzing the experimental data it is concluded that the dependency of surface roughness and material removal rate on parameters such as, Current, Working Gap, RPM, abrasive percentage, and machining time is a very sophisticated function. To analyze the relationship between response and machining parameters Artificial Neural Network (ANN) is employed and for obtaining the peak value of machining parameters to which maximum shift in surface roughness could be achieved, Genetic Algorithms is used.

The inferences that can be made on the basis of the obtained experimental data and analysis performed are enumerated below: -

1. Magnetic Abrasive Finishing process can help in achieving smoother surfaces as compared to the conventional finishing processes such as, lapping, grinding and honing, due to the formation flexible magnetic abrasive brush (FMAB).
2. It is evident in Fig. 43, with rise in current (taking other as constant) the shift in surface roughness increases. At a higher value of current in the electromagnet, the strength of produced magnetic field would also be high, which in return decreases the flexibility of the magnetic abrasive brush due to which normal force at the workpiece surface increases and hence the shift in surface roughness increases.
3. At a certain value of current, on increasing the gap between the brush and the workpiece, the shift in surface roughness decreases as we can see in Fig. 43, while with the increase in rpm the change in surface roughness increases up to a convinced value and then starts falling due to the increase in centrifugal force.
4. By keeping other parameters constant, with the increase in the abrasive percentage the change in surface roughness also increases.

5. By utilizing a sophisticated integration of Artificial neural network with the genetic algorithms, the optimum processing parameters for the maximum change in surface roughness and for maximizing Material Removal Rate are shown in Table 9 and Table 10 respectively.

6.1 SCOPE FOR FUTURE STUDY

MAF is a process which has vast scope of improvement and process enhancement in terms of the efficiency of energy as well as time. Following are some recommendations for future scope of research.

- In the present study, only a limited number of parameters that affects the performance of the MAF process are studied, and further research can be done to inculcate other factors such as the types of abrasives, amount of lubricant used, and the magnetic abrasive particles size etc.
- The machine on which the electromagnet was installed can be controlled numerically in order to allow more accurate control over the tool path, and machining gap.
- Mathematical and FEA based analysis can be done for study the effect of various performance parameters.'
- Other hybrid optimization methods can be used for optimization of the developed model, such as Ant Colony Method, Cuckoo Search, Artificial Bee Colony algorithm etc.

APPENDIX I

- Experiment Readings

S. NO.	CURRENT	GAP	RPM	% ABRASIVE	TIME	Raf(i)		Raf(f)		ΔRa	W(initial)	w (final)	Δw
						Horizontal	Vertical	Horizontal	Vertical				
1	0.4	1	112	40	10	0.279	0.208	0.17586	0.2706	0.02027	102.855	102.85	0.005
2	0.4	1.5	150	50	15	0.3312	0.2124	0.3832	0.1656	0.0026	106.556	106.554	0.002
3	0.4	2	220	60	20	0.566	0.2476	0.5016	0.2908	0.0106	107.313	107.315	0.002
4	0.4	2.5	300	70	25	0.461	0.2524	0.4864	0.2952	0.0141	103.964	103.961	0.003
5	0.8	1	150	60	25	0.6846	0.3298	0.6798	0.3314	0.0016	107.392	107.387	0.005
6	0.8	1.5	112	70	20	0.5986	0.2756	0.557	0.2796	0.0188	104.261	103.899	0.362
7	0.8	2	300	40	15	0.6244	0.2518	0.6842	0.337	0.0725	104.594	104.591	0.003
8	0.8	2.5	220	50	10	0.621	0.309	0.522	0.3154	0.0463	104.575	104.539	0.036
9	1.2	1	220	70	15	0.5892	0.295	0.5994	0.2718	0.0065	106.897	106.801	0.096
10	1.2	1.5	300	60	10	0.4886	0.2464	0.4702	0.281	0.0081	101.489	101.01	0.479
11	1.2	2	112	50	25	0.6382	0.3114	0.6378	0.3232	0.0057	98.6	98.601	0.001
12	1.2	2.5	150	40	20	0.6566	0.2838	0.658	0.3292	0.0234	102.385	101.961	0.424
13	1.6	1	300	50	20	0.6208	0.2738	0.5854	0.3102	0.0005	105.729	104.68	1.049
14	1.6	1.5	220	40	25	0.4842	0.2308	0.5674	0.359	0.1012	101.896	101.25	0.646
15	1.6	2	150	70	10	0.7658	0.3244	0.8322	0.3826	0.0623	104.835	104.837	0.002
16	1.6	2.5	112	60	15	0.458	0.2208	0.5086	0.2942	0.062	105.365	105.023	0.342

APPENDIX – II

- GA iterations for ΔRa optimization

Generation	Best Func- count	Mean f(x)	Stall f(x)	Generations
1	2000	-0.1229	-0.03298	0
2	3000	-0.1340	-0.05388	0
3	4000	-0.1400	-0.0768	0
4	5000	-0.1454	-0.09408	0
5	6000	-0.1456	-0.1095	0
6	7000	-0.1464	-0.1185	0
7	8000	-0.1464	-0.1251	1
8	9000	-0.1471	-0.1321	0
9	10000	-0.1471	-0.03298	0
10	11000	-0.1472	-0.1339	0
11	12000	-0.1472	-0.1341	0
12	13000	-0.1473	-0.1347	0
13	14000	-0.1473	-0.1363	1
14	15000	-0.1473	-0.1381	2
15	16000	-0.1473	-0.1408	0
16	17000	-0.1473	-0.1433	1
17	18000	-0.1473	-0.1434	2
18	19000	-0.1473	-0.1445	0
19	20000	-0.1473	-0.1456	1
20	21000	-0.1473	-0.1455	0
21	22000	-0.1473	-0.1461	0
22	23000	-0.1473	-0.1458	1
23	24000	-0.1473	-0.1444	2
24	25000	-0.1473	-0.1449	3
25	26000	-0.1474	-0.1457	0
26	27000	-0.1474	-0.1464	0
27	28000	-0.1474	-0.1465	0
28	29000	-0.1474	-0.1462	0
29	30000	-0.1474	-0.1446	1
30	31000	-0.1474	-0.1404	0
31	32000	-0.1474	-0.1425	1
32	33000	-0.1474	-0.1389	2

33	34000	-0.1474	-0.1411	3
34	35000	-0.1474	-0.1435	4
35	36000	-0.1472	-0.146	0
36	37000	-0.1472	-0.1465	0
37	38000	-0.1473	-0.1462	1
38	39000	-0.1473	-0.1465	2
39	40000	-0.1473	-0.1468	3
40	41000	-0.1473	-0.147	0
41	42000	-0.1473	-0.1472	1
42	43000	-0.1473	-0.1472	0
43	44000	-0.1473	-0.1472	0
44	45000	-0.1473	-0.147	0
45	46000	-0.1473	-0.1465	0
46	47000	-0.1473	-0.1448	0
47	48000	-0.1473	-0.1404	1
48	49000	-0.1473	-0.1419	2
49	50000	-0.1473	-0.144	3
50	51000	-0.1474	-0.1458	4
51	52000	-0.1474	-0.1465	5

x =1.5996 2.4986 299.9995 40.0011 19.9684

fval = 0.1474

- GA iterations for MRR optimization

Generation	Best Func- count	Mean f(x)	Stall f(x)	Generations
1	2000	-95.38	-45.07	0
2	3000	-96.98	-56.38	0
3	4000	-98.23	-66.77	0
4	5000	-99	-76.33	0
5	6000	-100.7	-83.4	0
6	7000	-100.8	-87.69	0
7	8000	-101.2	-91.04	0
8	9000	-101.5	-93.08	0
9	10000	-101.7	-94.22	0
10	11000	-101.9	-95.12	0
11	12000	-101.9	-95.7	0
12	13000	-101.9	-95.87	0

13	14000	-102	-95.78	0
14	15000	-102	-95.38	0
15	16000	-102	-95.93	0
16	17000	-102	-96.17	1
17	18000	-102	-97.95	2
18	19000	-102	-99.69	0
19	20000	-102	-99.5	0
20	21000	-102	-97.96	1
21	22000	-102	-98.95	2
22	23000	-102	-99.77	3
23	24000	-102.1	-100.7	0
24	25000	-102.3	-100.9	0
25	26000	-102.3	-100.4	0
26	27000	-102.3	-97.91	0
27	28000	-102.3	-97.07	0
28	29000	-102.3	-97.08	1
29	30000	-102.3	-98.78	2
30	31000	-102.3	-100.1	3
31	32000	-102.3	-101.2	4
32	33000	-102.4	-101.8	0
33	34000	-102.4	-101.9	0
34	35000	-102.4	-101.7	1
35	36000	-102.4	-101.9	0
36	37000	-102.4	-101.8	0
37	38000	-102.4	-100.9	1
38	39000	-102.4	-101.2	0
39	40000	-102.4	-100.5	1
40	41000	-102.4	-101.1	2
41	42000	-102.4	-101.6	3
42	43000	-102.4	-102.0	4
43	44000	-102.4	-102.2	0
44	45000	-102.4	-102.2	0
45	46000	-102.4	-102.2	0
46	47000	-102.4	-102.0	0
47	48000	-102.4	-101.2	1
48	49000	-102.4	-101.6	0
49	50000	-102.4	-101.0	1
50	51000	-102.4	-101.4	2
51	52000	-102.4	-101.8	3
52	53000	-102.4	-102.1	4
53	54000	-102.4	-102.2	0
54	55000	-102.4	-102.3	1
55	56000	-102.4	-102.3	2
56	57000	-102.4	-102.4	3
57	58000	-102.4	-102.4	0
58	59000	-102.4	-102.4	1

59	60000	-102.4	-102.4	0
60	61000	-102.4	-102.4	0
61	62000	-102.4	-102.4	0
62	63000	-102.4	-102.4	1
63	64000	-102.4	-102.4	0
64	65000	-102.4	-102.3	0
65	66000	-102.4	-102.3	1
66	67000	-102.4	-102.3	2
67	68000	-102.4	-102.3	3
68	69000	-102.4	-102.4	4
69	70000	-102.4	-102.4	0
70	71000	-102.4	-102.4	0
71	72000	-102.4	-102.4	1
72	73000	-102.4	-102.4	2
73	74000	-102.4	-102.4	0
74	75000	-102.4	-102.4	1
75	76000	-102.4	-102.4	0
76	77000	-102.4	-102.4	1
77	78000	-102.4	-102.4	2
78	79000	-102.4	-102.4	0
79	80000	-102.4	-102.4	0
80	81000	-102.4	-102.4	0
81	82000	-102.4	-102.4	1
82	83000	-102.4	-102.4	2
83	84000	-102.4	-102.4	0
84	85000	-102.4	-102.4	0
85	86000	-102.4	-102.4	1

Optimization terminated: average change in the fitness value less than options. Function Tolerance.

x = 0.4000 1.4657 300.0000 70.0000 20.9809

fval =102.409

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