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OPTIMIZATION OF MACHINING PARAMETERS FOR MINIMIZING SURFACE ROUGHNESS AND POWER CONSUMPTION DURING TURNING OF AISI 1045 STEEL

Ajit Kumar Sharma[1], Anil Arya[2],
Department Of Mechanical Engineering
[1] M.Tech (ME) Scholar, Azad Institute of Engineering & Technology, Lucknow
[2]Assistant Professor, Azad Institute of Engineering & Technology, Lucknow
Uttar Pradesh, India

***Abstract*— After well known formula relating tool life to cutting speed given by Taylor in 1907, a lot of research on the modelling and optimization of machining parameters for surface roughness, tool wear, forces, etc. has been done during last 100 years. However, a little research has been done to optimize the energy efficiency of machine tools. The energy efficiency of machines tools is generally very low particularly during the discrete part manufacturing. Reduction in power consumption, in addition to economical benefits, will also improve the environmental impact of machine tools and manufacturing processes. However, sustainability performance may be reduced artificially by increasing the surface roughness as lower surface finish requires lesser power and resources to finish the machining. But this may lead to more rejects, rework and time. Therefore, an optimum combination of power and surface finish is desired for sustainability performance of the machining processes. There is a close interdependence among productivity, quality and power consumption of a machine tool. The surface roughness is widely used index of product quality in terms of various parameters such as aesthetics, corrosion resistance, subsequent processing advantages, tribological considerations, fatigue life improvement, precision fit of critical mating surfaces, etc. But the achievement of a predefined surface roughness below certain limit generally increases power consumption exponentially and decreases the productivity. The capability of a machine tool to produce a desired surface roughness with minimum power consumption depends on machining parameters, cutting phenomenon, workpiece properties, cutting tool properties, etc. The first step towards reducing the power consumption and surface roughness in machining is to analyze the impact of machining parameters on power consumption and surface roughness.**

The results reveal that the developed predictive models provide a close relation between the predicted values and the experimental values for surface roughness and power consumption. The optimal machining parameters indicate that feed is the most significant machining parameter followed by depth of cut and cutting speed to reduce power consumption and surface roughness simultaneously. The optimization of machining parameters for minimum power requirement and surface roughness is expected to lead to the application of lower rated motors, drives and auxiliary equipments and hence save consumption of power not only during machining but as well as during build-up to machining, post machining and idling conditions.

***Index Terms*— Machine tools and Manufacturing processes, Surface Roughness, Power consumption in machining process.**

I. Introduction

The 1980s have witnessed an elementary modification within the means governments and development agencies have faith in surroundings and development. The two are not any longer considered reciprocally exclusive. It's been recognized that a healthy surroundings is important for a healthy economy. Energy and materials square measure the two primary inputs needed for the expansion of any economy and these square measure obtained by exploiting the natural resources like fossil fuels and material ores. The economic sector accounts for regarding common fraction of the world's total energy consumption and also the consumption of energy by this sector has virtually doubled over the last sixty years (Fang et al., 2011). The consumption of important raw materials (steel, aluminum, copper, nickel, zinc, wood, etc.) for industrial use has hyperbolic worldwide.

The zoom in producing has created several economic, environmental and social issues from warming to native waste disposal (Sangwan, 2011). There's a powerful want, notably, in rising and developing economies to enhance producing performance so there's less industrial pollution, and less material & energy consumption. Energy potency and merchandise quality became vital benchmarks for assessing any trade.

Manufacturing operations account for 37% of global energy demand (Diaz-Elsayed et al., 2015). U.S. manufacturing industry annually consumes 21.1 quadrillion BTU energy (about 21% of total U.S. energy consumption) and generates more than 1.4 billion metric tons of CO2 emissions (about 26%

of total U.S. CO_2 emissions) (Yuan et al., 2012). Machine tools have less than 30% efficiency (He et al., 2012) and more than ninety nine of the environmental impacts area unit thanks to the consumption of voltage employed by the machine tools in distinct half producing machining processes like turning and edge (Li et al., 2011). Worldwide, machine producing could be a USD sixty eight.6 billion business and extremely few energy assessments are conducted for distinct producing facilities (Diaz-Elsayed et al., 2015). Property performance of machining processes are often achieved by reducing the ability consumption (Camposeco-Negrete, 2013). If the energy consumption is reduced, the environmental impact generated from power production is diminished (Pusavec et al., 2010). Property performance could also be reduced by artificial means by increasing the surface roughness as lower surface end needs lesser power and resources to complete the machining. However, this could cause additional rejects, retread and time. Therefore, associate optimum combination of power and surface end is desired for property performance of the machining processes. there's an in depth reciprocality among productivity, quality and power consumption of a machine. The surface roughness is wide used index of product quality in terms of varied parameters like aesthetics, corrosion resistance, subsequent process blessings, tribological concerns, fatigue life improvement, exactitude work of important pairing surfaces, etc. however the action of a predefined surface roughness below sure limit typically will increase power consumption exponentially and reduces the productivity. the aptitude of a machine to provide a desired surface roughness with minimum power consumption depends on machining parameters, cutting development, piece of work properties, cutting implement properties, etc. the primary step towards reducing the ability consumption and surface roughness in machining is to investigate the impact of machining parameters on power consumption and surface roughness.

A. Objective and Scope of the Study

The objective of this study is to develop prophetical and improvement models for analyzing the influence of machining parameters on (i) surface roughness, (ii) power consumption, and (iii) finally on surface roughness and power consumption at the same time. The impact of cutting speed, feed and depth of cut are studied throughout the turning of AISI 1045 steel victimization inorganic compound cutting tools. This objective is achieved by:

- Development of prophetical and improvement models to work out the optimum machining parameters resulting in minimum surface roughness.
- Development of prophetical and improvement models to work out the optimum machining parameters resulting in minimum power consumption.
- Response Surface Methodology (RSM), Support Vector Regression (SVR) and Artificial Neural Networks (ANN) will be used to develop the predictive models. RSM and Genetic Algorithms (GA) will be used to develop optimization models.

II. Literature Survey

This chapter sets the background for this study. It is an assessment of the present state of the art of the wide and complex field of modeling and optimization of machining operations and their application in conventional machining processes.

A. Introduction

Merchant (1974) reported that in conventional machining, the machined components take only about 6% to 10% of the total available production time on machines being used. It has been estimated that this percentage would increase to 65% 80% in modern computer-based manufacturing (Armarego, 1996) due to advent of computer- based and automated machining systems. An CIRP (International Institution for Production Engineering Research) working paper (Armarego, 1996) quotes the findings of a survey by a leading cutting tool manufacturer as, “In the USA the correct cutting tool is selected less than 50% of the time, the tool is used at the rated cutting speed only 58% of the time, and only 38% of the tools are used up to their full tool-life capability”. Similarly, an earlier survey for machining aluminum alloy components in the U.S aircraft industry has shown that the selected cutting speeds were far below the optimal economic speeds (Finnie, 1956). One of the reasons for this poor performance is the lack of predictive models. The difficulties in realizing true predictive models for machining arise from the extreme physical phenomenon inherent in the system. Machining generates a highly inhomogeneous plastic flow where local stresses generate high rates of plastic deformation (up to 106s-1) that gives rise to inhomogeneous thermal fields, high temperatures (1200ºC in machining steel), and high pressures (10 MPa) (Ivester et al., 2000). This sort of advanced plastic flow is tough to predict even with subtle numerical softwares and also the basic knowledge on material behavior below such conditions is non-existent for many materials of sensible interest (Ivester et al., 2000).

This has inhibited the widespread use of the numerical modeling techniques. Thus, the event of empirical modeling and optimisation is gaining importance within the field of machining.

According to van Luttervelt et al. (1998) prophetic modelling and optimisation of machining operations is dole out in 3 phases: (i) basic modeling (ii) applied modelling and (iii) determination of best or near-optimal cutting conditions as shown in Figure two.1. Modelling of inputoutput relationship is taken into account as associate degree abstract illustration of a method linking causes and effects or remodeling method inputs into outputs (Markos et al., 1998). The ensuing model provides the fundamental mathematical input needed for formulation of the method objective perform. associate degree optimisation technique provides best or near-optimal answer to the general optimisation downside.

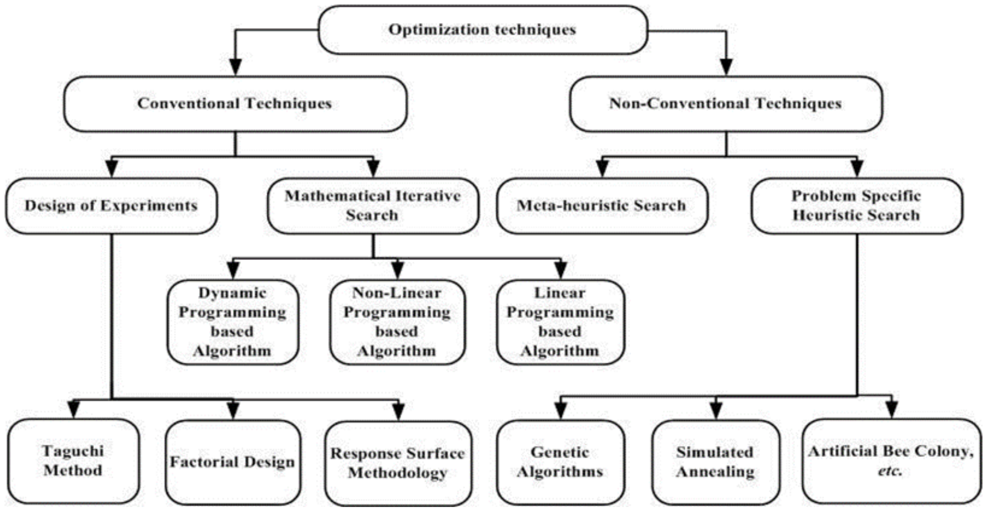

Figure 2.1: Conventional and non-conventional optimization techniques (adapted from Mukherjee and Ray, 2006)

III. EXPERIMENTAL SETUP AND PLANS

This chapter provides the details regarding the experimental setup and the plan to obtain the two performance characteristics – power consumption and surface roughness – for the research.

A. Introduction

Predictive modelling and improvement need choice of acceptable sets of machining parameters of the method. this will in the main be achieved by understanding the interrelation among the massive variety of parameters touching the method and distinctive the best machining conditions. Experiments square measure performed on a given machine so as to know the result of various method parameters on performance characteristics i.e. surface roughness and power consumption.

B. Material

The sample material for the analysis is AISI 1045 steel. There's a revived interest within the application of this steel thanks to its property. It 100 percent utile and virtually has indefinite life cycle. AISI 1045 steel is one among the steel grades wide employed in totally different industries (construction, transport, automotive, power, etc.). a number of the ordinarily used parts of 1045 steel square measure gears, shafts, axles, bolts, studs, connecting rods, spindles, rams, hydraulic pumps, etc. The chemical composition and mechanical properties of the AISI 1045 steel square measure given in Table three.1 and Table three.2 severally.

Twenty seven experiments were performed per the experimental style mentioned in section three.6. The 9 workpieces were machined from solid cylindrical bar to a final dimension of 250 millimeter length and forty seven millimeter diameter as shown in Figure three.1. the entire length to be machined throughout every reading is fifty millimeter. thirty millimeter length on both sides is provided for clamping the workpieces into 3 jaw chuck. each bit was accustomed perform 3 experiments. Therefore, ten millimeter steps were provided on the piece of work as shown within the figure. A pre-cut of one.5 millimeter depth was performed on every piece of work before actual turning employing a totally different cutter. This was tired order to get rid of the rust or hardened prime layer from the surface and to attenuate any result of non-homogeneity on the experimental results.

Table 3.1: Chemical composition of AISI 1045 steel in percentage weight

Material	C%	Mn%	P%	S%	Si%
AISI 1045 Steel	0.43	0.7	0.04	0.05	0.16

Table 3.2: Mechanical properties of AISI 1045 steel

Material	Density (kg/m^3)	Elastic modulus (GPa)	Yield strength (MPa)	Tensile strength (MPa)	Hardness (HB)	Elongation (%)	Poison ratio
AISI 1045 Steel	7.8	205	505	585	170	12	0.28

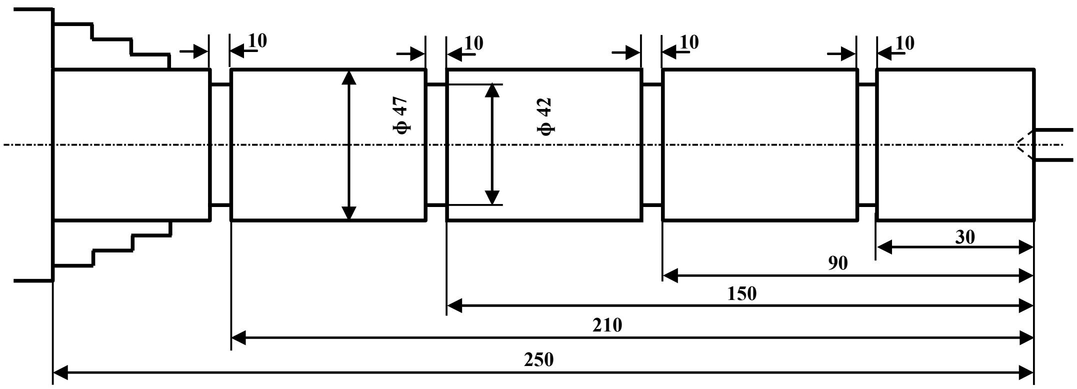

Figure 3.1: Detailed drawing of the cylindrical bar used in experimentation

C. Cutting Tool Inserts and Holder

Uncoated tungsten carbide tools were used for the experiments. The cutting tool used is proper for machining of AISI 1045 steel with ISO P25 quality. Sandvik inserts with the ISO TNMG 16 04 12 designation were mounted on the tool holder designated by ISO as PTGNR 2020 K16 having rake angle of 70, clearance angle of 60 and 0.4 mm nose radius. An insert mounted on the tool holder is shown in Figure 3.2.

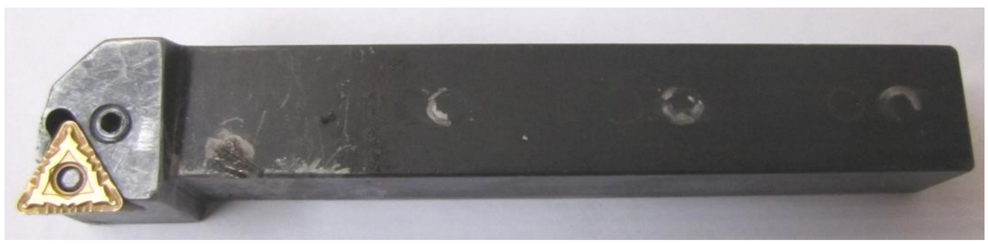

Figure 3.2: Insert mounted on the tool holder

D. Machine Tool

The turning experiments were carried out in dry cutting conditions using an HMT centre lathe. It has a maximum spindle speed of 2300 rpm and spindle power of 5.5 kW. Workpiece was held between chuck and tailstock; and the tool overhang was kept 20 mm to increase rigidity of the machining system as shown in Figure 3.3.

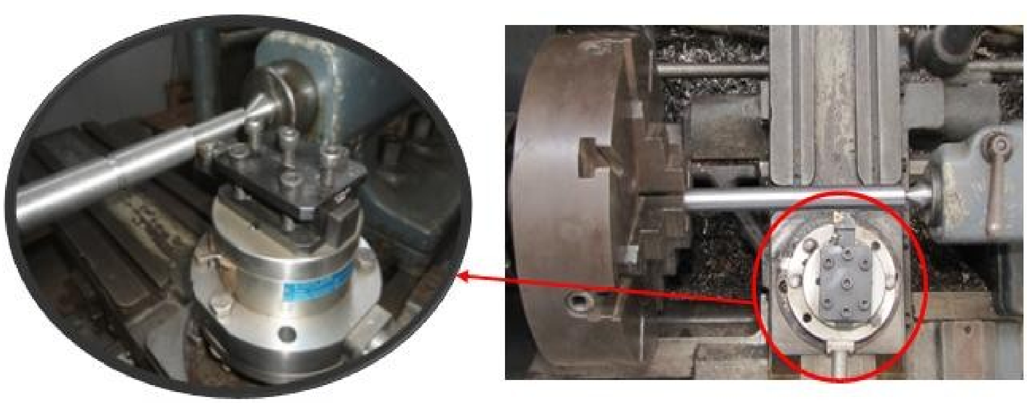

Figure 3.3: Tool overhung and workpiece clamped between chuck and tailstock
(All dimensions are in mm)

The experiments were conducted by turning the workpiece with feed direction towards the chuck of the lathe (referred to as "left feed direction") as is often the case during conventional turning. As the workpiece was comparatively long, workpiece was held in the tailstock during all experiments as shown in Figure 3.3.

E. Selection of Machining Parameters and their Levels

The choice of machining parameters was made by taking into account the capacity/limiting cutting conditions of the lathe, tool manufacturer's catalogue and the values taken by researchers in the literature. Cutting speed (*v*), feed rate (*f*) and depth of cut (*d*) are the input parameters chosen for the research.

The performance characteristics chosen to investigate the effect of machining parameters were surface roughness (R_a) and power consumption (P). Table 3.3 shows the three machining parameters and the three levels for each parameter.

Table 3.3: Machining parameters and their levels

Factor	Symbol	Level 1	Level 2	Level 3
Cutting speed (m/min)	*v*	103.31	134.30	174.14
Feed rate (mm/rev.)	*f*	0.12	0.16	0.2
Depth of cut (mm)	*d*	0.5	1.0	1.5

F. Experimental Design

In any experimental investigation, the results rely to an outsized extent on the info assortment methodology. the foremost most well-liked methodology of experimentation used by researchers may be a full factorial set of experiments, wherever experiments area unit applied for all mixtures of variables. A full issueial style of experiments (DOE) measures the response of each attainable combination of things and factor levels. These responses area unit analyzed to supply info regarding each main result and each interaction result. The experimental style for 3 turning parameters (v, f, d) with 3 levels (33) area unit organized by the Taguchi's L27 orthogonal array as shown in Table three.4. L27 is that the best suited array that has twenty seven runs and twenty six degrees of freedoms (DOF) that area unit over the desired eighteen DOFs. As per Taguchi's experimental style methodology, the entire DoFs of designated orthogonal array should be larger than or adequate the entire DoFs needed for the experiment and therefore L27 orthogonal array has been designated as per Taguchi (1990). The columns chosen for the most factors area unit one, 2, and five (Table three.4). the primary column of the table is assigned to the cutting speed (v), the second to the feed rate (f) and fifth to the depth of cut (d).

Table 3.4: An L_{27} Orthogonal array

Experiment No.	**Column Number**												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2

7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

G. Power Consumption Measurement

The power consumption has been measured through the indirect methodology by measurement the cutting forces. In literature there area unit 2 strategies – direct methodology mistreatment wattmeter or power device (e.g. Aggarwal et al., 2008; Balogun and Mativenga, 2013; Campatelli et al., 2014; Yan and Li, 2013) and indirect methodology mistreatment ergometer (e.g. Abhang and Hameedullah, 2010; Hanafi et al., 2012; He et al., 2011; Kuram et al., 2013). each strategies have their own benefits and limitations. The direct methodology measures precisely the power needed by the machine "system" as well as auxiliary power. This analysis aims at developing a relationship between cutting parameters and method performance (power and surface roughness throughout cutting). The auxiliary power mensuration doesn't add any price. associate indirect methodology of power mensuration by measurement the cutting forces was accustomed live the facility consumed throughout the experimentation. The schematic to live the forces is shown in Figure three.4. Kistler 9272 ergometer, shown in Figure three.5, is employed to capture the force signals throughout the cutting method in X, Y and Z directions (feed force, thrust force and cutting force). The ergometer consists of three-component force sensors fitted underneath high preload between a base plate and a high plate. every device contains 3 pairs of quartz plates, one sensitive to pressure within the Z direction and also the alternative 2 responding to shear within the X and Y directions.

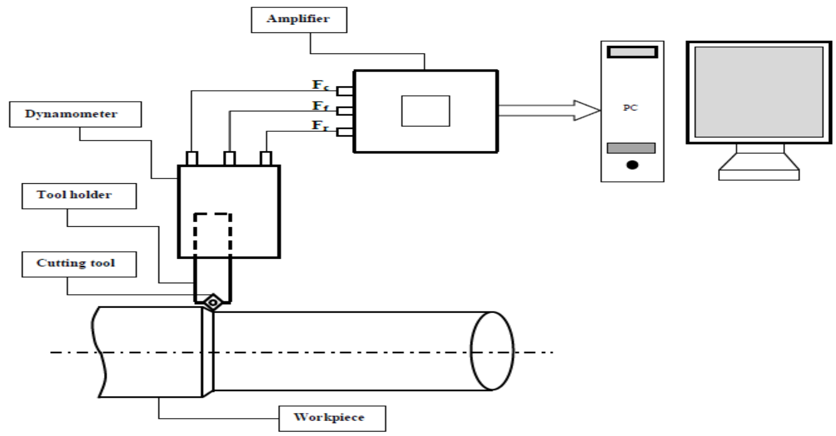

Figure 3.4: Schematic of experimental procedure to measure the forces

H. Surface Roughness Measurement

The workpiece shown in Figure 3.1 was cut into three parts each having an equal length of 50 mm for measuring the surface roughness. The final workpiece used for measuring the surface roughness is shown in Figure 3.8.

Figure 3.8: Workpiece used for measuring the surface roughness

The surface roughness of the finished surface is measured by inserting the piece of work on a V-block over a forged iron surface plate when every cut (Figure three.9). when the setup was prepared, trial cuts were taken and instrumentation was mark to make sure that the half quality adhered to the standard necessities of the first instrumentation Manufacturer (OEM), and to check the soundness of the machining method to it of the OEM's. The instrumentation was mark by measurement the far-famed diameter (12.4867 mm) of a high exactitude spherical ball. Figure 3.10 shows the surface roughness profile, measured on spherical ball that shows that the shape error (Pt) is significantly but the OEM such higher limit of zero.25 µm. This confirms the soundness of the experimental setup compared to the OEM's counseled specification. Once the soundness of the setup was confirmed the experiments were conducted and also the surface roughness was measured at 3 equally spaced locations round the circumference of the piece of work to get the statistically vital knowledge for take a look at so the mean of measurements was calculated. Thus, probable observation errors were unbroken comparatively tiny. The specifications of the measurement setup ar given in the Table 3.7.

Table 3.7: Specifications of the surface roughness measurement instrument

Factor	**Specification**
Make	Taylor Hobson
Model	Form Talysurf Intra
Speed of traverse	1 mm/sec □ 10 mm/sec
Nominal measuring range	1 mm
Resolution	16 nm
Pickup	Inductive type
Parameters measurable	$R_a/R_z/R_t$

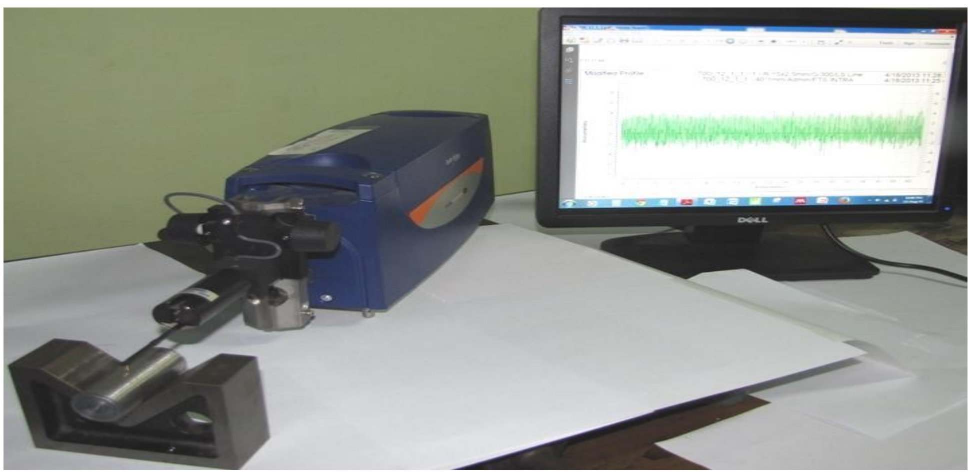

Figure 3.9: Taylor and Hobson profilometer used to measure surface roughness

IV. PREDICTIVE MODELLING AND OPTIMIZATION FOR POWER CONSUMPTION

In this chapter the experimental data of power consumption as a performance characteristic is used to develop power consumption predictive models using RSM, SVR and ANN techniques. Further, RSM and GA are used to obtain the machining parameters to optimize power consumption.

A. Introduction

The Asian nationn economy has veteran new economic process over the last decade (Green India Energy Summit, 2014). Today, Asian nation is that the ninth largest economy within the world. This high order of sustained economic process is inserting monumental demand on its energy resources. Asian nation is that the fourth-largest energy client within the world, trailing solely the us, China, and Russia (EIA, 2013). The New Policies situation (NPS) comes that India's share in world energy demand can will increase from 5.5% in 2009 to 8.6% in 2035 (Ahn and Graczyk, 2012). Asian nation is essentially smitten by fuel imports to fulfill its energy demand that makes it politically vulnerable. within the year 2013, India's energy import was forty 2.9% of total primary energy consumption and it's expected to exceed fifty three of the country's total energy consumption by 2030 (www.theenergyreport.com). The gross electricity generation (utilities) has exaggerated from meager 4073 KWH in 1947 to 963722 GWH at the tip of March, 2013. The electricity consumption (utilities and non-utilities) has exaggerated from meager 4182 GWH in 1947 to 852903 GWH at the tip of March, 2013. The expansion of demand has overtaken the facility offer and our country has been facing power shortage in spite of manifold growth over the years. Of the overall electricity consumption in 2012-13, business sector accounted for the biggest share (44.87%). As per the eighteenth electrical power survey, the power consumption is forecasted to be exaggerated to 1098995 letter of the alphabet and 1611808 letter of the alphabet by the year 2016- 2017 and 2021- 2022 severally. The demand and provide imbalance in energy is pervasive across all sources requiring serious efforts by Government of Asian nation to enhance energy provides. world energy demand is anticipated to grow by fifty three between 2008 and 2035 (Diaz et al., 2011).

B. Power Consumption in Machine Tools

Machine tool is one among the standard production equipments wide employed in the producing business. Machine tools have potency but half-hour (He et al., 2012) and quite ninety nine of the environmental impacts ar because of the consumption of power employed by the machine tools in distinct half producing machining processes like turning and edge (Li et al., 2011). price|the value|the price} of energy used over a ten- year amount is concerning a hundred times above the initial purchase cost of the machine tools wont to manufacture merchandise, and thus, if energy consumption is reduced, the budget items and also the surroundings impact generated from power production ar diminished (Pusavec et al., 2010b). in line with Liow (2009) machine choice additionally plays a crucial role in reducing the energy footprint of a machined product. The replacement of machines might not be a viable various attributable to capital investment concerned however the energy consumption throughout machining are often simply controlled by operational the machine tool at conditions requiring minimum energy. A survey of recent literature shows that current analysis has targeted on power consumption models for machine elements or machining processes (Li et al., 2014). Machine tools ar the first parts of a producing system, that consume a major quantity of energy for machining. The energy is primarily analyzed by considering energy characteristics of energy-consuming elements of machine tools. Machine tools need power throughout machining, build-up to machining, post machining and in loafing condition to drive motors and auxiliary equipments (Kant and Sangwan, 2014). However, the planning of a machine relies on the peak power demand throughout machining of fabric that is extremely high as compared to non-peak power demand of the machine tools. This results in higher unskillfulness of energy in machine tools. The improvement of machining parametersfor minimum power demand is anticipated to steer to the applying of lower rated motors, drives and auxiliary equipments and therefore save power not solely throughout machining however similarly as throughout build-up to machining, post machining and loafing condition. Additionally to the machining parameters, the facility demand throughout machining additionally depends upon piece of work properties and cutting implement properties. during this study, the work material is steel and cutting implement material is uncoated metal inorganic compound. this mixture is the foremost wide used combination within the business and any reduction in power consumption is anticipated to steer to high saving of power in absolute numbers.

V. Conclusion

This study presents prognosticative and improvement models for the prediction and improvement of machining parameters resulting in least power consumption and surface roughness throughout turning of AISI 1045 steel victimisation wolfram inorganic compound tools. Experimental started and arrange was developed to pick the machine, cutting implement, piece of work material, machining parameters and their levels, and experiments were conducted victimisation acknowledge Taguchi's orthogonal array to accumulate the ability consumption and surface roughness knowledge. The developed prognosticative and improvement models supported experimental knowledge, assist not solely in analyzing the influence of the various method parameters on the 2 most dominant machining criteria, however also are helpful for the optimality search of the varied constant combos for achieving the most fulfillment of the target needs.

VI. Limitations and Future Scope of the analysis

Predictive modeling and improvement could be a complicated and re-emerging field of analysis. The scope of the analysis work is endless thanks to sizable amount of variables concerned in machining of materials. The result of machining parameters like tool pure mathematics, tool coatings, coolants, etc. on the surface roughness and power consumption has not been studied. Further, the result of machining parameters on material removal rate is analyzed. This work is extended to incorporate the advanced materials like metallic element alloys and composites materials.

This study has optimized the ability consumption and surface end at the same time. However, in observe surface roughness isn't taken as a variable of the machining method however a hard and fast parameter (predefined vary by designers). Therefore, future analysis is directed at mapping of optimum machining parameters for minimum energy consumption for a spread of expected surface end. The results also can be analyzed victimization different improvement techniques like particle swarm improvement, simulated hardening, artificial bee colony, etc., and also the effectiveness of varied improvement techniques is compared.

References

[1] Abhang, L.B., Hameedullah, M., 2010. Power Prediction Model for Turning EN-31 Steel Using Response Surface Methodology. J. Eng. Sci. Technol. Rev. 3, 116–122.

[2] Aggarwal, A., Singh, H., Kumar, P., Singh, M., 2008. Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi's technique—A comparative analysis. J. Mater. Process. Technol. 200, 373–384.

[3] Arrazola, P.J., Umbrello, D., Davies, M., Jawahir, I.S., 2013. Recent advances in modelling of metal machining processes. CIRP Ann. - Manuf. Technol. 62, 695–718.

[4] Balogun, V.A., Mativenga, P.T., 2013. Modelling of direct energy requirements in mechanical machining processes. J. Clean. Prod. 41, 179–186.

[5] Bhattacharya, A., Das, S., Majumder, P., Batish, A., 2009. Estimating the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel using Taguchi design and ANOVA. Prod. Eng. 3, 31–40.

[6] Camposeco-Negrete, C., 2013. Optimization of cutting parameters for minimizing energy consumption in turning of AISI 6061 T6 using Taguchi methodology and ANOVA. J. Clean. Prod. 53, 195–203.

[7] Diaz, N., Redelsheimer, E., Dornfeld, D., 2011. Energy consumption characterization and reduction strategies for milling machine tool use, in: Glocalized Solutions for Sustainability in Manufacturing. Springer, pp. 263–267.

[8] Fang, K., Uhan, N., Zhao, F., Sutherland, J.W., 2011. A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. J. Manuf. Syst. 30, 234–240.

[9] Green India Energy Summit, 2014. http://www.greenindiasummit.com/#!about-the- summit/cle6 (assessed 15 December 2014)

[10] Hanafi, I., Khamlichi, A., Cabrera, F.M., Almansa, E., Jabbouri, A., 2012. Optimization of cutting conditions for sustainable machining of PEEK-CF30 using TiN tools. J. Clean. Prod. 33, 1–9.

[11] He, Y., Liu, B., Zhang, X., Gao, H., Liu, X., 2012. A modeling method of task-oriented energy consumption for machining manufacturing system. J. Clean. Prod. 23, 167–174

[12] India's economic growth is driving its energy consumption, 2013 http://www.eia.gov/todayinenergy/detail.cfm?id=10611 (assessed 15 December 2014)

[13] http://www.theenergyreport.com/pub/na/indias-widening-energy-deficit (assessed on 10 Dec 2014).

[14] Kant, G., Sangwan, K.S., 2014. Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining. J. Clean. Prod. 83, 151–164.