IJIRR

International Journal of Information Research and Review
Vol. 04, Issue, 09, pp.4466-4472, September, 2017

RESEARCH ARTICLE

COMBINED APPROACH OF PARTICLE SWARM OPTIMISATION AND TAGUCHI TECHNIQUE FOR IMPROVING PERFOMANCE AND PRODUCTION QUALITY IN INDUSTRIES USING NEURAL NETWORK MODEL

[1*]Ramreddy, B. and [2]Dr. Choudhary, D.

[1]Associate Professor, Dept. of Mech.Engg.G.N.D.Engg.College, Bidar, India
[2]Professor, Dept., of Mech. Engg.G.N.D.Engg, College, Bidar, India

ARTICLE INFO

Article History:

Received 14th June, 2017
Received in revised form
20th July, 2017
Accepted 17th August, 2017
Published online 27th September, 2017

Keywords:

Product Manufacturing,
Quality Management,
Taguchi Technique,
Particle Swarm Optimization,
Artificial Neural network

ABSTRACT

In this work, a hybrid model of Taguchi technique is presented for manufacturing process optimization in which critical quality parameter selected for study is surface roughness of automobile components. Proposed hybrid approach includes Taguchi technique, particle swarm optimization and Artificial Neural Network models for optimization. In this work, multi-objective optimization problem is degraded into single-objective optimization for manufacturing process. The main contribution of this work is to improve conventional optimization technique by improving optimal solution searching in the given global search space. Here we have introduced Neural network based prediction model which requires training data and testing data for predicting the surface roughness. For training, 9 specimens of the input data are considered and testing includes 18 specimens. During the optimization process, Taguchi technique is implemented first resulting in optimized output response in terms of surface roughness. For further improvement Particle Swarm Optimization is included which helps to find best fit solution for single-objective problem.

INTRODUCTION

During manufacturing process, a product passes through multiple stages of development which is known as product development life cycle. A general process of product development cycle is depicted in figure 1. According to this process, product specifications are considered as the first stage of development where requirements of the product are specified. Once the product specification analysis stage is completed, product design specifications are developed to meet the required criteria. In the next stage of product manufacturing, Computer-Aided Design (CAD) is used for analyzing design feature, detail design, design generation and prototype building. At this stage, a prototype designed is obtained which is further travelled through testing phase. In later stage of product manufacturing, Computer-Aided Manufacturing (CAM) is considered as a significant tool for product development cycle assessment. It is used for programming the numerically-controlled device which helps to perform various operation such as continuous manufacturing, testing the product, shipping and monitoring the performance

****Corresponding author: Ramreddy, B.,***
Asso. Professor, Dept., of Mech. Engg.G.N.D.Engg, College, Bidar, India.

Motivation or need of TQM improvement

The conventional techniques fail to provide continuous improvement in quality when large manufacturing is required. Hence, there is a need to develop an efficient approach for manufacturing quality improvement by replacing the current statistical techniques. In order to address this issue, Bendell *et al*. (2016) asserted that Taguchi technique are capable to provide a significant solution for improving the quality which are known as "on-line quality control methods" in the industrial manufacturing field. According to this strategy, quality improvement need to be implemented at the beginning of the product design phase. Along with online applications, offline quality improvement application scenarios are also discussed in (Bendell, 1988). In offline quality control scheme, minimum number of experiments are performed to obtain the optimum number of parameters for manufacturing quality management. In (Taguchi, 1989). Taguchi *et al*.dicussed about online and offline methods for qulaity improvement by applying Taguchi technique. This study shows that, still there is a significant gap is present between online and offline Taguchi technique based methods for quality improvement. In order to over come this issue and bridge the gap, we present a hybrid model for quality improvement.

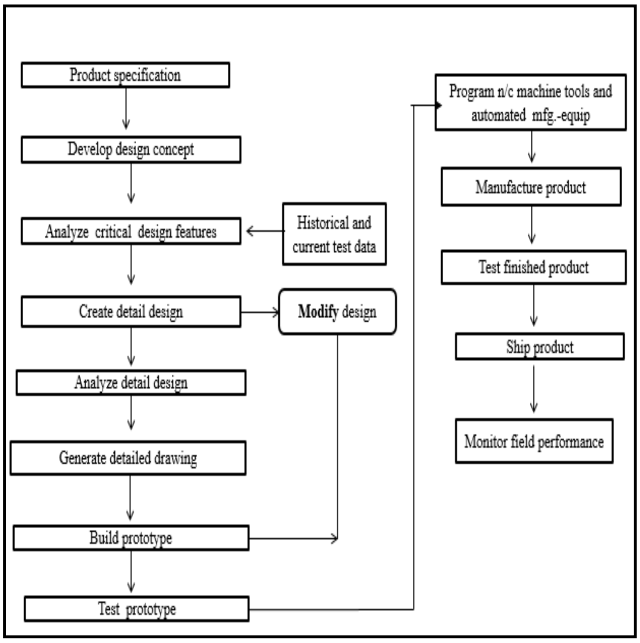

Fig.1. Product manufacturing and life cycle

Contribution of work

As discussed in previous section, still there is a need to improve the quality measurement and improvement techniques. To address this issue, in this work we develop a hybrid model for TQM technique. This model is combination of Taguchi technique and optimization technique. A synthetic data is formulated and Taguchi technique is applied to obtain the optimum parameters. In next phase of work, we incorporate optimization technique to obtain the accurate optimum parameters for improving the quality of manufacturing process.Rest of the article is organized as follows: section 4 deals with a brief discussion about recent works in this field of TQM. Proposed hybrid model is discussed in section 5, section 6 presents experimental study and finally section 7 presents concluding remarks of proposed approach.

Related work

This section provides a brief discussion about recent studies presented for quality improvement. In (Dubey, 2009). Dubey *et al*. discussed about Taguchi loss function based on the utility function. This technique uses multi-response optimization process with Taguchi technique for optimal performance resulting in quality improvement. Chong *et al*. (2004) discussed about total quality management and it's effect on the global market and performance of manufacturing. In order to carry out this study, a survey was performed in Australian companies which are based on the manufacturing process. This survey includes 89 production and operation managers. For analysis, multiple regression model is implemented. The main aim of this study is to establish a relationship between TQM analysis and customer satisfaction. For this purpose, Taguchi technique is a well-known technique and used widely in various industrial applications. Song *et al*. (2017) studied about working process of permanent magnet linear synchronous motors Based on the assumption Hsu *et al*. (2016) presented a study for SMT defects reduction in ceramic products and improving the product quality and cost efficient approach. In this work, Taguchi technique is implemented for analyzing the print wiping, oxygen content, thickness of substrate within minimum number of experiments thus optimal configuration is obtained. George *et al*. (2016) presented a study about agro-processing industries. According to industrial scenario in India, sugar industry is the second largest in agro-processing. Sugar industries have most complex evaporation process due to multiple effect evaporator. Hence, an optimization technique is required for better performance of manufacturing. This optimization is performed using Taguchi method. For evaporator optimization, quadruple effect evaporator is used in sugar industries and modeled using MATLAB Simulink tool. For further optimization, Taguchi technique is combined with Fuzzy logic optimization model.

Proposed model

In this section we present proposed approach for Taguchi optimization technique. First of all, conventional Taguchi technique is implemented. In next stage PSO (Particle Swarm Optimization) is implemented, as we are working on the optimization of surface roughness parameter and finally artificial intelligence technique is implemented for prediction the best configuration parameters.

Taguchi Technique

Here we present a brief introduction about Taguchi technique for surface roughness analysis. For this discussion steel material is used for various applications such as shafts studs, keys and stressed pins etc. Chemical composition of this material is presented in Table 1. As discussed before that Taguchi technique is well-known technique for tool quality optimization and widely used for various industrial applications. In order to measure the quality, orthogonal array scheme is used in Taguchi. In this experiment, orthogonal array is used for performance analysis and improvement by taking minimum number of experiments. Performance parameters which are obtained by using orthogonal array are converted into Signal-to-Noise ratio analysis. in further step, lower is better or larger is better conditions are selection based on the minimization and maximization parameters.

Table 2. Chemical composition for considered metal

S.No.	Metal	% Usage
1	Iron	98.38
2	Silicon	0.198
3	Vanadium	0.004
4	Sulphur	0.025
5	Manganese	0.761
6	Phosphorous	0.023
7	Aluminium	0.045
8	Molybdenum	0.012
9	Copper	0.056
10	Tungsten	0.045
11	Titanium	0.006
12	Carbon	0.436

Hence for lower is better, Signal-to-Noise ratio is given as:

$$S - N = -10 \log [\frac{1}{n}\sum_{i=1}^{n} y_i^2 \tag{1}$$

and for higher- is - better is given as:

$$S - N = -10 \log [\frac{1}{n}\sum_{i=1}^{n} y_i^{-2} \tag{2}$$

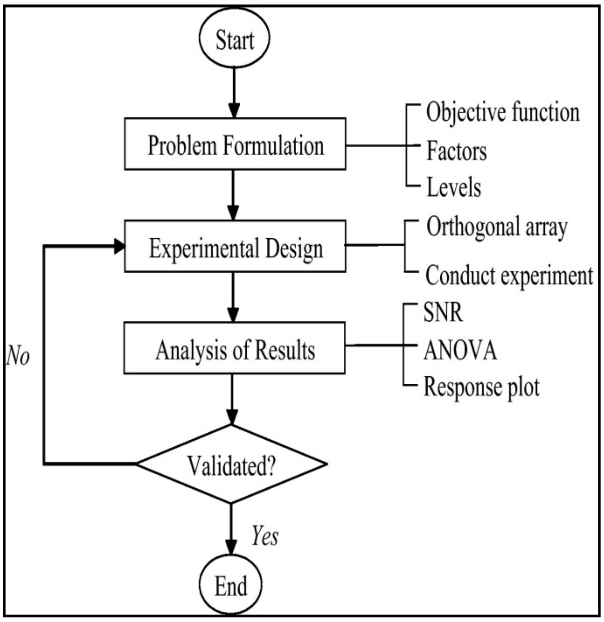

Fig. 2. Taguchi Technique

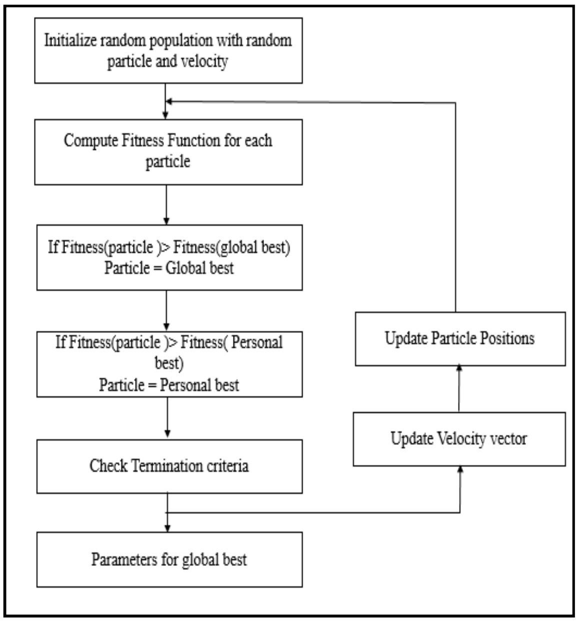

Fig. 3. General Approach for PSO

Where replication of each experiment is given by n and y_1 denotes the experimentally observed value for each experiment. In this work, Taguchi technique is used to develop an orthogonal array for 3 parameters which are known as speed of wheel, feeding rate and depth of cut. For each parameter, different values are taken. With the help of these parameters, minimum number of experiments can be computed as

$$Min_{Exp} = [(L-1) \times P] + 1 \quad (3)$$

Here values of L and P are considered as 3 hence equation (3) can be written as

$$Min_{Exp} = [\ (3-1) \times 1] + 1 = 7 \approx L_9 \quad (4)$$

A general implementation of Taguchi technique is defined in Figure 2.

In Figure 2, a general implementation model of Taguchi technique is presented. According to this model, initially a problem is formulated which contains the information about objective function analysis, factors required for experimental analysis and experimental levels. Next stage is called as experimental design stage where orthogonal array (OA) and experimental scenario is present. After applying the experimental design, result analysis is presented by computing SNR (Signal to Noise Ratio, ANOVA and response plot). Based on these parameters, outcome of Taguchi technique is validated, if validation is true then the process is ended else experimental design is implemented again to obtain the desired parameter.

Particle Swarm Optimization

This section, describes particle swarm optimization technique with Taguchi technique. This technique was introduced in 1995 by Kennedy. PSO is known as evolutionary optimization technique which is based on the social interactions and communication for learning the environment conditions. The main advantage of this technique is that it can be used for continuous or discrete optimization problem and gives better results in terms of optimization performance. According to this study, each particle travels in d dimensional space and tries to obtain best position in the given search space. Let us consider that the position and velocity of a particle is given as A^t_i and V^t_i respectively where t denotes number of iterations. In another way it can be represented such as $A = (a^t_{i1}, a^t_{i2}, ...)$ and $V^t_i = (v^t_{i1}, v^t_{i2}, ...)$ respectively. Here main aim of this technique is to obtain best solution for each particle i at titeration which is expressed by P^t_i. This can be defined as $P^t_i = (p^t_{i1}, p^t_{i2}, ...)$. For overall performance optimization, global best position need to be computed which is given as global best and denoted as P^t_g. For each particle it can be given as $P^t_g = (p^t_{g1}, p^t_{g2}, ...)$. With the help of this, velocity and position of each particle can be obtained by as expressed in Eq. (5).

Updated velocity is given as:

$$v^{t+1}_{id} = v^t_{id} + c_1 * r_1 * (p^t_{id} - x^t_{id}) + C_2 * r_2 * \ (p^t_{gd} - x^t_{id}) \quad (5)$$

Where velocity of i particle at t iterations denoted by v^t_{id}, d is the dimension of search space and v^{t+1}_{id} is the updated velocity ,c_1 and c_2 are correlation coefficients and r_1 r r_2 random numbers which are ranging from 0 to 1, p^t_{gd} is the global best position in given d dimensional subspace. Figure 3 shows a process of PSO technique used in this work..In the next stage, we combine both Taguchi and PSO techniques for obtaining the better optimization performance resulting in the better configuration parameters for TQM (Total Quality Management) technique.

Combination of Taguchi and P S O technique

In this section, a combination of Taguchi and PSO is presented. According to Taguchi model, orthogonal array is required for reducing the number of iterations effectively for given process. Generally, according to Taguchi technique, orthogonal array model is given as OA (N,k,s,t) where N denotes number of rows, k denotes total number of column or the parameters, s denotes the level of orthogonal array and strength is given by t.

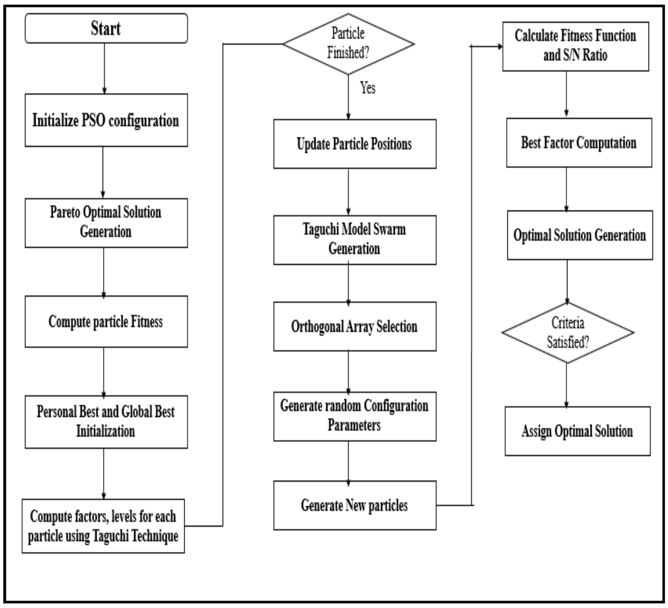

Fig. 4. Taguchi and PSO implementation without optimal solution

This process of iterative Taguchi model is initialized with the help of problem formulation, solution space definition, fitness function and orthogonal array selection. In the next stage, values of and number of levels for each parameter are estimate. Based on these parameters, total N number of experiments are conducted. Using this, signal to noise ratio can be computed as:

$$a = -20 \log (F)(d\text{ B}) \tag{6}$$

F denotes fitness function and α denotes signal to noise ratio. From this equation, it can be concluded that larger values of signal to noise ratio can be obtained if the fitness function value is minimized. Similarly, the response Table can be formulated using Eq. (7).

$$\overline{a\,(m,n) = \frac{s}{N} \sum_{1,OA(l,n)=m} al} \tag{7}$$

In order to reduce the computation time, optimization level difference need to be minimized. This approach is divided into two parts where in first part Taguchi implementation and PSO are carried out without generating a pre-optimal solution and in second part, a pre-optimal solution is generated then it is processed further for meeting the requirement criteria. First part of the algorithm is depicted in figure 4. According to this approach, below mentioned steps are followed:

Step 1: Initialization of Taguchi Configuration.
Step 2: PSO configuration parameter initialization.
Step 3: Define Pareto Optimal solutions.
Step 4: particle fitness computation.
Step 5: initialization of personal and global best solution.
Step 6: Factors and level computation for each particle.
Step 7: Update Particle positions for each particle.
Step 8: initialize Taguchi Swarm Generation and orthogonal array selection.
Step 9: New particle generation.
Step 10: compute fitness and S/N ratio. Step 11: optima solution selection.

Whereas in proposed model we introduce a local search and pareto optimal solution update process.According to propsoed approach, each parameter sequence is denoted as S= $(x_1, x_2 \ldots\ldots x_n)$. In previos section, we have discussed that each particle travels in the n diemnsional search space with a specified velocity. Position vector for each particle is given as $A_i = (a^t_{i1}, a^t_{i2} \ldots\ldots, a^t_{id})$. In this process, we initate computation from 0 iteration for each particel in the given population by considering velocity and and position parameters of each particle. Next stage belongs to generation of optimal solutions, fitness function computaiton for the initial population. Here our main aim is minimize the surface roughness for the given material. For that particular parameter Pareto Optimal solution is generated as follows:

Compute the objective values of feed rate, depth of cutting and speed of cutting. Sort the objective values as feed rate, depth of cutting and speed of cutting. Find an optimal Pareto solution. If the obtained solution lies in between and then solution is considered as a Pareto Solution. Furthermore, we compute fitness function for given each particle. This parameter is is condered as the adaptibility parameter for each population. If fitness function for any given population is high then there are high chances for population adaptibility and survival of the population. In this work, the problem is considered as a multi-objective problem. In order to perform the optimization we convert the problem into singleobjective and a utility function or weight function is computed for solving the problem. Therefore, a fitness function is defined by computing the weigthed sum for each particle given as:

$$f(x) = w_1 f_1(x) + w_2 f_2(x) + w_3 f_3 + \cdots + w_n f_n(x) \tag{8}$$

Where total n numebr of objectives are considered for optimization which are given as f_1, f_2, f_3 and f_n. According to proposed study, it follows the similar steps as mentioned in figure 4 but for further improvement some extnesion is added into the conventional optimization.This approach follows same process as mentioned before but it required two stages where the optimal solutions are obtained and best solution is selected from the solutions. Finally we apply ANN implementation for prediction the surface roughness parameters. This decription is presented in next section.

Neural Network Implementation

A neuron is the basic element of neural networks, and its shape and size may vary depending on its duties. Analyzing a neuron in terms of its activities is important, since understanding the way it works also help us to construct the ANNs. An ANN may be seen as a black box, which contains hierarchical sets of neurons (i.e. processing elements) producing outputs for certain inputs. Each processing element consists of data collection, processing the data and sending the results to the relevant consequent element. Each processing element consists of data collection, processing the data and sending the results to the relevant consequent element. The whole process may be viewed in terms of the inputs, weights, the summation function and the activation function 1. The inputs are the activity of collecting data from the relevant sources. 2. The weights control the effects of the inputs on the neuron. In other word an ANN saves its information over its links and each link has a weight. These weights are constantly varied while trying to optimize the relation between the inputs and outputs. 3. Summation function calculates of the net input readings from the processing elements. 4. Transfer (activation) function determines the output of the neuron by accepting the net input provided by the summation function. There are several transfer functions like summation function. Depending on the nature of the problem the determination of transfer and summation function is made. A transfer function generally consists of algebraic equations of linear or nonlinear form. The use of a nonlinear transfer function makes a network capable of storing nonlinear relationships between the input and the output. A commonly used function is sigmoid function because it is self-limiting and has a simple derivative. An advantage of this function is that the output cannot grow infinitely large or small. 5. Outputs accept the results of the transfer function and present them either to the relevant processing element or to the outside of the network. The functioning of ANNs depends on their physical structure. An ANN may be regarded as a directed graph containing a summation function, a transfer function, its structure and the learning rule used in it. The processing elements have links between them forming a layer of networks. A neural network usually consists of an input layer, a number of hidden layers and an output layer. Determination of data and the network model: The training and test data have been prepared using experimental patterns. In this work, the 13 patterns have been randomly selected and used as the test data. Cutting speed, Depth of cut, feed rate, rake angle have been used as input layer, while the tool life was used as output layer of the ANNs. In the ANN model logistic transfer function has been used and expressed as

$$NET_i = \sum_{j}^{n} w_{ij} x_j + w_{bi}$$

$$f(NET_i) = \frac{1}{1+e^{-NETi}} \qquad (9)$$

Where, NET_i is weighted sum of the input and output values are normalized between 0 and 1. W_{ij} weights of the connections between ith and jth processing elements wbi weights of the biases between layers 2 The training of the network Generally, there are three different learning strategies. First, the trainer may tell the network what it should learn (Supervised Learning), second, the trainer may indicate whether or not the output is correct without telling what the network should learn (Reinforcement Learning) and finally, the network learns without any intervention of the trainer (Unsupervised Learning). The learning set consists of the inputs and the outputs used in training the network. In our work we have used supervised learning approach. Since the number of neurons found in the input and output layers are known, the best performance of the network with the number of hidden layers is determined.

The neural network is developed using MATLAB tool. In the first step of the training, a determination of the learning algorithms is made. The number of hidden layers and the number of neurons for each hidden layer are determined. Then, the number of iterations is entered, and the training starts. The training continues either to the end of the iterations or reaching the target level of errors. A general process of neural network is as follows:

Step 1: Enter the input data: The following input data must be entered into the model Cutting speed, Feed Rate, Depth of Cut matrix follows. All data must have their values between 0–1. There is Breakdown of the data matrix into the input and output vector. Distribution of the input/output vector into the two sets for training and testing.
Step 2: Generation of random cutting conditions. The extent of conditions can be changed optionally.
Step 3: Calculation methodology for surface roughness.
Step 4: Preparation of data for training and testing of ANN.

Uniting of cutting conditions and other calculated values into a data matrix. Normalization of the data. Step 5: Use of ANN. The purpose of the neural network is to predict the surface roughness.Step 6: Selection of the type and architecture of the ANN and searching for optimum training parameters.Step 7: Procedure of training of the ANN by using the training set.Step 8: Testing of trained ANN. If testing is successful and the error of prediction is within the permissible limits, the empirical model is finished and ready for use. In case the testing is not successful, the training procedure must be repeated with another larger set of training data or the training parameters must be changed.

RESULTS AND DISCUSSION

In this section we present a complete experimental study using proposed hybrid approach. First of all, chemical composition of metal is analyzed as depicted in Table 1. For experimental study, we have considered selected parameters which are given in Table 2.

Table 2. Generalized Chemical composition

Parameter name	C	Fe	Mn	P	S	Others
Parameter value	0.37	98.8	0.7	0.035	0.045	0.05

Similarly, considered mechanical parameters are presented in Table 3.

Table 3. Mechanical properties

Ultimate Tensile strength (N/mm^2)	515
Yield Tensile strength(N/mm$^{2)}$	450
Elasticity(N/mm^2)	200
Hardness Vickers	155

Furthermore, cutting conditions which are used in this work are given in Table 4.In order to analysis the performance of the proposed approach, we have considered 9 specimens with the help of cutting condition combination. This combination is presented in Table 5. In this work our main aim is to provide an efficient approach for design optimization using Taguchi, PSO and ANN based techniques. Here we have presented a hybrid model for performance improvement. As discussed in previous section that the multi-objective optimization problem is transformed into single objective therefore we have considered surface roughness parameter for optimization and it is used in Taguchi, PSO and ANN.

Table 4. Cutting Condition parameters

Speed of cutting	$v(\frac{rev}{mm})$	560	640	960
Feed rate	$f(\frac{mm}{rev})$	0.16	0.17	0.20
Depth of cutting	$d(mm)$	0.2	0.3	0.4

Table 5. Cutting parameters for considered specimen

Specimen No.	$v(rev/min)$	$f\left(\frac{mm}{rev}\right)$	$d(mm)$
1	560	560	640
2	560	0.16	0.17
3	560	0.2	0.3
4	640	0.16	0.3
5	640	0.17	0.4
6	640	0.2	0.2
7	960	0.16	0.4
8	960	0.17	0.2
9	960	0.2	0.3

Table 6. Factor level representation

Cutting conditions	Factor for Level 1	level 2	level 3
$d(mm)$	0.2	0.3	0.4
$f\left(\frac{mm}{rev}\right)$	0.16	0.17	0.20
$v(rev/min)$	560	640	960

Table 7. Details of input and output Responses

Experiment number	$v(rev/min)$	$f(\frac{min}{rev})$	$d\ (mm)$	A	B	C	Output Response of surface roughness
1	560	0.16	0.2	1	1	1	3.4
2	560	0.17	0.3	1	2	2	3.35
3	560	0.20	0.4	1	3	3	4.42
4	640	0.16	0.3	2	1	2	3.3
5	640	0.17	0.4	2	2	3	3.95
6	640	0.20	0.2	2	3	1	3.90
7	960	0.16	0.4	3	1	3	3.27
8	960	0.17	0.2	3	2	1	2.87
9	960	0.20	0.3	3	3	2	2.48

Table 8. Signal to Noise ratio analysis

	Cutting condition			Factors				S/N
No. of trial	$v(\frac{rev}{mm})$	$f\left(\frac{mm}{rev}\right)$	$d(mm)$	A	B	C	R_a	
1	560	0.161	0.2	1	1	1	3.4	-10.76
2	560	0.17	0.3	1	2	2	3.35	-10.51
3	560	0.2	.4	1	3	3	4.42	-12.91
4	640	0.16	0.3	2	1	2	3.3	-10.56
5	640	0.17	0.4	2	2	3	3.95	-11.98
6	640	0.20	0.2	2	3	1	3.90	-11.80
7	960	0.16	0.4	3	1	3	3.27	-10.29
8	960	0.17	0.2	3	2	1	2.87	-9.16
9	960	0.20	0.3	3	3	2	2.48	-7.92

Table 9. Effect of surface roughness

Cutting condition	Level 1	Level 2	Level 3	Differece	Rank
v	3.72	3.74	2.85	0.89	1
f	3.36	3.40	3.61	0.25	3
d	3.39	3.069	3.85	0.781	2

This parameter is obtained from 9 specimens as depicted in Table 5. Total number of specimen considered are 27 but here we have used 9 specimen and rest of 18 are predicted using neural network prediction model. In this work, we consider 27 specimen considering depth of cut, cutting speed and metal feed rate. These constraints are considered as attributes.

For further improvement, we apply PSO technique along with Taguchi technique with neural network prediction modeling. Neural network helps to obtain the efficient prediction for various attributes. Here surface roughness is considered for optimization for multiple levels of operations. According to Taguchi technique, sui

Table 10. Comparative analysis

Sl.No	v(rev/min)	f(min/rev)	d(mm)	Taguchi	Proposed
1	560	0.16	0.2	3.60	3.45
2	560	0.17	0.3	3.303	3.34
3	560	0.20	0.4	4.312	4.4
4	640	0.16	0.3	3.274	3.39
5	640	0.17	0.4	4.121	3.99
6	640	0.20	0.2	3.841	3.91
7	960	0.16	0.4	3.212	3.22
8	960	0.17	0.2	2.762	2.85
9	960	0.20	0.3	2.633	2.46
10	560	0.16	0.3	3.278	3.45
11	560	0.16	0.4	4.087	3.98
12	560	0.17	0.2	3.651	3.44
13	560	0.17	0.4	4.153	4.31
14	560	0.2	0.2	3.851	3.79
15	560	0.2	0.3	3.492	4.33
16	960	0.2	0.4	3.44	3.65
17	960	0.17	0.2	2.96	2.9
18	960	0.2	0.4	3.44	3.5

Table factors can be selected based on their levels of experimental analysis where three factors are considered for all three levels are presented in Table 6. Later, an orthogonal array L9 *L*9 is taken as presented in Table 7. Generally, Taguchi technique depends on the below mentioned steps: Identification of performance response for optimization.2.Estimation of number of level for each parameter.3.Orthogonal array selection.4.Perform random experiment for given orthogonal array.5.Compute mean response and signal to noise ratio.6.Apply ANOVA analysis. 7.Optimal parameter selection. After applying this stage, PSO step is applied which is an iterative process. This optimization is applied on the surface roughness and for each experiment, a separate optimal value is obtained. These two techniques i.e. Taguchi and PSO are applied for 9 specimens, remaining experiment response is predicted using ANN.The ANN uses back-propagation model with sigmoid activation function. At this stage, 9 specimens are considered for training purpose and remaining specimens are used for testing. The output of neural network prediction is considered as predicted surface roughness.

ANOVA analysis for given cutting condition parameters is performed as presented in Table 8. Here inner array output is arranged in the last column of the Table where surface roughness and signal-to-noise ratio is considered as output and presented in outer array. Later we compute the average effect of the output response of surface roughness and signal-to-noise ratio for each factor of the experiment in each level. The outcome is presented in the Table 9.For each experiment is computed as: A= 3.4 +3.35 + 4.42/3=3.72. For parameter B it can be computed as: roughness at train 1 + roughness at experiment 4+ roughness at experiment 7= 3.4+3.3+3.27=3.36 and similarly, for depth of cut: (3.4+ 3.90 + 2.87) / 3 = 3.39. Finally, a comparative analysis of surface roughness is presented in Table 10. In this Table we show output response using Taguchi technique and proposed hybrid technique for 18 specimens.

Conclusion

In this work we have developed a hybrid approach for machining process where we predict surface roughness. First of all, surface roughness model data is obtained and modeled for surface roughness analysis. In next stage, Taguchi optimization technique is applied for process analysis, for further improvement in performance, particle swarm optimization technique is incorporated along with ANN model. For neural network, 9 specimens are considered for training and 18 specimens are considered for testing performance. A comparative study is carried out by considering conventional Taguchi technique and proposed hybrid optimization technique. Output response analysis shows that proposed prediction strategy obtains closer results when compared with Taguchi optimization technique and provides most suiTable optimal parameter to improve the manufacturing process. Table 10 shows that proposed hybrid approach provide significant performance with the help of ANN prediction scheme.

REFERENCES

Bendell, T. (Ed.), Taguchi Methods – Proceedings of the 1988. European Conference, Elsevier Applied Science, London,

Chong, V.K. and Rundus, M.J. 2004. “Total quality management, market competition and organizational performance”, British Accounting Review, Vol. 36, pp. 155-72.

Chou G.P.Y, Tsai J.T. and Chou J.H. "Modeling and Optimizing Tensile Strength and Yield Point on a Steel Bar Using an ANN With Taguchi PSO," in *IEEE Access*, vol. 4, no. , pp. 585-593, 2016

Dubey A.K. 2009. “Multi-response optimization of electro-chemical honingusing utility-based Taguchi approach.” Int J Adv Manuf Technol 41, 749.

George S. and Kyatanavar D.N. 2016. "Optimization of multiple effect evaporator using fuzzy logic integrated with Taguchi technique," *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, Chennai, pp. 1415-1419.

Hsu C.C., Chien C.S., Wei T.Y. Li Y.T. and Li H.F. 2016. "Taguchi DoE for ceramic substrate SMT defects improvement," 2016 11th International Microsystems, Packaging, Assembly and Circuits Technology Conference (IMPACT), Taipei, pp. 381-384.

Joseph, V.R. and Wu, C.F.J. 2002. Operation Window Experiment: A Novel Approach to Quality Improvement.Journal of Quality Technology, 34, 345-354.

Song J, Dong F, Zhao J, Lu S, S. Dou and Wang, H."Optimal design of permanent magnet linear synchronous motors based on Taguchi method," in IET Electric Power Applications, vol. 11, no. 1, pp. 41-48, 1 2017

Taguchi, G., Elsayed, E.A. and Hsiang, T. 1989. *Quality Engineering in Production Systems,* McGraw-Hill, New York, NY.

****