Multi Response Optimization of CNC End Milling - Review and Scope

Prajina N V[1] Dr. T D John[2]
[1]Assistant Professor [2]Professor
[1]LBS College of Engineering, Kasaragod, India [2] Govt. College of Engineering, Kannur (Rtd.), India

Abstract— CNC end milling is the most important milling process, widely used in the manufacturing industries due to its capability of producing complex geometric surfaces with responsible accuracy and surface finish along with flexibility and versatility. In order to build up a bridge between quality and productivity and to achieve the same in an economic way, the present study highlights optimization of CNC end milling process parameters to provide good surface finish and high material removal rate with less power consumption. In manufacturing context, multi-response optimization of machining processes is one of the most important areas of research to find out the best process environment for any machining operation. In this review literature survey for multi response optimization of CNC end milling is conducted and introduce a hybrid metaheuristic method as GA & MLPNN, and a combination of Taguchi, GRA and KPCA for multi response optimization.

Keywords: Multi response optimization, CNC end milling, GA, MLPNN, Taguchi, GRA, KPCA

I. INTRODUCTION

Todays' fast changing manufacturing environment requires the applications of optimization techniques in manufacturing processes to effectively respond to severe competitiveness and to meet the increasing demand of customized quality product. Proper selection of machining parameter is an important step in automated process planning in order to increase the productivity, improve quality and to reduce the cost. Cutting forces provide the basis for surface accuracy prediction and improvement, tool wear rate, the energy consumption within the machine tool depending on power consumption and operating time. Surface roughness is a mechanism of the technological quality of a product and a factor that greatly influences the manufacturing cost and quality. In this paper literature survey for multi response optimization of CNC end milling is done and it is found that there is a gap in simultaneous optimization of cutting forces, surface roughness and machining time. This work introduces a hybrid metaheuristic method as genetic algorithm and multi-layer perspective neural network and a combinatorial method as Taguchi, Grey Rational analysis (GRA) and Kernel Principal Component Analysis (KPCA) for multi response optimization.

II. LITERATURE SURVEY

Norfadzlan Yusup et..al[1] gives an overview and the comparison of the latest five year researches from 2007 to 2011 that used evolutionary optimization techniques to optimize machining process parameter of both traditional and modern machining. Five techniques are considered, namely Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) algorithm. Literature found that GA was widely applied by researchers to optimize the machining process parameters. In terms of machining performance, surface roughness was mostly studied with GA, SA, PSO, ACO and ABC evolutionary techniques. Sidda reddy et. al [2] in their study, minimization of surface roughness has been investigated by integrating design of experiment method, Response surface methodology (RSM) and genetic algorithm. To achieve the minimum surface roughness optimal conditions are determined. V. S. Thangarasu et. al [3] made an attempt to optimize the surface roughness and MRR of end milling by Taguchi based response surface methodology. This invites a multi-objective optimization problem which has been solved by design of experiment based optimization. The methodology has been found useful in optimization of more number of responses simultaneously with equal weight age. Bharat Chandra routara et.al [4] highlights a multi-objective optimization problem by applying utility concept coupled with Taguchi method through a case study in CNC end milling of UNS C34000 medium leaded brass. The study aimed at evaluating the best process environment which could simultaneously satisfy multiple requirements of surface quality. By Sanjit Moshat et. al [5] an attempt has been made to optimize quality attributes through surface roughness & MRR in a manner that these multi-criterions could be fulfilled simultaneously up to the expected level. This invites a multi-objective optimization problem which has been solved by PCA based Taguchi method. Patel K.P.et. al [6] experiments are conducted on AL 6351 –T6 material with four factors and five levels and try to find out optimum surface roughness by using Taguchi method. This paper attempts to introduce how Taguchi parameter design could be used in identifying the significant processing parameters and optimizing the surface roughness of end-milling operations. Ilhan et.al [7] illustrates the multi response optimization of cutting conditions and mathematical modeling of surface roughness of CNC turning parameters by Taguchi based response surface methodology. Anil Gupta et.al [8]

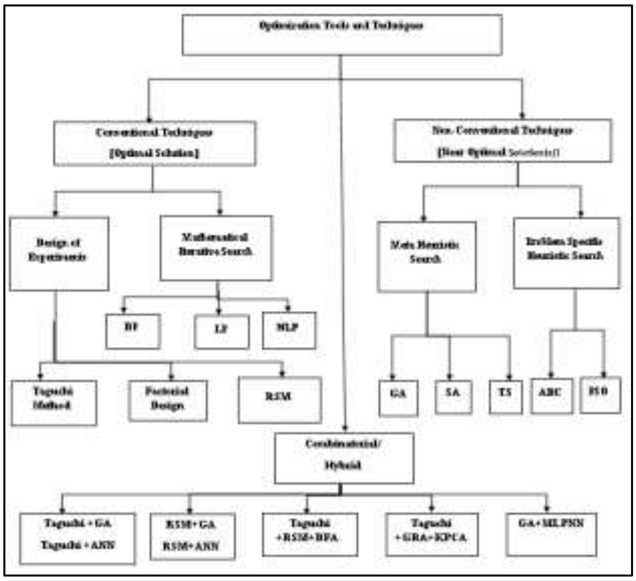

Fig. 1: Classification of Optimization Tools and Techniques.

presents the application of Taguchi method with logical fuzzy reasoning for multiple output optimization of high speed CNC turning of AlSi P-20 tool steel using TiN coated tungsten carbide coatings. The machining parameters (cutting speed, feed rate, depth of cut, nose radius and cutting environment) are optimized with considerations of the multiple performance measures as surface roughness, tool life, cutting force and power consumption. Amardeep S. Kang, Gurmeet S.et.al [15] highlights optimization of CNC end milling process parameters to provide good surface finish and high Material Removal Rate. The surface finish of the machined surface has been identified as quality attribute whereas MRR has been treated as performance index directly related to productivity. Attempt has been made to optimize quality and productivity in a manner that these multi-criterions could be fulfilled simultaneously up to the expected level. Multi-objectives related to quality and productivity has been accumulated to evaluate an equivalent single quality index (called grey relational grade); which has been optimized finally by Taguchi based Grey rational method. This work has successfully demonstrated the application of Taguchi based grey relational analysis for multi response optimization of process parameters in End milling of AISI H11 steel. Mahavir V.Chhabada et.al [17] in their paper multi-response optimization of machining parameters on CNC milling of EN 19 Alloy Steel with TiALN Coated Milling Cutter using GRA. Two different conditions have been taken to study comparative study of experimentations., a) Compressed air coolant b) Oil coolant condition It is observed that compressed air coolant condition gives better surface finish than oil coolant. Raneen Abd Ali, Mozamme Mia et.al [19] found that the tool path strategy has a significant influence on the end outcomes of face milling. As such, the surface topography respective to different cutter path strategies and the optimal cutting strategy is discussed in detail. The application and selection of tool path types and directions are crucial issues in the milling optimization of toolpath would contribute to improving the sufficiency of the milling process of the die and aerospace industries. Recently, due to increasing demand for manufacturing the complex parts with a large scale, the robotic milling system is used to perform this function. Khan A. Jamil M [2019] et.al has done the multi-objective optimization of energy consumption and surface quality in nanofluid SQCL assisted face milling. Multi-objective optimization was used to enhance the surface roughness and energy consumption in the face milling process. The results revealed that the reduction in the energy consumption was about 20.7% when using nano -fluid assisted milling. M. S. Sukumar, P. Venkata et.al [21] Taguchi Method has been used to identify the optimal combination of influential factors in the milling process. Milling experiment has been performed on Al 6061 material, according to Taguchi orthogonal array (L16) for various combinations of controllable parameters viz. speed, feed and depth of cut. An Artificial neural network (ANN) model has been developed and trained with full factorial design experimental data and a combination of control parameters have been found from ANN for the surface roughness (Ra) value, obtained from confirmation test. Experiments were carried out as per the Taguchi experimental design and an L27 orthogonal array was used to study the influence of various combinations of process parameters on surface roughness (Ra) and material removal rate (MRR) by Naresh N.et.al [13] As a dynamic approach, the multiple response optimization was carried out using grey relational analysis (GRA) and desirability function analysis (DFA) for simultaneous evaluation. The objective of the present work is to optimize process parameters namely, cutting speed, feed rate, and depth of cut in milling of AISI 304 stainless steel.

From the literature review it is identified that there is no work in multi response optimization of CNC end milling using combination of Taguchi, GRA and KPCA. It is clear from literatures that better prediction value is obtained from GA and ANN. So this paper introduces multi response optimization by GA and MLPNN.

III. COMBINATION OF TAGUCHI, CRA AND KPCA

A. Taguchi Method

Taguchi method is an ideal method to improve product quality, promote technological innovation, and increase the competitiveness of enterprises, which is helpful to develop low-cost and high-quality products within a relatively short time. To quantitatively describe the product quality loss, the concept of ‘‘quality loss function’’ is put forward and the signal-to-noise ratio (S/N) for each quality characteristic is applied to evaluate the robustness of the designed process parameters. There are three types of quality characteristics: the lower the better, the higher the better, and the nominal the best.

1) Lower the better is used when smaller value is desired S/N ratio:

$$\eta_i(k) = -10 \log \frac{1}{n} \sum_{j=1}^{n} y_{ij}^2 \ (k) \tag{3.1}$$

2) Larger the better is used when more substantial value is desired. S/N ratio:

$$\eta_i(k) = -10 \log \frac{1}{n} \sum_{j=1}^{n} 1/y_{ij}^2 \ (k) \tag{3.2}$$

3) Nominal the best is used when variation about the nominal or target value is minimum as shown by the S/N ratio given as:

$$\eta_i(k) = 10\log(\frac{\mu^2}{\sigma^2}) \quad \text{or} \quad \eta_i(k) = -10 \log (\sigma^2) \tag{3.3}$$

where $y_{ij}(k)$ is the observed data of the k^{th} performance index at the i^{th} experiment at the j^{th} trial; i = 1, 2…, m; j = 1, 2,.., n; k = 1, 2,…, s; n is the number of repetitions of the same experiment μ is the mean and σ is the variance.

B. Principle of GRA

Grey system theory is a systematic scientific theory to solve the problems with insufficient, poor, or uncertain information. Actually, the optimization problem of multiple performance indexes with lower-the-better characteristics itself contains a certain degree of uncertainty and ambiguity. Therefore, the grey system theory is very suitable for solving this multi response optimization problem. Based on this theory, GRA is carried out to evaluate the degree of correlation between the observed data (comparability sequence) and the desired value (reference sequence), and transform multiple performance characteristics into a single grey relational grade (GRG) value as the optimization criterion.

In order to avoid the inconvenience caused by different dimensions in the observed data and simplify the calculation, the first step for GRA is grey relational generating, that is to normalize these observed data to the range [0, 1]. Because S/N refers to the ratio between the desired part and the noise part, the larger S/N is the better, regardless of the nature of quality characteristics, S/N for each quality characteristic is normalized by the following equation:

$$\eta_i^*(k) = \frac{\eta_i(k) - \min \eta_i(k)}{\max \eta_i(k) - \min \eta_i(k)} \qquad (3.4)$$

where $\eta_i^*(k)$ the k^{th} comparability sequence after the process of grey relational generating ; max $\eta_i(k)$ and min $\eta_i(k)$ are the maximum and minimum values of the k^{th} sequence of S/N. Due to the fact that the larger normalized value corresponds to the better performance, the maximum normalized value is considered as the reference sequence, denoted by $\eta_0^*(k) = 1$.

Then the relationship between the observed data and the desired value can be clarified clearly by calculating the GRC, ξ between the comparability sequences and the reference sequence. The ξ for the k^{th} performance index at the i^{th} experiment can be expressed as:

$$\xi_i(k) = \frac{\min_k \Delta_i(k) + \rho \max_i \max_k \Delta_i(k)}{\Delta_i(k) + \rho \max_i \max_k \Delta_i(k)}. \qquad (3.5)$$

where $\Delta_i(k) = |\eta_0^*(k) - \eta_i^*(k)|$ is the k^{th} deviation sequence in absolute value between the reference sequence and the k^{th} comparability sequence; distinguishing coefficient $\rho \epsilon (0, +\infty)$ is a factor affecting the resolution of correlation analysis directly, which determines the distribution of GRC. The smaller the distinguishing coefficient, the greater the resolution. At last, a single GRG value, γ for the i^{th} experiment can be obtained by a weighted sum of the above GRC with the following formula:

$$\gamma_i = \sum_{k=1}^{s} \omega_k \xi_i(k) \qquad (3.6)$$

where ω_k denotes the weight of the k^{th} performance index, which meets $\sum_{k=1}^{s} \omega_k = 1$. Usually, equal weights are artificially set. The higher γ indicates the closer relational degree between the observed data and the desired value, which means that the corresponding combination of process parameters is closer to the optimal. At this point, the multi-response optimization problem has been fully transformed into a single objective optimization problem with γ as the optimization criterion. However, due to the non-linearity between the performance indexes, this optimization criterion is not very reasonable. In order to reveal the principal features of these performance indexes, KPCA will be introduced and an improved γ will be proposed, with the corresponding weights also obtained in the next section.

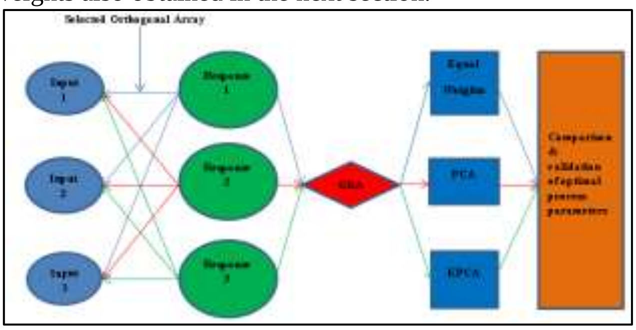

Fig. 2: Workflow diagram of multiresponse optimization using Taguchi, GRA and KPCA

C. Principle of KPCA

PCA is a linear mapping method that ignores the correlation of higher than the second order between the performance indexes. Therefore, the extracted principal features are not optimal, and the effect of PCA is affected to some extent. To solve this problem, KPCA is adopted. As a nonlinear expansion algorithm of PCA, KPCA uses the kernel-based technique to extract the principal components. That is to say, the principle of KPCA is that: at first, map the original vector to the high dimensional kernel space F through mapping function w, and then perform PCA. Here, the original vector refers to the above GRC for each performance index. The specific implementation steps for KPCA [18].

1) Constituting the original performance index array:

$\xi_i(k)$; i=1,2….,m; k=1,2….,s

$$\Xi = \begin{bmatrix} \xi_1(1) & \xi_1(2) \cdots & \xi_1(s) \\ \xi_2(1) & \xi_2(2) \ldots & \xi_2(s) \\ . & . & . \\ . & . & . \\ . & . & . \\ \xi_m(1) & \xi_m(2) \ldots & \xi_m(s) \end{bmatrix} \qquad (3.7)$$

where m and s are the number of experiments and performance indexes respectively.

2) Selecting the kernel function w and calculating the kernel matrix K

$$K_{\mu\nu} = K(\Xi_\mu, \Xi_\nu) = \langle \psi(\Xi\mu), \psi(\Xi\nu) \rangle$$
$$= \exp(-\|\Xi\mu - \Xi\nu\|^2 / (2\sigma^2)) \qquad (3.8)$$

Where $\Xi\mu$ and $\Xi\nu$ denote the performance index vector at the μ^{th} and νt^h experiment μ = 1,2,..,m; ν = 1,2,… ,m

3) Centering the kernel matrix K

$$K^*_{\mu\nu} = K_{\mu\nu} - \frac{1}{m}\left(\sum_{\omega=1}^{m} K\mu\omega + \sum_{\tau=1}^{m} K\tau\nu \right) + \frac{1}{m^2}\left(\sum_{\omega,\tau=1}^{m} K\tau\omega \right)$$

(3.9)

*4) Determining the eigenvalues and eigenvectors from the above centered matrix K**

$$\lambda_i^* \ \alpha_i = K^* \alpha_i \qquad (3.10)$$

where λ_i is the i^{th} eigenvalue, i =1, 2, … ;m ; α_i = (α_{i1} , α_{i2} , ….. α_{im})^T corresponding eigenvector. Assuming that $\lambda_1^* \geq \lambda_2^* \ldots.. \geq \lambda_m^*$, and the eigenvectors are normalized.

5) Calculating the contribution rate c(k) of the first s eigen values as the weight of the performance index and extracting the corresponding kernel principal components $p_i(k)$.

$$c(k) = \lambda_k^* / \sum_{i=1}^{m} \lambda_i^* \qquad (3.11)$$

$$p_i(k) = \sum_{j=1}^{s} \xi_i(j) \alpha_{kj} \qquad (3.12)$$

All the eigenvalues are arranged in descending order with respect to variance. Usually, the accumulative contribution rate of the first three eigenvalues reaches over 90% which means the first three kernel principal components hold the most amount of information in the data. The proposed new optimization criterion, c(k) can be constructed as:

$$\gamma_k(i) = \sum_{k=1}^{s} |p_i(k)| c(k) \qquad (3.13)$$

Based on this optimization criterion, the effect of each factor at different levels can be evaluated, and the optimum parameter combination corresponding to the maximum γ_k is obtained, which can be compared with that obtained from γ.

IV. HYBRID GA AND MLPNN

A. *Modelling of GA and Neural Network*

A well trained ANN is well generalized which gives proper output for those input also which has never been encountered with the network while training. Training a network is nothing but to set optimum weights of the links of two neurons. These weights, activation function, number of layers and neurons in a layer decide how well nonlinearity can be defined [21]. The diversity of data can enhance the learning and generalisation ability of neural network which can be obtained with a reduction in the similarity of data. Therefore, the data was normalized within the range [0,1] for both input and output data using equation:

$$X_n = \frac{(Y_{max} - Y_{min})}{(X_{max} - X_{min})}(X - \boldsymbol{X_{min}}) + Y_{min} \qquad (4.1)$$

Where, X_n, is the normalised value of variable X; X_{max} and X_{min} are the maximum and minimum of X respectively; Y_{max} and Y_{min} are the maximum and minimum of the normalized targets respectively[14].

B. *Multilayer Perception Neural Network (MLPNN)*

MLPNN consists of neurons in the input layer corresponding to the number of process parameters. The output layer consists of a single neuron, which corresponds to the response. A single hidden layer with N_h (number of hidden neurons) was used. These also hold weights biases in the hidden layer (w_{ij}, b_{ij}) and an output layer (w_{ik} b_{ik}). Sigmoid activation function was selected as activation function for both inputs and outputs. For training purpose, back propagation (BP) algorithm was used in MLPNN. Also other factors like learning rate(γ) and momentum rate(μ) were chosen. The performance of MLPNN was validated through Mean Square Error (MSE) as given in equation:

$$\text{MSE} = \frac{\boldsymbol{Sum(Y - targets)^2}}{\boldsymbol{length(Y)}} \qquad (4.2)$$

Where Y is the net of input values and target is the expected output value.

The learning rate parameter was used during the adjustment of weights and biases to control the speed of learning algorithm and activation functions (hyperbolic tangent sigmoid and log sigmoid). Similarly, the momentum rate and number of hidden neurons also greatly affect the outcome of MLPNN.

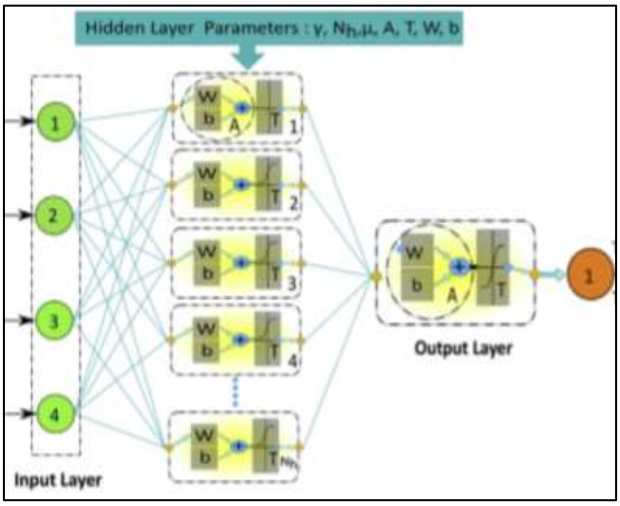

Fig. 4: Structure of MLPNN

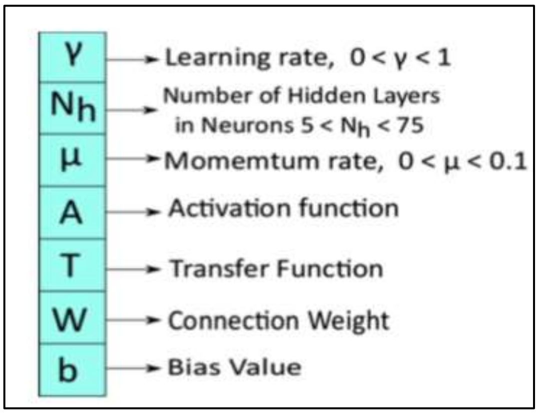

Fig. 3: Parameters of MLPNN

C. *Multi-Layer Perspective Neural Network optimized by Genetic Algorithm (MLPNN-GA)*

Conventional back propagation algorithm has a significant drawback that is to be trapped in local minimum. Critical features of GA are global searching and evaluation of parameters. Natural selection theory and evolution biology (survival of the fittest) theories were used to the global level solution passes through a selection of individual cross over and mutation. Network training was used for evaluation of MLPNN initial weights and biases. Exchange of weights and biases used to communicate between GA and MLPNN. A random group of weights and biases [w, b] primarily initiated by MLPNN program is shown in fig.5. which forms the population for GA. The current population is generated based on a generator. The fitness function is the difference between predicted output value and the actual output value. If the overall mean square error of GA is less than 0.005only, then the parameters are accepted. The equation below is used to calculate weights and biases.

$$N_w = (I_n + 1)*N_h + (N_h + 1)*O_p \qquad (4.3)$$

Where N_w is an array of weights and bias, I_n is the number of neurons in input layer, N_h is the number of neurons in the hidden layer and O_p is the number of neurons in the output layer.

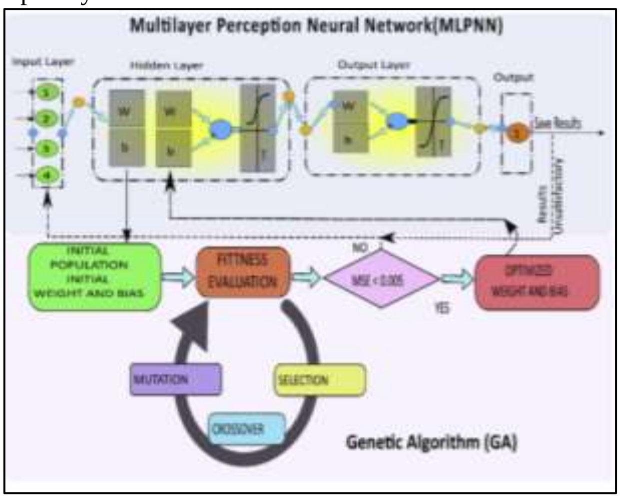

Fig. 5: Structure of MLPNN and GA

V. CONCLUSIONS

In order to meet the demand of todays' fast changing revolutionized industry efficient use of energy is an important factor. For reducing the energy consumption, increase the quality of product and fast response to the customers' demand multi response optimization of cutting force, surface roughness and machining time is to be conducted. CNC end milling is the most widely used method for producing complex geometric surfaces with enough accuracy, versatility and flexibility.

Literature survey reveals that a lot of methods are emerged for multi response optimization of CNC end milling as combination of design of experiments and metaheuristic methods.

Among those Taguchi based methods, RSM and desirability function, hybrid metaheuristic and ANN give better validation for multi response optimization of CNC end milling. Combination of Taguchi, GRA and KPCA, hybrid GA-MLPNN are two methods that are to be included in this area.

Non linearity in multi response optimization cannot be neglected. Taken into consideration of non-linearity of cutting process, a new method based on GRA and KPCA was proposed for the multi response optimization problem.

The proposed MLPNN & GA model will provide higher accuracy than other methods. The predicted values obtained by this method is very close to that obtained from the experimental results.

Application of nano fluids and optimization of tool path strategy are emerging concepts for efficient ultilisation of energy and to meet the customized quality product.

REFERENCES

[1] Norfadzlan Yusup , Azlan Mohd Zain , Siti Zaiton Mohd Hashim; Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007–2011); Expert Systems with Applications 39 (2012) 9909–9927.
[2] B. Sidda Reddy, J. Suresh Kumar and K. Vijaya Kumar Reddy; Optimization of surface roughness in CNC end milling using response surface methodology and genetic algorithm; International Journal of Engineering Science and Technology Vol. 3, No. 8, 2011, pp. 102-109
[3] V.S.Thangarasu, R.Sivasubramanian; Study of High Speed CNC Milling of Aluminium: Optimization of Parameters using Taguchi Based RSM; European Journal of Scientific Research ISSN 1450-216X Vol.7
[4] Bharat chandra routara, Saumya darsan mohanty, Saurav datta, Asish bandyopadhyay and Siba sankar mahapatra; Optimization in CNC end milling of UNS C34000 medium leaded brass with multiple surface roughnesses characteristics; Sadhana Vol. 35, Part 5, October 2010, pp. 619–629
[5] Sanjit Moshat, Saurav Datta, Asish Bandyopadhyay and Pradip Kumar Pal; Optimization of CNC end milling process parameters using PCA-based Taguchi method; International Journal of Engineering Science and Technology; Vol. 2, No. 1, 2010, pp. 92-102.
[6] Patel K. P; Experimental analysis on surface roughness of CNC end milling process using Taguchi design method; International Journal of Engineering Science and Technology (IJEST); ISSN: 0975-5462 Vol. 4 No.02 February 2012.
[7] Ilhan Asiltürk a, Süleyman, Neselib Multi response optimisation of CNC turning parameters via Taguchi method-based response surface analysis; Measurement 45 (2012) 785–794.
[8] Anil Gupta, Hari Singh, Aman Aggarwal; Taguchi-fuzzy multi output optimization (MOO) in high speed CNC turning of AISI P-20 tool steel; Expert Systems with Applications 38 (2011) 6822–6828.
[9] Vishwajit D. Patil1, Prof.Mrs.S.P.Kamble, Prof.Mr.Sachin.T.Bagde; Analysis On Multi Objective Optimization of CNC End Milling Machining Parameters of (Al 2024-T4) . Journal of Emerging Technologies and Innovative Research; March 2015, Volume 2, Issue 3 JETIR (ISSN-2349-5162)
[10] Naresh N. and Rajasekhar; Multi-response optimization for milling AISI 304 Stainless steel using GRA and DFA Advances in Materials Research, Vol. 5, No. 2 (2016) 67-80.
[11] M. Rajyalakshmi1, Dr. P. Suresh Babu; A Survey on Optimization of Process Parameters in Milling, International Research Journal of Engineering and Technology (IRJET) Volume: 05 Issue: 04 Apr-2018 ISSN: 2395-0072
[12] N.L.Bhirud,R.R.Gawande; Optimization of process parameters during end milling and prediction of workpiece temperature rise, Archive of mechanical engineering vol. xiv 2017.
[13] Unnikrishna Pillai, J, Sanghrajka, I, Shunmugavel, M, Muthuramalingam, T, Goldberg, M, Littlefair G; Optimisation of multiple response characteristics on end milling of aluminium alloy using Taguchi-Grey relational approach. Meas. J. Int. Meas. Confed. 2018, 124, 291–298.
[14] A. Anarghya, D. N. Harshith, Nitish Rao, Nagaraj S. Nayak, B. M. Gurumurthy, V. N. Abhishek, Ishwar Gouda S. Patil. Thrust and torque force analysis in the drilling of aramid fibrereinforced composite laminates using R SM and MLPNN-GA. Heliyon 4 (2018).
[15] Amardeep S. Kang, Gurmeet S. Cheema and Varun Gandhi; Indian Journal of Science and Technology, Vol 10(31), ISSN (Print) : 0974-6846 ISSN (Online) : 0974-5645 Optimization of Surface Roughness and Metal Removal Rate in End Milling using Taguchi Grey Relational Analysis, August 2017.
[16] Vishwajit D Patil1,.S.P.Kamble, Sachin.T.Bagde; Analysis On Multi Objective Optimization of CNC End Milling Machining Parameters of (Al 2024-T4) , Journal of Emerging Technologies and Innovative Research , March 2015, Volume 2, Issue 3 ; JETIR (ISSN-2349-5162).
[17] Mahavir V. Chhabada1 Prof. Shailesh D. Ambekar M; Multi-Response Optimization of Machining Parameters on CNC Milling of EN 19 Alloy Steel with TiALN Coated Milling Cutter using GRA IJSRD - International Journal for Scientific Research & Development Vol. 4, Issue 05, 2016 | ISSN (online): 2321-0613
[18] Ning Li1, Yong-Jie Chen1, Dong-Dong Kong Multi-response optimization of Ti-6Al-4V turning operations using Taguchi-based grey relational analysis coupled with kernel principal component analysis1; Adv. Manuf. (2019) 7:142–154.

[19] Raneen Abd Ali , Mozammel Mia 2 , Aqib Mashood Khan 1, Wenliang Chen 1, Munish Kumar Gupta 3 and Catalin Iulian Pruncu 4,5,* Multi-Response Optimization of Face Milling Performance Considering Tool Path Strategies in Machining of Al-2024; materials-12-01013
[20] Khan A. Jamil, M.;Salonitis,K, Sarfraz S.,Zhao,W.; Multi-objective optimization of energy consumption and surface quality in nanofluid SQCL assisted face milling. Energies 2019, 12, 710.
[21] M.S. Sukumar, P.Venkata Ramaiah, A.Nagarjuna Optimization and Prediction of Parameters in Face Milling of Al-6061 Using Taguchi and ANN Approach. 12th Global congress on manufacturing and management, GCMM 2014. Science direct. Procedia Engineering 97 (2014) 365 – 371.