Modelling and Optimization of Surface Roughness in Turning Process: A Review

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Abstract- *Most of the manufacturing processes are defined by the two major characteristics named as productivity and quality. Surface roughness is important quality characteristics for the selection of cutting parameters and machine tools in process designing. In actual practice, factors such as tool variables, work piece variables and cutting conditions are significantly influence the surface roughness. There has been a great deal of research activity performed in order to optimize various turning process parameters to improve surface quality. This paper aims at presenting the various methodologies and practices that are being employed for modeling and optimization of surface roughness in turning process. After reviewing papers it can be concluded that Taguchi method is the most commonly used and versatile, which is being applied efficiently in industrial applications for optimal selection of process variables in the area of machining. The fundamental tools for improving a process is shown in fishbone diagram by identifying the root causes of product quality.*

Keywords- Fishbone, Modelling and Optimization,Surface roughness,Taguchi method,Turning process.

I. INTRODUCTION

Automotive industries uses conventional machining processes such as turning, drilling, milling, shaping and planning and others to manufacture automotive components. Although each machining process has their own importance but turning is a versatile and useful machining operation. Recent developments in several methods of machining leads to increased industrial applications of turning. Turning has specific feature of producing complex geometric surfaces with acceptable accuracy and surface properties. Due to this feature of turning, it is the most important operation and is widely used in most of the manufacturing industries. Nowadays, all manufacturing industries have big challenge because of competitive and dynamic market environment. The main purpose of industries is to maximize profit by optimizing production activities. Production is said to be optimized when complex machining will be economically accomplished. As machining time decreases, productivity results increases which may result in quality loss and vice-versa. Better surface finish is the most required properties of machined parts where customers never compromise. Surface roughness is the main characteristic to define surface quality. It requires attention both from industry staff as well as in R&D team, because this greatly influences machining performances. Surface roughness is mainly due to process parameters such as tool geometry (i.e. nose radius, edge geometry, rake angle, etc.) and cutting conditions (feed rate, cutting speed, depth of cut, etc.). The optimal selection of the process parameters can be introduced during early stage of the product and processdevelopment to achieve the quality product with cost effectiveness. Productivity can be defined in terms of MRR and in machining conditions quality can be interpreted in terms of surface roughness. The optimization techniques have been applied to measure the right level or value of the parameters that have to be maintained for obtaining quality products/services. In conventional (manual) manufacturing systems, time consumed by the machined components is approximately 6% to 10% of the total production time available on machines being used. In present scenario manufacturing industries looks toward automating system by integrating computer technology in manufacturing. It leads to increase machining time upto 65%-80%. Newly developed techniques for optimization, Fuzzy Logic, Scatter Search technique, Ant Colony technique, Genetic Algorithm, Taguchi technique, Response Surface Methodology etc. are being employed successfully in industrial applications for optimal selection of process parameters in the machining area [1]. Among these Taguchi Method [2] is fluently using in industries for making product/process insensitive to any uncontrollable factors such as environmental variables.

II. TURNING PROCESS

Turning is common machining process in most of the production industry. Turning in the lathe is to remove extra material from the work-part to produce a cone-shaped or cylindrical smooth surface finish on the metal. During turning process the work is made to rotate about the lathe axis, and the tool is fed parallel to the lathe axis. Different shapes and design features such as holes, grooves, threads, tapers, various diameter steps, and even contoured surfaces can be imparted on work-piece by Turning process. Turning possess high tolerances and surface finishes, thus it is easy for adding precision rotational features to a component whose basic shape has already been formed. Hard turning is nothing but a ‘‘single point” cutting process, which is generally used in actual industrial production. It is performed on hardened steels (hardness ranging from 45 to 68 RHN) with the application of various tool materials preferably CBN having benefits such as short cutting cycle time, flexible process, better surface finish, maximum MRR and Eco-friendly when machining under dry condition. The peripheral speed of the work piece called cutting speed, movement of the tool parallel to the job axis for one revolution of job called feed, and movement of the tool perpendicular to the job axis is radial depth of cut of the tool are the process parameters which are illustrated in **Fig. 1**. The three primary controlling parameters in normal turning operation are cutting speed, feed rate and depth of cut. Optimization of these parameters results in achieving the minimum machining cost and production time. Prediction of performance of process plays crucial role for optimization.

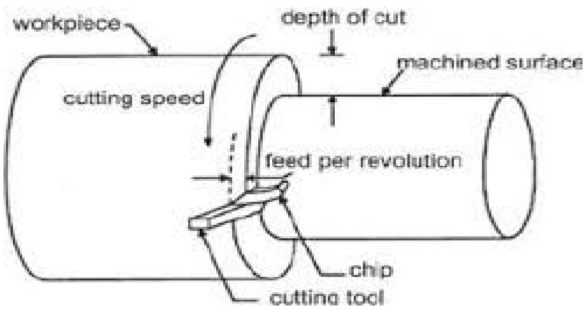

Fig. 1: Parameters in turning process

Dimensional deviation and surface finish are two major aspects of quality of machined work-part. A part is said to have good surface properties only if it possess minimum surface roughness and waviness and no flaws remaining on the part. The radial difference between provided depth of cut and the obtained depth of cut is termed as Dimensional deviation. Including primary factors researchers analyzed surface finish by considering the effect of number of factors such as work material characteristics, unstable built up edge, tool nose radius, tool angles, stability of material, tool and work piece setup, and use of cutting fluids, radial vibration, tool material, etc., on their experiment. Numbers of experiments have been conducted by researchers for continuous improvement of performance of turning process by employing different optimization technique.

III. SURFACE ROUGHNESS

The degree of smoothness of a machined part’s surface is known as Surface Roughness after it has been manufactured. The precision on the finished work-piece dimensions as so as the surface roughness are changed or the material mechanical characteristics are improved [3]. Industries like, aerospace, automobile die and mould manufacturing requires continual studies for products with better surface finish by implementing newly invented cutting technologies. The surface property of the machined part plays a vital role to determine the work-piece functional performance such as fatigue strength, corrosion resistance and tribological characteristics. For example, the fatigue life of machined part decreases with increase in surface roughness. Surface quality can dictate about how much effective the machining process is. Any advancement to the surface quality of the component can make a product more valuable. However, the surface quality depends on number of factors and improvement of surface finish is challenging task. In any machining process, machining conditions is important to determine the quality of surface developed. Thus, a systematic analysis of process parameters is crucial to identify their influence on the process outputs, which directly impacts on the process quality. The dimensional accuracy and surface finish of any manufacturing method have become essential because a customer expects improved quality. There are many factors that impacts surface finish in machining and, hence, the selection of analytical or empirical models for reliable prediction of machining becomes crucial. ANOVA has been carried out to determine the contribution of each factor on response. Better surface quality will be quite easier to achieve by maintaining optimum values of tool geometry rather than changing feed rates. Dimensional accuracy, form stability, surface fineness, fulfillment of functional requirements in given area of application, etc., are essential quality characteristics of the finished components. Highest MRR is obtained by rough cuts, where surface finish is not relevant factor to be considered. Surface finish has significant effect during finish turning process. Surface roughness is termed as the small, finely spaced deviations from nominal surface of machined parts. **Fig. 2** shows the surface roughness profile. The average surface roughness is given by,

$$Ra = \frac{1}{L}\sum_{i=1}^{L}|Yi|$$

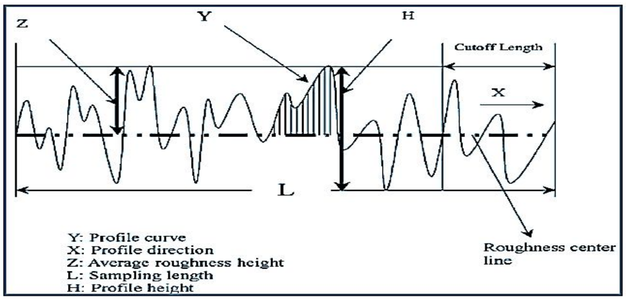

Fig. 2: Surface roughness profile

Where,

Ra → Arithmetic average deviation from mean line,
L → *S*ampling length and
Y → *O*rdinate of the profile curve [4].

Surface roughness of machined parts can be measured by applying different techniques such as, direct measurement, comparison based methods, non-contact techniques, on-process measurement, etc. Surface finish significantly determines functional properties of machined parts such as fatigue strength, wear rate, coefficient of friction, and corrosion resistance of the machined components. The most important parameter describing the surface integrity is surface roughness. Parts such as automobile, aerospace, and medical components need high precision in surface finish. The Cutting Speed (V_c), Feed (f), and the products V_c^2, f^2, V_c*f are significant terms on surface roughness parameters: arithmetic average of absolute roughness R_a, maximum height of the profile $R_t$and average maximum height of the profile R_z. Surface condition can be measured by several factors :

- Cutting parameters (cutting speed, feed, Depth of cut)
- Tool geometry (angle and sharpness of the cutting edge, corner radius, etc)
- The cutting tool material
- The nature of chips formed, cutting forces, etc.

The stylus type instruments are widely accepted to measure surface roughness. The stylus probe instrument is currently preferred for surface finish measurement:

a)Profilometer,
b)The Tomlinson surface meter,
c)The Taylor Hobson Talysurf and
d)Profilograph.

IV. METHODOLOGY

Many researchers have used different optimization techniques to optimize Surface Roughness, Material Removal Rate (MRR), and Tool Wear Rate during machining process. Following are some techniques which are mostly used for optimization:

1.Taguchi Method,
2.Artificial Neural Network (ANN),
3.Response Surface Methodology (RSM) and
4.Regression Analysis

4.1 Taguchi Method

The ideas of laying out the conditions of experiments involving multiple factors were first proposed by the Englishman, Sir R.A. Fisher. The method is popularly known as the factorial design of experiments. For a given set of factors full factorial design provides all possible outcomes. Partial fraction experiment allows conducting limited number of experiment which produces the most information. Taguchi has envisaged a new method of conducting the design of experiments which are based on well-defined guidelines. Genichi Taguchi, a Japanese quality management consultant, proposed a design experiment method popularly known as Taguchi Method. This method employs a special set of arrays called orthogonal arrays (OA). These standard arrays dictate the path to conduct minimum number of experiments which provides complete information about factors that affect the performance parameter. Professional statisticians accept the goals and improvements forwarded by Taguchi methods, for studying variation, especially by Taguchi's development of designs. After World War II, the Japanese manufacturers had to deal with lack of resources. Taguchi advances the techniques which supports the country to withstand and survive with limited resources. Taguchi revolutionized the manufacturing process in Japan by minimizing costs incurred. His ideas have been globally adopted by successful entrepreneur since it improvised production process at low cost and limited resources. To design robust systems that are reliable and easily applicable under uncontrollable conditions are main objective of Taguchi Method. [5]. Taguchi Methods mainly focused on cost savings by employing effective engineering tactics rather than advanced statistical technique without compromising in product quality. It includes shop floor to top management quality engineering. Upstream methods efficiently use to reduce variability and estimates cost effectiveness for small scale production and robust designs for large scale manufacturing and the market density. Shop floor techniques refer to real time methods for monitoring and affirmed in quality production based on cost. Taguchi design is a powerful and efficient designing method that operates consistently and optimally over a variety of conditions. To develop the best design, it is necessary to implement a strategically designed experiment, which signifies the process to many levels of design parameters. Taguchi's approach to design of experiments is easy to be understood and employed for user without detailed knowledge of statistics; hence it is widely accepted in the engineering and scientific field.

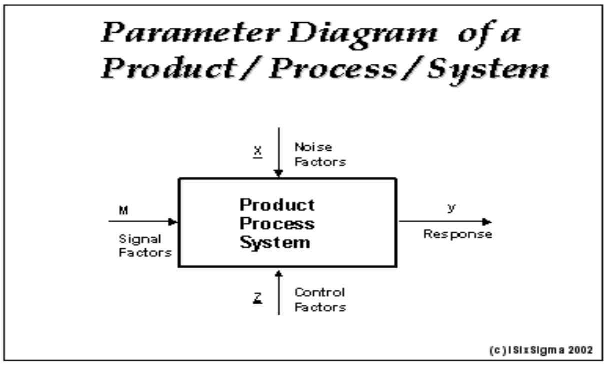

Fig. 3: Parameter (P) –diagram

To measure the performance characteristic deviating from the desired value quality loss function is widely used. The value of the loss function is measured in terms of signal-to-noise (*S/N*) ratio. Signal-Noise (S/N) ratio is first used by Taguchi as the quality characteristic of choice. S/N ratio is used as measurable value instead of standard deviation because, standard deviation is proportional to mean i.e. as the mean decreases, the standard deviation also deceases and vice versa. Noise factors cannot be controlled by product operator while Signalfactors are controllable and can be set or controlled by the operator of the product to obtain its intended functions. Regardless of the category of the performance characteristic, larger the *S/N* ratio gives rise to better performance characteristic. Therefore, highest *S/N* ratio corresponds to the level of optimal process parameters level. Furthermore, a statistical analysis of variance popularly known as ANOVA is carried out to analyze statistically significant process parameters. With *S/N* and ANOVA analyses, the optimal combination of the process parameters can be determined [6]. S/N ratio is measured in terms of decibel scale.

Followings are the concept behind the:

- Quadratic Loss Function - used to evaluate the loss incurred i.e. deviation from target performance by the user.
- Signal-to-Noise (S/N) Ratio - used for predicting the product quality by conducting experiments.
- Orthogonal Arrays (OA) - used for collecting required information about control factors with a reduced number of experiments.

To verify the optimal process parameters obtained from the parameter design a final confirmation experiment has been conducted.

Nominal-is-the-better:

$$S/N_T = 10*\log\left(\frac{\bar{y}}{s_y{}^2}\right) \quad 1.$$

Larger-is-the-better:

$$S/N_L = -10*\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i{}^2}\right) \quad 2.$$

Smaller-is-the-better:

$$S/N_S = -10*\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i{}^2\right) \quad 3.$$

Where

$\bar{y}$ - Average of observed data,
s_y^2-variance of *y*,
n - Number of observations and
y - Observed data.

These *S/N* ratios are expressed on a decibel scale. S/N_T is usedif the objective is to reduce variability compare to specific target, $S/N_L$is used for system optimization when the response is as maximum as possible, and $S/N_S$is preferred for optimized system when the response is as small as possible. Factor levels are said to be optimal if it maximize the appropriate *S/N* ratio.

Taguchi's Rule for Manufacturing:

Taguchi proposed that during the design of a product and its manufacturing process, variation can be easily eliminated. Quality engineering strategy designed by Taguchi is appropriate for both contexts. The process has three stages:

I. System design
II. Parameter design
III. Tolerance design

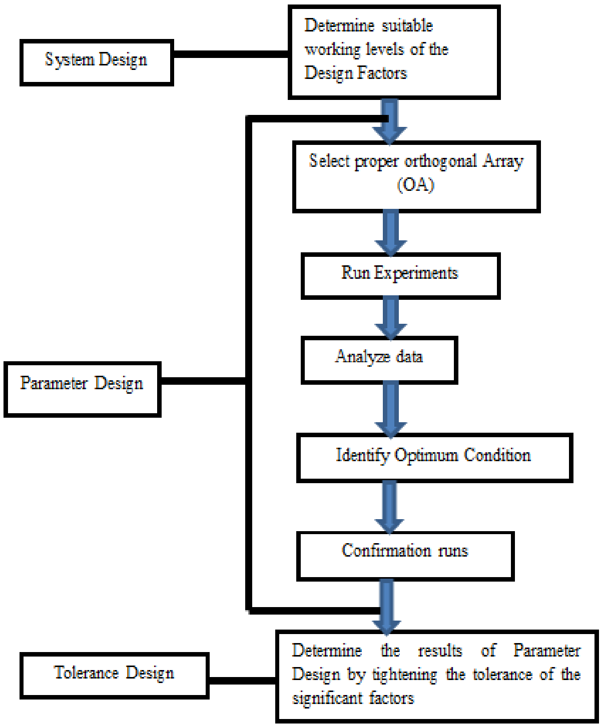

Fig. 4: Taguchi Design Procedure

Based on the degrees of freedom approach minimum number of experiments that are required to conduct which gives full information for Taguchi method can be calculated.

$$N_{Taguchi} = 1 + \sum_{i=1}^{NV}(L_i - 1)$$

For example, suppose 8 independent variables study having two levels for 1 independent variable and three levels for remaining 7 independent variables (L18 orthogonal array), based on the above equation 16 experiments has to be performed which is minimum. According to balancing property total number of experiments shall be multiple of 2 and 3. Thus 18 experiments are required to conduct for above case.

Steps Involved in Taguchi Method:

Following steps are necessary for parameter design in Taguchi Method to achieve larger-the-better characteristics [7]:

1.Select a suitable output quality characteristic to be optimized and its measurement system.
2.Select the control factors and their levels, find out possible interactions between these factors.
3.Select noise factors and their levels.
4.Select the appropriate orthogonal arrays (OA). And assign factors to OA's and locating interactions.
5.Carry out experiments as described by OA's.
6.Execute statistical analysis based on S/N ratio using ANOVA.
7.Based on optimal control factor level combination predicts optimal output performance level, and to verify the result conduct a confirmation experiment.

4.2 Artificial Neural Network (ANN)

Neural networks are very well known method to solve a statistical problem in many industrial situations. ANN makes ease to learn and establish complex non-linear and multi-variable relationships between process parameters, thus suitable for modeling various manufacturing functions. To estimate and improve surface quality in machining, artificial neural networks are employed as an alternative way. In the past, a many number of researchers used neural network models to study tool condition monitoring and predictions of tool wear and tool life. A multi-layer perceptron (MLP) is also known as feed forward network mainly consists of three layers named as input layer, one or more hidden layers and an output layer. These layers are connected in such a way that each neuron in one layer is linked to all neurons in the next layer. However, no any connection is possible between the neurons in the same layer and feedback connections are not conceded. The input layer, also known as the "buffer" layer, not allowed to perform information processing. Only one input has been assigned to each neuron, and it simply transmits the value between corresponding inputs to outputs. The neurons in the hidden and output layers perform necessary information processing. Signals are transmitted from the input layer to the output layer through the hidden layers in the same direction. Information is collected in the inter-neuron connections. To generate desired output patterns from given input patterns strengths or weights are assigned to the connections of network. In other words, by adjusting the values of the connections (weights) between neurons we can develop a neural network to perform a specific function. As each input is provided to the network, the output of the network is compared to the target. The deviation between the target output and the network output give rise to error. The average of the sum of these errors needs to be minimized. Number of weighted input signals from each of the preceding layer fed to each hidden or output neurons and generates only one output value. The **Fig. 5** illustrates a network with a single neuron. Here, the multiplication of scalar input (x_i) transmitted through a connection and its strength scalar weight (w) results a product (wx), again a scalar. The inputs given to the neuron may be from the actual environment or from any other neurons. Its output can be used as input to other neurons or fed directly into the environment. Also, this neuron has a scalar bias (bj). The output (y_i) is a result of an activation function, hence to achieve the desired end the network is trained by adjusting weights (*w*) and bias (*b*). The weights of the connections of the network are iteratively adjusted to establish the relationship between the input and output patterns.

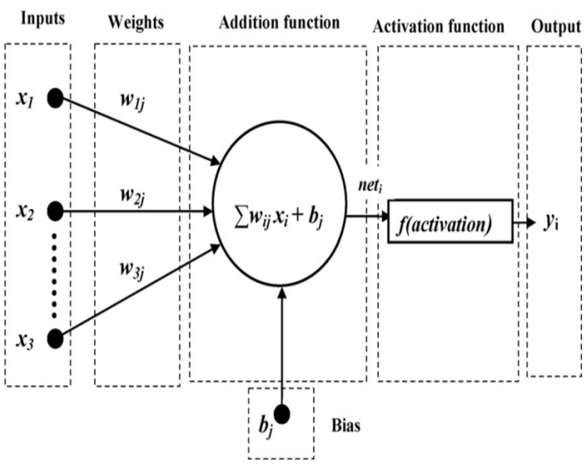

Fig. 5: The structure of an artificial neuron

The geometry of the problem decides the number of neurons in the input and output layers. Thus three neurons have assigned to the input layer, which receives the pattern and one neuron to the output layer, which processes extracted features to obtain the pattern class. However, there is no general rule to determine the number of neurons in a hidden layer and the number of hidden layers [8]. Hence, based on trial and error method the numbers of hidden layers and neurons in the hidden layer have been determined and generate least effective error. MATLAB Neural Network Toolbox is commonly preferred to design optimal neural network architecture. The neurons in the input layer have unity activation function (or transfer function). It means they simply transmit the (scaled) values of the pattern directly to the hidden layer. In the study of Li et al. [9], for the prediction of tool wear and work-piece surface roughness neural network models have also been integrated with analytical models such as Oxley's theory to develop a hybrid machining model. Neural networks can be used to generate difficult-to-model machining characteristic factors. To predict surface roughness Tsai and Wang [10] compared six types of neural network models and a neuro-fuzzy network in their study. Their study proved that multilayer feed forward neural network with hyperbolic tangent-sigmoid transfer functions leads to better result among feed-forward neural network models. O¨zel and Nadgir [11] designed a back-propagation neural network model for a range of cutting conditions to predict tool wear on chamfered and honed CBN cutting tools. For predicting tool wear Choudhry and Bartarya [12] compared the design of experiments technique and neural networks techniques and established the relationships between working temperature and tool flank wear. They found that amount of flank wear on a tool can be indirectly determined by monitoring the temperature at the cutting region and the surface finish by using a naturally formed thermocouple without interrupting the machining operation. They concluded that neural networks perform better results than design of experiments technique. Lee and Chen [13] monitored the vibrations caused by the tool and work-piece motions during machining and put forward an online surface roughness recognition system using neural networks. Even obtained good results it is not generally adopted because their study was limited to regular turning operations of mild steels.

4.3 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is nothing but a collection of statistical and mathematical approaches useful for developing, improving and optimizing processes [14]. The RSM is usually applied for a particular situation where performance measure or quality characteristic of the process influenced potentially by several input variables. Thus performance measure or quality characteristic is termed as response. Sometimes input variables or independent variables are subjected to the control of the scientist or engineer. The area of response surface methodology consists of experimental strategy for describing the space of the process or independent variables, empirical statistical modeling to establish an appropriate relationship between the yield and the process variables and optimization techniques for estimating the values of the process variables that produce target values of the response. The effect of two or more factors on quality criteria can be analyzed, and optimum solutions are achieved by utilizing this technique [15, 16]. In RSM design, it is compulsory to provide at least three levels for each factor. In this way, even untested factor values can be estimated using fewer experimental combinations and the combinations themselves [17]. The results are expressed in 3D series or counter map. Generally, a low-order polynomial in small region of the independent variable space is used. In most of the cases, either a first-order or a second ordermodel is used. In general, the first-order model is

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$

and the second-order model is

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

This first-order model would likely be appropriate as an approximation to the true response surface somewhat in a small region.

The second-order model is widely adopted in response surface methodology due to following reasons:

1. The second-order model is very flexible. Wide variety of functional forms is used, so it performs better as an approximation to the true response surface.
2. Parameters (the β's) in the second-order model is easily estimated. Least squares method can also be used for this purpose.
3. There is significant practical experience showing that second-order models work well in solving real response surface problems.

RSM is an important branch of experimental design. RSM plays vital role in developing new processes and optimizing their performance. RSM helps in quality improvement, including reduction of variability and improved process and product performance. If any variation is identified in key performance characteristics, results in poor process and product quality. The main aim of experiments related to manufacturing is to achieve the desired surface roughness, tangential force and flank wear of the optimal controlling parameters [18]. Therefore, the response surface optimization technique is better for determination of the best cutting parameters in turning. The goal of this study or techniques is to minimize surface roughness, tangential force and flank wear.

4.4 Regression Analysis

Regression analysis is a simple method for analyzing and establishing functional relationships among variables. The relationship can be expressed in the form of an equation or a model connecting the response or dependent variable and one or more explanatory or predictor variables. We represent the response variable by Y and the set of predictor variables by X_1 , $X_2, \ldots, Xp$, where p is the number of predictor variables or independent variables. The true relationship between Y and X_1 ,$X_2, \ldots, Xp$ can be approximated by the regression model

$$Y = f(X_1, X_2, \ldots, X_p) + \varepsilon,$$

where 'ε' is supposed to be a random error representing the discrepancy in the approximation. It justifies for the failure of the model to fit the data exactly as required. The function $f(X_1, X_2, \ldots, Xp)$ describes the relationship between Y and $X_1, X_2, \ldots, Xp$. An example is the linear regression model

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon,$$

Where $\beta_0, \beta_1, \ldots, \beta_p$ called the regression parameters or coefficients, are unknown constants to be calculated (estimated) from the data and 'ε' is a random disturbance or error.

Since regression analysis proposed simple methods for establishing a functional relationship among variables it is one of the most widely used statistical tools.

Steps in Regression Analysis

Regression analysis includes the following steps:

- Define the problem
- Selection of potentially relevant variables
- Data collection
- Model specification
- Choice of fitting method
- Model fitting
- Model validation and criticism
- Using the chosen model(s) for the solution of the posed problem.

A regression equation is also called as simple regression equation if it contains only one predictor variable. And equation containing more than one predictor variable is also known as multiple regression equation. The process or controlling parameters, resultant cutting forces and the surface roughness values obtained after conducting experiments were given as input to the software and regression equation was developed for each desired output. The regression coefficients are determined with the least square method by means of MINITAB 16 software.

V. SUMMARY

The main vision of today's economy is to perform manufacturing process at the minimum cost and time simultaneously improving machining efficiencies by optimizing machining parameters for different processes. Study of surface roughness structure and calculation of its value is quite complicated task through analytical formula. At the present time, there is no compromise in surface quality thus always seeks best machining method. For many engineering purposes Taguchi method best suits for experimental design due to ease of its application and is straightforward, making it a successful yet simple tool. It provides enough information to identify key parameters that have the most effect on the performance characteristic and ignore these parameters with low effect. It is said that the Taguchi method for quality evaluation approach is reliable if done manually. ANOVA helps to identify the significant parameters which most affect quality characteristics among design parameters. This analysis dictates the relative contribution of machining parameter and controls the response of turning operation [19]. The neural network models are compared with regression models. Comparatively, the neural network models provided better prediction capabilities because they can model more complex non-linearities and interactions than exponential and linear regression models can put forth. All data obtained from previous experiments are collected and have been used to compare the models based on prediction accuracy and can be used for testing relative biases, ability to extrapolate and others [20]. ANN produces an accurate relationship between cutting parameters and surface roughness. Therefore, ANN is also a good technique used for modeling surface roughness and helps to estimate close to real values before the machining stage [21]. The implementation of response surface optimization helps to find out the combination of input variable settings (cutting parameters) that together optimize the surface roughness index and cutting force components during the hard turning process. For all the responses in the set should meet the requirements for joint optimization. Composite desirability measures optimization achievement. Composite desirability ranges from zero to one for the all responses. One represents the ideal case. Zero indicates that one or more responses are outside acceptable limits [18]. Fig. 6 illustrates the set of parameters that influence surface roughness investigated by researchers.

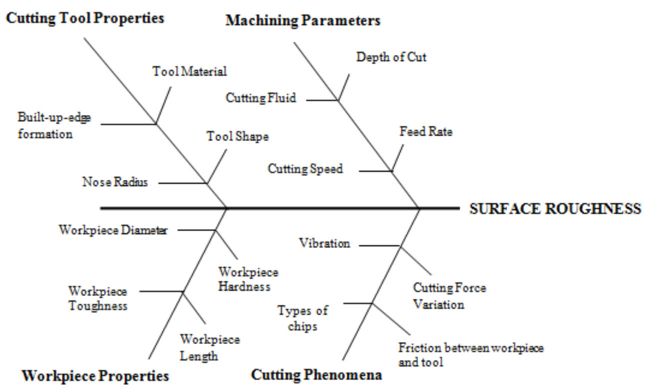

Fig. 6: Fishbone diagram with parameters that affect surface roughness

VI. CONCLUSION

The current work presented a review of the different approaches that are used for modeling and optimization of surface roughness. After studying many papers we observed that researchers used different techniques to optimize surface roughness, tool wear rate, material removal rate, cutting forces by controlling various machining parameters such as cutting speed, feed rate, depth of cut, tool nose radius etc. Taguchi Method, Artificial Neural Network, Regression Analysis, Response Surface Methodology are some techniques researchers usually preferred for analysis. A comparison of these approaches reveals that Taguchi Method takes into consideration the real machining phenomena. Information are stored and used to develop the models. On the other side, theoretical approaches are responsible for errors and limitations since it is based on conventions and idealizations. Here we conclude that Taguchi Method is the best option for optimization of surface roughness in turningoperation performed on conventional Lathe Machine Tool. There are still lot of investigation is going on such as cutting tool's deflection or introduction of thermal conditions to future models to obtain better surface finish for high accuracy machining.

REFERENCES

[1] Shirpurkar P P, Bobde S R, Patil V V and Kale B N (2012), "Optimization of Turning Process Parameters by Using Tool Inserts-A Review", International Journal of Engineering and Innovative Technology (IJEIT), Vol. 2, No. 6, pp. 216-223.

[2] Taguchi G (1986), "Introduction to Quality Engineering", Proceedings of Asian Productivity Organization, UNIPUB, White Plains, New York.

[3] Yallese MA, Chaoui K, Zeghib N, Boulanouar L, Rigal JF (2009), "Hard machining of hardened bearing steel using cubic boron nitride tool", J Mater Process Technology, vol. 209(2), pp. 92–104.

[4] Khalil AslamAwan and Yasir A Hadi (2008), "Prediction of Al and Cu Surface Roughness Based Regression Analysis Model", VI Mation Journal, Knowledge, Service& Production: IT as an Enabler, No. 1, pp. 32-39.

[5] Byrne D M and Taguchi S (1987), "The Taguchi Approach to Parameter Design", Quality Progress, Vol. 20, pp. 19-26.

[6] Nalbant, M., Gökkaya, H., Sur, G. (2007), "Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning", Materials and Design, vol. 28, pp.1379-1385.

[7] Nian C Y, Yang W H and Tarang Y S (1999), "Optimization of Turning Operations with Multiple Performance Characteristics", Journal of Material Process Technology, Vol. 95, pp. 90-96.

[8] Pala, M., Caglar, N., Elmas, M., Cevik, A., Saribiyik, M., (2008), "Dynamic soil structure interaction analysis of neural network", Construction and Building Materials, Vol. 22 (3), pp. 330–342.

[9] X.P. Li, K. Iynkaran, A.Y.C. Nee (1999), "A hybrid machining simulator based on predictive machining theory and neural network modeling", Journal of Material Processing Technology 89/90, pp. 224–230.

[10] K. Tsai, P. Wang (2001), "Predictions on surface finish in electrical discharge machining based upon neural network models", International Journal of Machine Tools and Manufacture, vol. 41 pp. 1385–1403.

[11] T. O¨zel, A. Nadgir (2002) , “Prediction of flank wear by using back propagation neural network modeling when cutting hardened H-13 steel with chamfered and honed CBN tools”, International Journal of Machine Tools and Manufacture, vol. 42, pp. 287–297.
[12] S.K. Choudry, G. Bartarya (2003), “Role of temperature and surface finish in predicting tool wear using neural network and design of experiments”, International Journal of Machine Tools and Manufacture, vol. 43 , pp. 747–753.
[13] S.S. Lee, J.C. Chen (2003) , “On-line surface roughness recognition system using artificial neural networks system in turning operations”, International Journal of Advanced Manufacturing Technology, Vol. 22, No. (7/8), pp. 498–509.
[14] Myers Raymond H. & D.C. Montgomery (2002), “Response Surface Methodology: process and product optimization using designed experiment”, A Wiley-Interscience Publication.
[15] AhmetAkdemir, SakirYazman, HaclSaglam, MesutUyaner (2012), “The Effects of Cutting Speed and Depth of Cut on Machinability Characteristics of Austempered Ductile Iron”, Journal of Manufacturing Science Engineering, Vol. 134, pp. 1-9.
[16] Neseli, S., Yaldız, S., and Tu¨rkes, E. (2011), “Optimization of Tool Geometry Parameters for Turning Operations Based on the Response Surface Methodology”, Measurement, Vol. 44, pp. 580–587.
[17] Kwak, J. S. (2005), “Application of Taguchi and Response Surface Methodologies for Geometric Error in Surface Grinding Process”, Int. J. Mach. Tools Manuf., Vol. 45, pp. 327–334.
[18] Bouacha, K., Yallese, M. A., Mabrouki, T., and Rigal, J. F. (2010), “Statistical Analysis of Surface Roughness and Cutting Forces Using Response Surface Methodology in Hard Turning of AISI 52100 Bearing Steel With CBN Tool”, Int. J. Refract. Met. Hard Mater., Vol. 28, pp. 349–361.
[19] Ali RizaMotorcu (2010), “The Optimization of Machining Parameters Using the Taguchi Method for Surface Roughness of AISI 8660 Hardened Alloy Steel”, Journal of Mechanical Engineering, Vol. 56, No. 6, pp. 391-401, UDC 669.14:621.7.015: 621.9.02.
[20] TugrulOzel and YigitKarpat(2005), “Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks”, International Journal of Machine Tools & Manufacture, Vol. 45, pp. 467-479.
[21] Karayel, D. (2009), “Prediction and control of surface roughness in CNC lathe using artificial neural network”, Journal of materials processing technology 209.7, pp. 3125-3137.