Parameter Optimization of MRR for EN31 Alloy: A Review

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Abstract— Metal Removal Rate in Turning is a material removal process in which the work piece material is removed with the help of the cutting tool. By using the turning process we can produce wide variety of products. The turning operation is performed on the lathe machine. Turning is used to produce typically rotational and axis- symmetric parts that have amenities such as threads, grooves, holes, contoured surfaces, tapers, and various diameter steps. Turning process can be applied to a number of materials including aluminium, copper and various types of steels. A number of researches have been conducted in MRR of EN31 and a vast literature review has been discussed towards the case study of industries. The basic principles of MRR are described and future scopes are also discussed. Finally, the range of material removal that can be achieved is discussed.

Key words: MRR, MRR of EN31

I. INTRODUCTION

Turning is the removal of materials outside diameter of a rotating cylindrical work piece. As, is used to minimize the diameter of a work piece generally to a specific dimension and to produce a smooth finish over the metal. Also, the metal piece is turned so that the parts have different diameters. As machining operation produces cylindrical shape, in its first form, it can be defined as an outer surface machining with the work piece to be rotated, with the use of the cutting tool of single point and with the power cutter parallel to work piece to remove the outside surface of the metal piece. The origin of turning dates to around 1300 BCE when the Ancient Egyptians first developed a two-person lathe. One person would turn the wood work piece with a rope while the other used a sharp tool to cut shapes in the wood. Ancient Rome improved the Egyptian design with the addition of a turning bow. [1] In the middle Ages a pedal replaced hand-operated turning, allowing a single person to rotate the piece while working with both hands. The pedal was usually connected to a pole, often a straight-grained sapling. An important early lathe in the UK was the horizontal boring machine which was installed in the Royal Arsenal in 1772 Woolwich. In comparison to other metal removing processes turning technique, strongly reduces the surface roughness and improves finish of work piece.

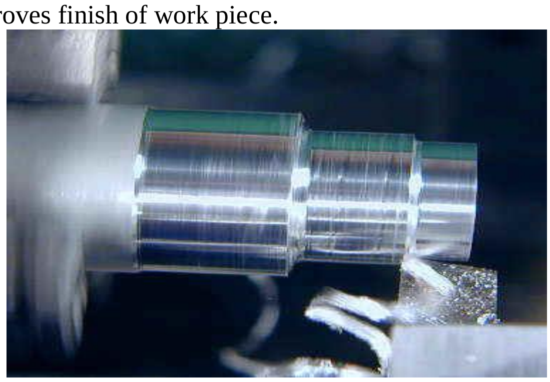

Fig. 1: Process of Metal Removal Rate

II. LITERATURE REVIEW

Metal Removal Rate by the use of Turning has been found as one of the most significant material removal process. Many researchers investigated and formulated the effect of metal removal rate in turning which has been focused to produce more removal of material with less surface roughness in various metals like Aluminium, Steel, Nickel, Copper and titanium alloy. Research and development efforts over the last decade have resulted in improvements in turning process and the spin-off of a series of related technologies.

Fang and Wang (2002) investigated for predicting surface roughness in finish turning operation by developing an empirical model by considering parameters: I piecework hardness (materials), food, cutting tip angle tool, cutting depth and cutting time. Data mining techniques were used with logarithmic transformation of data to develop an empirical model to predict surface roughness.[2] Suresh et al. (2002) focused on the machining of mild steel cutting tools tungsten carbide coated with Ti & N to develop a prediction model of surface roughness by using the response surface methodology. Genetic algorithms used to optimize the objective function and compared with the results of RSM. It was observed that GA program provided maximum values of surface roughness conditions of minimum and optimal machining.[3] Lee and Chen (2003) highlighted in artificial neural networks using a detection technique to control the effect of the vibration produced by the movement of the work piece and cutting tool during the cutting process developed a recognition system Online surface. The authors use tri axial accelerometer to determine the direction of vibration significantly affecting surface roughness then analyzed using a statistical method and accuracy compared both ANN and SMR. [4] Choudhury and Bartarya (2003) focused on the design of experiments and the neural network for prediction of tool wear. The input parameters were cutting speed, feed and depth of cut; flank wear, surface finish and temperature were selected as outputs. Empirical relationship between different answers and the input variables and also through neural network program helped predictions for the three response variables and the method was best for the prediction is compared. [5] Chien and Tsai (2003) developed a model for predicting the tool flank wear followed by an optimization model for the determination of optimum cutting conditions PH stainless steel machining. The back-propagation neural network was used to build the predictive model. The genetic algorithm was used to optimize the model. [6] Kirby et al. (2004) developed the prediction model for the surface roughness in turning operation. The regression model was developed by a single parameter court and vibration along the three axis were chosen for the system prediction of surface roughness. Using multiple regression analyses of variance and a strong linear relationship between the parameters (feed speed and vibration) response (surface roughness) was found.

The authors concluded that the speed and depth of cut of the head that does not necessarily have to be fixed for effective prediction model of surface roughness. [7] Ozel and Karpat (2005) studied for prediction of surface roughness and tool flank wear by using the neural network model compared to the regression model. Established measurement data of the surface roughness and tool flank wear to train the neural network models were used. Predictive neural network models to be able to better predictions of surface roughness and tool flank wear within the range of each were trained found. [8] Luo et al. (2005) conducted theoretical and experimental studies to investigate the intrinsic relationship between tool flank wear and operating conditions in metal cutting processes using carbide cutting inserts. The authors developed a model for predicting the wear land width combines mechanical cutting and an empirical model simulation tool flank. The study revealed that the rate cut was more dramatic effect on the life of the tool feed rate. [9] Kohli and Dixit (2005) proposed a method based on the neural network with the acceleration of the radial vibration of the tool holder as feedback. The back propagation algorithm is used to train the network model for predicting the surface roughness in turning process. The methodology was validated for turning dry and wet steel using high speed steel and carbide tool and noted that the proposed methodology was able to make an accurate prediction of surface roughness using small formation of size and testing data sets. [10] Pal and Chakraborty (2005) studied to develop a model of neural network back-propagation for prediction of surface roughness in turning operation and is used mild steel work pieces with high speed steel as the cutting tool to carry out a number of experiments. The authors used speed, feed, depth of cut and cutting forces as inputs to the neural network model for prediction of surface roughness. The work resulted in the intended surface roughness was very close to the experimental value. [11] Abburi and Dixit (2006) they developed based on knowledge for predicting surface roughness in turning process system. Fuzzy set theory and neural networks were used for this purpose. The authors developed rule to predict the surface roughness for the process variables as well as for their prediction for a given surface roughness. [12] Zhong et al. (2006) predicted the surface roughness of machined surfaces using nets with seven innings namely degree insertion tool, workpiece materials, cutting edge radius, angle, depth of cut, spindle speed and feed rate. [13] Kumanan et al. (2006) proposed a methodology for predicting the machining forces using multilayer perception trained by genetic algorithm (GA). The data obtained from experimental results of a turning process is explored to train artificial neural networks proposed (RNAs) with three inputs for output machining forces. ANN optimal weights were obtained using GA search. This hybrid function replacing made of GA and ANN found computationally efficient and accurate to predict the forces of machining for the machining conditions of entry. [14] Mahmoud and Abdelkarim (2006) studied in turning operation using high speed steel cutting tool 450 at an angle of approach. This tool proved he could carry out the cutting operation at higher speeds and longer service life of the traditional tool with a rake angle of 90 degrees. The study ultimately determines the optimum cutting speed for high production speed and minimum cost and tool, production time and operating costs. [15] Doniavi et al. (2007) using the response surface methodology (RSM) in order to develop the empirical model for the prediction of surface roughness, in deciding the optimal cutting condition in the transformation. The authors showed that the feed rate significantly influenced surface roughness. With increased surface roughness speed power was found to be increased. With the increase in the cutting speed decreased surface roughness. Analysis of variance showed that the influence of the feed rate and were in surface roughness of the cutting depth was applied. [16]

III. FUTURE PERSPECTIVES

In MRR, there are three categories for variable like-Lathe machine set up, work pieces and tool variables. Set up variable include-rotating speed and feed rate. Work piece variables include materials of work piece and dimensions of work piece like- length, diameter and hardness etc. Tool variables are tool dimensions, tool geometry, angle of tool and tool wear rate. This Study considers about work piece, tool and set up variables. There is scope for considering more factor levels, interactions; to optimize a selected set of parameters. The following suggestions may improve useful work:

- A comparison between different optimization techniques can also be studied to check the better among them.
- Some response like tool vibration, wear rates etc. can also be calculated of the work piece obtained.
- Different material and different optimization technique can be applied to find the interaction between selected set of parameters.
- Tool variables can also be optimized by Taguchi approach.
- Level of factor can be increased for further study.

REFERENCES

[1] Homepage http://www.mechgrid.com/turning-types-of-turning-process.html
[2] Feng C.X. (Jack) & Wang X., (2002), "Development of Empirical Models for Surface Roughness Prediction in Finish Turning", International Journal of Advanced Manufacturing Technology, Volume 20, pp.. 348–356
[3] P. prasanna, dr. ch. penchalayya, dr. d. anandamohana rao, (2013) optimization and validation of process parameters in friction stir welding on AA 6061 aluminium alloy using gray relational analysis, International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622
[4] Lee S.S. & Chen J.C., (2003), "Online surface roughness recognition system using artificial neural networks system in turning operations" International Journal of Advanced Manufacturing Technology, Volume 22, pp.. 498–509.
[5] Choudhary S.K. & Bartarya G., (2003), "Role of temperature & surface finish in predicting tool wear using neural network & design of experiments", International Journal of Machine Tools & Manufacture, Volume 43, pp.. 747–753.
[6] Chien W.-T. & Tsai C.-S., (2003), "The investigation on the prediction of tool wear & the determination of optimum cutting conditions in machining 17-4PH

stainless steel", Journal of Materials Processing Technology, Volume 140, pp.340–345

[7] Kirby E. D., Zhang Z. & Chen J. C., (2004), "Development of An Accelerometer based surface roughness Prediction System in Turning Operation Using Multiple Regression Techniques", Journal of Industrial Technology, Volume 20, Number 4, pp.. 1-8

[8] Özel T. & Karpat Y., (2005), "Predictive modeling of surface roughness & tool wear in hard turning using regression & neural networks", International Journal of Machine Tools & Manufacture, Volume 45, pp.. 467–479

[9] Antony J., (2000), "Multi-response optimization in industrial experiments using Taguchi's quality loss function & Principal Component Analysis", Quality & Reliability Engineering International, Volume 16, pp..3-8

[10] Kohli A. & Dixit U. S., (2005),"A neural-network-based methodology for the prediction of surface roughness in a turning process", International Journal of Advanced Manufacturing Technology, Volume 25, pp..118–129

[11] Pal S. K. & Chakraborty D., (2005), "Surface roughness prediction in turning using artificial neural network", Neural Computing & Application, Volume14, pp. 319–324.

[12] Abburi N. R. & Dixit U. S., (2006), "A knowledge-based system for the prediction of surface roughness in turning process" Robotics & Computer-Integrated Manufacturing, Volume 22, pp.. 363–372

[13] Zhong Z. W., Khoo L. P. & Han S. T., (2006), "Prediction of surface roughness of turned surfaces using neural networks", International Journal of Advance Manufacturing Technology, Volume 28, pp.. 688–693.

[14] Kumanan S., Saheb S. K. N. & Jesuthanam C. P., (2006), "Prediction of Machining Forces using Neural Networks Trained by a Genetic Algorithm", Institution of Engineers (India) Journal, Volume 87, pp.. 11-15

[15] Mahmoud E. A. E. & Abdelkarim H. A., (2006), "Optimum Cutting Parameters in Turning Operations using HSS Cutting Tool with 450 Approach Angle", Sudan Engineering Scoeiety Journal, Volume 53, Number 48, pp.. 25-30

[16] Doniavi A., Esk&erzade M. & Tahmsebian M., (2007), "Empirical Modeling of Surface Roughness in Turning Process of 1060 steel using Factorial Design Methodology", Journal of Applied Sciences, Volume 7, Number17, pp.. 2509-2513.