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GENETICALLY EVOLVED ARTIFICIAL NEURAL NETWORKS BUILT WITH SPARSE DATA FOR PREDICTING DEPTH OF CUT IN ABRASIVE WATERJET CUTTING

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ABSTRACT

In this paper, genetically evolved Artificial Neural Networks **(ANN)** built with sparse data for predicting the depth of penetration of Abrasive Water Jets **(AWJs)** into the material is proposed. Sparse data was collected during the cutting trials on Steel 1.4301 and AlMgSi0.5 alloy with AWJs considering various process parameters like jet pressure, abrasive mass flow rate, jet traverse rate, diameter of focusing nozzle, stand of distance, number of passes and type of abrasive material. The data was generated by employing abrasive water injection jet (**AWIJ**) and abrasive water suspension jet (**AWSJ**) systems. In developing ANN using conventional Back Propagation **(BP)** learning algorithm, random selection of parameters such as weights, learning rate parameter, momentum parameter is quite tedious and error prone. Hence, the proposed method attempts to select the weights by Genetic Algorithms (**GA**) in order to develop ANN in an optimal manner. Performance of the proposed method is compared with that of ANN built with BP learning algorithms and regression models, both built with abundant data. Finally, the effectiveness of the proposed method for situations with sparse data is demonstrated.

1. INTRODUCTION

Abrasive water Jet **(AWJ)** Cutting is an unconventional cutting process influenced by many process parameters like hydraulic, abrasive, mixing and cutting parameters. Modeling of such complex processes assumes significance in view of their use for predicting the performance of process and controlling the process. Among the different methods of modeling, analytical, empirical and semi empirical methods are well known. For AWJ cutting process, analytical models developed so far are based on several theories such as theories of erosion, fracture mechanics etc. and with several assumptions on material related parameters [1-2]. A theoretical model for predicting the depth of cut was based on Finnie's theory of erosion with a single abrasive particle [3-4]. An analytical model developed for predicting the depth of cut based on the concepts of micro cutting, inter granular fracture at shallow angles and near orthogonal angles of impact [6]. All these analytical models are far from reality due to various assumptions made in simplifying the modeling of cutting process. On the other hand, attempts made to develop empirical and semi empirical models are based on the data collected from experiments. A semi empirical model for predicting the depth of cut in case of different types of granites was proposed [7]. A semi-empirical model for predicting the depth of penetration of jet in cutting of polymer matrix composites was developed [8]. These empirical and semi empirical models presume the general form of the model and are developed using dimensional analysis and regression analysis. Limitations of the above techniques demand the need to develop an efficient and generic approach that is free from process as well as material related assumptions. Towards this, the models based on AI techniques such as expert systems, ANN, fuzzy logic etc. are found to be more robust and flexible [9]. Models based on soft computing approaches such as fuzzy, ANN approaches can easily capture the process non linearity with out considering the physical phenomenon of the process. A very few attempts were made to employ fuzzy, fuzzy-genetic and neuro-genetic approaches for modeling of AWJ cutting process [10-13]. ANN and fuzzy logic were employed for developing the relation between jet pressure, traverse rate, stand of distance as input parameters and strip width cleaned as an output parameter in waterjet cleaning process [10]. A model was developed for predicting the depth of cut in milling with AWJs using fuzzy set theory [11]. In this approach, the data obtained from the experiments conducted by varying jet pressure, abrasive mass flow rate, jet traverse rate and nozzle diameter were used to build an inference engine for fuzzy model. A fuzzy-genetic approach was proposed for selecting optimal process parameters in achieving the desired depth of cut with AWJs [12]. A Neuro-Genetic approach was proposed for selecting optimal process parameters in achieving the desired depth of cut considering the variation in bore diameter of focusing nozzle [13]. In general, fuzzy modeling demands the selection of suitable membership function with parameters for any specific application. Further, these parameters need to be adjusted based on the obtained results. Moreover, the development of rule base requires expertise in AWJ cutting process. All these models work well when they are built with abundant data generated from planned experiments. Contrastingly, job shop environment processes different materials at different times using different process parameters. Such data generation is unplanned and is known as "*Sparse Data*". Any model that can be built with sparse data will be of immense use for the job shop applications since such a model can be used to select process parameters whenever similar materials need to be processed with AWJs. Therefore, it is worthwhile to consider the development of models considering the sparse data. It is well known that ANN is a proven modeling technique in capturing the knowledge of complex processes due to their massively parallel processing, learning and noise suppression capabilities. Due to this, the present work considers ANN modeling technique for building the models for sparse data. However, this modeling needs the selection of suitable parameters for the network structure i.e. weights, number of hidden layers, number of hidden nodes in each layer, learning rate parameter and momentum parameter etc. which is a tedious and time consuming process. Moreover, conventional BP learning algorithm used for training ANN suffer from the drawback of random selection of initial weights which can produce non-optimal structure of ANN. Further, the gradient descent search algorithm cannot handle discontinuous connection weights [14-15]. Hence, there is a need to find a robust search technique that can choose optimal weights for evolving ANN structure. A combined genetic-back propagation learning algorithm and encoded BP parameters in the individuals together with the network structure for two application domains, digit recognition and logic functions was proposed [16]. It was shown that a single layer network is enough to form an arbitrarily close approximation to any nonlinear decision boundary [17].

In this paper, an attempt is made to employ GA based guided search technique for choosing optimal weights in developing ANN models for sparse data generated continuously from AWJ cutting process.

2. METHODOLOGY

(i) To develop regression and ANN models built with conventional BP and GA based training algorithms.

(ii) To assess their performance in predicting the depth of cut in AWJC by considering abundant data generated from planned experiments.

(iii) To demonstrate the feasibility of ANN models with GA based weight selection for situation where sparse data is generated during AWJ cutting process.

3. REGRESSION AND ANN MODELS FOR PREDICTION OF DEPTH OF CUT

In order to develop regression and ANN models for predicting the depth of cut with AWJs, the experiments were conducted on black granite with trapezoidal section using full factorial experimentation i.e. $5^3 = 125$ by varying each parameter at 5 levels i.e. jet-pressure (60, 130, 200, 270, 350 MPa), jet traverse rate (30, 70, 150, 230, 325 mm/min) and abrasive mass flow rate (30, 50, 90, 130, 170 g/min) [12]. From this, 70% data was randomly selected for developing the models and the remaining 30% data was used for validating the models.

3.1 Regression Model

For developing the regression model, multiple regression procedure was employed. The general form of regression equation is

$$\mathbf{h} = K\, \mathbf{p}^{a}\, \mathbf{m_f}^{b}\, \mathbf{v}^{c} + d \qquad (1)$$

The development of model considered certain data set, using which the various constants and exponents were determined. The model was validated with the remaining data obtained from the experiments.

3.2 ANN Model with BP Learning Algorithm

For developing ANN model with BP learning algorithm, the data generated from the full factorial experiments was considered with jet pressure, abrasive mass flow rate and jet traverse rate as input parameters and depth of cut as response variable. Fig.1 shows the general structure of ANN. BP algorithm uses gradient based search procedure to select the weights that can give the minimum error in prediction of depth of cut. To select the weights, the following relation was used.

$$E = \frac{1}{2}\sum_{i=1}^{n}(h_{ai} - h_{pi})^2 \tag{2}$$

In order to select the suitable number of hidden nodes, different networks were developed by varying the number of hidden nodes in the hidden layer from 1 to 30 and keeping the other parameters like learning rate parameter, momentum parameter and number of epochs constant at 0.001, 0.1, and 600 respectively. BP algorithm is a serial search technique that randomly selects one point in the search space of weights and updates these weights continuously. This process of initial random selection of weights will affect the performance of the network. In order to study the influence of initial random choice of weights, the network was initialized with 30 different initial weights. Other network parameters such as number of hidden nodes, learning rate parameter, momentum parameter and number of epochs were kept constant at 5, 0.01, 0.1, and 600 respectively.

3.3 Development of ANN Model Using GA Based Weight Selection

One of the important issues in the development of ANN model is the selection of suitable weights for the network structure. Conventional way of selecting the weights using BP learning algorithm does not yield optimal selection of weights for the chosen structure of network. Hence, the present work proposed to use GA based weight selection for optimizing the weight selection for training ANN. In this method, GA starts with certain weights initially for all the points and then searches simultaneously for the optimal weights. Each chromosome represents all the connection weights including the biases for the ANN. The sample 2-2-2 network structure with weights representation is shown in Fig**.**2. By considering these weights and training data set, Mean Absolute Error **(MAE)** in prediction of depth of cut is estimated using the equation (3).

$$\textbf{Minimize}\ (MAE = \frac{\sum_{i=1}^{n} | h_{ai} - h_{pi} |}{n}) \tag{3}$$

By subjecting the chromosomes to genetic operations like crossover and mutation, new chromosomes are generated. This process is continued until the chromosomes that give MAE less than or equal to a predefined MAE.

3.3.1 Coding of Weights

In this work, each chromosome is represented in binary form. Sample weight matrices coded and represented in the form of a chromosome is shown in Fig.3. For the l-m-n (l-input nodes, m-hidden nodes, n-output nodes) ANN structure, the total number of weights to be determined is (l+n)m. Hence, each weight is considered as a gene with k-bits length. The total length of chromosome is (l+n)m times k-bits. Each weight of the ANN including the biases was decoded with a precision of 10 bits length giving 4 decimal points accuracy in representation of weights in the range of 0 to 1.

3.3.2 Objective Function

The objective of the present work is to select the weight matrices for the specific network structure, which will give minimum prediction error. In this study, mean absolute error **(MAE)** between predicted and experimental depth of cut is selected as a performance measure. So, the objective function is minimization of MAE with the selection of suitable weight matrices. Fitness values of each individual in the population are calculated using the equation (4).

$$F = \frac{1}{(1 + MAE)} \tag{4}$$

Roulette-wheel selection procedure was used to select the good strings in the population to form the mating pool for the next generation.

In developing the ANN model with GA based weight selection using abundant data, a single hidden layer network with 3-4-1 network structure was considered. The training and validating data set considered for developing ANN model with BP learning algorithm was used for this modeling. In developing ANN models with GA based weight selection for the sparse data obtained from AWIJ and AWSJ systems, the total data set was divided into different data clusters based on the criterion of having certain sets of data with different combinations of process parameters. In Table 1, the details of each data cluster are given. From each of these clusters, 70% of the data was selected for generating the models and the remaining 30% data was used for validating the developed models. Input parameters considered for each modeling, the total size of data set for each cluster, the size of data set selected for developing the models and for their validation, the type of materials cut and the type of abrasive material used are given in Table 2. In selecting the number of hidden nodes, the models with different hidden nodes were tried out and the one that gave minimum MAE in prediction was selected as the best structure of ANN. The number of hidden nodes selected for each model used with sparse data is shown in Table 2. Similarly, the same sparse data was used for developing the regression models also.

For GA based weight selection, the population size of 20 individuals was considered with each individual chromosome having a length based on the number of hidden nodes. Each gene, specifying the weight in the range of 0 to 1, was represented with 10 bits, giving a solution with precision of 4 decimal points for each weight. For different genetic operations such as crossover and mutation, single point cross over with crossover probability, 0.8 and bitwise mutation with mutation probability, 0.001 were chosen respectively for the purpose of achieving the MAE less than or equal to zero as shown in Fig.11.

4. RESULTS AND DISCUSSION

In this section, the first part deals with the assessment of ANN results obtained with BP learning algorithm and regression model for predicting the depth of cut considering the abundant data. The suitability of ANN models with GA based weight selection in predicting the depth of cut was studied with abundant data. The second part deals with the assessment of ANN models with GA based weight selection in predicting the depth of cut with sparse data.

4.1. ANN and Regression models with Abundant Data

Among the 125 sets of data from the experiments, the size of data considered for determining the constants and exponents in the regression equation (1) is 88, the remaining 37 sets of data were used for validating the model. The regression equation is

$$h = 8.76 \times \frac{p^{0.692} m_f^{0.174}}{v^{0.541}} - 3.42 \tag{4}$$

From the equation (4), it can be observed that the performance trends match well with those trends presented by the previous researchers [18]. Positive exponents for pressure and abrasive mass flow rate indicate an increase in depth of cut with an increase in pressure and abrasive mass flow rate and the negative exponent for traverse rate indicates the decrease in depth of cut with an increase in traverse rate. The regression model was validated by predicting the depth of cut for 33 sets of data. Fig.4 shows the comparison of the experimental results with the results predicted with the model. Fig.5 shows the variation of error in predicting the depth of cut using regression analysis and mean and standard deviation of this error distribution is 2.26 and 2.92 respectively.

In Fig.6, the variation of MAE in predicting the depth of cut with different hidden nodes is shown. The variation in mean and standard deviation of the prediction error are shown in Fig.7. From the results presented in Fig.7, it can be observed that an increase in the number of hidden nodes in the hidden layer beyond 10 is found to deteriorate the performance of ANN. This can be attributed to an increase in the size of network that will over fit the data and give poor performance [15]. Though the network with 4-hidden nodes has less mean error, its standard deviation is high compared to the network with 5-hidden nodes. Hence, the network with hidden layer of size 5-hidden nodes was chosen as an optimum network for this study. In Fig.8, the depth of cut predicted with 3-5-1 network structure is plotted against the experimental results. Fig. 9 shows the variation of error in predicting the depth of cut using BP learning algorithm. Mean and standard deviation of this error distribution is 2.24 and 2.55 respectively. In Fig.10, the MAE in prediction of depth of cut using ANN with different initial weights is shown. From this, it can be observed that the MAE is found to vary with different initial weight chosen for deriving the ANN structure. This can be attributed to the fact that the weights may not change during the training phase due to their value being stuck at local minima [14-15].

Even though the trend in variation of depth of cut using regression modeling with the process parameters is the same as that observed with ANN models, accuracy of prediction with regression models is inferior to that of ANN models. This clearly demonstrates the suitability of ANN model for prediction of depth of cut in complex processes like AWJs. However, ANN with BP has the draw back of choosing non-optimal weights during training phase. Similarly, learning rate parameter and momentum rate parameter are also chosen randomly.

Fig.12 shows the depth of cut predicted by ANN with GA based weight selection for abundant data generated from full factorial experiments. Fig.13 shows the variation of error in predicting the depth of cut and mean and standard deviation of this error is 1.87 and 2.38 respectively. These values are smaller than those observed from ANN trained with BP learning algorithms and regression models. This can be attributed to the nature of GAs that will search parallelly through the total weight space and find out optimal/near optimal weights. This clearly shows the suitability of GA based weights selection for the ANN in accurate prediction of depth of penetration with AWJs.

4.2 ANN Model with GA Based Weights Selection with Sparse Data

In order to study the suitability of ANN model with GA based weight selection for sparse data, this model was developed by considering the sparse data presented in Table 1. Table 3 shows the mean and standard deviation of the error in prediction of depth of cut with ANN using GA based weight selection and regression models considering the sparse data. Even though prediction performance of regression models is comparative to ANN models with some data sets, these models are inferior to ANN with GA based selection in terms of overall performance. This can be observed from the mean and standard deviation of the error in prediction of depth of cut for each model. The standard deviation of all the models developed by the proposed approach is less than that noticed with regression analysis except for the model 4. Moreover, this deviation is considerably large. Thus, this study clearly demonstrates the effectiveness of ANN with GA based weights selection for modeling the AWJ cutting process with sparse data.

5. CONCLUSIONS

This paper covered the procedure for developing ANN based models considering the continuously available unplanned data, i.e. sparse data from AWJ cutting. The proposed ANN developed with GA based weight selection does not demand for an expensive and time consuming planned experiments. The investigations showed the suitability of GA based weight selection process for training instead of BP learning algorithm for building ANNs. It has also shown the applications of regression analysis when the functional form can easily be derived with abundant data. When the data is sparse, the functional form of the process cannot be known easily thus illustrating the flexibility of the proposed method for building the prediction models for AWJ cutting. As the present approach considered the selection of optimal/near optimal selection of weights with GA, future attempts can be directed towards using such an approach for selecting the network topology so that ANN model can be developed easily.

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NOMENCLATURE

h	- Depth of Cut
p	- Jet Pressure
$\mathbf{m_f}$	- Abrasive Mass Flow Rate
v	- Traverse rate
K, a, b, c, d	- Regression Constants and Exponents
MAE	- Mean Absolute Error
$\mathbf{h_{ai}}$	- Actual depth of cut for the i^{th} element in the validating dataset
$\mathbf{h_{pi}}$	- Predicted depth of cut from the ANN model developed for the i^{th} element in the validating dataset
n	- Size of Testing Data Set
NoP	- Number of Passes
$\overline{X}$	- Mean of the error distribution in prediction of the depth of cut
S	- Standard deviation of the error distribution in prediction of the depth of cut
ζ	- Limit on MAE
F	- Fitness function

Table 1. Process Parameters Employed for Sparse Data Generation in AWJ Cutting

	Process Parameters					
Model No	**Pressure** (MPa)	**Diameter of Focusing nozzle** (mm)	**Stand of distance** (mm)	**Abrasive Mass Flow Rate** (kg/min)	**Traverse Rate** (mm/min)	**Number of Passes**
1	300	0.3	1.5	0.5-1-1.5-2-2.25-2.5	20-40-80-120-160-200	1
2	100-150-200	0.6	5	0.13-0.43-0.45-0.49-0.73-0.78-1.07-1.23-1.25-1.6-1.7-2.32-2.37-2.4-2.49-3.18	500-1000-1500-2000-2500	1
3	100	0.7	2-5-10-20-40-80-120-160-180	0.4-0.5-0.9-1-1.5-1.9-2.3-2.7-3.2	200	1
4	100-150-200	0.7	5	1.5	50-100-200-500	1
5	150	0.7	2	0.53-1.35-1.87-2.52-2.91-1.5	500-100-200-500	1
6	150	0.7	2	0.53-0.62-1.14-1.35-1.53-1.6-1.87-2.08-2.2-2.52-2.81-2.91	200	1
7	100-150-200	0.6	2	0.5-1-1.5	10-15-20-50-100-270-500-1000	1-2-4-6-8-10-12-16-24
8	100-150-200	0.7	5	0.4-0.43-0.53-0.55-0.8-0.9-1.35-1.45 1.87-1.9-2.3-2.45-2.5-2.52-2.91-3.2-	200	1
9	200	0.4-0.5-0.6-0.7	5	0.5-1-2-2.5	200	1
10	100	0.7	2-5-10-20-40-80-120-160	1	200	1

Table 2. Details of Sparse Data Modeling

Parameters	Model Number									
	1	2	3	4	5	6	7	8	9	10
Input Parameters	m_f , v	m_f , v, P	m_f , x	P, v	m_f , v	m_f	m_f , v, P, NoP	m_f , P	m_f , d_f	x
Work Piece Material	AlMgSi0.5	AlMgSi0.5	Steel 1.4301	AlMgSi0.5	AlMgSi0.5	AlMgSi0.5	AlMgSi0.5	AlMgSi0.5	Steel 1.4301	AlMgSi0.5
Abrasive Material	Olivin	Barton HP 120	Barton HP 120	Barton HP 120	Barton HP 120	Barton HP 120	Barton HP 80	Barton HP 120	Barton HP 120	Barton HP 120
Size of Total Data Set	32	85	19	14	9	15	46	40	16	8
Size of Training Data Set	23	60	14	10	7	11	32	28	12	6
Size of Validation Data Set	9	25	5	4	2	4	14	12	4	2
Number of Hidden Nodes	4	5	5	4	5	4	8	5	5	3
Type of Process	AWIJ	AWSJ	AWSJ	AWSJ	AWSJ	AWSJ	AWSJ	AWSJ	AWSJ	AWSJ

Table 3. Mean and Standard Deviation of Error Distribution in Prediction of Depth of Cut with Sparse Data

	Model Number																			
	1		2		3		4		5		6		7		8		9		10	
	Reg	ANN	Reg	ANN	Reg	ANN	Reg	ANN	Reg	ANN	Reg	ANN	Reg	ANN	Reg	ANN	Reg	ANN	Reg	ANN
$\overline{X}$	2.30	3.22	4.49	7.56	16.79	21.5	7.69	2.15	7.8	7.91	4.12	2.13	11.06	15.07	14.81	19.04	3.58	4.33	42.75	52.67
S	1.61	2.38	1.36	1.99	1.18	1.37	2.9	4.71	1.25	0.35	4.73	1.74	8.2	11.12	4.65	9.87	1.97	2.37	8.75	1.06

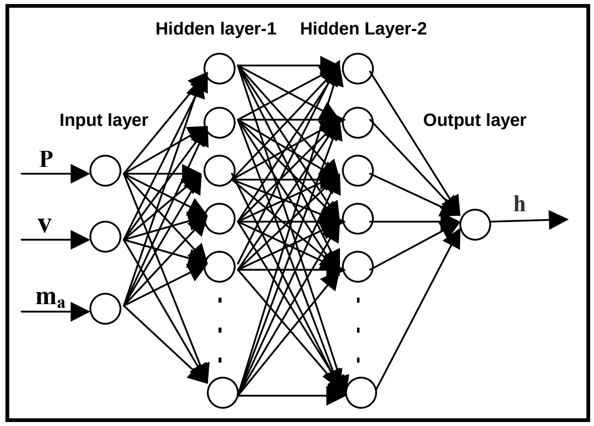

Figure 1. General Structure of the ANN

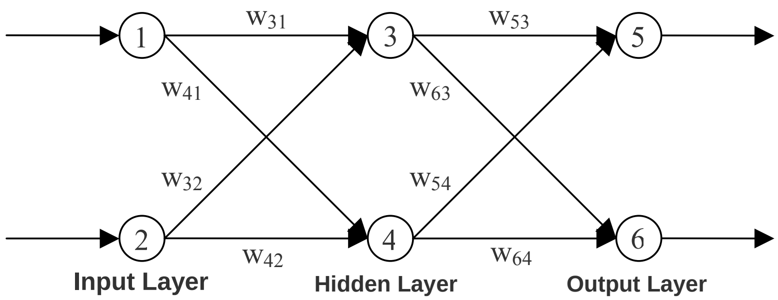

Figure 2. General Configuration of 2-2-2 ANN

← **Chromosome** →

Gene 1	Gene 2	Gene 3	Gene 4	Gene 5	Gene 6	Gene 7	Gene 8
w_{31}	w_{32}	w_{41}	w_{42}	w_{53}	w_{54}	w_{63}	w_{64}
10011	11011	11101	10011	11001	11111	10000	10101

Figure 3. Sample Binary Coded Weight Matrices in the Form of a Chromosome

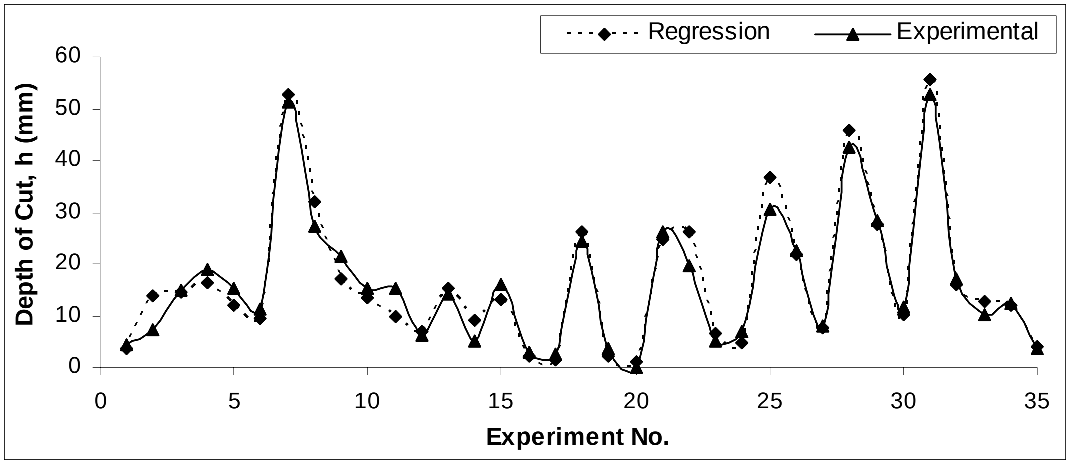

Figure 4. Comparison of Predicted Depth of Cut by Regression Analysis with the Experimental Results

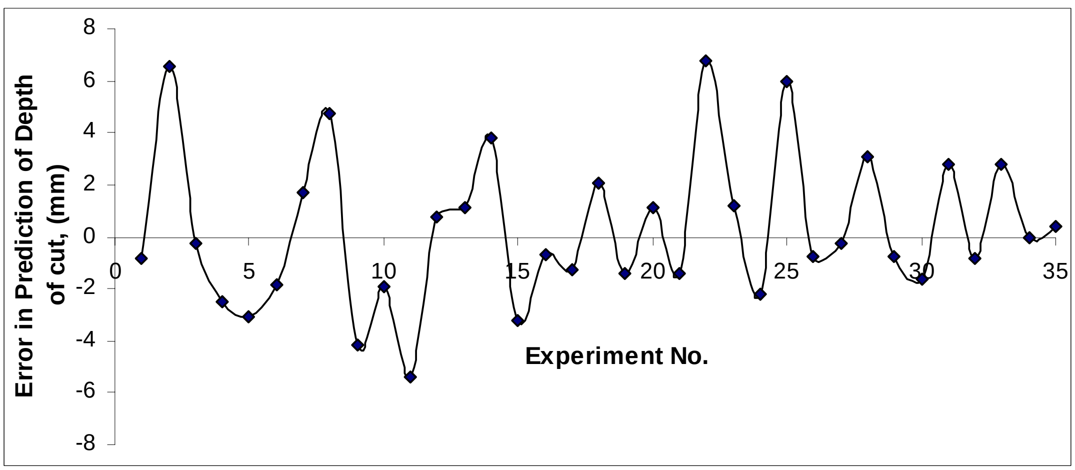

Figure 5. Variation of Error in Prediction of Depth of Cut Using Regression Analysis

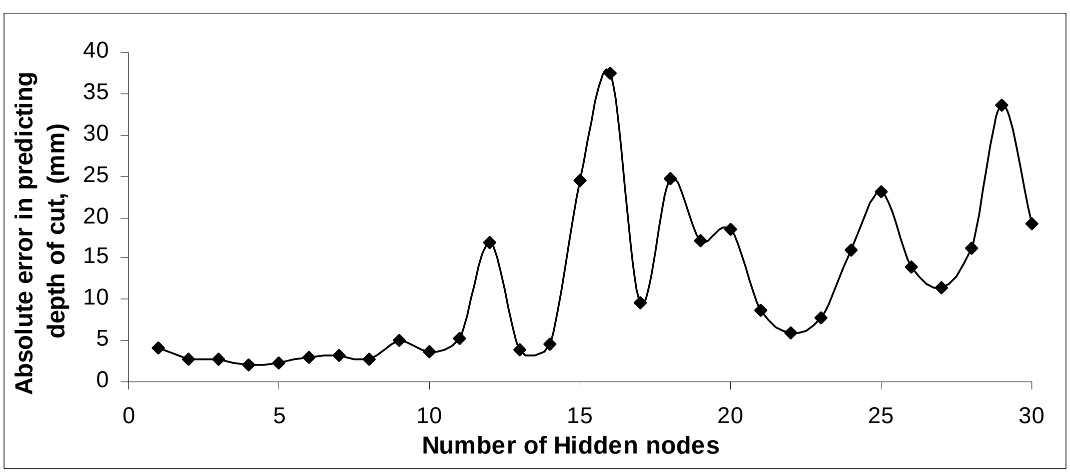

Figure 6. Variation of Absolute Error with Number of Hidden Nodes of the ANN

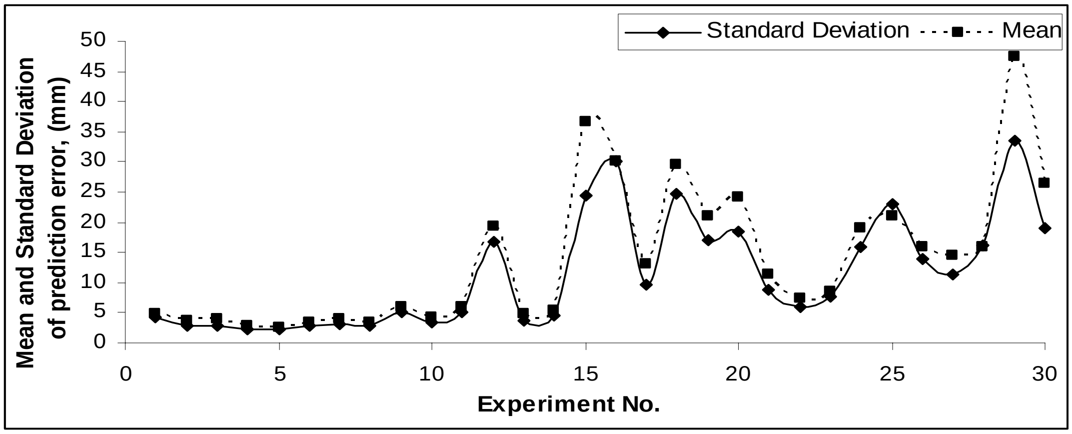

Figure 7. Variation of Mean and Standard Deviation of Prediction Error Distribution with Number of Hidden Nodes

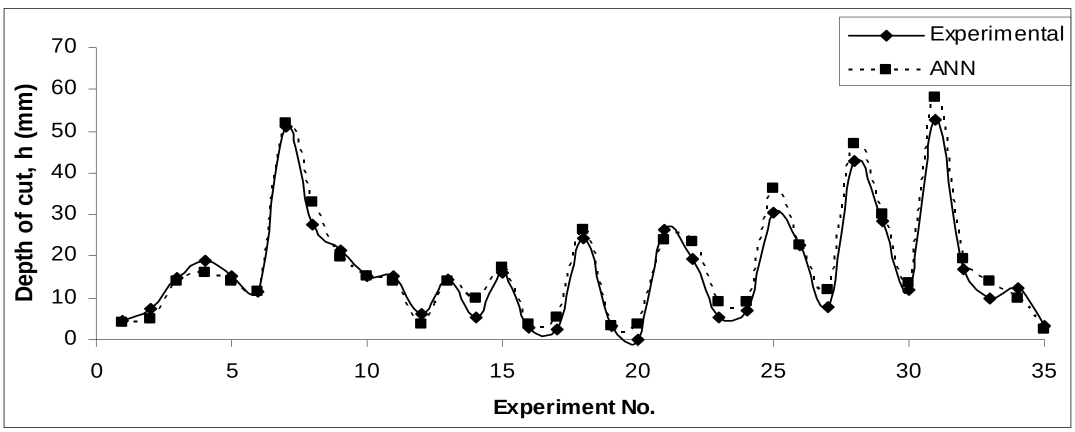

Figure 8. Comparison of Depth of Cut Predicted by 3-5-1 Structured ANN Trained by Conventional BP with Experimental Results

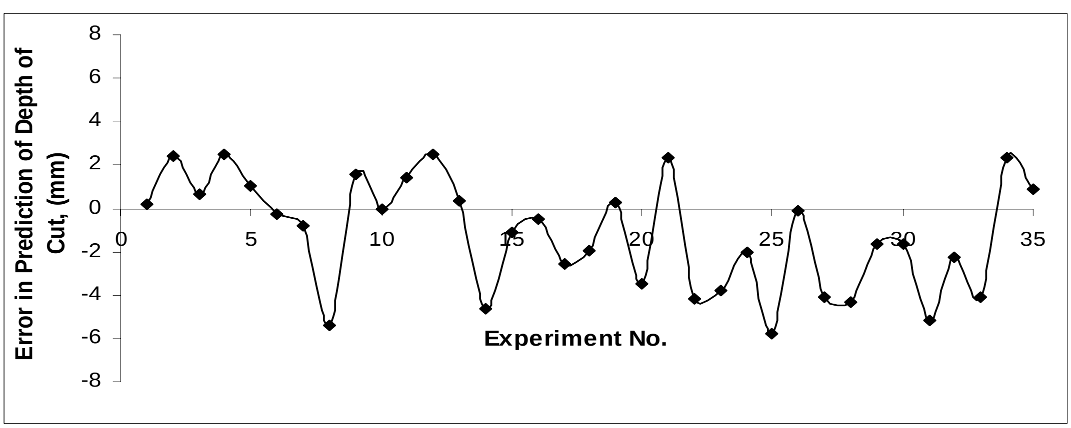

Figure 9. Variation of Error in Prediction of Depth of Cut with 3-5-1 Structured ANN Structure Trained by Conventional BP

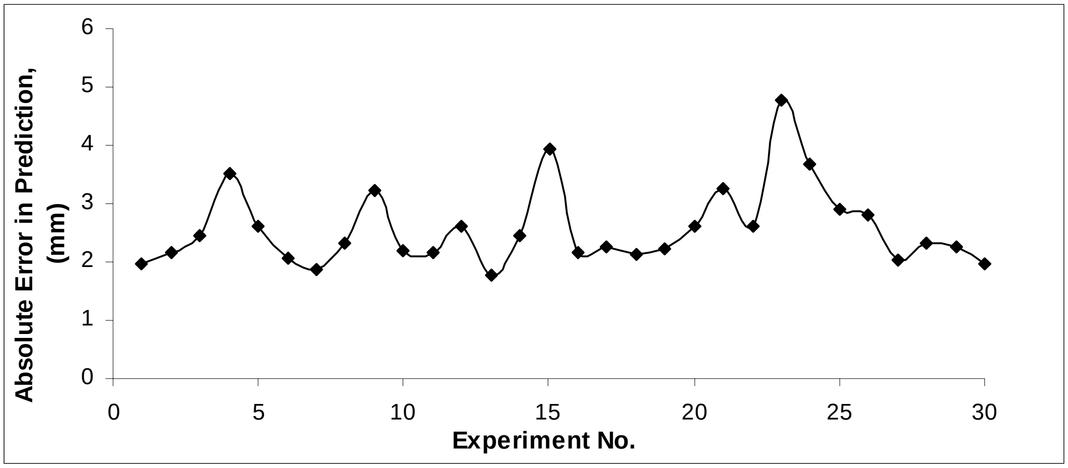

Figure 10. Variation of Error in Prediction of Depth of Cut with Specific Structure of ANN with Different Initial Weights

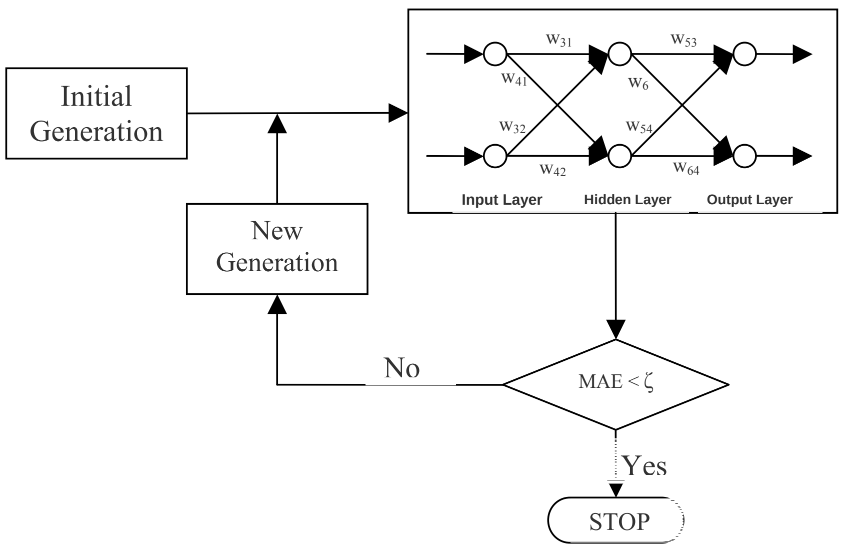

Figure 11. Structure of the Proposed GA Based Weights Selection for ANN Model for Predicting the Depth of Cut

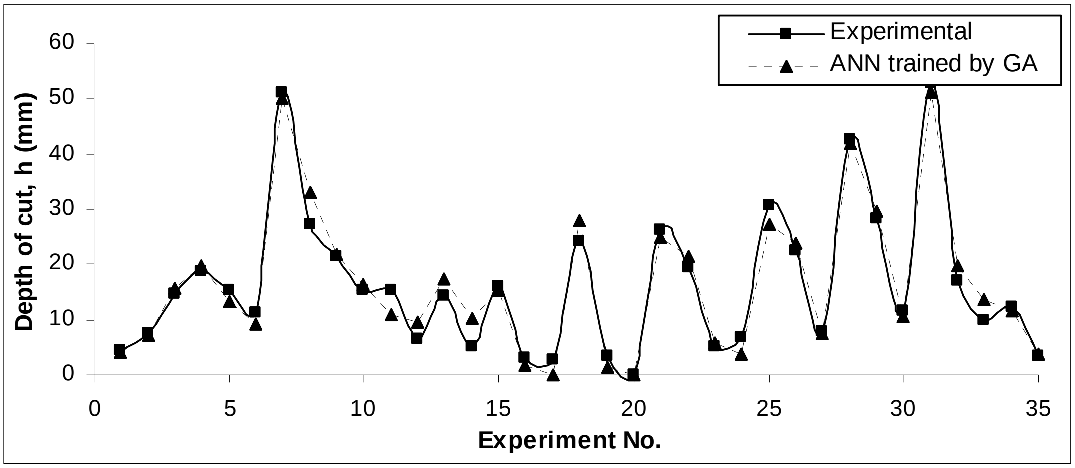

Figure 12. Comparison of Depth of Cut Predicted by 3-4-1 Structured ANN Trained with GA Based Weight Selection with Experimental Results

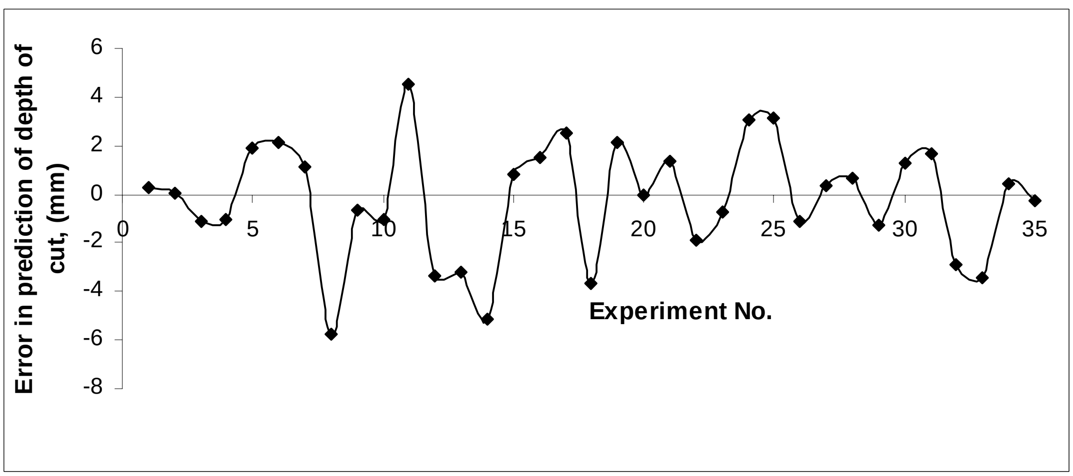

Figure 13. Variation of error in prediction of Depth of Cut by ANN by 3-4-1 structure with GA Based Weight Selection