LITERATURE REVIEW

The significance of surface roughness of machined components and optimization of surface roughness in metal machining has been discussed in previous chapter. The outline of the thesis has also been presented. This chapter deals with a comprehensive review of research work reported in the field of machining (turning and milling). On the basis of literature review, the research gaps have been identified and the research objectives have been finalized.

2.1 Introduction

Metal machining has been an important manufacturing process for centuries. The investigation of effect of machining parameters on performance of the process began in early decades of twentieth century. The existence of an optimum cutting speed for maximizing the material removal rate in single pass turning operations was first recognized by Taylor in 1907, who established an empirical relationship between tool life and cutting speed (Eq.2.1) (Kalpakjian, 1995). This equation is still in common use today, either in its original form or as a modified version.

\[ VT^n = C \]  
(2.1)

Where, 

V= cutting speed;

T= tool life;

n = constant;

C= constant.

Researchers paid much attention to increase the productivity and decrease the unit production cost. In 1950, Gilbert employed an analytical technique to determine the
cutting speed so as to minimize the machining cost for a single pass turning operation with fixed feed rate and depth of cut (Aggarwal and Singh, 2005).

During 1950s and onwards, the tremendous demand of the high quality product shifted the research trends towards the surface quality of the machined products. Albrecht in 1956 investigated the effect of speed, feed, depth of cut and nose radius on the surface finish of a steel work-piece. Ansell and Taylor (1962) studied the effect of tool material on the surface finish of a cast-iron work-piece. Chandiramani and Cook (1964) studied the effect of varying cutting speeds on the surface finish and observed the deterioration of surface finish due to formation of built up edge (Aggarwal and Singh, 2005).

The use of computers in selection of machining parameters dates back to the early 1960’s. The surface roughness models developed by Dickinson (1968) considered the effect of feed rate and nose radius based on the motion geometry in a turning process and concluded that the effect of cutting speed to be insignificant. However, a different conclusion was presented by Shaw (1966), where that cutting speed has been considered to have a significant impact on surface roughness. The surface roughness model developed by Karmakar (1970) considered the effect of depth of cut along with feed rate and cutting speed in a turning process (Aggarwal and Singh, 2005).

Rasch and Rolstadas (1971) develop surface roughness prediction model using regression and multiple correlation analysis during turning process. Material quality, tool quality, tool nose radius, feed, speed and cutting time have been considered as cutting parameters. After 1980’s significant work have been carried out by the researcher to investigate and formulate the effect of machining parameters on the surface roughness. A number of research studies have been reported on the surface quality of the machined workpiece.
The quality of a machined workpiece is greatly influenced by various parameters including cutting conditions, tool geometry, tool material etc. Proper selection of cutting conditions for achieving a desired surface finish is not an easy task because the mechanism behind the formation of surface roughness is highly dynamic, complicated and process dependent (Benardos and Vosniakos, 2002; Zhang et al., 2006). Therefore, prediction of the surface roughness of machined parts has been an important area of research.

2.2 Review of Research Literature

With the increased usage of complex designs and severe working environments, more emphasis is being laid on achieving high surface finish products. The manufacturing industries are targeting to produce high precision products with high surface finish at low manufacturing cost so as to compete in the international market. The surface finish is one of the critical performance parameters that has an appreciable effect on several properties of machined parts such as fatigue behavior, corrosion resistance, creep life, wear, tolerance etc. (Routara et al., 2008). Thus surface finish of finished products generally plays an important role in manufacturing industries.

In manufacturing industries, the machine-tool operators make choice of machining parameters to obtain the desired value of surface finish through repetitive experimentation by trial and error that can be expensive and time consuming. Therefore, selection of an appropriate combination of machining conditions and the prediction of the surface roughness values before carrying out actual machining operation has been an important area of research.

A number of studies have been carried out to investigate the effect of tool materials, tool geometry, cutting parameters etc. on the surface roughness, through development of an empirical model for prediction of the surface roughness, using
statistical design techniques, fuzzy-set-based technique and neural network modeling etc. The research reported on the topic has also been reviewed by several authors. A brief discussion in this regard has been presented in this section.

Benardos and Vosniakos (2003) reported a review on prediction of surface roughness in machining. The authors classified published works into four major categories, (i) approaches based on machining theory to develop analytical models and/or computer algorithms to represent the machined surface (ii) approaches that examine the effects of various factors through the conduct of experiments and the analysis of the results (iii) approaches based on used designed experiments (DOE) and (iv) artificial intelligence (AI) techniques. A comparison of these two techniques (DOE and AI) reveals that the AI models take into consideration the particularities of the equipment used and the real machining phenomena, the information that is stored in the experimental data used to develop the models. On the other hand, the theoretical approach is based on conventions and idealizations, which are responsible for errors and limitations. Other advantages of the AI technique are that the models reported seem to be the most realistic and accurate, they probably exhibit the highest level of integration with computers and that this technique can be used in conjunction with other more conventional techniques.

Aggarwal and Singh (2005) discussed about the techniques (traditional and modern) used for optimization of machining parameters in turning. The geometric programming, geometric plus linear programming, goal programming, sequential unconstrained minimization technique, dynamic programming etc have been considered as traditional optimization techniques, whilst fuzzy logic, scatter search technique, genetic algorithm, Taguchi technique and response surface methodology have been considered as modern optimization techniques. The review of literature
reveals that design of experiment-based approaches have been successfully employed in industrial applications for optimal settings of process variables.

Chandrasekaran et al. (2010) presented a review on the application of soft computing techniques (fuzzy logic, NN, GA, SA, ACO, and PSO) in prediction and optimization of machining conditions for machining performance (surface finish, dimensional accuracy, tool life, tool wear, cutting force and process optimization) for various machining conditions in turning, milling, drilling, and grinding operations. The authors used both the MLP and RBF neural networks. The later are known for their ability to train the neural network much faster as compare to MLP but require more training data and provide slightly inferior accuracy. The Fuzzy sets and combination of Fuzzy sets and neural networks have been used for predicting the surface roughness in turning, milling, and grinding. The Fuzzy set based methods are especially advantageous when the expert knowledge is available.

Al-zubaidi et al. (2011) presented a review on application of ANN in milling process for prediction of surface roughness, cutting force, tool life and tool wear. The authors summarized the review as (i) Significant application of back propagation algorithm based neural networks for prediction of response (ii) the prediction accuracy observed using ANN models appears to be more than that obtained using traditional statistical approaches. (iii) more attention paid to the studies on surface roughness prediction as compared to those on cutting forces and tool wear, due to the important role played by surface integrity of the machine parts.

Yusup et al. (2012) presented a comprehensive review of research on optimization of machining parameters during traditional and modern machining using evolutionary techniques during 2007-2011. The authors considered five techniques, namely genetic algorithm (GA), simulated annealing (SA), particle swarm optimization
(PSO), ant colony optimization (ACO) and artificial bee colony (ABC) algorithm and made a comparative study for optimization of machining parameters. The GA has been found to be widely used for optimization of machining parameters followed by PSO, SA, ABC and ACO. The application of ABC algorithm mostly focuses on optimization of process parameters of modern machining such as WEDM, ECM, ECDM, USM, grinding multi-pass milling. The ACO has not much been explored in the subject area for the duration of review. The GA and the PSO have mostly been used for optimization of multipass turning operation. The SA technique has been widely used for the optimization of machining parameters for AWJ and end milling process. The ACO technique has been employed mostly for the optimization of machining parameters during end milling, turning and multipass turning.

The review of research presented above by various authors indicate that metal machining has been an interesting topic to researches and useful to industries. A exhaustive review of research on the effect of machining parameters on surface roughness in metal machining has been presented in following sub-sub-sections. The review has been classified into two major categories. These are (i) according to machining process i.e. turning and milling (ii) according to work piece materials (ferrous and non ferrous) (iii) according to analysis methodologies. The analysis methodologies are classified into three subcategories (a) approaches based on design of experiments (experimental investigation, factorial design, Taguchi method, response surface methodology etc.) (b) approaches based on soft computing techniques (fuzzy logic, neural network, genetic algorithm, simulated annealing, particle swarm optimization etc.), and (c) approaches based on hybrid techniques. The presentation of literature review has been depicted in Figure 2.1.
2.2.1 Turning

Turning is the primary machining process, employed in most of the production industry to bring the workpiece into the required symmetrical shape and size with desired surface finish. The machine operators make use machining guidelines and their own experience for making a choice of machining parameters, in order to achieve the best possible surface finish. Due to inadequate knowledge of the complexity and factors affecting the surface finish, an improper decision may cause poor surface finish and high rejection, leading to high production costs. Proper selection of cutting tools and
process parameters for achieving a high surface finish in the turning operation is a critical task (Davim et al., 2007).

Many studies have been carried out to investigate and formulate the effect of cutting conditions for the optimization of surface roughness in turning using different techniques. A review of research in the relevant area is presented in this section.

2.2.1.1 Ferrous metals and alloys

The ferrous metals are most commonly used in manufacturing plants such as automotive, machine tools industries to produce mechanical components, where the surface finish is significantly important. In recent years, many studies have been reported on the surface finishing in the machining of ferrous metals. A brief review of research in the relevant area is given below:

a) Turning of ferrous metals - Application of design of experiments

The design of experiments is widely employed to build empirical models based on experimental data. The researcher’s intuition plays a great role in this approach but a high understanding of the phenomenon is also necessary for the experiment to yield a meaningful result. The experimental approach is mainly adopted in cases where there can be no analytical formulation of the cause and effect relationships between various factors and response variables (Benardos and Vosniakos, 2003). Several studies have been carried out to formulate the empirical relationship between cutting conditions and surface roughness using design of experiments. A brief review of research in the relevant area is given below.

Choudhury and Baradie (1997) investigated the effects of the main cutting parameters such as cutting speed, feed, and depth of cut, on surface roughness in turning EN 24T steel with uncoated carbide inserts. The first order and second order prediction models were developed in terms of cutting parameters. The first order
prediction model is based on 12 experimental data sets (2-level full factorial design with four center points) while second order prediction model makes use of 24 experimental data sets (8 factorial points, 4 center points and 12 star points). The response surface methodology has been used to analyze the effect of cutting parameters on surface roughness. On the basis of statistical analysis the second-order model has been found to be adequate as compared to first order model. Also, the feed has been found to be the most significant cutting parameter for surface roughness.

Nian et al. (1999) studied the influence of cutting parameters on multiple performance characteristics (tool life, cutting force and surface finish) in turning of S45C steel bars using tungsten carbide tool. The cutting speed, feed and depth of cut were considered as independent cutting parameters. The L₉ orthogonal array based Taguchi method was employed to optimize the cutting parameters for multiple performance characteristics. It has been found that the Taguchi method provides a simple, systematic and efficient methodology for the optimal selection of the cutting parameters. In addition to this, feed has been found most significant parameter that’s affect the surface roughness.

Abouelatta et al. (2001) developed correlation between surface roughness and cutting tool vibration in turning free cutting steel with cemented carbide cutting tool. A 2-level full factorial design was used to develop surface roughness prediction model in terms of rotational cutting speed, feed rate, depth of cut, tool nose radius, tool overhang, approach angle, work piece length, work piece diameter and machine tool vibration. The prediction model involving both the cutting parameters and the tool vibrations have been found more accurate as compared to those involving the cutting parameters only.

Davim, (2001) studied the effect of cutting speed, feed and depth of cut on surface roughness parameters namely, average surface roughness and maximum peak to
valley height of surface roughness during turning of free machining steel. The L_{27} orthogonal array based design matrix was used for execution of turning experiments using cemented carbide tool. A correlation has also been established between turning parameters and surface roughness parameters using regression analysis. The ANOVA has also been employed to identify the most significant parameter. The cutting speed has been found to be the most significant parameter followed by the feed, whereas depth of cut has no significant effect on the surface roughness.

Ghani et al. (2002) experimentally investigated the effect of speed, feed and depth of cut on tool life, surface finish and vibration during turning of nodular cast iron (3.27 % C, 2.03 % Si, 0.68 % Mn, 0.05 % S, 0.02 % P and remaining as Fe) using ceramic tool. Total nine experiments were conducted to explore the variation in surface finish of the workpiece due to increased tool wear. Also, the effect of vibration on the flank wear in the direction of main cutting force and radial cutting force has been investigated. The tool life of the alumina ceramic inserts has been found unsatisfactory. On the other hand, variation in surface finish with the progress of the flank wear under all cutting conditions has been found almost constant.

Noordin et al. (2003) studied the performance of a multilayer tungsten carbide tool during turning of AISI 1045 steel (0.45% C, 0.72 % Mn, 0.20 % Si, 0.015 % P, 0.018 % S, 0.10 % Cu, 0.09 % Ni, 0.07 % Cr and remaining as Fe). The effect of cutting speed, feed and the side cutting edge angle on surface roughness and cutting force (tangential component) were investigated. The cutting experiments were performed according to face centered, central composite design (CCD) at constant depth of cut under dry cutting condition. The feed has been found the most significant factor influencing the surface roughness and the tangential force. Additionally, the cutting
speed has also been found to provide a secondary contribution to the tangential component of cutting force.

Ozel et al. (2003) experimentally investigated the effect of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and resultant of three components of cutting forces (tangential, radial and feed force). The turning experiments were conducted on AISI H13 steel according to two level full factorial design using cubic boron nitrite inserts. Statistical analysis of variance (ANOVA) was performed to identify statistically significant trends in the measured surface roughness and cutting force data. The first order effects of workpiece hardness, cutting edge geometry, feed rate and cutting speed on surface roughness have been found statistically significant. The interaction term of the edge geometry and the workpiece hardness, the edge geometry and the feed rate, and the cutting speed and feed rate have also been found significant for surface roughness. On the other hand, the effect of cutting-edge geometry, workpiece hardness and cutting speed on cutting force components have been found to be significant.

Sahin and Motorcu (2004) investigated the effect of cutting parameters (cutting speed, feed rate and depth of cut) on surface roughness in turning of mild steel (0.418 % C, 0.176 % Si, 0.141% Ni, 0.242 % Cu, 0.487 % Mn, 0.188% Cr, 0.0224 % P, 0.0176 % Co and remaining as Fe). Total 18 sets of turning experiments were carried out using TiN- coated carbide tool. The response surface methodology has been used to develop the first order and the second order surface roughness prediction models in terms of cutting parameters. The analysis of models suggests the feed rate has the highest effect on the surface roughness. The surface roughness seems to increase with increase in the feed rate but decreases with increase in the cutting speed and the depth of cut.
Singh and Rao (2005) studied the effect of cutting conditions on surface roughness in hard turning of the bearing steel (AISI 52100) with mixed ceramic inserts of aluminium oxide and titanium carbonitride. Based on the 3-level full factorial design, total 81 turning experiments were carried out. The surface roughness prediction model was developed in terms of cutting conditions (cutting speed, feed rate, effective rake angle and tool nose radius) using RSM. The feed has been found to be the dominant factor affecting the surface roughness followed by the nose radius, cutting speed and effective rake angle. In addition to this, the effect of interaction terms of the nose radius and the effective rake angle, and feed and nose radius, on surface roughness have also been found significant. Also, the surface roughness tends to increase with increase in feed and effective rake angle while it tends to decrease with increase in the cutting speed and nose radius.

Aslan et al. (2006) obtained optimal cutting parameters (cutting speed, feed rate and depth of cut) for minimum surface roughness and flank wear in turning of hardened AISI 4140 steel (0.4 % C, 0.9% Mn, 1.0 % Cr, 0.2% Mo and remaining as Fe) with Al2O3 + TiCN mixed ceramic tool using L27 orthogonal array based Taguchi technique. The ANOVA has also been employed to estimate percentage contribution of each cutting parameter on surface roughness and on flank wear. In addition to this, the relationship between the cutting parameters and the responses (surface roughness and flank wear) have been developed using multiple linear regression. The results indicate the cutting speed to be the only statistically significant factor that influences the tool wear (with a 30% contribution). Only two interactions, cutting speed-feed rate (with a 28 % contribution) and feed rate-axial depth of cut (with a 23 % contribution) have been found to be significant to influence the surface roughness. The optimum set of
machining conditions for minimum surface roughness has been obtained at highest level of cutting speed, mid level of feed and lowest level of depth of cut.

Nalbant et al. (2006) used $L_9$ orthogonal array based Taguchi methodology to obtain the optimal cutting parameters for minimum surface roughness while turning of AISI 1030 steel (0.276 % C, 0.110% Si, 0.610% Mn, 0.040% P, 0.050% S and remaining as Fe) using TiN coated tools. The insert radius, feed rate, and depth of cut were considered as cutting parameters. The ANOVA analysis has also been employed to estimate the percentage contribution of significant cutting parameters on surface roughness. The insert radius (with a 48.54% contribution) and feed rate (with a 46.95 % contribution) have been found the main parameters to influence the surface roughness. The minimum surface roughness has been obtained at lowest level of feed, highest level of nose radius and lowest level of depth of cut.

Aslantas and Ucun (2008) examined the machinability of austempered ductile iron (ADI). To emphasized the role of austempering process, ductile iron (3.68 %C, 1.97 % Si, 0.35% Mn, 0.06 % P, 0.034 % S, 0.001% Mg, 0.017 % Cr, 0.051% Ni, 0.001% Mo, 1.3% Cu, 0.0025 % Al, 0.006 % Co, 0.0031% Sn and remaining as Fe) specimens were first austenitized in salt bath at 900°C for 120 minutes (ADI) followed by quenching in salt bath at 250°C (ADI-250) and 375°C (ADI-375) for 120 minutes. Then turning experiments were carried out on ADI, ADI-250 and ADI-375 at various cutting speeds, a constant depth of cut and constant feed rate using ceramics and cermet tool inserts. The performance of both ceramic and cermet tools have been evaluated on the basis of workpiece surface roughness and flank wear. The results reveal that ceramic cutting tools are not suitable for machining the ADI material at low cutting speeds with respect to surface roughness. In addition, in case of ceramics tool, the cutting forces have found to be unaffected by variations in austempering temperature at
low cutting speed, while in case of cermet cutting tools, the cutting forces appear to get affected by variation in the austempering temperature. For surface roughness, both the tools appear to be suitable for machining of the ADI material at higher cutting speeds.

Bhattacharya et al. (2008) evaluated the contribution of cutting parameters on surface roughness indicators and power consumption in turning of AISI 1045 steel (0.5% C, 0.15% Si, 0.6% Mn, 0.05% S, 0.04% P and remaining as Fe) with coated carbide tool (SNMG 120408). The cutting speed, feed rate and depth of cut were considered as cutting parameters while the average surface roughness ($R_a$), root-mean-square roughness ($R_q$), and maximum peak-to-valley roughness ($R_t$ or $R_{max}$) were considered as surface roughness indicators. The $L_{16}$ orthogonal array based Taguchi design and analysis of variance (ANOVA) have been employed to evaluate the contribution of cutting parameters on surface roughness indicators and power consumption. The cutting speed appears to be the most significant parameter for the surface roughness indicators ($R_a$, $R_q$ and $R_t$) with a contribution of 83%. The contribution of feed rate has been observed to be 6.9% and 11.4% for roughness parameter $R_a$ and $R_q$, respectively. The depth of cut was found to be a significant factor for $R_t$ with a contribution of 11.3%. The cutting speed has also been observed to be the most significant factor to reduce the power consumption with a contribution is 77.4%, followed by the depth of cut (13.2%). The feed rate has no significant effect on the power consumption.

Galanis and Manolakos (2010) studied the effect of cutting speed, feed rate and depth of cut on surface roughness in turning of AISI 316L stainless steel femoral heads using TiN–Al2O3–TiC-coated carbide cutting tool. The 3-level full factorial design coupled with RSM has been used to investigate the effect of cutting parameter on surface roughness. The second order surface roughness prediction model was developed
in terms of cutting parameters. The depth of cut has been found as a main influencing factor affecting the surface roughness. The surface roughness is found to increase with increase in depth of cut and feed rate, but it decreases with increase in the cutting speed.

Bouchelaghem et al. (2010) investigated the wear behavior of CBN tool during hard turning of AISI D3 (2 % C, 0.29 % Mn, 0.31% Si, 0.011% P, 0.009 % S, 1.14 % Cr, 0.259 % Ni and remaining as Fe). In addition, the effect of cutting parameters (feed, speed, depth of cut and nose radius) and tool wear on surface roughness, cutting forces and rise in temperature has also been investigated using 2-level full factorial design with RSM. It has been concluded that wear phenomenon in CBN inserts takes place due to abrasion process. The cutting force has been found to increase with the increase of depth of cut, while the surface roughness increase with increase in feed rate and decreases with the increase in of cutting speed.

Neseli et al. (2010) investigated the influence of tool geometry (nose radius, approach angle and rake angle) on the surface finish in turning of AISI 1040 steel with Al2O3/TiC tool. The turning experiments were planned according to 3-level full factorial design. The surface roughness prediction model was developed in terms of tool geometry using regression analysis. The effect of tool geometry on surface roughness has been investigated using ANOVA and RSM. The result shows that the tool nose radius has dominating effect on the surface roughness followed by approach angle and rake angle. In addition to this, a good agreement between the predicted and measured surface roughness has been observed.

Kiyak et al. (2010) experimentally investigated the effect of machining conditions (workpiece diameter, depth of cut and tool overhang) on surface quality and tool wear in turning of AISI 1050 steel. Total 28 sets of turning experiments (3-level of workpiece diameter, 2-level of depth of cut and 4 level of tool overhang) have been
conducted. The results reveal that the surface roughness increases with increase in depth of cut and tool overhang. Also, increase in the tool overhang causes the decrease in tool wear.

Sahoo and Sahoo (2011) investigated the effect of cutting parameters (speed, feed and depth of cut) on surface roughness in turning of D2 steel (1.55 %C, 11.8 % Cr, 0.4 % Si, 0.4 % Mn, 0.7 % Mo, 0.5 % V, 0.6 % W, 0.03 % S, 0.03 % P and remaining as Fe) using TiN coated carbide insert. The surface roughness prediction model has been developed using regression analysis. The L_{27} orthogonal array based Taguchi parameter design and response surface methodology have been used to investigate the effect of cutting parameters. The result reveals the feed to be the most significant parameter followed by the depth of cut. The effect of cutting speed has been found insignificant. The optimum parametric combination for minimum surface roughness is found to be the highest level of cutting speed, lowest level of feed and highest level of depth of cut.

b) Turning of ferrous metals - applications of soft computing techniques

Soft computing is a computational approach which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision. The soft computing techniques have received a lot of attention due to their potential to deal with highly nonlinear, multidimensional, and ill-behaved complex engineering problems. A brief review of research in the relevant area is given below.

Lee et al. (2000) described the use of polynomial networks to construct the machining database in turning of S45C steel using tungsten carbide tool. The experiments were planned according to 3-level full factorial design. The complicated relationships between the cutting parameters (cutting speed, feed rate, and depth of cut) and cutting performance (tool life, surface roughness, and cutting force) were
established through polynomial network. Experimental results reveal that the machining database has a high accuracy in prediction of cutting performance in turning operations.

Chien and Chou (2001) conducted turning experiments on 304 stainless steel with carbide insert. In order to develop a predictive model based on artificial neural network theory, total 96 turning experiments were conducted. Out of the experimental data sets, 56 were used for training the network and remaining data sets were used to validate the network. The cutting force and tool life models have been developed in terms of cutting speed, feed and depth of cut. Further, the genetic algorithm and the ANN were incorporated to obtain the optimum cutting conditions for the maximum metal removal rate under the constraints of the expected surface roughness and expected surface roughness associated with the tool life. The error between the experimental and predicted values for surface roughness, cutting force and tool life have been found to be 4.4 %, 5.3% and 4.2 % respectively.

Kohli and Dixit (2003) conducted turning experiments on mild steel (about 0.35 % C) using high speed steel (HSS) and carbide tools. The surface roughness prediction model was developed using neural-network-based methodology. Total 59 turning experiments were carried out considering the cutting speed, feed and depth of cut as process parameters. Out of the experimental data sets, 19 data sets have been used to train the network, 11 data sets for testing purpose and remaining 29 data sets for validation of the developed network. The network model has been trained using the back-propagation algorithm. The learning rate, the number of neurons in the hidden layer, the error goal, as well as the training and the testing dataset size, have been found automatically in an adaptive manner. The proposed methodology has been found to be quite effective for fewer training and testing data sets. In most of the cases, the
experimental value has been found to be close to the predicted value of surface roughness.

Pal and Chakraborty (2005) conducted a set of 27 turning experiments on mild steel using high speed steel tool. The speed, feed and depth of cut have been selected as input process parameters. The values of cutting force and surface roughness obtained during turning has been used to develop back propagation neural network model for the prediction of surface roughness and cutting forces. Out of total 27 experimental data sets, 20 data sets have been selected for training the network and remaining seven have been used for testing the network. The optimum network architecture has been selected on the basis of mean square error and the convergence rate. The performance of the trained neural network has been tested with experimental data. The experimental values and predicted values of surface roughness and that of the cutting forces have been found to be in good agreement.

Abburi and Dixit (2006) developed a knowledge-based system based on neural networks and fuzzy set theory for prediction of surface roughness in turning. The knowledge acquired from the shop floor has been used to train the neural network. The number of data sets has been obtained from the trained network. Further, these data sets have been fed to a fuzzy-set-based rule generation module. A large number of IF–THEN rules have been generated. The performance of the developed knowledge-based system has been evaluated with the experimental data of dry and wet turning of mild steel (about 35 % carbon) with HSS and carbide tools. The cutting speed, feed, depth of cut, acceleration of radial vibration of tool holder, use of cutting fluid, length and diameter of the workpiece have been considered as input parameters and the surface roughness as the output parameter. The result indicates that the length and diameter of the workpiece have insignificant effect on surface roughness while cutting speed, feed,
depth of cut, acceleration of radial vibration of tool holder and use of cutting fluid have
significant effect on surface roughness.

Manna and Salodkar (2007) described a procedure to obtain the machining
conditions for turning operation considering minimization of unit cost of production as
an objective function. The optimality conditions for single point cutting operations have
been determined using dynamic programming. The machining cost has been obtained
considering actual machining time, tool reuse time, set-up time, tool life, and tool
changing time. The mathematical models have also been developed considering the
Krononberg’s data used for standard turning operation. The authors also used L_{27}
orthogonal array based Taguchi method to obtain optimal machining parameters so as
to achieve better surface finish and to identify the most effective parameter that’s affect
the cost of production during turning of E0300 alloy steel. The models so developed
can help directly in estimation of minimum unit cost of production under various
machining conditions during turning. Also, cutting speed has been found most
significant parameter on the surface roughness height, as compared to the depth of cut
and feed rate.

Davim et al. (2007) investigated the effect of machining parameters on surface
roughness during turning of free machining steel using cemented carbide tools. The
feed rate, depth of cut and cutting speed have been considered as the independent
machining parameters. The experiments were conducted as per L_{27} orthogonal array.
The experimental data has been used for the development of surface roughness
prediction model using artificial neural network (ANN). The ANN model has been
trained using error back-propagation training algorithm (EBPTA). In addition to this,
3D surface plots were generated to study the interaction effects of cutting conditions on
surface roughness parameters. The analysis reveals that cutting speed and feed rate have
significant effect in reducing the surface roughness, while the depth of cut has the least effect.

Nalbant et al. (2007) experimentally investigated the effect of uncoated, PVD and CVD coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning of AISI 1030 Steel (0.365 % C, 0.799 % Mn, 0.247 % Si, 0.0166 % P, 0.0422 % S and remaining as Fe). A total of 60 sets of experiments have been conducted according to full factorial design. The surface roughness prediction models for different inserts have been developed in terms of feed rate, cutting speed, insert radius and depth of cut using artificial neural networks (ANN). The Back-propagation scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) algorithms with the logistic sigmoid transfer function have been used to train and test the ANN. The experimental values and ANN predictions have been compared with statistical error analyzing methods. The SCG model with nine neurons in the hidden layer produced absolute fraction variance (R²) values about 0.99985 for the training data set and 0.99983 for the test data set. Also, mean error percentage (MEP) for training and testing data sets has been found to be 1.13458 and 1.88698 respectively.

Horng and Chiang (2007) obtained optimal machining conditions to minimize multiple performance characteristics (flank wear and surface roughness) in turning of the Hadfield steel (1.204 % C, 0.70 % Si, 12.217 % Mn, 0.036 % P, 0.007 % S, 2.836 % Cr, 0.024 % Ni and remaining as Fe) using Al2O3/TiC mixed ceramic tool. The cutting speed, feed rate, depth of cut and nose radius have been considered as the independent machining parameters. The experiments were carried out according to L₉ orthogonal array based Taguchi methodology. For the optimization of machining process an integrated approach based on grey relation analysis and fuzzy algorithm has been used. The combination of minimum flank wear and surface roughness have been
obtained at low level of cutting speed, low level of feed, low level of nose radius and highest level of depth of cut.

Raj and Namboothiri (2009) investigated the effect of tool geometry (nose radius) and cutting parameters (feed, speed, and depth of cut) on surface roughness in dry turning of SS 420 steel (0.15% C, 12.0–14.0% Cr, max 1.0% Si, max 0.04% P, max 1.0% Mn, max 0.03% S, and the remaining as Fe). The experiments were carried out according to $L_{27}$ orthogonal array based Taguchi methodology. The RSM has been used to develop empirical surface roughness prediction model. The empirical model and the improved genetic algorithm (IGA) have together been used to obtain optimum cutting parameters for minimum surface roughness. The result reveals that the minimum surface roughness occurs at the combination of low value of feed, mid-value of cutting speed, low value of depth of cut and high value of nose radius. Further study reveals the proposed IGA approach to perform better as compared to conventional genetic algorithm (CGA) in terms of simplified concept, easy implementation and greater effectiveness.

Caydas and Ekici (2010) predicted surface roughness values of AISI 304 austenitic stainless steel (0.0452 % C, 1.78 % Mn, 0.32 % Si, 0.019 % S, 0.0397 % P, 18.35 % Cr, 8.9 % Ni, 0.456 % Mo, 0.0312 % Nb, 0.768 % Cu, 0.0001 % Ti, 0.06 % V and remaining as Fe) in CNC turning operation. The turning experiments were carried out according to 3 level full factorial designs. The surface roughness prediction models were developed in terms of cutting speed, feed and depth of cut using artificial neural network and three different types of support vector machines (SVMs) such as least square SVM (LS-SVM), Spider SVM and SVM-KM. The cutting speed, feed rate and depth of cut have been considered as input parameters. The prediction ability of all three SVMs have been found better as compared to ANN.
c) Turning of ferrous metals - applications of hybrid techniques

The hybrid techniques are the combination of design of experiments and soft computing techniques. The hybrid have been employed this technique to investigate the effect of cutting parameters on surface roughness and obtain optimal combination of cutting parameters for minimum surface roughness in turning of ferrous materials. A brief review of the research in the relevant area is given below.

Suresh et al. (2002) studied the effect of cutting parameters (cutting speed, feed, depth of cut and nose radius) on surface roughness during turning of mild steel. A set of 81 turning experiments based on 3 level full factorial design were carried out using TiN-coated tungsten carbide cutting tool. First order and second order surface roughness prediction models, in terms of cutting parameters have been developed using the experimental data sets. An attempt has also been made to optimize the second order surface roughness prediction model using genetic algorithms (GA). The optimization by GA has been observed to yield the minimum and maximum values of surface roughness and their respective optimal machining conditions with high accuracy.

Al-Ahmari (2007) developed empirical models for prediction of tool life, surface roughness and cutting force during turning of austenitic AISI 302 steel using carbide inserts. A set of 28 turning experiments were carried out with cutting speed, feed rate, depth of cut and tool nose radius as independent parameters. The multiple linear regression analysis (RA), response surface methodology (RSM) and computational neural networks (CNN) were employed to develop the models. The computational neural network model appears to be better than those obtained using the multiple linear regression analysis and the response surface methodology on the basis of percentage relative error. Also, it has been found that the RSM models are better than RA models for predicting tool life and cutting force models.
Sharma et al. (2008) investigated the effect of machining parameters on surface finish, cutting forces, passive force and feed force in turning of adamite steel ((1.85% C, 0.65% Si, 0.75% Mn, 0.048% P, 0.035% S, 1.60% Cr, 1.2% Ni, 0.3% Mo and remaining as Fe) with indexable coated carbide insert (CCMT090304). The feed, cutting speed, depth of cut and approach angle have been considered as machining parameters. A total of 51 turning experiments were conducted to develop prediction models using regression analysis and artificial neural network (ANN). In addition to this, a comparison between the experimental values and those ANN model based predicted values has been made on the basis of percentage error. The cutting force appears to be increasing with increase in approaching angle, feed and depth of cut where as it shows a decreasing trend with cutting speed. Also, the surface roughness has been found to increase with increase in feed but indicate a negative trend with approaching angle, cutting speed and depth of cut. The prediction ability of ANN model has been observed at 76.4% accuracy.

Chavoshi and Tajdariln (2009) studied the effect of workpiece hardness and spindle speed on surface roughness in hard turning of AISI 4140 steel. Total 18 sets of turning experiments (5 level of hardness and three level of spindle speed) have been carried out using CBN cutting tool. Surface roughness prediction models have been developed using artificial neural network (ANN) and regression analysis. Finally, a reverse ANN model is constructed to estimate the hardness and spindle speed from surface roughness values. It has been observed that the surface roughness prediction ability of ANN model is much higher than regression model. Also, the hardness of workpiece has been found most significant factor affecting the surface roughness. The surface roughness increases with increase in hardness. The effect of spindle speed on surface roughness has been found only partially significant.
2.2.1.2 Non-ferrous metals and alloys

The non ferrous metals are commonly used in automotive and several other aerospace industries due to some advantages such as high resistance, light weight, good transmission, heat treatable, high tensile strength, high heat and corrosion resistance. In recent years, due to the importance of non ferrous metals in manufacturing industries, a number of studies have been carried out to investigate the effect tool geometry, cutting parameters etc. on surface roughness of machined components. A brief review of the research in the relevant area is presented in this section.

a) Turning non ferrous metals - applications of design of experiments

In the recent past, many studies have been reported on the investigation of the effect of cutting parameters on surface roughness and the development of surface roughness prediction model in turning of non ferrous metals using design of experiments. A brief review of the research in the relevant area is given below.

Kirby et al. (2005) employed L$_9$ orthogonal array based Taguchi parameter design to make optimal selection of machining parameters for minimum surface roughness during turning of aluminum workpieces. The spindle speed, feed rate, depth of cut and tool nose radius were considered as control parameters. Varying room temperature and more than one insert of the same specification have been treated as noise factors. The confirmation runs have been conducted to verify the results. The minimum surface roughness has been achieved at the combination of highest level of spindle speed, lowest level of feed, lowest level of depth of cut and highest level of nose radius.

Hascalik and Caydas (2007) investigated the effect of cutting conditions on surface roughness and tool life in turning of Ti-6Al-4V alloy (89.464 % Ti, 6.08 % Al, 4.02 % V, 0.22 % Fe, 0.18 % O, 0.02 % C, 0.01 % N and 0.0053% H) using
tungsten carbide (CNMG 120408-883) insert. An attempt has been made to obtain optimal combination of cutting parameters (feed rate, depth of cut and cutting speed) for achieving the minimum surface roughness and maximum tool life using $L_9$ orthogonal array based Taguchi methodology. The feed rate has been found to be the most significant cutting parameter affecting the surface roughness while the cutting speed to be the most significant factor affecting the tool life. The minimum surface roughness has been obtained at highest level of cutting speed, lowest level of feed and depth of cut. The maximum tool life has been obtained at highest level of depth of cut, lowest level of cutting speed and feed.

Gaitonde et al. (2007) utilized multi response optimization method based on Taguchi technique with the utility concept, for simultaneous minimization of surface roughness and specific cutting force in turning of brass using K10 carbide tool. The minimum quantity of lubricant (MQL), cutting speed and feed rate have been considered as process parameters. The turning experiments have been planed according to $L_9$ orthogonal array based design. The analysis of means (ANOM) and analysis of variance (ANOVA) on multi-response signal-to-noise (S/N) ratio have been employed for obtaining the optimal parameter levels and identifying the level of importance of the process parameters. The result indicates that the surface roughness and the specific cutting force get simultaneously minimized at highest level of MQL, mid level of cutting speed and at the lowest level of feed rate. Also, the feed rate appears to be the most dominant parameter affecting the surface roughness followed by minimum quantity of lubricant and cutting speed.

Bhushan et al. (2010) experimentally investigated the influence of cutting parameters on surface roughness of workpiece and wear rate of tool. The cutting speed, depth of cut and feed rate have been considered as cutting parameters. A total of 64
turning experiments were conducted on two different materials, the 7075 Al alloy and the 10 wt.% SiC particulate metal-matrix composite using both the tungsten carbide and the polycrystalline diamond (PCD) inserts. It has been observed that the surface roughness on the turned Al alloy is less as compared to the turned Al alloy composite, machined under the same machining conditions with both the inserts. Also, wear of the tungsten carbide and the PCD inserts has been found less for Al alloy as compared to that for Al alloy composite.

Chen et al. (2010) analyzed the effect of cutting conditions on tool vibrations and surface roughness in precision turning of A6061-T6 material (0.40 to 0.8 % Si, 0.7 % Fe max, 0.15 to 0.40 % Cu, 0.15 % Mn max, 0.8 to 1.2 % Mg, 0.04 to 0.35 % Cr, 0.25 % Zn max, 0.15 % Ti max and remaining as Al) using diamond cutting tool. The spindle speed, feed rate, depth of cut and status of lubrication were considered as cutting conditions. The empirical models for tool vibrations (longitudinal and transverse) and surface roughness have been developed using a D-optimal design based on the response surface methodology. The results reveal that the spindle speed and the feed rate have the greatest influence on the longitudinal vibration amplitude while the feed rate and the cutting depth have been found most significant parameters affecting the transverse vibration amplitude. In addition to this, the minimum surface roughness has been obtained at high spindle speed, low feed rate and low depth of cut with lubrication.

b) Turning of non ferrous metals - applications of soft computing techniques

The study of the effect of cutting parameters on surface roughness and optimal selection of cutting parameters for minimum surface roughness in turning of non ferrous materials using soft computing techniques is an emerging area. A brief discussion on the work reported in relevant area is given below.
Ezugwu et al. (2005) studied the effect of cutting conditions on several response parameters in turning of nickel-based, Inconel 718, alloy (0.08 % C, 0.35 % Si, 0.35 % Mn, 0.15 % S, 18.6 % Cr, 17.8 % Fe, 3.1 % Mo, 5.0 % Nb and Ta, 0.9 % Ti, 0.5 % Al, 0.3 % Cu and remaining as Ni) with PVD-coated carbide insert. The speed, feed rate, depth of cut, cutting time and coolant pressure have been considered as cutting conditions while tangential force, axial force, spindle motor power consumption, machined surface roughness, average flank wear, maximum flank wear, and nose wear have been considered as response parameters. The artificial neural network (ANN) model has been developed using 102 experimental data sets for the prediction of output parameters. For the minimum value of response parameters, the optimum cutting speed has been found in the range 25-35 m/min while the optimum feed rate, corresponding to the minimum surface roughness and nose wear has been observed within 0.27 and 0.28 mm/rev. Also, a good agreement between the experimental values and the predicted values has been observed.

Zhong (2006) investigated the effect of machining conditions on arithmetic average surface roughness ($R_a$) and the maximum peak to valley height ($R_t$) in turning of aluminum and copper workpieces. The tool insert grade, workpiece material, tool nose radius, rake angle, depth of cut, spindle rate, and feed rate have been considered as independent parameters. A total of 304 turning experiments were conducted using coated carbide, polycrystalline and single crystal diamond inserts. A systematic approach has been followed to obtain an optimal neural network. The reliability of the optimal neural network has further been tested by prediction of the roughness of parts turned on another lathe. The results prove the good surface roughness heights prediction capability of the network.
c) Turning of non ferrous metals - applications of hybrid techniques

The research investigation on the effect of cutting parameters on surface roughness and optimization of cutting parameters for minimum surface roughness in turning of nonferrous materials using hybrid techniques is an emerging area. Very few studies have been reported in this area.

Tsourveloudis (2010) developed relationship between surface roughness and critical machining parameters during turning of Ti6Al4V (0.001 % N, 0.017 % C, 0.003 % H, 6.45 % Al, 0.03 % Cu, 0.21 % Fe, 4.18 % V, 0.02 % O and remaining as Ti). The surface roughness prediction model has been developed in terms of feed rate, cutting speed and the depth of cut using response surface methodology (RSM) and the adaptive neuro-fuzzy inference system (ANFIS). Total 32 turning experiments were conducted at different combinations of cutting parameters. The feed rate has been identified as the most significant machining parameter for the surface roughness followed by the depth of cut. The prediction ability of the ANFIS has been found superior to that of the RSM.

2.2.2 Milling

Among various machining processes, milling is one of the most commonly used material removal operation in manufacturing industries. The milling is used for making profiles, slots, pocket in precision molds and dies and other operations, such as engraving, surface contouring etc. This process is capable to remove material at a faster rate with a reasonably good surface finish.

With the increased usage of complex molds and die designs, more emphasis is being laid on achieving good surface finish during milling. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent. It is very difficult to calculate the value of surface roughness through theoretical analysis. Therefore, machine operators usually make use of “trial and error” approaches to set-up
machining conditions during milling to achieve the desired surface quality, that can be expensive as well as time consuming (Zhang et al., 2006).

To overcome these problems, many researchers investigated the effect of machining parameters on surface roughness in milling and applied different approaches for optimal selection of machining parameters so as to minimize surface roughness. A brief review of research based on published work in the relevant area is presented in following subsections.

2.2.2.1 Ferrous metals and alloys

The ferrous materials are very important of in manufacturing industries. Manufacturer of several mechanical components require very high surface finish with high dimension accuracy at reasonable metal removal rate. In past two decades attention has been paid towards the study of machining parameters for minimum surface roughness during milling operation. A brief review of research in the relevant area is given below.

a) Milling of ferrous metals - applications of design of experiments

In the field of metal machining, studies have been carried out to formulate the empirical relationship between cutting conditions and surface roughness, so as to investigate the effect of machining conditions on surface quality. A brief review of research in the relevant area is given below.

Alauddin et al. (1995) studied the effect of cutting parameters (cutting speed, feed and axial depth of cut) on surface roughness during the end milling of 190 BHN steel using HSS slot drill. For this purpose, total 24 machining experiments were conducted to collect the set of data for surface roughness values. The first order and second order prediction models have been developed using response surface methodology. The analysis of the first order model shows that the effect of cutting speed and axial depth of cut on surface roughness is insignificant. However, their effect
has been found significant in the second order model. The results also indicate that the surface roughness increases with increase in either feed or axial depth of cut, while an increase in cutting speed decreases the surface roughness.

Alauddin and Hashmi (1996) investigated the effect of cutting speed and feed on surface roughness in end milling of Inconel 718 (0.08 % C, 0.35 % Si, 0.35 % Mn, 0.60 % Ti, 0.80 % Al, 1.00 % Co, 3.00 % Mo, 5.00 % Cb, 17 % Fe, 19.00 % Cr, 52.82 % Ni) using uncoated carbide inserts under dry conditions. The first order and second order empirical models for surface roughness were developed to optimize machining parameters for minimum surface roughness using RSM based on CCRD method. The feed has been found to be the most significant machining parameter in both the models. The cutting speed has been found significant in the first order model while it is insignificant in the second order model.

Mansour and Abdalla (2002) analyzed the effect of machining parameters (cutting speed, feed rate and axial depth of cut) on surface roughness in end milling of EN 32 steel with coated tungsten carbide inserts. For this purpose, total 24 machining experiments were performed to collect the set of data for surface roughness values. The first order and second order surface roughness prediction models were developed in terms of machining parameters using RSM. The analysis of both the models indicates that the surface roughness increases with increase in feed and axial depth of cut while it decreases with increase in cutting speed.

Ghani et al. (2002) analyzed the effect of cutting parameters on surface roughness and cutting force in end milling of AISI H13 hardened steel (0.37 % C, 0.9 % Si, 0.46 % Mn, 0.014 % P, 0.02 % S, 0.11% Ni, 5.34 % Cr, 0.4 % Cu, 1.25 % Mo, 1 % V and remaining as Fe) with TiN coated carbide inserts using L_{27} orthogonal array based Taguchi approach. The cutting speed, feed rate and depth of cut were considered
as cutting parameters. The pareto analysis of variance (ANOVA) has been employed to evaluate the percentage contribution of each cutting parameter on surface roughness and cutting force. An attempt has also been made to optimize the cutting parameters for minimum surface roughness and cutting force. The results show that the optimal combination of cutting parameters for low resultant cutting force and good surface finish is obtained at high cutting speed, low feed rate and small depth of cut. The feed has been found to be the most significant parameter affecting the cutting force while cutting speed appears to have dominating effect on surface roughness.

Reddy and Rao (2004) investigated the influence of tool geometry (radial rake angle and nose radius) and cutting conditions (cutting speed and feed rate) on surface roughness during end milling of AISI 1045 steel (0.485 % C, 0.390 % Si, 0.991 % Mn, 0.0138 % P, 0.020 % S and remaining as Fe). For this purpose, total 54 machining experiments (27 for wet machining and 27 for dry machining) were conducted using four fluted solid TiAlN-coated carbide end mill cutters to collect the set of data for surface roughness values. The surface roughness prediction models for both the dry and the wet end milling conditions were developed using regression analysis. The optimization of the models was carried out for minimum surface roughness using genetic algorithms. It has been found that proper selection of parameters eliminates the use of cutting fluids during machining and hence makes machining more environments friendly.

Reddy and Rao (2005) experimentally investigated the effect of solid lubricant on surface quality, cutting forces and specific energy during end milling of AISI 1045 steel (0.485 % C, 0.390 % Si, 0.991 % Mn, 0.0138 % P, 0.020 % S and remaining as Fe). The end milling experiments were conducted using solid coated carbide end mill of different tool geometry (radial rake angle and nose radius). For this purpose, total 81
milling experiments according to 3-level full factorial design, were conducted. The graphite and molybdenum disulphide have been employed as solid lubricants. An attempt has also been made to compare the results obtained in wet machining with solid lubricant assisted machining. The results reveal that the use of solid lubricant successfully reduces the cutting forces, specific energy, surface roughness and chip size during end milling. Also, a significant reduction in friction between tool and workpiece has been observed in molybdenum disulphide assisted machining as compared to that with graphite assisted and wet machining.

Iqbal et al. (2007) investigated the effects of cutting parameters on tool life and surface roughness in hard-milling of AISI D2 steel (1.4–1.6 % C, Cr % 11–13, max 0.4 % Mn, max 1.1 % V, 0.7–1.2 % Mo, max 0.03 % P, max 0.03 % S, max 0.6 % Si and remaining as Fe) and X210 Cr12 steel (2–2.2 % C, 11.5 % Cr, max 0.6 % Mn, max1.0 % V, max 1.0 % W, max 0.03 % P, max 0.03 % S, max 0.6 % Si and remaining as Fe) using coated carbide ball-nose end mills. The hardened steel microstructure, work piece inclination angle, cutting speed and radial depth of cut have been considered as cutting parameters. The D-optimal base response surface methodology has been employed to developed empirical models for tool life and surface roughness. The SEM and EDS analyses of the worn-out tools have also been carried out to study the effect of different levels of parameters. The results indicate that the major tool damage mechanisms are notch wear, adhesion, and chipping. The severity of chipping appears to be relatively smaller as compared to that of adhesion and notch wear. In addition to this, for the tool life, the workpiece material seems to be the most influential parameter followed by the rotational speed of the tool. Also, the machinability of AISI D2 steel has been found poorer than that of X210 Cr12 steel. On the other hand, the workpieces inclination
angle appears to be the most influential parameter for surface roughness, the higher values of inclination angle produces better surface finish.

Gopalsamy et al. (2009a) experimentally investigated the machinability of IMPAX HI HARD hardened steel (0.37% C, 2.0 % Cr, 1.4 % Mn, 0.3 % Si, 1.0 % Ni, 0.2 % Mo and remaining as Fe). The cutting speed, feed, depth of cut and width of cut have been considered as process parameters while volume of material removed, surface finish, tool wear and tool life were considered as response variables. The optimum process parameters were evaluated using L_{18} orthogonal array based grey Taguchi method for both rough and finish machining experiments. The coated carbide inserts were used for rough machining operations and ball end mill cutters were used for finish machining experiments. An orthogonal array, grey relations, grey relational coefficients and analysis of variance (ANOVA) have been applied to study the performance characteristics of machining process parameters. For the rough machining, the width of cut and depth of cut have been found to be the most influencing parameters corresponding to tool life, tool wear and volume of material removed. For finish machining, the cutting speed has been found the most influencing parameter corresponding to tool life, tool wear and surface finish.

Gopalsamy et al. (2009b) investigated the effect of cutting speed, feed, depth of cut and width of cut on surface finish and tool life in end milling of annealed steel (0.37 % C, 2.0 % Cr, 1.4 % Mn, 0.3 % Si, 1.0 % Ni, 0.2 % Mo and remaining as Fe) using PVD coated inserts. An attempt has also been made to optimize the machining parameters for minimum surface roughness and maximum tool life using L_{18} orthogonal array based Taguchi method. The results indicate that cutting speed is the most influential parameter for tool life and surface roughness. The minimum surface roughness has been achieved at higher level of cutting speed, higher level of feed,
higher level of depth of cut and lowest level of width of cut. The tool wear appears to take place due to chipping and adhesion.

b) Milling of ferrous metals - application of soft computing techniques

Work has been reported on the study of the effect of cutting parameters on surface roughness. Efforts have also been made to obtain optimal combination of cutting parameters for minimum surface roughness. A brief review of research in the relevant area is given below.

Savas and Ozay (2007) investigated the effect of machining parameters on surface roughness in tangential turn-milling process of SAE 1050 steel composition using end-milling cutter of high speed steel. The depth of cut, workpiece speed, tool speed and feed rate were considered as machining parameters. The authors also proposed an approach for optimization of cutting parameters for minimum surface roughness using genetic algorithm. It has been inferred from the analysis that as depth of cut and feed rate increase, the surface roughness also increases. In addition, a good correlation has been obtained between the predicted values of surface roughness and those obtained experimentally.

Razfar et al. (2010) proposed an approach to determine the optimal cutting parameters for minimum surface roughness in face milling of X20Cr13 stainless steel (0.15 % C, 1.00 % Si, 1.00 % Mn, 0.04 % P, 0.03 % S, 0.75 % Ni, 14 % Cr and remaining as Fe). The approach is based on artificial neural network (ANN) and harmony search (HS) algorithm. A predictive model for surface roughness in terms of cutting speed, feed per tooth, depth of cut and engagement of tool with work piece has been obtained using a feed forward neural network. For this purpose, a number of machining experiments based on statistical 3- level full factorial design of experiments method were carried out to collect a set of data for surface roughness values. Out of 81
experimental data sets, 73 data sets were used for training the network and remaining data sets were used for testing purpose. The optimal cutting parameters for minimum surface roughness have been obtained using harmony search algorithm. Additional experiments have been performed to validate the optimum surface roughness values predicted by the HS algorithm. A good correlation has been obtained between the predicted and the experimentally obtained surface roughness values.

Rai et al. (2010) investigated the effect of machining parameters on surface roughness in face milling of high chromium steel i.e AISI H11steel (0.33-0.43 % Mn, 0.20-0.50 % Si, 0.80-1.20 % Cr, 4.75- 5.50 % Ni, max 0.3 % Mo, 1.10- 1.60 % V, max 0.25 % Cu, max 0.03 % P, max 0.03 % S and remaining as Fe) using carbide cutters. The surface roughness prediction model has been developed in terms of cutting speed, feed and depth of cut using artificial neural networks (ANN). The experiments have been designed according to L_{27} orthogonal array based Taguchi methodology. Out of 27 experimental data sets, the 22 data sets have been used for training purpose and remaining 5 data sets have been used for testing the network. A Multilayer perceptron (MLP) network using feed forward error back propagation has been used as the neural network architecture to describe the process model. The Pearson correlation coefficient has also been calculated to analyze the correlation between the system inputs and selected system output (surface roughness). The Pearson correlation coefficient indicates a strong correlation between the feed per tooth and surface roughness, followed by cutting speed.

Parmar and Makwana (2012) employed artificial neural networks to develop surface roughness prediction model for end milling of mild steel with carbide tool. The prediction model has been developed in term of spindle speed, feed and depth of cut using MATLAB. For this purpose, total 27 milling experiments were performed to
collect the data sets for surface roughness values. From the experimental data sets 24 data sets were used for training remaining 3 data sets were used for testing of the network. The result shows that the prediction of surface roughness based on the ANN model is quite close to the experimental results. The average and the maximum prediction error for the data set has been found to be 3.5% and 8.74% respectively.

c) Milling of ferrous metals - application of hybrid techniques

A few studies have been carried out to investigate the effect of cutting parameters on surface roughness in milling of ferrous materials using hybrid techniques. Efforts have also been made to obtained an optimal combination of cutting parameters for minimum surface roughness. A brief review of the research in the relevant area is given below.

Reddy and Rao (2004) experimentally investigated the effect of tool geometry (radial rake angle and nose radius) and cutting conditions (cutting speed and feed rate) on surface roughness in end milling of AISI 1045 steel (0.485 % C, 0.390 % Si, 0.991 % Mn, 0.0138 % P, 0.020 % S and remaining as Fe). Total 81 machining experiments based on statistical 3-level full factorial design of experiments method were conducted to collect the data set for surface roughness values. All the experiments were carried out using solid coated carbide end milling cutters. The first and second order surface roughness prediction models were developed in terms of machining parameters using response surface methodology (RSM). Further, the model selected for optimization was validated by the Chi square test. An attempt was also made to optimize the surface roughness prediction model using genetic algorithms (GA). The GA appears to be quite useful for obtaining optimum machining parameters to achieve the best possible surface quality.

Iqbal et al. (2007) developed a fuzzy expert system for optimization of machining parameters during milling of AISI D2 steel for maximum tool life and
workpiece surface finish. The experimentation has been carried out according to 2-level half factorial design using coated carbide inserts. The experimental data were converted into useful information using ANOVA and numeric optimization. This information was used to develop knowledge-base in the form of IF–THEN rules. The work piece material hardness, cutter’s helix angle, milling orientation (up/down) and coolant were considered as independent parameters while output response variables were tool life, surface roughness and cutting forces. The result reveals that the proposed approach has ability to maximize the tool life and minimize the surface roughness that too simultaneously. This expert system has been found effective and efficient for optimizing the hard-milling process.

2.2.2.2 Non ferrous metals and alloys

The non-ferrous materials are also used in manufacturing industries. Several machined component require high surface finish with high dimension accuracy. In the recent years, many studies have been reported on surface finishing of machined parts in milling of non-ferrous materials. A brief review of research in the relevant area is given below:

a) Milling of non ferrous metals - application of design of experiments

In the recent years, a lot of work has been carried to study the effect of cutting parameters on surface roughness using design of experiments in milling of non ferrous materials. A brief review of the research in the relevant area has been presented in this section.

Wang and Chang (2003) studied the effect of machining parameters on surface roughness during slot end milling of AL2014-T6 alloy using two flute end mills. The cutting speed, feed, depth of cut, concavity and axial relief angles of the end cutting edge of the end mill were considered as machining parameters. Total 72 slot milling
experiments (36 for dry machining and 36 for wet milling) were carried out to collect the set of data for surface roughness values. Surface roughness prediction models for both the dry and the wet cutting conditions were developed using RSM. The surface roughness obtained during dry machining has been observed to get reduced by applying cutting fluid at same machining condition. The cutting speed, feed, concavity and axial relief angles have been found as significant factors affecting the surface roughness in dry machining while feed and concavity angle appear to be significant for the wet machining.

Bagci and Aykut (2005) analyzed the effect of machining parameters on surface roughness during CNC face milling of cobalt-based alloy i.e stellite 6 (1.07 % Si, 0.485 % Mn, 28.166 % Cr, 1.92 % Ni, 0.96 % Mo, 5.17% W, 0.01 % Ti, 2.88 % Fe, 0.041 % Ta, 1.09 % C, remaining as Co) using TiN coated face milling cutter. The cutting speed, feed and depth of cut were considered as independent machining parameters. An attempt has also been made to optimize the machining parameters for minimum surface roughness using L27 orthogonal array based Taguchi method. Further, the confirmation experiments corresponding to the optimal levels of cutting parameters have been conducted to demonstrate the effectiveness of the optimization method. It has been found that surface roughness is significantly influenced by cutting speed, feed rate and depth of cut. The minimum surface roughness is achieved at lowest level of depth of cut, highest level of cutting speed and lowest level of feed.

Zhang et al. (2006) analyzed the effect of machining conditions on surface roughness during CNC face milling of aluminum using coated carbide inserts. The spindle speed, feed rate and depth of cut have been considered as control factors while operating chamber temperature and the tool wear have been considered as noise factors. The optimum conditions for minimum surface roughness have been obtained using L9
orthogonal array based Taguchi methodology. The ANOVA has also been carried out to identify the significant factors affecting surface roughness. Finally, confirmation experiments have been carried out to verify the results. The results indicate that spindle speed and feed rate have a major impact on surface roughness in comparison to the depth of cut. In addition to this, one of the noise factors (tool wear) has been found to be statistically significant. The results obtained after the conformation runs indicate the ability of the Taguchi method to obtain the optimum cutting conditions for minimum surface roughness with minimum experimentations.

Kopac and Krajnik (2007) employed L$_{18}$ orthogonal array based Taguchi method to optimize flank milling parameters for multi performance characteristics (cutting force, surface roughness and metal removal rate). The milling experiments were conducted on Al alloy 5083 (4.5% Mg, 1% Mn, 0.15 % Cr and remaining as Al) using coated carbide inserts. Coolant application, number of flutes, cutting speed, feed rate, axial depth of cut and radial depth of cut have been considered as milling parameters. The results indicate that the flank milling with two or three flutes is superior to four-fluted tool. Also, it has been found the reduced feed rates appear to improve the process performance and tool life while maximal cutting speed does not yield optimal performance.

Yang and Chuang (2008) investigated the influence of the machining parameters on surface roughness and dimensional accuracy of groove width during end milling of high-purity graphite under dry machining. The cutting speed, feed rate, and depth of cut were considered as machining parameters. The experiments were conducted according to 2-level full factorial design. The analysis of variance (ANOVA) has been used to identify the most influential parameter. Simultaneously, mathematical models for surface roughness and groove difference have been developed using regression
analysis. The feed rate has been found to be the most significant factor affecting the groove difference and the surface roughness in end milling process. The minimum surface roughness has been obtained at low value of feed rate.

Routara et al. (2008) investigated the effect of machining parameters and types of workpiece material on surface roughness using response surface methodology. The end milling experiments were carried out on three different workpiece materials namely aluminium 6061-T4 (0.2% Cr, 0.3% Cu, 0.85% Mg, 0.04% Mn, 0.5% Si, 0.04% Ti, 0.25% Zn, 0.5% Fe and remaining as Al), brass (0.095% Fe, 0.9% Pb, 34% Zn and remaining as Cu) and mild steel AISI 1040 (0.42% C, 0.48% Mn, 0.17% Si, 0.02% P, 0.018% S, 0.1% Cu, 0.09% Ni, 0.07% Cr and remaining as Fe) using CVD coated carbide tools. Total 375 end milling experiments were conducted on the aforementioned three materials (i.e. 125 experiments for each material according to 5-level full factorial design). The spindle speed, depth of cut and feed rate have been considered as independent parameters while five roughness parameters (centre line average roughness, root mean square roughness, skewness, kurtosis and mean line peak) were considered as dependent parameters. The second-order prediction models in terms of the machining parameters have been developed for each of the five roughness parameters using regression analysis. An attempt has also been made to obtain optimum cutting conditions with respect to each of the five roughness parameters. It has been observed that the response surface models for different roughness parameters are specific to workpiece materials. The error in prediction of the optimum conditions for different roughness parameters in general varies in the range of 4% to 13%.

Tsao (2009) investigated the effect of milling parameters on multiple performance characteristics (flank wear of tool and surface roughness of workpiece) during end milling of aluminum alloy A6061P-T651 with PVD coated end mills. The
coating type, helix angle, primary relief angle, cutter diameter, depth of cut, width of cut, feed rate, and spindle speed were considered as milling parameters. The $L_{27}$ orthogonal array based grey–Taguchi method has been used to investigate the effect of parameters on multiple performance characteristics and to obtain an optimal set of parameters. A set of confirmation runs corresponding to the optimal levels of end milling process parameters have been carried out to demonstrate the effectiveness of the grey-Taguchi method. The cutter diameter and the feed rate have been found to be the most significant parameter for the flank wear and the surface roughness respectively.

b) Milling of non ferrous metals - application of soft computing techniques

A lot of work has been carried out to investigate the influence of cutting parameters on surface roughness in milling of non ferrous materials using soft computing techniques. Attempts have also been made to obtain optimal set of cutting parameters for minimum surface roughness. A brief review of research in the relevant area is given below

Benardos and Vosniakos (2002) developed surface roughness prediction model during CNC face milling on Aluminum alloy using the neural network approach. The data used for training and testing the network performance was derived from the experiments conducted according to the $L_{27}$ orthogonal array based Taguchi design of experiments method. The ANN model was developed in terms of feed rate per tooth, the cutting speed, the engagement (ratio of cutting width to the cutting tool diameter), wear of the cutting tool, the use of cutting fluid and the three components of the cutting force. The Levenberg–Marquardt algorithm has been applied to train the feed-forward artificial neural network. The result shows that the mean square error between the experimental and predicted values to be 1.86 % (a very small value), which indicates the excellent prediction ability of the proposed model.
Dweiri et al. (2002) investigated the effect of machining conditions on surface roughness in down milling on alumic-79. The spindle speed, feed, depth of cut and number of flutes have been considered as machining parameters. An adaptive neuro fuzzy inference system (ANFIS) was proposed to optimize the machining condition for minimum surface roughness. The ANFIS approach has been found to be effective for optimization of surface roughness in down milling. Also, the four-flute cutter seems to produce a better surface finish than the two-flute cutter.

Peng lo (2003) developed an adaptive-network based fuzzy inference system (ANFIS) for prediction of surface roughness in end milling of aluminium 6061 alloy using HSS milling cutter. For this purpose, total 72 machining experiments were carried out to collect the set of data for surface roughness values. The spindle speed, feed rate and depth of cut were considered as input parameters, and surface roughness was considered as output parameter. Two different membership functions (triangular and trapezoidal) have been employed during the training of ANFIS. It has been found that the adoption of both the triangular and the trapezoidal membership functions yields satisfactory results. In addition, the feed rate has been found to be the most significant factor influencing the surface roughness followed by spindle speed, while the effect of depth of cut on surface roughness appears to be negligible.

Brezocnik et al. (2004) studied the influence of cutting conditions (spindle speed, feed rate, depth of cut, and vibrations) on surface roughness in end-milling of 6061 aluminium. The authors proposed genetic programming to predict surface roughness values. Two independent data sets (i.e. 120 training data set and 36 testing data set) have been obtained by conducting the machining experiments followed by measurements. On the basis of the training data set, different prediction models for surface roughness have been obtained. The validation of the models has been carried
out using testing data sets. The models appear to be depicting good prediction ability. Also, the surface roughness seems to be most influenced by the feed rate.

Oktem et al. (2005) studied the effect of machining parameters on surface roughness in end milling of an aluminium 7075-T6 (1.6 % Cu, 2.5 % Mg, 0.23 % Cr, 5.40 % Zn and remaining as Al) using AlTiN PVD coated tool. The cutting speed, feed, axial depth of cut, radial depth of cut and machining tolerance have been considered as machining parameters. The 3-level full factorial design of experiments has been used for experimentation. Optimization has been carried out by coupling neural network and genetic algorithm. The result shows good correlation between the predicted values of surface roughness with those obtained experimentally.

Tansel et al. (2005) proposed genetically optimized neural network systems (GONNS) for selection of optimal cutting conditions in end milling of Aluminum 6061 using TiAlN coated two flute cutter. The GONNS makes use of back-propagation (BP) type neural networks (NN) to establish the relationship between input and output. The cutting speed, feed, depth of cut and machining tolerance have been considered as input parameters. Further, the performance of the GONNS has been tested in two case studies. For this purpose, total 81 machining experiments were carried out to collect the output data. In the first case study, optimal operating conditions for maximum metal removal rate have been obtained by keeping the cutting forces in the desired range. In the second case study optimal operating conditions have been calculated to obtain the best possible compromise between the roughness of machined mold surfaces and the duration of finishing cut. The analysis reveals that the GONNS yields optimal values for cutting conditions with high accuracy.

Zain et al. (2010) developed ANN models in terms of cutting speed, feed rate and radial rake angle for predicting the surface roughness during end milling using
uncoated, TiAIN coated and SN_{TR} coated cutting tools of titanium alloy (Ti-6Al-4V). For this purpose, total 24 machining experiments were carried out to collect the set of data for surface roughness values. A review of several previous studies associated with the modeling issue has also been carried out to assess capability of the ANN. The Matlab ANN toolbox was used for modeling. The Feed-forward back-propagation algorithm has been employed as the algorithm with traingdx, learngdx, MSE, logsig as the training, learning, performance criteria and transfer functions, respectively. With three nodes in the input layer and one node in the output layer, eight networks were developed by using different numbers of nodes in the hidden layer. It has been found that the 3–1–1 network structure of the SN_{TR} coated cutting tool yields the best ANN model in predicting the surface roughness values. This study concludes that the model for surface roughness in the milling process could be improved by modifying the number of layers and nodes in the hidden layers of the ANN structure. In addition to this, the best surface finish has been obtained at the combination of high cutting speed, low value of feed and minimum radial rake angle.

Kakati et al. (2011) studied the effect of spindle speed, feed, and depth of cut on surface roughness during end milling of aluminium alloy using a carbide tool. The artificial neural network (ANN) has been used to establish the relationship between the surface roughness and the machining parameters. For this purpose, a number of machining experiments based on statistical 3-level full factorial design of experiments method were carried out to collect the set of data for surface roughness values. Out of 27 experimental data sets, 24 were used for training and remaining 03 data sets has been used for testing the network. The feed forward back propagation algorithm was used for modeling purpose. The results reveal that the spindle speed has inverse effect on surface roughness. Also the surface roughness appears to increase with increase in feed rate and
depth of cut. However, the effect of depth of cut has been found least on surface roughness.

Hossain and Ahmad (2012) proposed surface roughness (Rₐ) prediction models using ANN and Adaptive neuro-fuzzy inference system (ANFIS) during ball end milling of Aluminum. The prediction models were obtained in terms of cutter axis inclination angle, spindle speed, feed rate, radial depth of cut and axial depth of cut. The data set obtained from the experiments has been divided into training data set and testing data set (68 data set for training and 16 data set for testing). The training data set is used to train different ANN and ANFIS models for Rₐ prediction, and the testing data set is used to validate the models. Better performing ANFIS and ANN models are selected based on the minimum value of root mean square error (RMSE). The predicted surface roughness values obtained from ANFIS model have been compared with the theoretical equation output, ANN and response surface methodology (RSM) on the basis of RMSE and MAPE. The ANFIS model seems to yield better results in prediction of surface roughness as compared to theoretical equation, ANN model and RSM model.

c) Milling of non ferrous metals - Application of hybrid techniques

Studies have been reported on the effect of cutting parameters on surface roughness in milling of nonferrous materials using hybrid techniques. Efforts have also been made to obtain optimal combination of cutting parameters. A brief review of the research in the relevant area is given below.

Oktem et al. (2005) presented a study on determination of optimum cutting conditions for minimum surface roughness in end milling of mold surfaces of aluminum 7075 -T6 (1.6 % Cu, 2.5 % Mg, 0.23 % Cr, 5.40 % Zn and remaining as Al) using coated carbide tool. The modeling and analysis approach employed response surface
methodology (RSM) coupled with genetic algorithm (GA). The RSM has been used to obtain fourth order surface roughness model in terms of cutting parameters namely feed, cutting speed, axial depth of cut, radial depth of cut and machining tolerance. For this purpose, a number of machining experiments based on statistical 3-level full factorial design of experiments method were carried out to collect the set of data for surface roughness values. The genetic algorithm has been employed to optimize these cutting parameters for minimum surface roughness. Further, the predicted optimum cutting conditions have been validated with an experimental study. It has been observed that the prediction of optimum values by the GA correlates very well with the experimentally obtained values.

Erzurumlu and Oktem (2005) presented the experimental studies for end milling of aluminum (7075-T6) mold cavity (1.6 % Cu, 2.5 % Mg, 0.23 % Cr, 5.40 % Zn and remaining as Al) using PVD AlTiN coated solid carbide end mill cutter. In the study, the feed, cutting speed, axial–radial depth of cut and machining tolerance were considered as independent parameters. The machining experiments based on statistical 3-level full factorial design have been carried out in order to collect the set of data for surface roughness values. An effective fourth order RS model has been proposed using experimental results. The ANN model based on multilayer feed forward back-propagation algorithm has also been developed. The comparison between the RS and the ANN model has been made on the basis of error analysis. The result shows that the predicted surface roughness based on the ANN model is in a close agreement to the experimental values as compared to that predicted using the RSM model.

Kadirgama et al. (2008) studied the effect of machining parameters (cutting speed, feed rate, axial depth and radial depth of cut) on surface roughness during milling of aluminium alloy (AA6061-T6) using carbide coated inserts. For this purpose,
27 machining experiments were carried out to collect the set of data for surface roughness values. An attempt has also been made to optimize machining parameters for minimum surface roughness through an approach based on the response surface methodology (RSM) and the radian basis function network (RBFN). The surface roughness prediction model has been obtained in terms of machining parameters. The RSM based first order model and that based on the RBFN indicates the feed rate to be the most significant factor affecting the surface roughness. Also, prediction through the RBFN based model has been found more accurate as compared to the RSM based one.

Kadirgama et al. (2010) investigated the effect of machining parameters on surface roughness during end milling of aluminium alloys 6061-T6 (95.8-98.6 % Al, 0.04-0.35 % Cr, 0.15-0.4 % Cu, max 0.7 % Fe, 0.8-1.2 % Mg, max 0.15 % Mn, 0.4- 0.8 % Si, max 0.15 % Ti, max 0.25 % Zn). The cutting speed, feed, axial depth and radial depth were considered as machining parameters. The empirical surface roughness model has been obtained in terms of machining parameters. For this purpose, total 27 milling experiments were carried out to collect the set of data for surface roughness values. The response ant colony optimization (RACO) approach has been used to optimize machining parameters for minimum surface roughness. The approach is based on both the response surface methodology (RSM) and the ant colony optimization (ACO). Finally, the prediction model has been validated through experimentation based on the error analysis. The analysis of the model displays the feed rate to be the most significant factor affecting the surface roughness. Also, the hybrid approach has been observed to the quite useful for effective prediction.

Yazid and Khorram (2010) studied the effect of machining parameters on surface roughness and material removal rate during face milling of aluminum 6061-T6 using coated carbide inserts. An attempt has also been made to obtain an optimal set of
machining parameters for minimum surface roughness and maximum material removal rate. The RSM and ANN have been used to develop prediction models. For this purpose, total 30 milling experiments were performed to collect the sets of data for surface roughness and material removal rate values. The result shows that cutting speed and feed are the most significant factors affecting the surface roughness while the depth of cut and feed rate appear to be significant factors in case of material removal rate.

2.3 Research Gaps

The review of research literature reveals, a number of research gaps have been identified and are outline below.

- A number of studies have been carried out to develop the surface roughness prediction model and investigate the effect of machining parameters on surface roughness during the machining of different materials. Further, the AISI-1019 and EN-353 steels, which are very important, have not been fully explored. A study on these materials will be a useful research contribution.
- The studies reported on the development of surface roughness prediction models are limited. Large number of studies has been carried out to investigate the effect of machining parameters on surface roughness during machining, on the basis of DOE. Therefore development of surface roughness prediction model along with investigation of effect of machining conditions on surface roughness for machining the AISI-1019 and EN-353 steels will be a useful contribution.
- Various modeling approach i.e. RSM, soft computing and hybrid techniques have been used for development of surface roughness prediction models. The support vector machines are also useful techniques and needs to be explored.
Studies reported on comparison of modeling techniques for surface roughness prediction accuracy are very limited. Work in this direction would be quite useful contribution.

2.4 Research Objectives

The AISI-1019 and EN-353 steels are widely used as a engineering material in various industries such as automotive industries, aerospace and aircraft industries where surface finish is the most important factor (www.Azom,2012; www.shreekrishnaauto, 2012). The literature reveals that very few studies have been carried out to develop surface roughness prediction models and to analyze the effect of machining conditions (cutting speed, feed, depth of cut and tool nose radius) on surface roughness during the machining (turning and end milling) of AISI-1019 and EN-353 steels. Accordingly, the main objective of this study is the development of surface roughness prediction models using various modeling approaches such as, RSM, ANN and SVMs; and analyze the effect of machining conditions (cutting speed, feed, depth of cut and tool nose radius) on surface roughness during the machining (turning and end milling) of AISI-1019 and EN-353 steels. In order to achieve the above objective, the following sub-objectives need to be invariably accomplished:

1. Development of surface roughness prediction models based on RSM, ANN, SVMs and analyze the effect of machining conditions (cutting speed, feed, depth of cut and tool nose radius) on surface roughness during the turning of AISI-1019 steel.

2. Development of surface roughness prediction models based on RSM, ANN, SVMs and analyze the effect of machining conditions (cutting speed, feed, depth of cut and tool nose radius) on surface roughness during the turning of EN-353 steel.
3. Development of surface roughness prediction models based on RSM, ANN, SVMs and analyze the effect of machining conditions (cutting speed, feed rate, depth of cut and tool nose radius) on surface roughness during the end milling of AISI-1019 steel.

4. Development of surface roughness prediction models based on RSM, ANN, SVMs and analyze the effect of machining conditions (cutting speed, feed rate, depth of cut and tool nose radius) on surface roughness during the end milling of EN-353 steel.

5. Identification of the optimal combination of machining parameters for minimum surface roughness for both the turning and end milling of AISI-1019 and EN-353 steels.

6. Identification of the best approach for prediction of surface roughness on the basis of statistical error analysis in all four cases.

2.5 Summary

This chapter presents an exhaustive review of research on surface roughness in machining especially turning and milling, based on published literature. The research gaps have been identified and objectives of the proposed research have been finalized. The next chapter describes the approaches used for development of surface roughness prediction models.