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Multi- Objective Optimization of Process Variables in Turning by Artificial Neural Network and Genetic Algorithm

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Abstract - *This work focuses on a hybrid neural network coupled with genetic algorithm for multi-response optimization in turning process. Firstly a Back Propagation Neural Network (BPNN) structure is developed to predict the output responses surface roughness and tool wear and then the multi objective genetic algorithm (MOGA) is applied for minimizing the responses obtained from the BPNN to have an optimized cutting condition. For modelling generally ANN architectures, learning/training algorithms and nos. of hidden neurons, transfer function are varied to achieve minimum error, but the variation is made in random manner. So here Design of Experiment (Taguchi method) with help of ANOVA has been implemented to achieve the optimal ANN architecture. Non dominated sorting genetic algorithm (NSGA-II) is applied to obtain the process parameters having minimum surface roughness and Flank wear simultaneously.*

Key Words: Optimisation, Turning, ANN, Genetic Algorithm

1. INTRODUCTION

The turning is the one most commonly employed operation in metal cutting to produce round shaped parts by a single point cutting tool on lathes. Turning is used to reduce the diameter of the work piece, usually to a specified dimension, and to produce a smooth finish on the metal. Surface finish is an important quality characteristic that may dominate the functional requirements of many component parts as well as production cost. Good surface finish is necessary to prevent premature fatigue failure, creep, to improve corrosion resistance, to reduce friction, wear, noise and finally to improve product life. Surface finish is a more subjective term denoting smoothness and general quality of a surface. Surface roughness represents the random and repetitive vertical deviations of a real surface from its ideal or nominal form.

Tool wear and surface roughness prediction plays an important role in machining industry for gaining higher productivity, product quality, manufacturing process planning and also in computer aided process planning. The flank wear (VB) of cutting tools is often selected as the tool life criterion as it determines the diametric accuracy of machining, its stability and reliability. The productivity of a machining system and machining cost, as well as quality, the integrity of the machined surface and profit strongly depend on tool wear and tool life. Sudden failure of cutting tools leads to loss of productivity, rejection of parts and consequential economic losses. Flank wear occurs on the relief face of the tool and is mainly attributed to the rubbing action of the tool on the machined surface during turning operation.. The flank wear take place during turning can't be neglected due to their significant impact on surface integrity and dimensional inaccuracy of machined component. The surface finish of the machined component primarily depends upon the amount of average flank wear. An increase in the amount of average flank wear leads to reduction in nose radius of the cutting tool which in turn reduces the surface quality along the job axis.

The maximum utilization of cutting tool is one of the ways for an industry to reduce its manufacturing cost. Hence tool wear has to be controlled and should be kept within the desired limits for any marching process. Tool wear mainly depends upon the machining parameters for turning a particular work piece material. In order to maximize productivity and overall economy from a manufacturing process, an accurate process model must be constructed for turning operation.

ANN refers to the computing systems whose fundamental concept is taken from analogy of biological neural networks. Many day to day tasks involving intelligence or pattern recognition are extremely difficult to automate, but appear to be performed very easily by animals. The neural network of an animal is part of its nervous system, containing a network of specialized cells called neurons (nerve cells). Neurons are massively interconnected, where an interconnection is between the axon of one neuron and dendrite of another neuron. This connection is referred to as synapse. Signals propagate from the dendrites, through the cell body to the axon; from where the signals are propagate to all connected dendrites. A signal is transmitted to the axon of a neuron only when the cell 'fires'. A neuron can either inhibit or excite a signal according to requirement. Each artificial neuron receives signals from the environment, or other artificial neurons, gather these signals, and when fired transmits a signal to all connected artificial neurons. Input signals are inhibited or excited through negative and positive numerical weights associated with each connection to the artificial neuron. The firing of an artificial neuron and the strength of the exciting signal are controlled via. A function referred to as the activation function. The summation function of artificial neuron collects all incoming signals, and computes a net input signal as the function of the respective weights and biases. The net input signal serves as input to the transfer function which calculates the output signal of artificial neuron. However ANNs are far too simple to serve as realistic brain models on the cell levels, but they might serve as very good models for the essential information processing tasks that organism perform.

A MOO generally deals with two or more objective functions which need to be optimized simultaneously. Many of the recently developed evolutionary algorithms have derived from the two original, independent concepts, the evolutionary strategy (ES) developed by Richenberg in 1973 and Genetic Algorithm (GA) proposed by Holland in 1975. Vector Evaluated Genetic Algorithm (VEGA) developed by Schaffer in 1985 considered to be the first multi-objective evolutionary algorithm (MOEA) which was a population based approach. Goldberg in1989 suggested the use of Pareto-based approach fitness assignment strategy, where he suggested the use of non-dominated ranking and selection to move the population towards the Pareto front. Vector evaluated genetic algorithm (VEGA), non-dominated sorting genetic algorithm and NSGA-II are examples of GA based multi-objective solution methods. In the present work, Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) has been used to obtain the optimal combination of process parameters.

The ANN can be used easily for modelling the process for which difficult to get mathematical model. Generally ANN architectures, learning/training algorithms, nos. of hidden neurons, transfer function in hidden layer, and initial weight are varied. But if the variation have been made in random manner the model obtained is not so efficient. So here, there is a high necessity of developing an orderly manner for selecting process parameters and their levels for improving the performance of ANN. Design of Experiment (Taguchi method) can be applied to create an efficient model. To study the performance of ANN 4 process parameters such as Training function, number of hidden neurones, transfer function in hidden layer, and transfer function in output layer are selected in 3 levels by creating Taguchi's L9 orthogonal array, and ANOVA is applied to find out which of the above factors have more importance on the ANN modelling. Thus optimal process modelling of Surface roughness and Flank wear of tool in turning process is developed with the best levels of above parameters. And NSGA II is applied on developed ANN model to determine the optimal solution point from best performance to capture a number of solutions simultaneously.

2. MODELING BY ARTIFICIAL NEURAL NETWORK

2.1 Experimental setup and data collection

Manufacturing industry always trying to minimize the surface roughness and tool wear parameters. But it is not easy to determine, on which input parameters like cutting speed, feed, depth of cut, the above output response can be minimized. Even though number of optimization approaches are there to determine the optimum machining parameters, the literature survey reveals that there has a scope to combine the different methods in artificial intelligence approach for optimization.

Here the turning operation is conducted on AISI 1020 steel bar of 50 mm diameter and 350 mm length in HMT NH26 lathe machine. The composition of AISI 1020 is listed in weight percentage as C 0.23%, Mn 0.60%, P 0.04%, S 0.5% and Fe remaining. In the present experimental study, cutting velocity, feed and depth of cut have been considered as input parameters. The process variables with their units, notations and levels are listed in Table 1

Table.1 Parameters and their levels for turning operation

Parameters	Levels		
Cutting Speed, V_C (m/min)	70	90	120
Feed rate, f (mm/rev)	0.08	0.12	0.14
Depth of cut, d (mm)	0.1	0.4	0.8

Experiments have been carried out using Taguchi's L27 Orthogonal Array (OA) experimental design which consists of 27 combinations of cutting velocity, feed and depth of cut. According to the design catalogue, three process parameters (without interaction) to be varied in three finite levels. Surface roughness (Ra) and flank wear (Vb) are taken as output response. L27orthogonal array and experimental results are shown in Table2. From 27 numbers of experiments, it is very clear that the variation in surface roughness and flank wear parameters is stochastic and random in nature and very difficult to predict the output characteristics accurately by mathematical equation. So Artificial Neural Network (ANN) with back propagation algorithm has been adopted here to model the turning process. One of the advantages of using the neural network approach is that a model can be constructed very easily based on the given input and output and can be trained to accurately predict process dynamics.

Table.2 Orthogonal array and machining data for turning operation

	L27 Orthogonal array			Real data				
Expt.no:	Vc	f	d	Vc	f	d	Ra	Vb
1	1	1	1	70	0.08	0.1	1.93	0.074
2	1	1	2	70	0.08	0.4	2.02	0.08
3	1	1	3	70	0.08	0.8	2.07	0.079
4	1	2	1	70	0.12	0.1	2.49	0.081
5	1	2	2	70	0.12	0.4	2.59	0.084
6	1	2	3	70	0.12	0.8	2.63	0.082
7	1	3	1	70	0.14	0.1	3.25	0.083
8	1	3	2	70	0.14	0.4	3.34	0.085
9	1	3	3	70	0.14	0.8	2.65	0.072
10	2	1	1	90	0.08	0.1	1.65	0.083
11	2	1	2	90	0.08	0.4	1.88	0.086
12	2	1	3	90	0.08	0.8	1.93	0.079
13	2	2	1	90	0.12	0.1	2.16	0.08
14	2	2	2	90	0.12	0.4	2.3	0.084
15	2	2	3	90	0.12	0.8	2.4	0.081
16	2	3	1	90	0.14	0.1	2.63	0.087
17	2	3	2	90	0.14	0.4	2.77	0.078
18	2	3	3	90	0.14	0.8	2.91	0.082
19	3	1	1	120	0.08	0.1	1.42	0.083
20	3	1	2	120	0.08	0.4	1.55	0.086
21	3	1	3	120	0.08	0.8	1.59	0.087
22	3	2	1	120	0.12	0.1	2.02	0.085
23	3	2	2	120	0.12	0.4	2.16	0.086
24	3	2	3	120	0.12	0.8	2.21	0.08
25	3	3	1	120	0.14	0.1	2.54	0.083
26	3	3	2	120	0.14	0.4	2.63	0.081
27	3	3	3	120	0.14	0.8	2.73	0.088

2.2 Analysis of ANN Parameters

There has number of combination of parameters for ANN modeling. It is unrealistic to analyze all combination of ANN parameters, its levels and effects on the ANN performance. Therefore L9 orthogonal array are designed to check the performance of ANN model in MATLAB. The parameters and its level taken and L9 orthogonal array used in this work is shown in Table.3. Other fixed parameters are network architecture -Feed forward back propagation and number of neurons in input layer and in output layer are 3 and 2 respectively.

Sl.No	Process parameter	Levels		
		Level 1	Level 2	Level 3
1	Training function	TRAINSCG	TRAINGDA	TRAINLM
2	Number of hidden neurons	8	4	12
3	Transfer function in hidden layer	LOGSIG	PURELIN	TANSIG
4	Transfer function in output layer	LOGSIG	PURELIN	TANSIG

Table -3: Process parameter and their levels for ANN

Generally the inputs and targets that dealt with an ANN model are of various ranges. These input and targets are needed to be scaled in the same order of magnitude otherwise some variables may appear to have more significance than they actually do, which will lead to form error in the model. Here the data of neural network model was scaled in the range of 0.1 to 0.9.The min-max data normalization technique was used for this purpose using the following equation.

$$N = \frac{(R - R_{\min}) \times (N_{\max} - N_{\min})}{(R_{\max} - R_{\min})} + N_{\min}$$

Where, *N* is the normalized value of the real variable, Nmin=0.1 and Nmax=0.9 are the minimum and maximum scaled range respectively, *R* is the real value of variable, and Rmin and Rmax are the minimum and maximum values of the real variable, respectively

Here the influence of input parameters i.e learning/training algorithms, transfer function in hidden layer nos. of hidden neuron on performance parameters ,mean square error (MSE), correlation coefficient (R) are investigated by creating 9 ANN models with help of NN tool box of MATLAB (R2010a) . To find the effect of each artificial neural network parameters on performance measure such as Mean square error (MSE) and correlation coefficient (R) is investigated through ANOVA in MINITAB software. Data used for this analysis are consolidated as shown in the Table 4 . The main effect plot for MSE and R are drawn.

Table - 4 : Data for ANOVA

Trial No :	Training Function	No; of Hidden neurons	Transfer Function in hidden layer	Transfer Function in output layer	R	MSE
1	SCG	4	LOGSIG	LOGSIG	0.61458	0.06187
2	SCG	8	PURELIN	PURELIN	0.73063	0.02219
3	SCG	12	TANSIG	TANSIG	0.31429	0.05385
4	GDA	4	LOGSIG	TANSIG	0.35499	0.10324
5	GDA	8	TANSIG	LOGSIG	0.67325	0.06676
6	GDA	12	LOGSIG	PURELIN	0.61589	0.00803
7	LM	4	TANSIG	PURELIN	0.92828	0.03364
8	LM	8	LOGSIG	TANSIG	0.998	0.03373
9	LM	12	PURELIN	LOGSIG	0.68339	0.01647

Chart-1 shows the main effect plot for MSE. From that the assessments are the training function is Levenberg-Marquardt (LM) algorithm , 12 nos. of neuron at hidden layer, transfer function LOGSIG in hidden layer , transfer function PURELIN in output layer are liable for the lowest MSE.

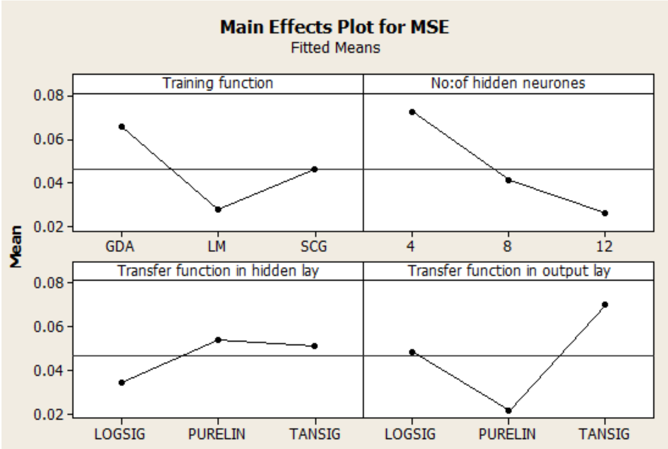

Chart – 1 : Main Effect plot for MSE

Chart-2 shows the main effect plot for R. From that the assessment are, the training function isLevenberg-Marquardt (LM) algorithm , 8 nos. of neuron at hidden layer, transfer function LOGSIG in hidden layer, transfer function PURELIN In output layer are liable for the highest R.

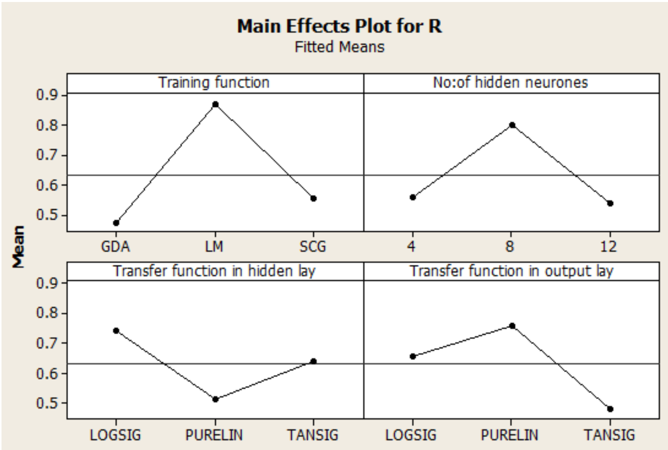

Chart – 2 : Main Effect plot for R

2.3 Proposed ANN model

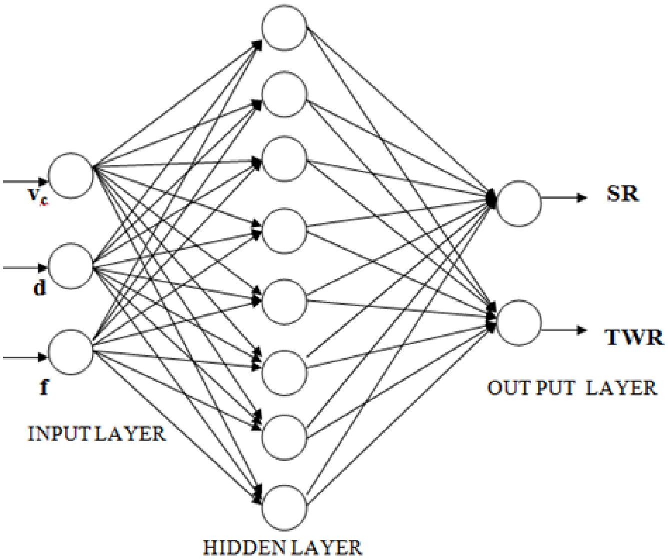

Fig -1: Proposed ANN model

An Orthogonal array of L9 is created and ANOVA is done to study the effect of ANN parameters such as training algorithm, transfer function and number of hidden neurons. From the main effect plot for MSE it is found that the optimum ANN model will have Leveberg-Marquadart algorithm for training, LOGSIG transfer function in hidden layer, PURELIN transfer function in output layer and 12 number of neurons in hidden layer. But from the main effect plot for training R all parameters are same as in MSE except number of neurons, which is found be 8.Since correlation plot is coincident with target value for training R, the number neurons be selected in this work as 8. The proposed ANN model is shown in Fig-1. The chosen optimal process parameters are Levenberg-Marquardt training algorithm, 8 nos. of hidden neurons, LOGSIG transfer function in hidden layer, and PURELIN transfer function in output layer in the basis maximum test R value. A new ANN model is created by neural network toolbox in MATLAB(2010a). By simulating the ANN model, the output response for 27 numbers of experiment is predicted and the predicted data is very much coincides with the actual experimental result.

3. MULTI OBJECTIVE OPTIMIZATION USING NSGA II

3.1 Introduction to NSGA II

The real world engineering problems are usually conflicting in nature, preventing simultaneous optimization of each objective. Here two performance parameters Of turning process have been considered. That is Surface Roughness(SR) and Tool Wear rate (TWR). GA based neural network for optimization of turning process are shown inFig-2

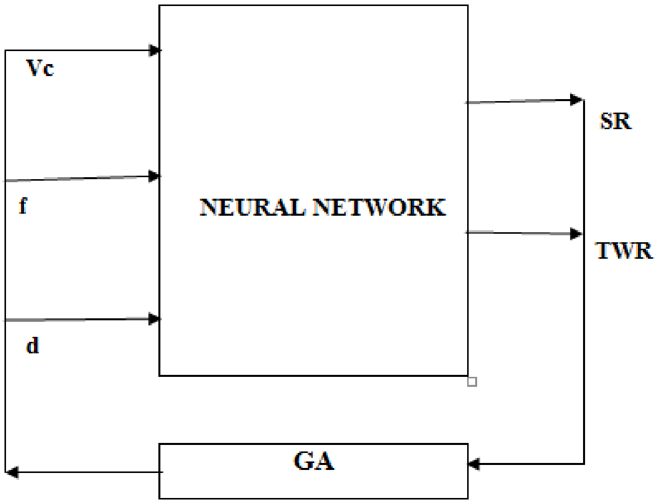

Fig-2 :GA based neural network for optimization

The GA is a powerful, general-purpose optimization tool widely used to solve optimizing problems in the mathematics, engineering and so on. Genetic algorithm works with a population of feasible solutions and, therefore, it can be used in multi-objective optimization problems to capture a number of solutions simultaneously. A single objective optimization algorithm provides a single optimal solution. However, most of the multi objective problems, in principle, give rise to a set of optimal solutions instead of a single optimal solution. Genetic algorithm works with a population of feasible solutions and, therefore, it can be used in multi objective optimization problems to capture a number of solutions simultaneously. NSGA-II is fast and elitist multi objective Genetic Algorithm flow chart of which is given in Fig-3

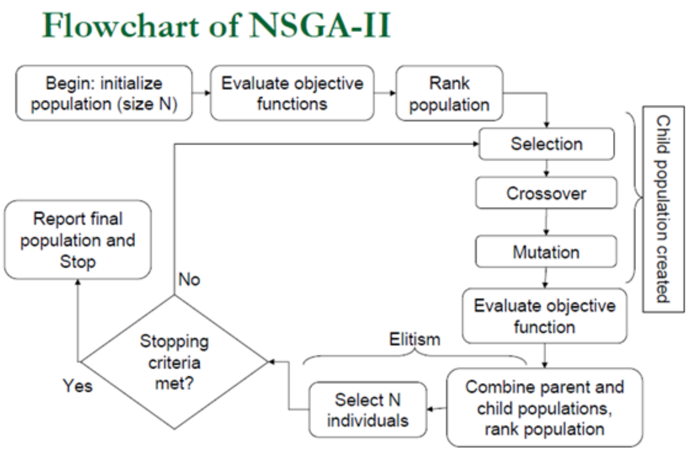

Fig-3 :Flow chart for NSGA II

Randomly an initially parent population (solution) *P* of size *N* is generated. In order to identify the non-domination level, each solution is compared with every other solution and checked whether the solution under consideration satisfies the rules given below.

Obj.1[i] > Obj.1[j] and Obj.2[i] ≥ Obj.2[j], Or Obj.1[i] ≥ Obj.1[j] and Obj.2[i] > Obj.2[j], $i \neq j$ where, i and j are chromosome numbers.

Now if the rules are satisfied, then the selected solution is marked as dominated. Otherwise, the selected solution is marked as non-dominated. In the first sorting, all the non-dominated solution ($N1$) is assigned rank 1. From the remaining $N-N1$ dominated solution from the first sorting, again solution are sorted and the non-dominated solutions in second sorting are assigned rank 2. This process continues until all the solutions are ranked. Each solution is assigned fitness equal to its non domination level (rank 1is the best level, rank 2 is the next-best level, and so on).

Multi objective problems are special in the sense that they have not a unique solution. The family of solutions of a multi-objective optimization problem is composed of all those elements of the search space, which are such, that the corresponding objectives cannot be all simultaneously improved. This is known as the concept of Pareto optimality

3.2 Application of NSGA II to ANN model

For solving optimization problem using GA, it needs fitness value. The fitness values are the objective function values. Therefore, there is a need of function or equation, which relates the decision variable with the objective. In the present study objectives minimization of surface roughness and tool wear, which are functions of decision variables namely ,cutting speed , feed, and depth of cut. But there is no such mathematical equation, which relates these objectives with the decision variable. In this study, ANN model has been developed to establish the relationship between input (decision variable) and output (objectives). This trained ANN model has been used to determine the objective function values.

Here an attempt has been made to optimize the two responses (SR and Flank wear) of turning process using Non Dominated sorted genetic Algorithm (NSGA-II). For implementing the algorithms a multi-objective minimization problem with 3 parameters (decision variables) and 2 objectives were formulated as follows.

$$\text{Minimize } \mathbf{y}=f(\mathbf{x}) = (f1(\mathbf{x}), f2(\mathbf{x}))$$

Subject to

$$70 \leq Vc \leq 120$$

$$0.08 \leq f \leq 0.14$$

$$0.1 \leq d \leq 0.8$$

The objective function $\mathbf{y}=f(\mathbf{x})$ formed by the ANN model is to be minimized. A code is generated using MATLAB(R2010a) for the optimum Artificial neural network model which have the pattern of [3-8-2] structure, learning algorithm is Levenberg-Marquadart ,LOGSIG transfer function in hidden layer, PURELIN transfer function in output layer. This code is shown in Appendix A which is used as the fitness function in NSGA II. The optimization experiment is also implemented by GA toolbox in MATLAB(2010a). The Process parameter and functional setting of NSGA-II algorithm are tabulated in Table-5. Three experimental runs are conducted by varying pareto front population fraction at three different levels namely at 0.2,0.35,and 0.5 being kept other factor constant as in Table-5.

Table - 5 : Process parameter and functional setting of NSGA-II algorithm

Sl.No:	Types of operation and parameter	Functions or parameter value used
1	a)Population type	Double vector
	b)Population Size	60
	c)Creation function	Feasible population
2	Selection function	Tournament
3	Reproduction Cross over fraction	0.8
4	Mutation function	Adaptive feasible
5	a) Cross over function	Intermediate
	b) Cross over ratio	1
6	Distance measure function	Distance crowding
7	Migration a)direction	Forward
	b)Fraction	
8	Stopping criteria	
	a)Number of generations	15
	b)Stall generations	100
	c)Functional tolerance	1×10^{-6}

4. RESULTS AND DISCUSSION

Performance of pareto optimal set can be measured according to convergence and spread. Convergence means that the Solutions come from different directions so as eventually meet and the Solutions will uniformly spread. From the experiments conducted by varying the pareto fraction value at 0.2,0.35 and 0.5, best convergence is obtained at 0.35 which is shown in Chart-5 and optimal set of turning parameters are shown in Table-6.

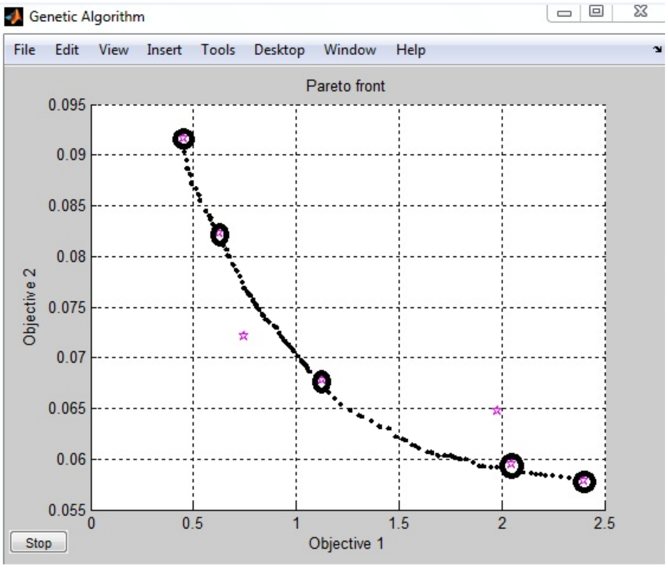

Chart-5:Best convergence at pareto fraction 0.35 (Objective 1-SR,objective 2-Flank wear)

Table - 6 : Optimal set of turning parameters by NSGA II

Sl. No:	Cutting speed (m/min)	Feed (mm /rev)	Depth of cut (mm)	Surface roughness (µm)	Flank wear (mm)
1	83.037	0.108	0.235	2.046	0.06
2	106.418	0.112	0.273	0.451	0.092
3	99.083	0.084	0.331	1.129	0.068
4	107.761	0.102	0.387	0.745	0.072
5	104.538	0.095	0.431	0.627	0.082
6	83.898	0.107	0.433	2.402	0.058
7	108.698	0.109	0.533	1.98	0.065

In this work attention is concentrated in method of modeling and optimization. Artificial neural network modeling can be applied to model the manufacturing process where under the situation that a modeling equation cannot be formed directly. By using NSGA-II algorithm an optimal set of reading is obtained for multi objective optimization. Therefore the process Engineer can select the input parameters according to the environment of machining operation.

5. CONCLUSIONS

The primary objective of this investigation was to develop a new approach for optimization which is a combination of artificial neural network and genetic algorithm to optimize the responses namely surface roughness and Flank wear in turning, which can be implemented successfully with help of MATLAB (R2010a).

For artificial neural network modeling Design of experiment (TAGUCHI method) is applied to study the effect of various ANN parameters on the model and an efficient model is created to predict the output responses. The model has been proved to be successful in terms of agreement with experimental results as the relative errors are very less. From the relative error plots it is found that data predicted are significantly fit to the model. The proposed model can be used in optimization of cutting process for efficient and economic production by forecasting the responses in turning operations.

NSGA –II algorithm is applied on ANN model developed and to obtain optimal set of turning parameters to minimize the surface roughness and tool wear parameters. The NSGA-II algorithm is implemented by varying the pareto fraction ,which is the parameter for multi objective optimization at three different levels . But it is found that the pareto fraction has no much significance to generate the optimal set of readings at lowest number of number generation. By increasing the number of generations pareto fraction value may have importance. This artificial intelligence approach is aimed to find an integrated solution to the existing problem of modeling and optimization of manufacturing processes for which formulating an optimization model is not straightforward. In machining industry the objective is to attain maximum surface finish. The important cause of surface roughness is the vibration of work piece and cutting tool. Therefore there has a scope of application of neuro-genetic approach for optimization of machining by considering the vibration amplitude

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