CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Until 1990’s, many researchers optimized cutting parameters using traditional optimization techniques for maximization or minimization problem. Later, many researchers implemented non-traditional optimization techniques for combined and multi-objective optimization problem. After 2000, researchers have done experimental work to study the effects of parameters on performance measures. The experimental studies were used for theoretical analysis and predictions using Artificial Neural Networks (ANN), Fuzzy logics, Multiple Regression Analysis etc. This chapter presents the various literatures available on machining problems.

2.2 Literature Review

Agapiou [1] determined the optimum machining conditions for single-pass and multi-pass operations using Nelder-Mead simplex method. The objective function was a combination of minimum product cost and minimum production time prioritized through their weight coefficients. The structure of the objective was analyzed and the procedure for construction was discussed. The superiority of the combined objective function over single objective, sensitivity analysis for the weighted coefficients and the constant multiplier used to normalize the objective function are also discussed via numerical examples. Chen et al. [2] developed an optimization model for a continuous profile using simulated annealing approach. In this machining model, straight turning, taper turning and circular turning were simultaneously considered. The usefulness of the developed
model is established through test examples. The authors suggested that the proposed model could be integrated with CAD/CAM system for determining the optimal machining parameters, thereby reducing the manufacturing cost of machining process. Kee [3] studied the development of constraint optimization analysis and strategies for selecting the optimum cutting conditions of multi-pass rough turning operations. Simple strategies such as using equal cutting conditions for all passes have been found to be always valid. Numerical case studies supported the importance of using developed optimization strategies rather than handbook recommendations. Tolouei-Rad et al. [4] described the development and utilization of method of feasible direction to determine optimum machining parameters for single tool and multi-tool milling operations. The unit cost, unit time and total profit rate due to the application of the proposed optimization technique is 38%, 42% and 350% better than handbook recommendations respectively. Bhaskara Reddy et al. [5] used genetic algorithm to select optimal depth of cut to achieve minimum production cost in multi-pass turning operations. The resulting unit production cost using the proposed methodology is lower than commonly practiced method of selecting minimum depth of cut in the finish pass and a number of rough passes of equal size. The authors suggested that the proposed algorithm could be integrated with Computer Aided Process Planning (CAPP) for sequencing the operations and also for generation of Numeric Control (NC) codes. Kyung Sam Park et al. [6] presented a survey on various approaches like Computer Aided Design (CAD), Operations Research (OR) and Artificial Intelligence (AI) to determine optimal machining parameters for various performance measures. The findings of the survey state that the use of AI techniques would be valuable for the intended purpose. James Kennedy et al. [7] developed PSO,
which is a population-based search procedure that could yield global optimum solution. An important feature of PSO is that it has very few parameters to adjust. It has been proven by many researchers that PSO could yield best result quickly when compared to other optimization techniques. One of the advantages of PSO is that it takes real numbers as particles. The searching is an iterative process and the terminating criterion is either maximum number of iterations or the minimum error condition. Meng et al. [8] described a machining theory to calculate optimum cutting condition in turning for minimizing cost or maximizing production rate. The required constants for the modified Taylor tool life equation were determined using the machining theory. The authors concluded that the proposed approach has greatly reduced the experimental work needed for tool life data. Lee et al. [9] constructed a polynomial network to learn the relationships between cutting parameters and cutting performance such as surface roughness, cutting force and tool life. Sequential quadratic programming was applied to the networks for searching optimal cutting parameters for achieving maximum production rate. Onwubolu et al. [10] implemented Genetic Algorithm (GA) for the determination of the cutting parameters in multi-pass machining operations. The objective is to minimize the unit production cost subjected to twenty practical constraints. Experimental results showed that the proposed GA is both effective and efficient when compared to the results of Simulated Annealing (SA), fuzzy possibilistic-GA and Linear Programming approaches.

Wang et al. [11] presented a deterministic approach for the selection of economic cutting conditions in single pass turning operations. Apart from validating the optimization strategy and computer program, the authors have also demonstrated the suitability of the developed program for on-line applications in computer aided
manufacturing systems. Choudhri et al. [12] suggested GA to find the optimum machining conditions in turning. In this work, two objective functions, namely unit production time and unit production cost, were optimized after satisfying few practical constraints. The proposed algorithm was found to perform better than a goal programming technique. Saravanan et al. [13] applied GA in multi-objective optimization model for surface grinding operation from an adopted literature and showed that GA performs better than the quadratic programming technique. Wong et al. [14] developed four improved fuzzy models for four different cutting tools. GA was used to optimize the selection of cutting parameters. The results were validated with previous literature and machining data handbook. Franci Cus et al. [15] proposed GA for the determination of cutting parameters in milling operations. Experimental results show that GA is both effective and efficient in solving the optimization problem and also can be integrated with an intelligent manufacturing system. Saravanan et al. [16] applied GA and SA to optimize machining parameters for continuous profile machining. The objective function is to minimize production cost subject to a set of practical constraints. Of the two algorithms, SA produces marginally better results than GA. Vijaykumar et al. [17] proposed Ant Colony Optimization (ACO) algorithm to find optimal machining parameters for multi-pass turning operation. The results were compared and the proposed technique was found to be effective than techniques carried out by other researchers. Annie Venugopal et al. [18] carried out experiments to study the effect of grain size, grain density, depth of cut and feed on surface roughness and surface damage. Mathematical model were developed and analyzed using ANalysis Of VAriance (ANOVA). GA has been developed to optimize the grinding conditions for maximum
material removal rate. The proposed model offers a solution to reduce the cost of machining, thereby making silicon carbide a more commercially viable material for industrial applications. Juan et al. [19] investigated the optimal cutting parameters for minimizing production cost on rough machining of high speed milling operation. The mathematical model was formulated based on polynomial network and optimization was carried out using SA. The authors also illustrated the proposed approach using practical example in high speed machining operation. Uros Zuperl et al. [20] developed Neural Network (NN) to describe the multi-objective optimization of cutting conditions for machining. An illustrative example was discussed in detail to demonstrate the procedure and performance of the NN approach. The authors concluded that the proposed approach is suitable for fast determination of optimum cutting parameters during machining, when there is no enough time for deep analysis.

Amiolemhen et al. [21] optimized machining parameters to determine minimum product cost of converting a cylindrical bar stock into a continuous finished profile involving seven machining operations such as facing, turning, centering, drilling, boring, chamfering and parting-off operation. Experimental results show that the proposed genetic algorithm is both effective and efficient. Baskar et al. [22] developed ACO for surface grinding operations to minimize production cost and maximize production rate subject to constraints such as thermal damage, wheel wear parameters, machine tool stiffness and surface finish. It was observed that ACO has outperformed 5% higher than GA and 17% higher than quadratic programming technique. Ezugwa et al. [23] developed ANN model for the analysis and prediction of the relationship between cutting and process parameters during high speed turning of nickel-based Inconel 718 alloy. A very
good agreement between predicted and experimental data was achieved and hence the model can be used for analysis and prediction of complex relationship between cutting conditions and process parameters. Asokan et al. [24] developed PSO for optimizing cutting parameters of surface grinding operation with a multi-objective function of minimizing production cost and maximizing production rate per work piece, besides obtaining best possible surface finish. It was observed that PSO outperformed quadratic programming technique and GA. Moreover, PSO could able to converge the global optimal solution at a faster rate. Baskar et al. [25] implemented various operations research techniques such as GA, Tabu search (TS) algorithm, ACO and PSO for optimizing machining parameters of multi-milling operation. The authors concluded that PSO algorithm always yields best result when compared to other algorithms and handbook recommendations. Wang et al. [26] presented a hybrid of SA and GA optimization technique to select the optimal machining parameter for multi-pass milling operations. This approach used the strengths of SA and GA and overcame their weakness. It is evident from the results that this hybrid approach was more effective than conventional methods. Indrajit Mukherjee et al. [27] appraised the application potential of several modeling such as statistical regression technique, ANN, Response Surface Methodology (RSM) etc., and optimization techniques such as SA, GA and TS algorithm in metal cutting processes. Ramon Quiza Sardinas et al. [28] used GA for optimizing cutting parameters and made a remark on the advantages of multi-objective optimization approach over single objective function. An application sample was developed and its results were analyzed for different machining conditions. Tansel et al. [29] proposed Genetically Optimized Neural Network System (GONNS) for the selection of optimal
cutting condition from the experimental data, when analytical or empirical mathematical models were not available. The authors presented the relationships between the cutting conditions and machine related variables. Optimal operating conditions were also calculated to obtain the best possible compromise between roughness of machined surface and the duration. Baskar et al. [30] developed GA, Hill Climbing Algorithm (HCA) and Memetic Algorithm (MA) to find optimum cutting parameters for multi-tool milling operations like face milling, corner milling, pocket milling and slot milling. Significant improvement was observed in using these techniques when compared to handbook recommendations and method of feasible direction.

Franci Cus et al. [31] proposed ANN to optimize cutting parameters for machining operation. The objective was to increase the productivity and reduce the production cost. When there is no enough time to analyze the effect of cutting parameters on the performance measures, the ANN approach was suitable for fast determination of the objective. An illustrative example was also discussed in detail to explain the robustness of the proposed approach. Raid Al-Aomar et al. [32] used GA to determine near optimal settings to both machining and production process parameters so that the overall per order production cost is minimized. The experimental results and the sensitivity analysis showed the robustness of the proposed GA. Finally, the effectiveness of GA was illustrated by outperforming the solution obtained from two-level and three-level full factorial designs. Lee et al. [33] studied the effect of feed rate, depth of cut and grit size in SiC grinding for maximum material removal rate subjected to some constraints. The authors have proved that PSO methodology was superior to GA and also able to converge global optimum solution very quickly. Wang et al. [34] involved the
use of analytical, empirical and hybrid predictive models for predicting optimum cutting conditions. The performance measures are cutting force, tool life, chip form and surface roughness. Non-linear programming techniques were used for single pass operations while GA was adopted for multi-pass operations. The authors concluded that the proposed methodology is very generic in nature and so they can be applied for other operating conditions, work material and cutting tools. Finally, they suggested the need to validate these methodologies. Yigit Karpat et al. [35] considered the non-linear relations between the machining parameters and the performance measures. These correlations were obtained using NN models through experimental data. PSO is used to handle the multi-objective optimization problem. The results indicate that the proposed PSO method is both effective and efficient and can be utilized in solving complex turning problems. Sathish Kumar et al. [36] determined optimum cutting parameter for CNC multi tool drilling system by using GA, SA and ACO. The authors concluded that the proposed ACO generated superior solution than SA and GA. Alakesh Manna et al. [37] described the procedure to obtain machining condition of turning operation by considering unit cost of production using dynamic programming technique and also investigated the influence of cutting parameters on surface roughness. The developed model evolved minimum production cost under various combinations of machining conditions. Cutting speed had significant effect on surface roughness when compared to feed and depth of cut. Indrajit Mukherjee et al. [38] applied empirical modeling technique for the prediction of two-stage grinding process. SA, GA and a modified TS algorithm were employed to determine optimal process parameters. Computational results showed that the modified TS algorithm performs better and also offer opportunities to be extended for other metal
cutting optimization problem than SA and GA. Srinivas et al. [39] proposed a methodology for selecting optimum machining parameters in multi-pass turning using particle swarm intelligence. The methodology was illustrated with examples of bar turning and a component of continuous form. The author concluded that PSO could give stable optimal feasible solutions within a reasonable computational time. Rodolfo et al. [40] introduced a SA strategy to adjust feed for regulating drilling force through the network using computational resources of CNC. This strategy has provided better transient response and performance index than the initial fuzzy controller.

Zarei et al. [41] presented a Harmony Search (HS) algorithm to determine optimum cutting parameter for multi-pass face milling. An illustrative example demonstrated the ability of the HS algorithm and for validation purpose; GA was used to solve the same problem. Comparison of results revealed that the HS algorithm could obtain optimum solution with higher accuracy when compared to GA. Venkata Rao et al. [42] applied Artificial Bee Colony (ABC), PSO and SA algorithm for parameter optimization of a multi pass milling process. Minimization of production time was the objective considered, subjected to various constraints such as arbor strength, arbor deflection and cutting power. The accuracy and quick convergence to global optimum solution of ABC and PSO were very high as compared to SA algorithm. Jayabal et al. [43] studied the effect of process parameters on thrust force, torque and tool wear in drilling of coir fiber reinforced composites using Nelder-Mead Simplex method and GA. Input variables are drill bit diameter, cutting speed and feed rate. The proposed procedure was used to find the optimum machining parameters to reduce tool wear and also to predict the responses of drilling operation. Alauddin et al. [44] developed mathematical
models for surface roughness using speed and feed using RSM. The constructed surface roughness contours could able to select a combination of parameters for machining time reduction without increasing the surface roughness. Yu-Hsuan et al. [45] developed an in-process surface recognition system using accelerometer, proximity sensor and ANN model to predict surface roughness of machined parts in end milling. It was observed that ANN surface recognition model is economical, efficient and able to produce a high accuracy rate of 96-99% predicting accuracy for variety of combinations of cutting conditions. Ali et al. [46] considered 16 most influential parameters on surface roughness in grinding operation. A three layer fuzzy model was used to correlate the parameters for surface roughness. The effectiveness and high performance of the model were demonstrated by a worked example and also found that the model became simpler, more effective, superior in modeling non-linearity and conceptually clearer than other approaches. Dae Kyun Baek et al. [47] analyzed the effects of insert run out errors and the variation of the federate on the surface roughness and the dimensional accuracy in face milling operation using a surface roughness model. The optimal feed rate was obtained by bisection method for maximizing material removal rate. The verification results confirmed that the developed surface roughness model and optimization scheme were good enough in controlling roughness while maximizing the material removal rate. Mansour et al. [48] developed a mathematical model for surface roughness in end milling process using RSM. The authors concluded that the first order equation is valid within the speed range of 30-35 m/min and second order equation in the range of 24-38 m/min. The contours developed enabled the selection of proper speed and feed to increase the metal removal rate without sacrificing the quality of the surface finish produced. Bernard et al.
presented the results of a series of experiments performed to examine the validity of a theoretical model for evaluation of cutting forces and machining error in ball end milling of curved surfaces. Cutting force decreased with an increase in milling position angle, while two force components are hardly affected by the milling position angle. The machining error generally decreased with an increase in milling position angle. Theoretical and experimental results showed reasonably good agreement. Luis et al. [50] studied the importance of optimization techniques in selecting the appropriate tool from their geometry, base material and coating point of view. Testing was carried out using coated carbide tools and Polycrystalline Cubic Boron Nitride (PCBN) tools. In stamping die industry, High-Speed Milling (HSM) allowed reduced manufacturing time up to 10% with an improvement in the quality of the machined parts.

Benardos et al. [51] presented NN modeling approach for the prediction of surface roughness in CNC face milling. ANN based procedure predicted the surface roughness with a mean error of 1.86% and found consistent throughout the entire range of values. The authors suggested that for the given surface roughness, tool and work piece material, it is necessary to determine the optimum cutting condition. Tandon et al. [52] implemented PSO to optimize machining parameters of milling accompanied by ANN for predicting cutting forces. Both feed and speed were considered during optimization but depth of cut was not considered in the optimization problem. Machining time is reduced up to 35% and the proposed technique is found to be efficient and robust. Jorge et al. [53] estimated the forces developed during milling using two supervised neural networks. Verification experiments were conducted to evaluate these two models. Radial basis network is shown to be superior than back propagation networks.
Orthogonal design and equally spaced dimensioning showed to be a good way to select the training experiments. Ship-Peng Lo [54] presented an Adaptive Network based Fuzzy Inference System (ANFIS) for predicting surface roughness in end milling process. While comparing with the experimental data, the author found that the prediction accuracy reached as high as 96%. Moreover, the changes in feed have the most impact on surface roughness followed by spindle speed. The depth of cut had the least impact. Grzesik et al. [55] assessed the surface quality in turned, ground and honed specimen. Statistical, fractal and NN based approaches were examined and compared for surface finish characterization. Results of ANN showed a close matching between the model output and the directly measured surface profile. Ghani et al. [56] used orthogonal array, signal-to-noise ratio and Pareto ANOVA to analyze the effect of milling parameters on surface finish and cutting force. The study proved that the Taguchi method is suitable to solve the stated problem with minimum number of trails as compared to full factorial design. Lamikiz et al. [57] proposed a model to estimate the cutting forces in inclined surfaces machined both up milling and down milling on aluminium alloy and tool steel. Validation tests were carried out on different slopes and machining conditions. The results provided errors below 10% and both the value and shape of the predicted forces matched with the measured cutting force. Ming-Yung Wang et al. [58] analyzed the influence of cutting condition and tool geometry on surface roughness in slot end milling. Surface roughness models for both dry and coolant cutting were built using RSM and experiments. Surface roughness generally increases with increase in feed, concavity and axial relief angles, while concavity angle is more than 2.5°. Brezonenik et al. [59] proposed Genetic programming to predict surface roughness in end milling. It was
established that the surface roughness was most influenced by feed rate whereas the vibration increased the prediction accuracy. Prediction accuracy of surface roughness by the developed model was very good for both the training and tested data set. Hasan Oktem et al. [60] coupled RSM with GA to determine the optimum cutting conditions to get minimum surface roughness in milling of mold surfaces. The proposed GA was able to reduce the roughness value in the mold cavity from 0.412 µm to 0.375 µm, which constitute about 10% improvement. Finally, the optimum cutting conditions recommended by GA is verified with the experimental measurement.

Babur Ozcelik et al. [61] developed a statistical model based on RSM for surface roughness estimation in a high-speed flat end milling process. The author found that the estimation capability of the first and second order models developed using experimental results were observed to be in good fit with the actual measured values. Hasan Oktem et al. [62] determined best cutting parameters to minimize surface roughness in end milling by coupling design of experiments, NN and GA. Measurements were performed to validate the optimum values predicted by GA and it is clearly seen that a good agreement is observed between the predicted values and experimental measurements. Suresh Kumar et al. [63] investigated the role of solid lubricant assisted machining on surface quality and cutting forces. ANOVA has been performed to find the influence of different factors on surface finish. The results indicated that there is a considerable improvement in the process performance with solid lubricant to that of machining with cutting fluids. Palani Kumar et al. [64] assessed the influence of machining parameters on the machining of glass-reinforced polymer composite material. Full factorial design was used for experimentation and assessed using response table, response graph, normal probability
plot, interaction graphs and ANOVA technique. Hector Siller et al. [65] proposed a mechanistic approach to study the cycle time prediction of high speed milling for sculptured surfaces with high feed rates. Discrepancies between programmed and actual feed rates were evaluated. Comparing the two cases demonstrated, the proposed model was capable of predicting cycle time with a maximum error of 5-22%. Abou et al. [66] discussed the development of the first and second order models for predicting the cutting force produced in end milling using RSM to study the effect of cutting parameters on cutting force. It was found that the interaction feed with axial depth was extremely strong and the interaction of feed with radial depth of cut was observed to be quite significant. The predictive models produced values of the cutting force close to those readings recorded experimentally with a 95% confident interval. Asif Iqbal et al. [67] focused on the enhancement of tool life and surface finish using ANOVA, optimization module and prediction module. The proposed expert system could able to recommend helix angle of the tool, milling orientation and also could predict tool life, surface roughness and cutting force for a high speed milling operation. Optimization module provided the selection of milling parameters according to the desired objective while the prediction module provided the prediction of performance measures for the combination of parameters finalized by the optimization module. Julie et al. [68] presented Taguchi design to optimize surface quality in a CNC face milling operation. The authors conducted experiments based on orthogonal array design and analyzed using ANOVA and finally verified by conducting the confirmation tests that the Taguchi design was successful in optimization for surface roughness. Oguz Colak et al. [69] used Gene Expression Programming (GEP) method for predicting surface roughness of milling surface with
cutting parameters. The author claimed 91% predicting accuracy level of the proposed GEP method over the method of experimental data. Some differences were observed between experimental and predicted values in low spindle speed and depth of cut, but there was a good correlation in high speed and high depth of cut. This study simplified surface roughness process monitoring. Omar et al. [70] introduced a generic and improved model to simultaneously predict the cutting force and the surface quality during side milling operation. The authors incorporate the effects of tool run out, tool deflection, system dynamics, flank wear and the tool tilting on the surface roughness. They also presented a technique to calculate the instantaneous chip thickness and finally found that the prediction model agreed well with the experimental results.

Hun-Keun Chang et al. [71] proposed a real time surface roughness prediction method using a sensor system. Surface roughness was measured based on the relative motion between tool and work piece using Cylindrical Capacitive Displacement Sensor (CCDS). A simple linear regression model was developed to predict surface roughness using the measured signals. The close relation between the machined surface and the roughness predicted was found to be about 95%. Ghassan et al. [72] proposed machine vision-based topography for surface roughness measurement and compared the same with the stylus-based measurements. Results showed that intensity-topography compatible model gives more superior results compared to the light-diffuse model with close values to the traditional stylus-based data. Tuncay et al. [73] developed RSM and ANN model to predict surface roughness on mold surfaces. A statistical three level full factorial design of experiments was carried out to collect surface roughness values. The RSM model and ANN are compared based on computational cost, cutting forces, tool life and dimensional
accuracy and it is found that the maximum test errors were 2.05% and 1.48% respectively. El-Sonbaty et al. [74] developed an ANN model for the analysis and prediction of cutting conditions for achieving specific surface roughness profile. The input parameters are the rotational speed, feed, depth of cut, pre-tool flank wear and vibration level. The accuracy of the predicted profiles was found to be 94% when compared to the actual measured profiles of test specimens. Moreover, the predicted profiles exhibited more details than the actual measured roughness profiles. Bikramjit Podder et al. [75] investigated end milling operation using microcrystalline straight grade carbide inserts under conventional wet, cryogenic cooling with liquid nitrogen (LN₂) and High Pressure (HP) cooling. Tool life, tool failure mode, chip morphology and surface finish were studied. HP cooling is found to be better than LN₂ cooling and in particular 275% times better than present machining conditions. Chipping of cutting edge was most predominant tool failure mode. 54% tool life reduction was observed by LN₂ cooling compared to conventional wet cooling. Finally, the authors found that LN₂ and HP cooling could able to produce better surface finish when compared to conventional wet cooling. Cheng et al. [76] presented a theoretical and experimental analysis of nano-surface generation in ultra-precision raster milling. An optimization system was established for optimizing the cutting conditions and a series of experiments were also conducted. The results show that the theoretical model has predicted well the trend of variation of surface roughness under various cutting condition and cutting strategies. Sahoo et al. [77] developed fractal dimension models for the surface topography in CNC end milling of three different material using RSM. The investigation indicated that the cutting parameters and their interactions influence the surface topography. The other
attempt was to estimate optimum machining conditions for producing best possible surface with minimum fractal dimension which greatly depends on specific tool-work piece material combination. Vedat Savas et al. [78] presented GA for optimization of cutting parameters leading to minimum surface roughness in the tangential turn-milling process. Testing was also done to study the effects of cutting parameters on the surface roughness. As depth of cut and feed rate increased, the surface roughness also gets increased. It is concluded that GA prediction has errors in the measurement regions between 2-7%. Vimal et al. [79] realized the need for personalized products in satisfying the ever-growing needs of the consumer. This research provided a predictive model using design of experiments strategy to obtain optimized machining parameters using GA for a specific surface roughness in ball-end machining of polypropylene. The deviation of the predicted result from the measured results was found to be 8.43%. Chen Lu [80] reviewed the advantages and disadvantages of various methodologies that were employed to predict surface roughness. The author revealed that the main advantages of AI approaches were that the models created seem to be the most realistic and accurate and further added the dominance of ANN as a powerful tool, easy to use and have a good prospect for the future application.

Azlan Mohd Zain et al. [81] applied GA to find optimal cutting conditions for obtaining minimum surface roughness. The analysis of the study proved that GA technique performed better than experimental sample data, regression modeling and RSM. Daekeon Ahn et al. [82] proposed a methodology to predict the surface roughness of layered manufacturing processed parts such as sphere model and teapot model. The author arrived an accuracy level of surface roughness less than 1μm based on the
prediction accuracy results. Chakguy Prakasvudhisarn et al. [83] combined support vector machine (a machine learning technique) and PSO to predict surface roughness and to determine optimal cutting condition for the roughness specification. PSO was found to be an effective and efficient algorithm by robustly finding near optimal and consistent results with short computer code and quick convergence. Paulo Davim et al. [84] studied the influence of cutting parameters on surface roughness in Medium Density Fibreboard (MDF) milling. The authors concluded that with appropriate cutting parameters, it is possible to obtain surface with $R_a$ less than 10 $\mu$m. Further, the milling tests showed the importance of cutting speed on the evolution of the surface roughness as a function of Material Removal Rate (MRR). Yung-Kuang et al. [85] applied design of experiments to optimize parameters in end milling high-purity graphite under dry machining. Dimensional accuracy and surface roughness were studied. Mathematical predictive model was developed using regression analysis. The feed rate was found to be the most significant factor and for a low feed rate, it increased the flank wear of the tool but improved surface quality. Wen-Hsien et al. [86] used ANFIS with GA to predict the surface roughness in end milling process. The authors have also used Hybrid Taguchi-Genetic Learning Algorithm (HTGLA) in ANFIS to determine optimal parameters to minimize error. Experimental results showed that the prediction error of the HTGLA based ANFIS approach is 4.06%, which outperformed the prediction error 4.17% from ANFIS method given in the Matlab toolbox. Eyup Sabri [87] discovered the role of step over ratio in surface roughness prediction studies of end milling operations. Experiments were conducted and two ANN structures were constructed; one with considering step over ratio and the other without considering step over ratio. Average RMS error of the
ANN model considering step over ratio is 0.04 and without considering is 0.26. So the first model proved to be capable of predicting surface roughness while the second model has remarkable deviations from the experimental values. Devi Kalla et al. [88] studied the machining of carbon fiber reinforced polymers in a helical end mill and developed a methodology for predicting the cutting forces by transforming specific cutting energies from orthogonal to oblique cutting. Predictions were in good agreement with the experimental data in unidirectional laminate but lesser agreement in multidirectional laminate. Ilhan Asilturk et al. [89] implemented full factorial design of experiment to increase the confidence limit and reliability of the experimental data during turning. The authors compared the multiple regressions and neural network based models with the statistical methods and found that ANN model could estimate with higher accuracy when compared to the other methods. Azlan Mohd Zain et al. [90] discussed the utilization of ANN for predicting the surface roughness in the milling process. Based on the experiments conducted, the author concluded that the use of high speed and low feed and rake angle is highly recommended for better surface finish. The authors have suggested that AI approaches have the potential to be applied for optimization problems.

Tongchao et al. [91] established empirical models for cutting force and surface roughness in milling using four factor-four level orthogonal experiments. The results of ANOVA indicated that the linear model best fits the variation of cutting force while the quadratic model best described the variation of surface roughness. Surface roughness under some cutting parameters is less than 0.25 µm which showed that finish milling is an alternative to grinding process in die and mold industry. Feng Jiang et al. [92] analyzed the effect of the cutting parameters on surface roughness in different cooling
and lubrication conditions. The surface roughness under Minimum Quantity Lubricant (MQL) was the best while dry cutting condition was the worst. The author concluded that the experimental results showed good agreement with the estimated results using the proposed exponential and quadratic model. Angus Jeang [93] determined the optimal cutting parameters required to minimize the cutting time while maintaining an acceptable quality level. The equation for predicting cutting time was determined by CATIA software along with response surface methodology. The proposed approach could produce automatic product and process design that may lead to cost reduction and quality improvement. Jawahir et al. [94] presented a method for determining the chip breakability and the achievable surface roughness for the given chip groove, work material and a set of cutting conditions. Chip breakability, surface roughness and specific cutting pressure are shown to be the most significant machinability parameters to be considered in a finish turning operation. Chua et al. [95] developed relations between the tool life, cutting force, power consumption and the cutting conditions using multiple regression analysis through factorial design of experiments. Based on the analysis, it was found that the tool life model is dependent on depth of cut while the cutting force and power consumption models are dependent on speed, feed and depth of cut. Yang et al. [96] used Taguchi method to find optimal cutting parameters for turning operations and employed ANOVA to investigate the cutting characteristics of steel bars. The authors found the optimal cutting parameters and the key cutting parameters that affect the cutting performance. The improvement of tool life and surface roughness from the initial cutting parameters to the optimal cutting parameters was about 250%. Experimental results confirmed the effectiveness of the proposed approach. Janez Kopac et al. [97]
stressed the importance of optimization of cutting parameters in any finish machining. The examples were analyzed in workshop planning, optimized cutting conditions and near-net-shape technology. All the three plans were valid in case of sequential phases of machining operations. The savings in machining costs were not so distinct because of the use of high quality and more expensive tools, but they were significant in connection with the quality of the machining parts. Janez Kopac et al. [98] analyzed the influences of the machining parameters on surface roughness. The statistical design and analysis of experiments were used for assessing the interaction in the fine turning process. The experimental result gave the appropriate machining parameters to be selected for various combination of tool-work piece material. The authors have explained the result of choosing parameters randomly without any experimentation and also the need for having a large nose radius for achieving low surface roughness. Nian et al. [99] employed orthogonal array, multi-response signal-to-noise ratio and ANOVA to study the performance characteristics in turning operations. Experimental results were provided to illustrate the effectiveness in using Taguchi method. The author concluded that the tool life, cutting force and surface roughness could be improved simultaneously using the proposed approach instead of engineering judgement. Cheung et al. [100] established and evaluated a model-based simulation system for analyzing the surface roughness in ultra-precision diamond turning. The analysis includes the effects of process parameters, tool geometry and relative vibration between the tool and work piece. It was found that the system can accurately predict the surface roughness under various cutting conditions.

Lee et al. [101] described the use of polynomial network to construct the machining database in turning operation. The relationships between the cutting
parameters and the tool life, surface roughness and cutting force were accurately correlated by a self-organizing adaptive modeling technique. Experimental results showed that the machining database has a high accuracy in the prediction of cutting performance in turning operation. Paulo Davim [102] studied the influence of cutting conditions on the surface finish in turning operation. Taguchi based machining experiments were performed and the work pieces were evaluated using two different profilometers. The correlations were obtained by multiple linear regressions and finally concluded that cutting velocity has greater influence on roughness than feed and the depth of cut has no significant influence on the roughness. The results obtained proved that the error in the proposed approach in prediction was lower than geometrical theoretical model. Paulo Davim et al. [103] proposed GA to select optimum cutting conditions in turning and drilling aluminium matrix composites. The obtained results show that machining was perfectly compatible with the cutting conditions for cutting time of industrial interest and in agreement with the optimal machining parameters. Numerical and experimental models based on GA are a matter of scientific interest and large industrial applications. Suresh et al. [104] dealt with the study and development of a surface roughness prediction model for machining mild steel using RSM. GA was used to give minimum and maximum values of surface roughness and their respective optimal machining conditions. Yongjin et al. [105] used fuzzy adaptive modeling technique to predict surface roughness. The approach completely eliminated the expensive and time consuming experimental data and also avoided empirical equations, as they are sensitive to specific domain applications. Usage of fuzzy rule enables the implementation of human expert knowledge to control the process variations. Anselmo et al. [106] found
cutting conditions, which made tool life in dry cutting closer to that obtained with fluid without affecting the surface roughness and without increasing the cutting power. The cutting fluid is avoided due to ecological and human health problems. The authors concluded the need to reduce cutting speed, increase feed and nose radius to avoid the cutting fluid from the process. Shinn-Ying et al. [107] proposed ANFIS to establish the relationship between the surface image and the actual surface roughness. Based on this approach, surface roughness can be predicted using the optimal cutting parameters. Experimental results showed that the proposed ANFIS-based method outperforms the existing polynomial network-based method in terms of modeling and prediction accuracy. The advantages of the proposed method were non-contact measurements, ease of automation and high accuracy. Janez Kopac et al. [108] determined optimal cutting conditions for achieving desired surface roughness with a minimal number of experimental runs. The results revealed the fact that the majority of machining processes are performed outside the optimal cutting conditions, which has an essential impact on the process efficiency and the direct costs of machining. Risbood et al. [109] explored the possibility of predicting surface finish and dimensional deviation by measuring forces and vibration using neural networks. For non-slender jobs, dimensional deviation is insignificant. It was observed that some statistical variation in job quality is invariably present. Hence, in few cases, the predicted values differed considerably from the measured values. Therefore, it was suggested that soft computing techniques were preferred to account for uncertainties and imprecision. Benardos et al. [110] presented the various methodologies and practices employed for the prediction surface roughness. Each approach with its merits and demerits were outlined. The present and the future trends
were also discussed. The approaches were discussed based on machining theory, experimental investigations, design of experiments and AI. The advantages of AI approaches were that they are more realistic and accurate. Moreover, particularities of equipment used and real machining phenomena are taken into consideration. In this study, surprisingly, a combined effort of both AI and analytical modeling to validate the theoretical models was not found in the literature.

Paulo Davim [111] studied the influence of cutting conditions on tool wear while turning metal matrix composites. Taguchi’s design of experiment was followed and an orthogonal array and ANOVA were used to investigate the cutting parameters. These correlations were obtained by multiple linear regressions and finally confirmation tests were performed to compare the results of experiments and correlations. The influence of cutting velocity was 42.3%, cutting time was 29.6% and feed was 10.2% on tool wear. The influence of feed was 32.5%, cutting velocity was 28.7% and cutting time was 20.8% on surface roughness. Nandi et al. [112] developed an expert system based on Fuzzy Basis Function Network (FBFN). GA based training with the help of data taken from an empirical expression is adopted. Results of the developed FBFN were compared with those of real experiments and those of empirical expression were also made. The developed FBFN was found to predict surface finish in ultra-precision turning with quite reasonable accuracy. Noordin et al. [113] presented the findings of an experimental investigation of the effect of feed rate, Side Cutting Edge Angle (SCEA) and cutting speed on the surface roughness and tangential force in turning steel. ANOVA revealed that feed is the most significant factor influencing the surface roughness followed by SCEA, while cutting speed provided secondary contribution to the tangential force. The
quadratic model developed using RSM was reasonably accurate and can be used for prediction of performance measures. Yue Jiao et al. [114] developed Fuzzy Adaptive Network (FAN) for surface roughness model in turning operations. FAN could continuously improve the initially obtained rough model based on the daily operating data. To illustrate this approach, the influence of machining parameters on surface roughness was established and then the model is verified by the results of pilot experiments. Finally, a comparison with the results based on statistical regression was provided. Wassilla Bouzid [115] developed empirical models for tool life, surface roughness and cutting force for calculating optimum cutting conditions in turning to achieve maximum production rate. The coefficients of these models were determined based on the experiments. The author explained the relation of feed to the roughness, which depends on cutting speed and finally concluded that the proposed method was capable of selecting the appropriate conditions. Mohamed Dabnum et al. [116] described a surface roughness model for turning glass-ceramic material using factorial design of experiment and RSM. The author concluded that a small number of designed experiments are required to generate much useful information for developing the predicting equation of surface roughness. Feed rate is the main influencing factors on roughness followed by cutting speed and depth of cut. The surface roughness contours are useful in determining the optimum cutting conditions for a given surface roughness. Tugrul Ozel et al. [117] utilized NN to predict the surface roughness and tool flank wear over the machining time for variety of cutting conditions in finish turning. The trained data set from measured surface roughness and tool flank wear were used to predict surface roughness and tool flank wear for other cutting conditions. After comparison, the predictive NN model was
found to be better than regression model. Segonds et al. [118] studied the characteristics behavior of slender work pieces under the effect of tangential cutting force during NC turning. Experimental verification validated the proposed model and machining with another material shows how this method can be extrapolated. Abburi et al. [119] developed NN and fuzzy set theory for the prediction of surface roughness in turning process. The trained data sets were fed to a fuzzy set based rule generation module. The developed rule base was used for predicting the surface roughness for the given process variables and the vice versa was also possible. The major advantage of the present methodology is its ability to develop an accurate knowledge based system with limited amount of training and tested data, which was demonstrated by large number of validation data. Fredrik Gunnberg et al. [120] performed tests to study the behaviour of tool geometry and cutting parameters on residual stresses and surface topography while turning steel. Three models viz surface (S0), surface (S10-S50) and surface (S70-S1300) were created. Different cutting parameters have different effect on the level of residual stress generated on the surface and below the surface. Cutting speed increases tensile stress on the S0 surface and increased feed generates higher compressive stresses. Depth of cut did not affect residual stresses. More negative rake angle produces more compressive stresses.

Tzeng et al. [121] developed Taguchi dynamic approach to optimize turning parameters for producing high dimensional precision and accuracy. Factors associated with cutting tool and feed had the most significant effects on the dimensional variation of the test piece. Eight parameters such as speed, feed, depth of cut, coolant, coating type, chip breaker, nose radius and insert shape were optimized and the dimensional variation
was reduced to 45.61% of the initial conditions. The proposed method not only optimized dimensional accuracy but also improved surface roughness. Erzan Aslan et al. [122] employed Taguchi’s technique to experimentally study the behaviour of cutting parameters on flank wear and surface roughness using orthogonal array and ANOVA. Cutting speed was significantly influencing tool wear and only two interactions namely cutting speed-feed rate and feed rate-axial depth of cut have significantly influencing the surface roughness. Paulo Davim et al. [123] conducted turning experiments based on orthogonal array with prefixed cutting parameters in steel work pieces. ANOVA was employed to investigate the machinability of the work steel. The result of the tests showed that with the appropriate cutting parameters, it is possible to obtain surface roughness less than 0.8 µm that allows eliminating cylindrical grinding operations. Daniel Kirby et al. [124] discussed the development of a surface roughness prediction system for a turning operation using fuzzy-net modeling technique. Surface roughness prediction model was trained by the data given by accelerometer measurement of turning parameters and vibration data. A series of validation runs indicate that this system had a mean accuracy of 95%. Al-Ahmari [125] developed empirical model for tool life, surface roughness and cutting force for turning operations. Three data mining techniques such as regression analysis (RA), RSM and NN were used to develop the machinability model. It was found that NN model is better than RA and RSM models and in particular, RSM model was better than RA model for predicting tool life and cutting force. Chih-Wei Chang et al. [126] analyzed experimental results using Taguchi method for the identification of optimum machining conditions. The findings indicated that the rotational speed contribute 42.68% had the most dominant effect on laser assisted machining
performance, followed by feed, depth of cut and pulsed frequency. The advantage of using laser assisted machining is its ability to produce better surface quality; material removal rate and moderate tool wear than conventional machining. Gaitonde et al. [127] determined optimum amount of MQL and cutting parameters during turning to minimize surface roughness and specific cutting force. The optimization result indicated that MQL of 200ml/h, cutting speed 200m/min and a feed rate of 0.05 mm/rev are essential to simultaneously minimize surface roughness and specific cutting force. Jenn-Tsang Horng et al. [128] attempted to model the machinability evaluation through the RSM. The effects of cutting speed, feed rate, depth of cut and tool corner radius were studied to reduce tool flank wear and surface roughness. Central Composite Design (CCD) and ANOVA were employed for analysis. Sequential Approximation Optimization (SAO) was used to find optimum values of machining parameters. Results show that flank wear was influenced by cutting speed and interaction effect of feed rate and nose radius on surface roughness. The optimal machining parameters reduced 9.25% flank wear and 8.74% surface roughness when compared to the initial machining parameters. Lalwani et al. [129] investigated the effect of cutting parameters on feed force, thrust force, cutting force and surface roughness in finish turning. Experiments were designed based on RSM and central composite method. Depth of cut is dominant to feed force and thrust force followed by feed rate, whereas feed is dominant to cutting force followed by depth of cut. Feed is the major influencing factor with respect to surface roughness followed by cutting speed and depth of cut. Aman Aggarwal et al. [130] optimized cutting speed, feed, depth of cut, nose radius and cutting environment to achieve favourable tool life, cutting force, surface roughness and power consumption using Principal Component Analysis (PCA).
Orthogonal array and Taguchi method was used for conducting the experiments. It was concluded that middle level speed and nose radius, lower level feed and depth of cut will always yield optimal result.

Birhan Isik [131] examined surface roughness of unidirectional Glass-Fiber Reinforced Plastic (GFRP) composite on the basis of depth of cut, feed rate, tool geometry and cutting speed. The conclusions drawn from this study are; the surface roughness decreases with increase in cutting speed and tool radius; surface roughness increases with increase in feed and rake angle. Increase in depth of cut does not have important effect on surface roughness. Thangavel et al. [132] presented fractional factorial experimentation approach to study the effect of turning parameters on surface roughness. The prediction model was created by RSM technique. Lesser depth of cut did not significantly affect the roughness but increase in depth of cut has improved surface finish. The most significant interactions were found between feed and nose radius. Paulo Davim et al. [133] developed surface roughness model using ANN to investigate the effects of cutting conditions. The analysis revealed the cutting speed and feed rate have significant effects in reducing the surface roughness while depth of cut has the least effect. The minimal surface roughness can be obtained with the combination of low feed rate and high cutting speed. Sahin [134] used orthogonal design, signal to noise ratio and analysis of variance for determining cutting parameters on tool life. The author concluded that percentage contribution of cutting speed, tool hardness and feed rate on tool life are 41.63, 32.68, 25.22 respectively. Further, the author compared the tool life between ceramics and Cubic Boron Nitride (CBN) tools. The author found that CBN tool performed better than ceramic tool. Cemal Cakir et al. [135] examined the effect of
cutting parameters on surface roughness through the mathematical model developed by turning experiments. Additional investigation was carried out using two well known coating layers on the carbide inserts. The total average error of the model was determined to be 4.2% and 5.2% for insert 1 and insert 2 respectively, which proved the reliability of the equations established. Muammer Nalbant et al. [136] investigated the machining using uncoated, Physical Vapour Deposition (PVD) and Chemical Vapour Deposition (CVD) coated cemented carbide inserts. Keeping depth of cut as constant, machining experiments were conducted using cutting speed and feed. The training and test data of the ANN were prepared using experimental patterns for the surface roughness. In the input layer of ANN, the coated tools, feed rate and cutting speed values were used while at the output layer the surface roughness values are used. The experimental values and ANN predictions were compared by statistical error analyzing methods. In the field of surface roughness prediction, ANN is a good alternative to conventional empirical modeling based on linear regressions. Muthukrishnan et al. [137] studied the surface roughness of composite bars under different cutting conditions. Experimental data were tested with ANOVA and ANN techniques. ANOVA revealed that feed rate has highest influence (51%) on surface roughness followed by depth of cut (30%) and cutting speed (12%). The results of ANN model showed close matching between the model output and the directly measured surface roughness. Durmus Karayel [138] presented neural network approach for the prediction and control of surface roughness in turning operation. The desired surface roughness was entered in the control system and the controller determined the cutting parameters. The obtained surface roughness value was fed back to the comparison unit and was compared to the reference value and the
difference was sent to the controller. This continued until the permitted value was obtained and its corresponding cutting parameters were sent to the CNC turning system. In conclusion, ANN was able to predict suitable cutting parameters for a certain surface roughness prior to the machining operation. Tian Syung Lan et al. [139] proposed Taguchi method to optimize cutting speed, feed, depth of cut and tool nose runoff to achieve required surface roughness and tool life. Confirmation experiments were conducted to indicate the effectiveness of the proposed Taguchi method. The authors contributed a satisfactory technique for improving multiple machining performances and optimizing the machining parameters in CNC turning. Chorng et al. [140] investigated the optimization of cutting parameters for CNC turning operation using Grey relational analysis and Taguchi method. Roughness average, roughness maximum and roundness were the quality targets. The depth of cut was identified to be the most influencing parameter on roughness average and cutting speed on roughness maximum and roundness. ANOVA revealed that depth of cut is the most significant factor according to the weighted sum grade of the roughness average, roughness maximum and roundness.

Nikolaos et al. [141] developed a surface roughness model using RSM for turning of femoral heads from stainless steel. First order and second order models predicting equations for surface roughness were established based on the experimental results. Depth of cut was the main influencing factor on the surface roughness. Roughness increased with increased in depth of cut and feed, but decreased with increase in cutting speed. The authors claimed that the predicted surface roughness of the samples was found close to the experimental results within a 95% confidence level. Yang et al. [142] used Differential Evolution (DE) algorithm based ANN for the prediction of surface roughness
in turning operations. The author compared the results with Back Propagation (BP) based ANN and found that the error percentage to be very close. It was also concluded that multi-objective differential evolution algorithm outperformed non-dominated sorting genetic algorithm. Vijaya Kini et al. [143] studied the effect of cutting parameters on surface roughness and MRR. Empirical model for turning GFRP are formulated using factorial experiments. Feed is the main influencing factor on roughness followed by depth of cut and cutting speed. Feed-nose radius and speed-nose radius interaction have the highest influence. For MRR, depth of cut was main factor followed by nose radius. Speed-nose radius had the highest influence. The contour plots were useful in determining the optimum cutting conditions to obtain desired surface roughness and material removal rate.

2.3 Conclusion

In this chapter, efforts were taken to review the literature on machining problems that have used various optimization techniques. The papers were classified based on the study of optimization techniques in various machining problems, implementation of various optimization methods in milling and turning operation. This chapter also summarizes the current state-of-the-art and the limitations existing in the previous approaches. Some of the limitations reviewed are taken care of in the present research work. In the succeeding chapter, the pilot experiments conducted based on design of experiments in milling and turning operation using CNC machine and surface roughness tester are discussed.