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Modeling and Prediction of Machining Process by Response Surface Method (RSM) & Artificial Neural Network-A Literature Review and Suggest Approach

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ABSTRACT:In this proposed study, the experimental results corresponding to the effects of different feed, various depth of cuts and different cutting speed on the surface quality of the ferrous and nonferrous material work pieces have been investigated using response surface method (RSM) and artificial neural networks (ANN).Taguchi method is a powerful tool for the design of high quality systems. It provides simple, efficient and systematic approach to optimize designs for performance, quality and cost. Taguchi method is efficient method for designing process that operates consistently and optimally over a variety of conditions. To determine the best design it requires the use of a strategically designed experiment. Taguchi approach to design of experiments in easy to adopt and apply for users with limited knowledge of statistics, hence gained wide popularity in the engineering and scientific community. The desired cutting parameters are determined based on experience or by hand book. Cutting parameters are reflected on surface roughness, surface texture, material removal rate and dimensional deviation turned product.RSM and neural network-based models used for the prediction of surface roughness were compared for various cutting conditions in turning. The data set obtained from the measurements was employed to and tests the neural network model. The trained neural network models will be used in predicting the various response for cutting conditions. A comparison of neural network models with RSM model will be carried out to improve the productivity

KEYWORDS: Taguchi Method, Response Surface Method, Artificial Neural Network , Machining Process

I.INTRODUCTION

Metal cutting is one of the most significant manufacturing processes in material removal. Metal cutting can be defined as the removal of metal from a work piece in the form of chips in order to obtain a finished product with desired size, shape, and surface roughness. There are different methods of metal cuttings and turning is one of the commonest among these methods. Turning is the process of machining external cylindrical and conical surfaces. It is usually performed on a lathe.In last forty years there is tremendous research in machining and development in technology. With increase in completion in market and to attain high accuracy now a days the nonconventional machining are become lifeline of any industry. One of the most important non conventional machining methods is turning. Productivity by nonconventional turning is high but its high accuracy, finishing, ability of machining any hard materials and to produce intricate shape increases its demand in market.

It has long been recognized that conditions during cutting, such as feed rate, cutting speed and diameter of cut, should be selected to optimize the economics of machining operations. Turning of hard material substantially different from metallic materials due to its mechanical properties. The turning of this material may generate delimitation of finished part on work piece. The objective of this research is to study the effect of cutting speed, feed, and diameter of cut, machining time on metal removal rate, power consumption, surface roughness, productivity and the dimensional accuracy.

Taylor showed that an optimum or economic cutting speed exists which could maximize material removal rate. Considerable efforts are still in progress on the use of hand book based conservative cutting conditions and cutting tool selection at the process planning level. The need for selecting and implementing optimal machining conditions and

most suitable cutting tool has been felt over the last few decades. Despite Taylor's early work on establishing optimum cutting speeds in machining, progress has been slow since all the process parameters need to be optimized. Furthermore, for realistic solutions, the many constraints met in practice, such as low machine tool power, torque, force limits and component surface roughness must be overcome.In this proposed study, the experimental results corresponding to the effects of different feed, various depth of cuts and different cutting speed on the surface quality of the ferrous and nonferrous material work pieces have been investigated using response surface method (RSM) and artificial neural networks (ANN).Taguchi method is a powerful tool for the design of high quality systems. It provides simple, efficient and systematic approach to optimize designs for performance, quality and cost. Taguchi method is efficient method for designing process that operates consistently and optimally over a variety of conditions. To determine the best design it requires the use of a strategically designed experiment. Taguchi approach to design of experiments in easy to adopt and apply for users with limited knowledge of statistics, hence gained wide popularity in the engineering and scientific community. The desired cutting parameters are determined based on experience or by hand book. Cutting parameters are reflected on surface roughness, surface texture, material removal rate and dimensional deviation turned product.
RSM and neural network-based models used for the prediction of surface roughness were compared for various cutting conditions in turning. The data set obtained from the measurements was employed to and tests the neural network model. The trained neural network models will be used in predicting the various response for cutting conditions. A comparison of neural network models with RSM model will be carried out to improve the productivity.

II. LITERATURE SURVEY

Turning is a key machining process in the field of manufacturing sector where the demand of high productivity and high quality is steadily increasing. It is a primary operation in most of the production process in the industry. The turning operation produces the components, which have critical feature that require specific surface finish. The operator working on the lathe use their own experience and machining guidelines in order to achieve the best possible surface finish .Due to inadequate knowledge of the complexity and factor affecting the surface finish in turning operation ,an improper decision may cause high production costs and a low machining quality. So It is very necessary to consider the impact of human parameter, environment parameters and machine parameter along with the process parameter. The theory of experimentation suggested by Hilbert is a good approach to formulate the field data base model for a complex man machine system .The concept of least square multiple regression curves as suggested by Spiegel is used to optimize the formulated model. Turning **is** a widely used machining process in manufacturing. Therefore, a best selection of cutting parameters to make happy an economic objective within the constraints of turning operations is a very significant assignment. Traditionally, the selection of cutting conditions for metal cutting is left to the machine operator Surface roughness, power consumption, material removal rate and productivity has received serious attention for many years. A considerable number of studies have investigated the general effects of the speed, feed, and depth of cut on the turning process [1]. Some researchers studied on the mach inability of aluminum-silicon alloys [2]-[7]. The influence of several factors (speed, feed, and depth of cut) on cutting force and surface roughness has investigated by using orthogonal tests in turning Si-Al alloy [3]. The results showed that the surface roughness may be improved by using diamond tool. Recently, in order to obtain reasonable cutting parameters in turning casting aluminum alloy ZL108. The main influential factors of cutting force have been investigated by using carbide tool YG8 [4]. The results indicated the depth of cut had great influence on stability of whole cutting process in rough machining. The experimentation has carried out to simplify best analysis for non-ferrous materials [3]. For cast iron (CI) and steels, they employed the criteria of reducing the machining cost to a minimum. Several monograms were worked out to facilitate the practical determination of the most cost-effective machining environment. They pointed out that the more tricky- to machine materials have a restricted range of parameters over which machining can be carried out and thus any attempt at optimizing their costs are artificial. They have suggested the use of Lagrangian multipliers for optimization of the constrained problem of part cost, with cutting power as the main restraint. In 1970, the researchers have discussed the use of goal programming and geometric programming to selection of machine they optimized cutting speed and feed rate to yield minimum production cost [9], [16]. In 1991, the researchers have described the design and development of an analytical tool for the selection of machine parameters in drilling [13]. Geometric programming was used as the basic methodology to determine values for feed rate and cutting speed that minimize the total cost of machining SAE 1045 steel with cemented carbide tools of ISO P-10 grade. Surface finish and machine power were taken as the constraints while optimizing cutting speed and feed rate for a given depth of cut [10]-[12].

Some aspects of machining have gone through revision when the experimental results showed the new parameters involved in metal cutting. Many new alloys have also been developed to react to today applications. As a

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result, there will be always a need for continuous research and improvement to tool materials, cutting conditions, cutting parameters and environmental parameters to optimize the output. The quality of surface roughness is extremely important in the case of machined components that have been designed to withstand cyclic loads. Pal and Chakraborty (2005) studied on development of a back propagation neural network model for prediction of surface roughness in turning operation and used mild steel work-pieces with high speed steel as the cutting tool for performing a large number of experiments. The authors used speed, feed, depth of cut and the cutting forces as inputs to the neural network model for prediction of the surface roughness. The work resulted that predicted surface roughness was very close to the experimental value. The problem is formulated as a Taguchi dynamic parameter design, together with a fine-tuning of the BP neural network output.(Ming-Der Jean et al 2005) proposed the application of an artificial neural network with a Taguchi orthogonal experiment to develop a robust and efficient method of depositing alloys with a favorable surface morphology by a specific micro welding hard facing process..Tsai et al. developed an in-process surface roughness prediction system in end milling. Vibration and rotation data were collected using an accelerometer and proximity sensors. BP neural networks with four input and one output neurons, which were spindle speed, feed rate, depth of cut, and vibration average per revolution as inputs, and surface roughness as output. The system accuracy was 96.99% under various cutting conditions. (Chang et al 2002) proposed the selection of training samples for model updating using ANNs. One unique feature of ANNs is that they have to be trained to function. In developing an iterative ANN technique for model updating structures, it was shown that the number of training samples required increases exponentially as the number of parameters to be updated increases. Training the neural networks using these samples becomes a time-consuming task. Taraman *et al* [1974] developed a mathematical model for the surface roughness in a turning operation in terms of cutting speed, feed and depth of cut. Utilizing PL1 language and an IBM 360/50 computer, the model was used to generate contours of surface roughness in planes containing the cutting speed and feed at different levels of depth of cut. The surface roughness contours were to select the machining conditions at which an increase in the rate of metal removal was achieved without sacrifices in surface finish.The surface roughness model was developed by utilizing Response Surface Methodology. Sundaram *et al* [1981]developed mathematical models to predict surface finish in fine turning of steels Part I. This paper outlines the experimental development of mathematical models for predicting the surface finish of AISI 4140 steel in fine turning operation using TiC coated tungsten carbide throw-away tools. A novel experimental design called the Rota table design was used for the experimental procedures. Variables included in the model are: cutting speed, feed, depth of cut, and time of cut of the tool. Statistical coding was used for the experimental variables. First order (log transformed) models were developed. For tools that exhibited lack of fit for the first-order models, a second-order model was developed. Multiple regression analysis was used in developing these prediction models. Hassan andSuliman[1990]studied a two-stage method for obtaining mach inability data for the steel turning process. In the first-stage, different mathematical model types are developed and compared for the turning process of medium carbon steel. The parameters of the models are established by curve fitting of experimental data which are collected from experiments conducted especially for this work. In the second stage, the model type(s) producing the best estimates of performance is/are used as aid in process optimization. Consequently, optimal mach inability data is obtained for maximum removal of metal. This paper aims at developing modeling tools for turning medium carbon steels (225-275 BHN) with tungsten carbide tip (Sandvik Coromant SNMG 12 04 04-15).Mathematical programming was applied to determine optimum cutting conditions by both deterministic and probabilistic models. Also, the optimal cutting conditions were approached by a manufacturing economics-based model consisting of cost elements required for a machining operation.The proper selection of cutting tools and process parameters for achieving high cutting performance in a turning operation is a critical taskThe mathematical model formulate by J.Paulo Davim V.N.Gaitonde and S.R.Karnik focus on surface roughness parameter Average roughness (Ra) and maximum peak to valley height (Rt) .The ANN model was developed with the cutting condition such as speed ,feed and depth of cut as the affecting process parameter. The experiments were planned as per L27 orthogonal array with three level define for each of the factor in order to develop the knowledge base for ANN training using error back propagation training algorithm (EBPTA).3D surfaces plot are generated using ANN model to the interaction effects of cutting conditions on surface roughness parameters. The analysis reveals that cutting speed and feed rate have significant effects in reducing the surface roughness, while the depth of cut has the least effect.

III. IDENTIFICATION OF RESEARCH GAP

The machining process specially turning process is used widely in industry and has countless applications. Traditionally, the process has been used to reduce the diameters of a cylindrical work piece or to change a work piece of non- circular to that of circular cross section. This is done by rotating the work piece about the axis of the machine's

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spindle and removing the work piece material with the cutting tool which is feed in the axial direction. The ever increasing competition in product functionality has forced a product designer to seriously design the product components. One of the areas where there is a scope for improvement is a manufacturing process. Especially metal cutting (Turning), one of the most widely used manufacturing processes which has changed considerably. Therefore, an optimal selection of cutting parameters to satisfy economic, environmental and social objectives within the constraints of turning operations is a very important task. The challenge of modern machining industries is mainly focused on the achievement of high quality; in terms of work piece surface finish, high production rate, fewer wear on the cutting tools, economy of machining in terms of cost saving and increase the performance of the product with reduced environmental impact.

The proposed RSM and ANN will be used to best explain the CNC turning operation with the help of advanced technologies is targeted as an accomplishment of this research work. From the literature review the scope of work in the machining of ferrous and nonferrous material are as follows

- Literature review : From the literature review it was found that the researchers are only used RSM as a tool for predicting the surface roughness but there is no research in the field of material removal rate , productivity , power consumption and few more parameters. So the present work focused on the RSM and ANN tool to analyze the performance of CNC machining in the turning of ferrous and nonferrous material.
- Industry point of view : most of the machining industry are interested to know which parameters are most influencing and how the responses are vary w.r.t. the input and how we can achieved the best possible response

IV. PROPOSED METHODOLOGY

The objectives of the present work are to increase the material removal rate, reduced the production cost, machining time required, minimized the power consumption, during the CNC turning of ferrous and nonferrous material. The important objectives of the research are as follows:

- To formulate the Taguchi's Design of Experiment (DOE) plan for conducting the various experiments .
- Selecting the various levels of independent parameters affecting the dependent variables.
- Conducting the experiments by using Design of experiments for the analyse the performance of CNC turning
- Measure the various parameters such as cutting speed, feed and depth of cut.
- To formulate the second degree response surface model by using MINTAB software.
- To carry out the Analysis of variance (ANOVA) by using Taguchi's array.
- To optimized the independent parameter to find out the best set of parameters.
- To carry out the sensitivity analysis, to measure the impact of various parameters.
- To study the effect of interaction on the various responses.
- To predict the various response by using feed forward back propagation neural network.
- To compare the RSM and ANN model to validate the result.

To fulfill the basic objectives following methodology will be proposed

- **Step1 : Critical Literature review on the machining process. :** This is the most important step in the research . it helps to identify the scope of research .
- **Step2 : Identification of the area of research :** This is the second stage of research after identifying the research gap.
- **Step 3 : Identification of various parameter under investigation :** Following figure 4.1 shows the various process parameters involved in the research.

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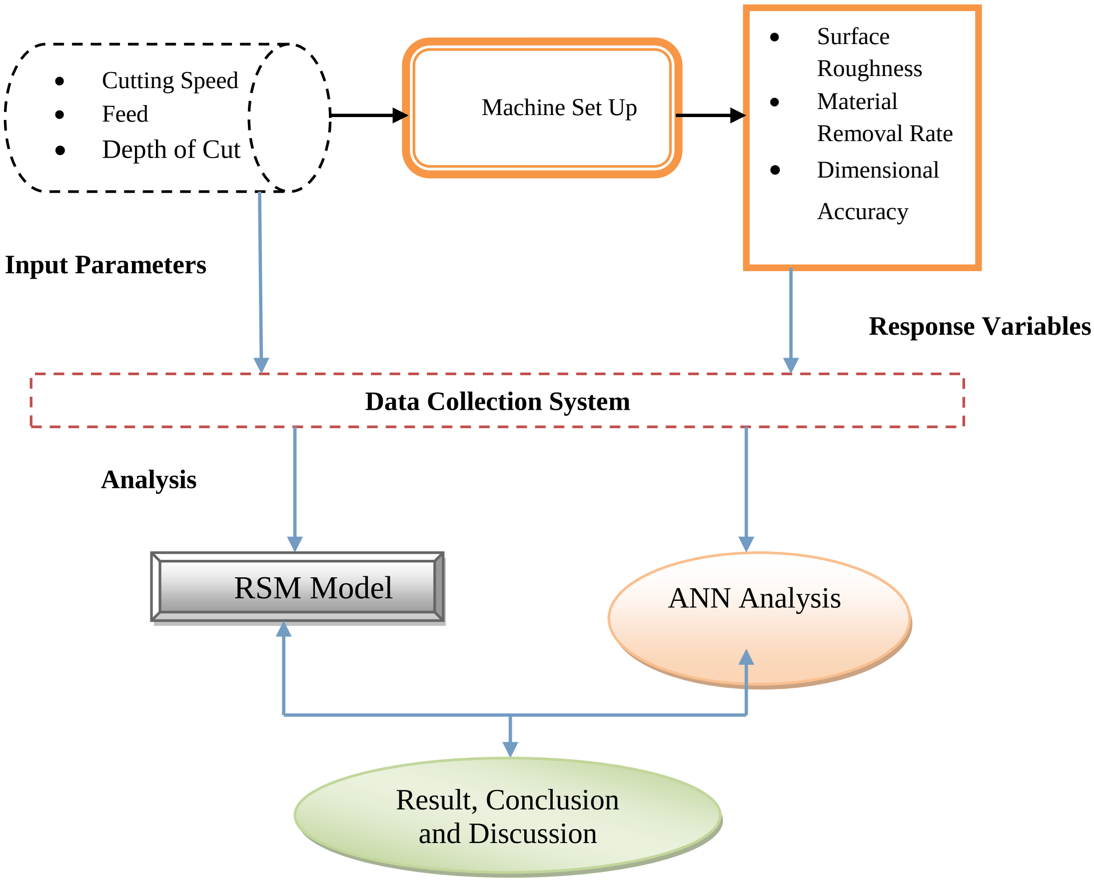

Fig 1: Proposed Research Methodology

- **Step 4: Selection of experimental plan by using DOE :** This will helps to decide the plan of experimentation.
- **Step 5 : Selection of test point , test sequence and test envelop. :** Test envelop is the span of input variables between minimum and maximum. Test sequence is the way in which the variables can change during the experimentation. Test point is the specific point at which the variable is set for the experimentation.
- **Step6 : Collection of Instrument for measuring the various variables.**
- **Step7: Data collection/ Execution of the Experiment :** In this the data is collected through the various experimentation.
- **Step 8 : Model formulation by using Response Surface method (RSM) :**

Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes. The application of RSM to design optimization is aimed at reducing the cost of expensive analysis methods and their associated numerical noise.

Originally, RSM was developed to model experimental responses (Box and Draper, 1987), and then migrated into the modelling of numerical experiments. The difference is in the type of error generated by the response. In physical experiments, inaccuracy can be due, for example, to measurement errors while, in computer experiments, numerical noise is a result of incomplete convergence of iterative processes, round-off errors or the discrete representation of continuous physical phenomena. Response surface design methodology is often used to refine models after important factors have been determined using factorial designs.

The most extensive applications of RSM are in the particular situations where several input variables potentially influence some performance measure or quality characteristic of the process. Thus performance measure or quality characteristic is called the response. The input variables are sometimes called independent variables. The field of

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response surface methodology consists of the experimental strategy for exploring the space of the process or independent variables, empirical statistical modeling to develop an appropriate approximating relationship between the yield and the process variables, and optimization methods for finding the values of the process variables that produce desirable values of the response.

In general, the relationship between the response *y* and independent variables $\xi_1, \xi_2,...,\xi_k$ is

$$y = f(k\ \xi_1,\xi_2,...,\xi_k) + \varepsilon \quad (1)$$

where the form of the true response function *f* is unknown and perhaps very complicated, and *ε* is a term that represents other sources of variability in *f.* Usually *ε* includes effects such as measurement error on the response, background noise, the effect of other variables, and so on. Usually *ε* is treated as a statistical error, often assuming it to have a normal distribution with mean zero and variance σ^2.

Then

$$E(y) = \eta = E [f (\xi_1,\xi_2,...,\xi_k)] + E (\varepsilon) = f (\xi_1,\xi_2,...,\xi_k) \quad (2)$$

The variables *k* ξ ,ξ ,...,ξ 1 2 in Equation (2) are usually called the natural variables, because they are expressed in the natural units of measurement, such as degrees Celsius, pounds per square inch, etc. In RSM work it is convenient to transform the natural variables to codedvariablesx_1, x_2 ..., x_k which are usually defined to be dimensionless with mean zero and the same standard deviation. In terms of the coded variables, the response function (2) will be written as

$$\eta = f(x_1, x_2 ..., x_k) \quad (3)$$

Because the form of the true response function *f* is unknown, we must approximate it. The successful use of RSM is critically dependent upon the experimenter's ability to develop a suitable approximation for *f.* A low-order polynomial in some relatively small region of the independent variable space is appropriate. In many cases, either a first-orderor a second order model is used. The first-order model is likely to be appropriate when the experimenter is interested in approximating the true response surface over a relatively small region of the independent variable space in a location where there is little curvature in *f.* the first-order model with interaction in terms of the coded variables is

$$\eta = \beta_0+ \beta_1x_1+ \beta_2x_2+ \beta_{12}x_1x_2 \quad (4)$$

Adding the interaction term introduces curvature into the response function. Often the curvature in the true response surface is strong enough that the first-order model is inadequate. A second-order model will likely be required in these situations. For the case of two variables, the second-order model is

$$\eta = \beta_0+ \beta_1x_1+ \beta_2x_2+\beta_{11}x_1^2+ \beta_{22}x_2^2+ \beta_{12}x_1x_2 \quad (5)$$

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

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

   RSM is a tool which is designed to develop a direct mathematical relationship relating the controllable parameters to the experimental responses. This enables to estimate and explore more simply the effect that parameters would have on responses.[12]

A. Response Surface plots

To understand how the response changes in a given direction by adjusting the design variables, Response Surface plots is very helpful. In general, the response surface can be visualized graphically.This three-dimensional graph shows the response surface from the side and it is called a response surface plot. The graph is helpful to see the shape of a response surface; hills, valleys, and ridge lines. The function *f* (*x1, x2*) can be plotted versus the levels of *x1* and *x2* as shown as fig 2.

$$y = f(x1, x2) + e$$

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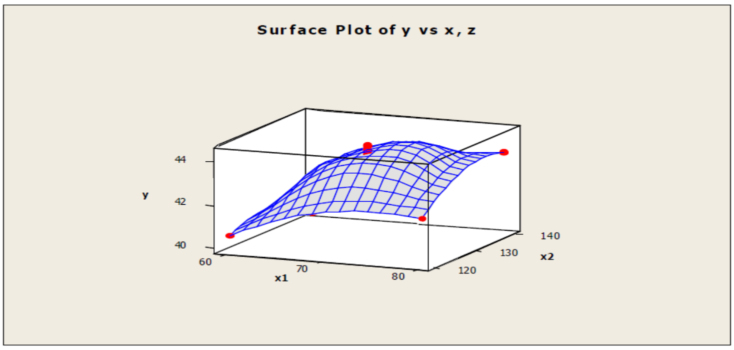

Fig 2 Response surface plot

In this graph, each value of *x1* and *x2* generates a *y*-value. This three-dimensional graph shows the response surface from the side and it is called a response surface plot. Sometimes, it is less complicated to view the response surface in two-dimensional graphs.

B. Contour Plots

Contour plots play a very important role in the study of the response surface. By generating contour plots using software for response surface analysis, the optimum is located with reasonable accuracy by characterizing the shape of the surface. The response can be represented graphically, either in the three-dimensional space or as contour plots that help visualize the shape of the response surface. . In order to understand the surface of a response, graphs are helpful tools. But, when there are more than two independent variables, graphs are difficult or almost impossible to use to illustrate the response surface, since it is beyond 3-dimension. For this reason, response surface models are essential for analyzing the unknown function *f*. If a contour patterning of circular shaped contours occurs, it tends to suggest independence of factor effects while elliptical contours as may indicate factor interactions. Contours are curves of constant response drawn in the x_1, x_2 plane keeping all other variables fixed. Each contour corresponds to a particular height of the response surface, as shown in fig 3.

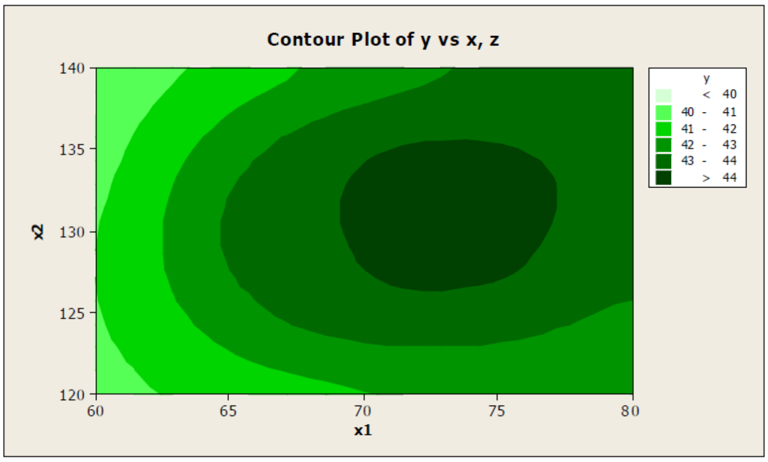

Fig 3: Contour plot

- **Step 9 : Optimization of the Model formulated . :** In this step the best set of input parameters are identified to maximize of the minimize the response variables.
- **Step10: Sensitivity analysis of the formulated model.** : it will help to find out the influence of input parameters wrt response variables.
- **Step11: Prediction of various response by using Artificial Neural network (ANN)**

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V.RESULT & DISCUSSION

The present study will help to analyze the machine process to minimize the surface roughness and maximize the material removal rate and the dimensional accuracy during the machine process to meet the objectives.

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