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STATISTICAL MODEL BASED OPTIMAL PREDICTION ON DRILLING PARAMETERS

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ABSTRACT

The drilling is an imperative machining practice in the mechanical field for fitting or cutting the materials devoid of any disturbance. Various elements are basically employed within the automobile applications on account of the light weight, exceptional firmness and the moderate cheapness. The effectiveness of the drilled opening for the material shields is expanded by minimizing the eccentricity factor. The eccentricity is a degree of the nature of a drilled hole, and the process is based on input parameters. The significant intention of the suggested procedure is to built a mathematical modeling with the support of the optimization techniques. The mathematical modeling is done by minimizing the time consumed in the case of extension of the real time experiment. It is utilized to predict the diameter of the drill whole entry and exit, material removal rate and the eccentricity factor for the drilling process. Different optimization algorithms are utilized to find the optimal weights α and β of the mathematical modeling. All the optimum results demonstrate that the attained error values between the output of the experimental values and the predicted values are near equal to zero in the designed model. From the results, the minimum error 97.2% is determined by the mathematical modeling attained in the Artificial Fish Swarm Optimization (AFSO) process.

Indexing terms/Keywords

Drilling, cutting speed, feed rate, material removal rate, Eccentricity factor, Artificial Fish Swarm Optimization (AFSO).

Academic Discipline And Sub-Disciplines

Mechanical; Manufacturing

SUBJECT CLASSIFICATION

Drilling; Process time reduction

TYPE (METHOD/APPROACH)

Mathematical modeling; Optimization; Artificial Fish Swarm Optimization

INTRODUCTION

1. Introduction

In machining process, drilling is most significant processes which are commonly used to compose holes for screws, rivets and bolts. However, drilling is a difficult function which is illustrated by the existence of extrusion by the drill chisel edge and cut by the rotating cutting lips [1]. A more number of research attempt have been made in the recent past to fully portray the drilling process of fiber reinforced composite materials. The efforts have been made in the direction of optimization of the operating variables and conditions for reducing the drilling induced damage [2]. The cutting parameters and tool geometry/material must be cautiously preferred to attain best performance on the drilling operation, i.e., to attain best hole quality, which signifies negligible damage to the machined component and satisfactory machined surface [3]. The deep hole drilling (DHD) method is a semi destructive MSR (mechanical strain relaxation) technique that contains drilling a hole through the thickness of the component, assessing the diameter of the hole, trepanning a core of material from around the hole and at last re-measuring the diameter of the hole [4]. Deep holes drilling methods are used for composing holes with a high length-to–diameter ratio, better surface finish and straightness. In order to overcome the major problems associated with deep holes drilling [5]. Various processes, including laser, plasma, and chemical machining, are employed for this reason. Furthermore, mechanical drilling is the most familiar method as it delivers higher quality, better productivity, and improved economic efficiency.[6] Composites have a low co-efficient of thermal expansion, which can afford a greater dimensional stability when needed. in spite of modern developments in near-net shape processing, composite parts often need post-mould turning and drilling to meet dimensional tolerance, surface quality[7]. The machining of materials is not the same as the machining of conventional metals. Hence, the spindle speed, drill diameter, feed rate of the machining performance should be selected carefully in the machining of materials [8]. High-speed deep drilling of steel (AISI 1045) is a material components which is an especially interesting industrial process, due to the broad use of steel as a base material for various kinds of high-value industrial components, like moulds, automobile power trains and several difficult structural elements in mechanical engineering [9]. The quantity of heat loss from the flow zone into the tool based on the thermal conductivity of the tool, tool shape and the cooling technique used to lower its temperature. The heat generated during a cutting operation is the summation of plastic deformation involved in chip formation, the friction between tool and work piece, and between the tool and chip [10]. Composite structures are more and more used in high performance applications because of greater strength to weight ratio and stiffness to weight ratio. The drilling parameters have the major contribution for the delaminating /defects in holes machined in composites [11]. The drilling has the highest application in assembling components produced of composite materials. For an example, it has been founded that, over 100000 holes are needed in a small aircraft engine. This operation is often conducted using traditional twist drills [12]. The quality of the drilled hole based on the thrust force and torque generated during drilling, which in turn is exaggerated by the factors such as tool geometry, speed, feed etc [13]. The effect on the characteristics of drilling dynamics of the cutting force can be considered as a function of the processed material hardness and cutting layer thickness.[14] The cutting velocity and feed rate are the two most significant operating variables in the drilling process. These variables are under the direct control of the operator. Both these variables are to be optimized to make good quality hole [15]. A fraction (up to 15%) of drilling and fracturing waste may constitute impurities and solids, minerals (including heavy metals) and organic substance from geologic developments, polymers and further chemical additives, and prop pants, which are sand or high-strength ceramic particles/grains used during fracturing to keep shale fractures open and allow free flow of gas and oil to the well.[16] Most of the researchers examined the influence of cutting speed, feed, drill size and fiber volume fraction on the thrust force, torque and surface roughness in drilling processes of fiber reinforced epoxy composite materials[17]. For a given set of composite the appropriate selection of the mention parameters would lead to the acceptable drill hole quality [18]. In recent years, utilization of composite material in many engineering fields has undergone incredible enhancement. Reduction of weight and raise performance properties in transformation of plastic materials, automotive and aeronautic pieces, axes and rollers for printing and medical prostheses and surgical tools application have paved a path to enhancement of engineering materials [19].

2. Literature Review

In 2012, Girolami *et al* [20] have proposed the death of bees has been correlated with the use of neonicotinoid-coated seed and the toxic particulates emitted by pneumatic drilling machines. The position of the bar was changed by two operators at various distances from the drilling machine. A single pass was shown as sufficient to kill all the bees exposed to exhaust air on the emission side of the drill, when bees were subsequently held in high relative humidity. The extent of toxic cloud around driller was evaluated at the height of 0.5, 1.8 and 3.5 m and proved to be about 20m in diameter, with an ellipsoidal shape. The survival rate of the bees was not substantially increased using the modified drill and was lower than 50%.This new evaluation of bee mortality in the area is an new and creative biological test to prove the hypothetical efficiency of driller modifications.

In 2013, Amini *et al* [21] have proposed the Vibration drilling (VD) is a process in which longitudinal wave is used to improve drilling conditions. A rotary VD tool was designed and fabricated for performing VD. This tool is able to apply longitudinal wave through an ultrasonic transducer and horn to a drill in a rotary mechanism. Some parameters such as the thrust force, chip, and burr were measured and compared together in both conventional and ultrasonic methods. The morphology chip was changed and transformed from continuous chips into discontinuous chips. Due to the elimination of drill skidding, there is no oversize in the hole entrance in VD. But in outer diameter, the drill entrance cannot be properly maintained because of the heavy thrust force and drill skidding.

In 2013, Rajesh Kumar *et al* [22] have used soft computing techniques such as multiple regression, artificial neural network (MLP and RBF) models to propose predict rock properties by taking drill bit speed, penetration rate, drill bit diameter and equivalent sound level produced during drilling as the input parameters. RBF neural networks have been applied for predicting the rock properties. Two center initialization strategies for the RBF units have been investigated in the hidden layer, namely, random selection of centers and CDWFCM algorithms. Results from the analysis demonstrate that neural network approach is efficient while compared with statistical analysis in diagnosing rock properties from the sound level produced while drilling.

In 2013, Lee *et al* [23] have proposed a new drilling machine, Digger, to efficiently drill six holes simultaneously on decomposed granite road cuts to facilitate revegetation. The Digger consists of a base machine (0.7 m3-level excavator) and a mounting body with six hydraulic motors instead of a bucket. The results that drilling diameter 10 cm and depth 10 cm were large enough to result in better plant germination and growth. The time-motion and revegetation results that the Digger can be a promising technology to restore decomposed granite road cuts. Effects of shade net on the revegetation were inconclusive, because of no statistical differences to coir geotextile and to no mulching.

In 2013, Navid Zarif Karimi *et al* [24] have proposed drilling is a very common machining operation to install fasteners for assembly of laminates. However, delamination, is an very important concern for reinforced composite materials in the drilling of fiber; because it reduces their compressive residual strength. Taguchi method is used for design of the experiment. The outcomes highlight the significance of the feed rate for maximizing the compressive residual strength of drilled laminates. The most significant effects was produced by the feed rate and drill point angle on the adjusted delamination factor. The end results prove that root mean square (RMS) can be used for monitoring thrust force and AE energy for compression force.

In 2013, Vaibhav Phadnis *et al* [25] have proposed Drilling carbon fibre reinforced plastics (CFRPs) is typically cumbersome due to high structural stiffness of the composite and low thermal conductivity of plastics. Appropriate selection of drilling parameters is believed to mitigate damage in CFRPs. In a composite laminate, a unique three-dimensional (3D) finite element model of drilling, accounting for complex kinematics at the drill-work piece interface is developed. Cohesive zone elements are used to simulate interply delamination in a composite. The developed numerical model is shown to agree reasonably well with the experiments. The model is used to predict optimal drilling parameters in carbon/epoxy composites. The FE model predicted the drilling thrust force and torque with reasonable accuracy when compared to experimental results.

3. Proposed methodology

The Mathematical Modeling is employed to effectively to predict various parameters such as the Diameter of the drill hole entry d_1 and exit d_2, Eccentricity factor (E_f) and the material removal rate (M) of the Drilling process. In this regard, the standard inputs include the Cutting speed ('V' in m/min), Feed rate ('f' in mm/rev), average cutting torque ('M_T' in Nm) and average feed force ('F_F' in N), which are utilized by the mathematical modeling along with the optimization method for estimating the superlative outputs of the drilling. In the statistical illustration, it is efficiently utilized to arrive at the perfect mathematical statement for finding the best arrangement of the drilling technology. Further, in the preparation of the technique 80% of the dataset is utilized for the training function and the remainder deployed for the validation of the scientific model. The mathematical modeling with the optimization comes out with flying colors by ushering in the optimal weight α and β. Several optimization methods like the Harmony Search (HS), Artificial Fish Swarm Optimization (AFSO), Tabu Search (TS) and Particle Swarm Optimization (PSO) are effectively employed to ascertain the optimal weight of the system. The optimal values go a long way in reducing the inaccuracies and proficiently forecast the Diameter of the drill hole entry, Eccentricity factor and the material removal rate of the drilling process, thereby considerably scaling down the financial outlay, and the time-frame envisaged in the planned model. It is worth to mention that the whole procedure gets suitably and properly implemented in the working structure of the MATLAB 2014 tool. The following Figure 3.1 shows the flow chart for the mathematical modeling with AFSO.

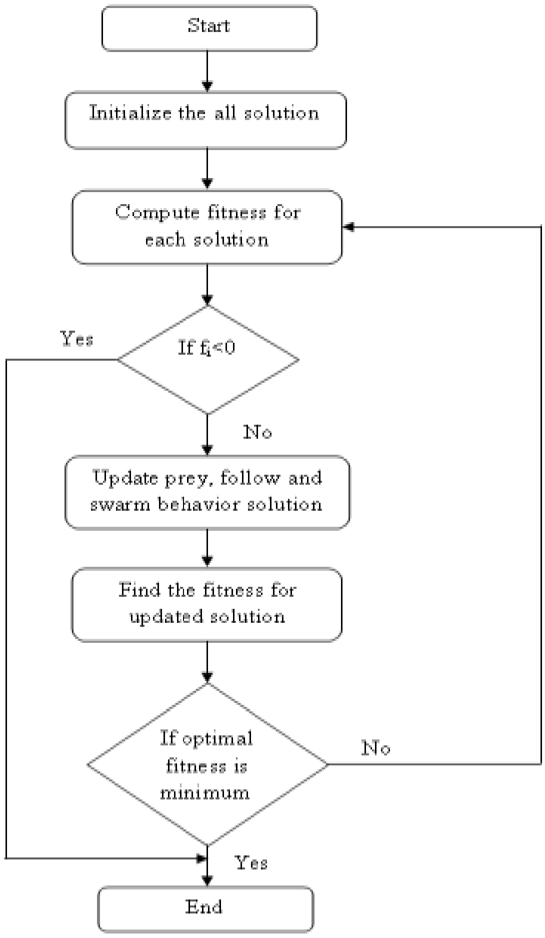


Figure: 3.1 Flow chart for Mathematical modeling with AFSO

3.1 Mathematical modeling

In the mathematical modeling, the identified input and output datasets are employed to train the model for locating the optimal output equation of the innovative technique. In this procedure, input represents several drilling constraints and the output includes the diameter entry and exit, Eccentricity factor and material removal rate of the procedure. At the outset, arbitrary weights α and β are allocated in the network within a specific range. When the preparation of the data set is complete, it is in the range of 80:20 for training and testing purpose respectively. In the mathematical modeling the optimization methods are employed to evaluate the optimal weight α and β of the system for reducing the inaccuracy value of the model. Several optimization techniques are effectively employed to ascertain the optimal weight of the system in which the optimal weight is achieved in the AFSO. The data sets are managed by the system for achieving the base slip by utilizing the weights α and β, which are modified for ascertaining the output of the input parameters. In the mathematical modeling, which is generally dependent on various optimizations of the weights, the identified inputs with the optimal weights are taken as per equation (4). In this innovative modeling, the Artificial Fish Swarm Optimization (AFSO) strategy is used to attain the optimal weight.

3.2 Artificial Fish Swarm Optimization (AFSO)

In the environment, the fish is competent to locate further nutritious zone by being making investigation independently or pursuing certain other fish which is on its way to such a zone, as it is proved that the zone inhabited by maximum fish is usually the most nourishing one. The basic plan of the AFSO is to reproduce the various facets of fish conduct like the praying, swarming, and continuing with the local investigation of fish independently for achieving the global optimum. The surroundings where an AF resides is essentially the solution space and a similar situation exists for other AFs also. Its subsequent conduct is dependent on its present situation and its local ecological state (including the excellence of the question solutions at the current situation and the states of close by companions. An AF is most likely to maneuver the ecosystem by means of its own actions along with those of its companions.

In Figure 3.2.1 the AF is aware of the exterior insight by its visualization illustrated. D Represents the current state of the AF and the visual relates to the visual distance, and D_v indicates the visual location at certain particular moment. If the condition at the visual location is superior to that at the current state, it moves a step ahead in the same direction, and achieves the D_{next} condition. Or else, it continues the inspecting tour in the visualization. If the number of inspecting tours conducted by the AF is more, the awareness regarding the entire states of the vision achieved by the AF is great. Certainly, there is no need for traveling through the whole complicated or countless states, which enable location of the global optimum by allowing certain local optimum accompanied by certain hesitancy.

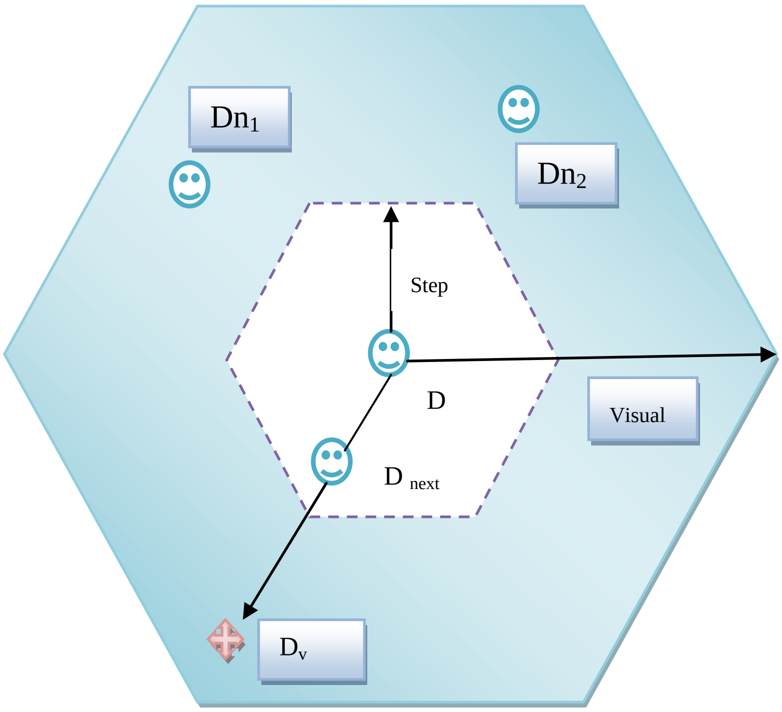


Figure 3.2.1 Vision of artificial fish swarm algorithm.

3.2.1 Initialization

Initialize the input parameters such as weight α and β which is defined as the α_i , β_i is an initial solution of fish and i is a number of solutions and also initialize the parameters such as step, this process is known as initialization process.

$$D_i = (D_{0j}, D_{1j} ......D_{nj})$$

Where, D_i defines an initial solution, *i* ε [1, 2, … 10] and *j* ε [1, 2, … 140]. Since, i^{th} value is considered as the number of solution and j^{th} value is considered as length of solution.

$$D_i = \begin{bmatrix} (No \quad of \quad hidden \quad neuron * No \quad of \quad input \quad data) + \\ \\ No \quad of \quad hidden \quad neuron \end{bmatrix} \qquad (1)$$

Here Total input = 4; Hidden neuron (h) = 20

Based on equation (1), the attained solution length is 140 and the solution range lies between $-10 \le D_{ij} \le 10$ .The input data which are cutting speed, feed rate, average feed force and average cutting torque. According to the initial solution based four outputs such as diameter entry and exit, eccentricity factor and material removal rate are evaluated.

A non dimensional eccentricity factor E_f is defined accordingly the following equation

$$E_f = \left[\frac{d_{1\max} \quad or \quad d_{2\max}}{d_{hole}} \right] \qquad (2)$$

In machining parameters of all drilled hole on the composite material demands the highest material removal rate for a given set of speed and feed rate.

$$M = \left(\Pi / 4 \right) d_{hole}^2 N \times F_r \qquad (3)$$

3.2.2 Fitness function

Evaluate the fitness value of each fish solution by using equation (4) and then calculate the best solution values.

$$F_i = \sum_{j=1}^{h} \alpha_i \frac{2}{\left[1 + \cosh \sum_{i=1}^{N} (D_i \beta_{ij}) - \exp \sum_{i=1}^{N} (D_i \beta_{ij}) \right] - 1} \qquad (4)$$

Here

$$\cosh(D) = \frac{\exp(D_i \beta_{ij}) + \exp(-D_i \beta_{ij})}{2} \qquad (5)$$

Where, α and β are weights, D is the input parameters, i is the number of inputs, j is the number of weights, N is a number of the input data and h is the number of hidden neurons.

Find the new solutions for the process update the new fishes based on the prey, follow and swarm behavior.

3.2.3 Prey behavior

This illustrates the basic biological nature which relates to the food. Let us assume that the state of the artificial fish is D_i which randomly opts for a state D_j within in the bounds of its sensing range. If D_j is greater than D_i , then let us shift to D_j . If not, , choose the random criterion D_i to ascertain whether it satisfies the forward stipulations, by repeating a number of times. In spite of this, if the forward stipulations are not met, then shift arbitrarily one step ahead. The food intensity in this location of fish is called the objective function value. The distance between the artificial fish is expressed by $d_{i,j} = \| D_i - D_j \|$ where I and j represent arbitrary fish.

$$D_j = D_i + visual.rand() \qquad (6)$$

$$D_i^{(t+1)} = D_i^{(t)} + \frac{D_j - D_i^{(t)}}{\| D_j - D_i^{(t)} \|}.step.rand \qquad (7)$$

Where produces random numbers between 0 and 1 and the maximum step size of artificial fish means the step. Visual is the visual distance and then the artificial fish occurs only in the inner radius of the circle to the length of the field of vision various acts.

3.2.4 Swarm behavior

Supposed the current state of artificial fish is $D_i(d_{i,j} < Visual)$ number of artificial fish is $n_f if (n_f < \delta)$ indicates the partners have more food and less crowded, if F_c better than F_i ,then go forward toward the centre of the direction of the partnership, otherwise prey behaviour.

$$D_i^{(t+1)} = D_i^{(t)} + \frac{D_c - D_i^{(t)}}{\| D_c - D_i^{(t)} \|}.step.rand \qquad (8)$$

3.2.5 Follow Behavior

Supposed the state of artificial fish is D_i explore its optimal state $D_{\max}$ from Visual neighbors , the number of partner of $D_{\max}$ is $if (n_f < \delta)$ indicates that near distance have more food and not too crowed further move to the front of $D_{\max}$ position; otherwise perform foraging behavior by using equation (7).

3.2.6 Optimal solution

In accordance with procedure detailed above, the optimal weights are achieved and thereafter the optimal fitness is attained which is defined as $F_{optimal}$ and depending upon the relative optimal fitness the output is arrived at. As per the optimal equation the outputs are forecast which include the Diameter of the drill hole entry d_1 and exit d_2 , Eccentricity factor (E_f) and the material removal rate (M) of the drilling process.

$$F_{i(optimal)} = \sum_{j=1}^{h} \alpha_{(optimal)i} \frac{2}{\left[1 + \cosh \sum_{i=1}^{N} (D_i \beta_{(optimal)ij}) - \exp \sum_{i=1}^{N} (D_i \beta_{(optimal)ij}) \right] - 1} \qquad (9)$$

Where, α and β are weights range from -500 to 500, X is the input parameters, i is the number of inputs, j is the number of weights and h is the number of hidden neurons. Then find the error value by use equation (9).

$$E_i = \sqrt{\frac{\sum_{i=1}^{ND} (D_i - P_i)^2}{ND}} \qquad (10)$$

Where ND is the number of the data, D is the desired value and P is the predicted value, i= 1,2,….n. By using this formula, the error value is getting from the difference between desired value and predicted value.

4. Result and Discussion

Drilling process parameters the optimization process results are taken from the working platform of MATLAB 2014 with the system configuration, i5 processors with 4GB RAM is used in ANN process. Drilling process drill speed and feed rate and average values are considered to predict the output parameters optimization process utilized to predict experimental results. Based on the objective function the parameters which are drill hole entry d_1 and exit d_2 , Eccentricity factor (E_f) and the material removal rate (M) are taken in the process. The major objective of the model is to forecast the output like realtime experiment to minimize the error.Subsequently, the optimal solutions of the input constraints are arrived at with the assistance of the amazing artificial fish swarm optimization (AFSO).

4.1 Mathematical modeling with Optimization techniques

Mathematical modeling with the optimization methods like the AFSO, PSO, HS and TS yields the least error value for the optimal equation with the optimal weights α and β. In the captioned techniques the least error is better achieved in the artificial fish swarm optimization (AFSO) techniques compared to the other techniques. Figure 3 elegantly exhibits the average least error value of the parameters which are diameter entry, exit, eccentricity factor and material removal rate. Figure 4.1.1 makes it absolutely clear that the mathematical model with the optimization method has been able to achieve the least error value of the Drilling parameters. The error value is determined by means of the test data values and forecast values. Average error of the AFSO process is 0.27 and its value compared to the PSO the difference is 67.23% and HS technique is 64%.The error value is varied based on the objective function of the optimization technique. Tabu search technique has the error value is 0.85 it compared with AFSO error minimized as 47.23%.All the drilling parameters the minimum least error of artificial fish swarm optimization compared with other techniques 60% error will be minimized.

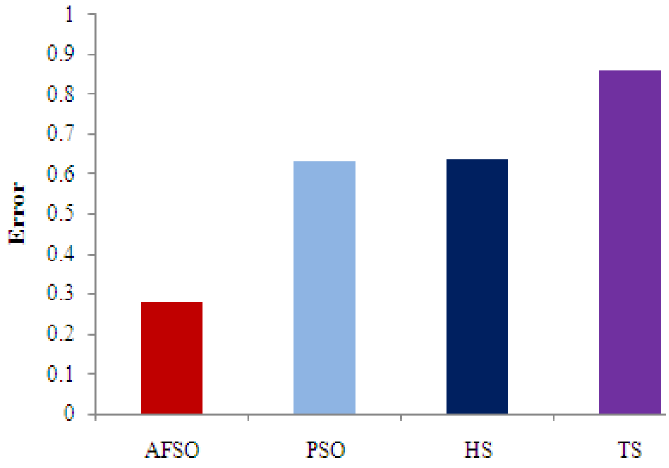


Figure: 4.1.1 Error graph for Optimization technique

4.2 Convergence graph

The graphs showing below successfully show the average fitness graph for the drilling parameters based on the iteration of the AFSO, HS, TS and PSO by altering the weights in the range of -500 to 500, and thus the error values are determined. The error graph is drawn with the iteration symbolized in the X-axis and fitness in the Y–axis.

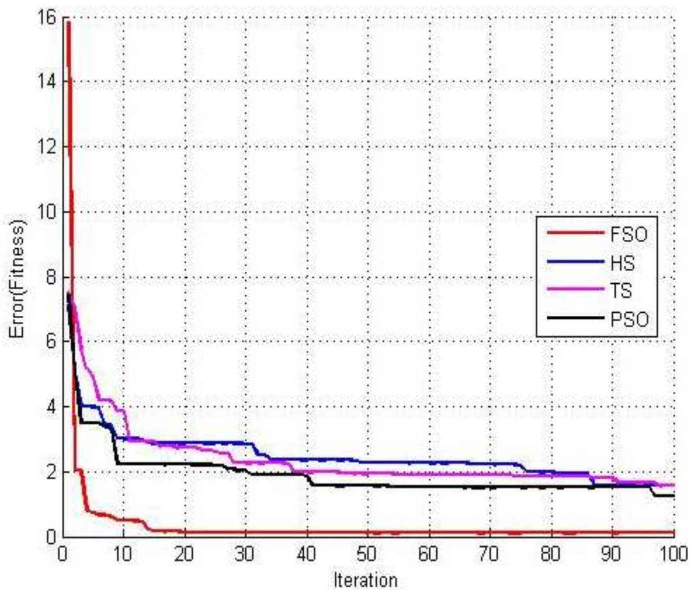


Figure: 4.2.1 Convergence Graph

Figure 4.2.1 illustrates that the convergence graph is plotted among the iteration and fitness estimations of the different strategies. The graph fundamentally resolves the AFSO procedure presents the minimum fitness in the least iteration. Through the chart, the AFSO approach takes the minimum iteration for offering the ideal result and it attains the greatest estimation of the fitness. The minimum error of AFSO is 0.053 in 100th iteration the performance of the graph iteration raised the fitness will be minimized. AFSO process contrasted with the HS, TS and is 70.7%.When the minimum fitness value of the suggested approach is compared to the PSO the error difference is 0.46. Entirely the presentation of the drilling parameter eccentricity factor, diameter entry, exit and material removal rate of the predicted values is almost equal to the experimental values. Initial fitness value is 16.53 in all algorithms the target function f the technique based minimize error value of the model. Overall the maximum fitness of 2.358 is reached in the HS technique whereas the competence of the AFSO process is 93.6% .Through the graph the artificial fish swarm Optimization approach obviously specifies the ideal fitness value with the competent results.

4.3 Predicted values for different algorithm

Mathematical modeling process consists of two divergent procedures such as the training and testing process. In the training process, 80% of data is deftly used by duly modifying the weights and the remainder 20% effectively employed in the testing process. Drilling parameters are diameter entry; exit, eccentricity factor and material removal rate are forecasted by using the cutting speed, feed rate, average feed force and verge cutting torque. Below tables shows that the experimental drilling parameter values and forecasted drilling parameters values based on the optimization technique.

Table: 4.3.1 Original value of the testing data

Input				Output			
Cutting speed (V)	Feed rate (F)	Average cutting Torque (M_T)	Average feed force (F_F)	Diameter entry (d_1)	Diameter exit (d_2)	Eccentricity factor (E_F)	Material removal rate (M)
900	0.1	0.063	30.98	6.089	5.064	1.113	2190.199
1300	0.1	0.064	24.6	6.233	5.118	1.176	3528.724
1300	0.2	0.082	50.94	6.856	5.194	1.355	9373.151
1500	0.2	0.082	50.94	6.865	5.195	1.366	10997.7
1700	0.05	0.054	19.9	5.629	5.129	1.13	2133.072

4.4 Error values of output parameters in different algorithm

In this section, the number of data is varied and the error calculated for some input data such as speed and feed rate and torque, feed force based Drilling parameters of the drilling process the error graph are shown below. Table 4.3.1 and 4.3.2 shows that the original and predicted values for the testing data with the artificial neural network with the optimization process. Numerical modeling structure is trained by use of the objective function then tested values are predicted. The predicted values and experimental value nearly equal to the AFSO process. Diameter entry and exit value based on the eccentricity factor the difference is 98.2% in AFSO compared to the PSO 48.63%. Drilling process input parameters the speed, feed rate, cutting torque and feed force based predict the output values. Maximum and minimum of drill hole parameter based predict the Eccentricity factor here the initial testing data the E_F is 1.113 the predicted value is 1.17 in AFSO process it's a nearby value of the optimization process. All the testing data the eccentricity value of the original is compared to AFSO, PSO, HS and TS is 99.96%, 99.5%, 99.56% and 99.4%.ArIthmatical model with proposed optimization compared to the other techniques the difference is 56.38% material removal rate also the nearby value attained in the AFSO. All the drilling parameters the predicted value of AFSO process 96.5% nearby experimental values.

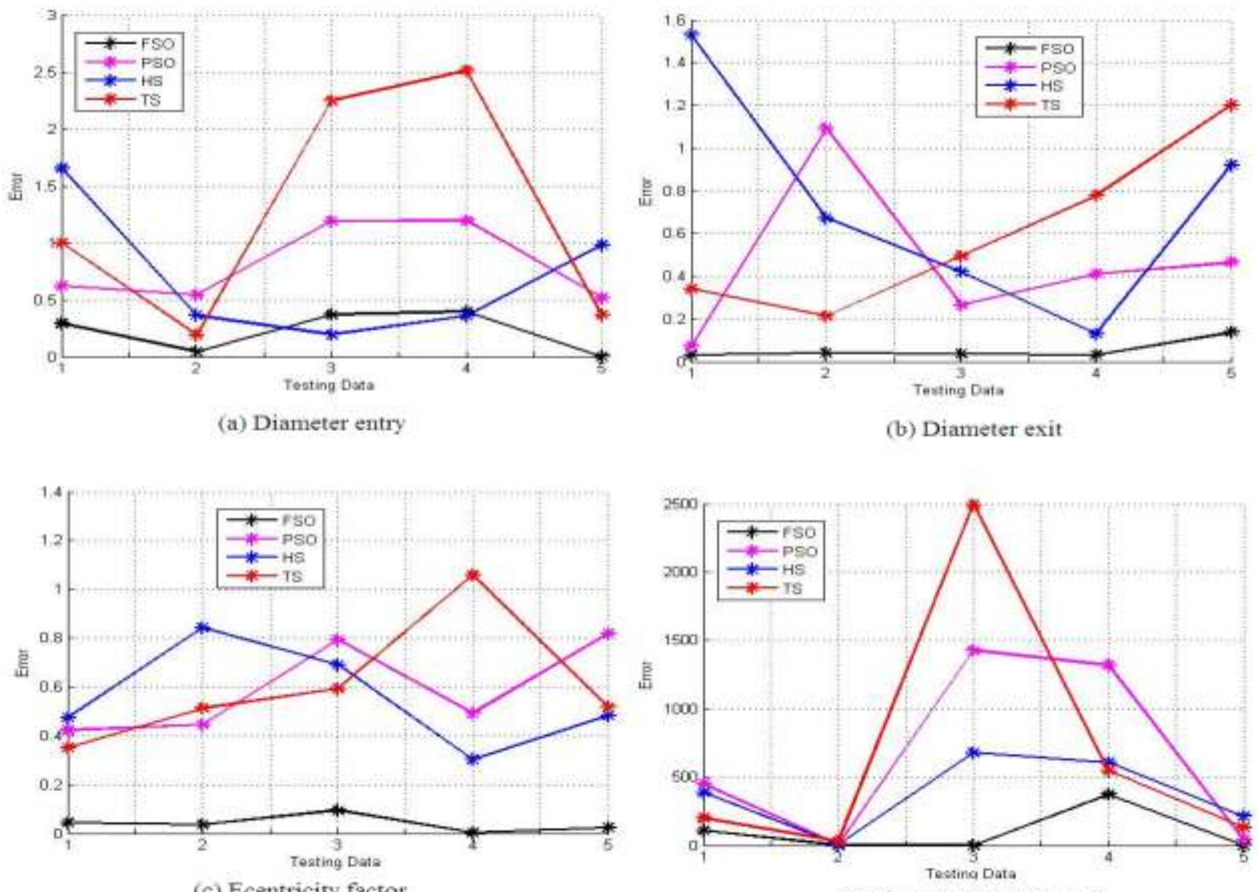
4.4.1 Error values of output parameters in different algorithm

In this section, the number of data is varied and the error calculated for some input data such as speed and feed rate and torque, feed force based Drilling parameters of the drilling process the error graph are shown below. The figure 4.4.1 shows that the error value with the number of data varying for the diameter entry, exit, eccentricity factor and material removal rate for AFSO,PSO,HS and TS. For the data the minimum error value of diameter entry is 0.2753 shown in figure (a).For the minimum error is compared to PSO 63.23%. First data the error is 0.29 its compared with PSO the error minimized as 96.44%,TS is 93.65% and the HS is 94.3% the performance of the graph in diameter entry shows that the data 2 to 5 the error is same performance for the all techniques. Figure (b) shows the diameter exit also the minimum error value 0.05 compared to other techniques minimum value. Eccentricity factor minimum error value for the different data shown in figure (c) first data the minimum error value is 0.03 in AFSO, 0.07 for PSO, 1.53 for HS and 0.34 for TS similar values are attained in all techniques. Then the material removal rate shows the figure (d) the material wastage of drilling process has minimum value in optimization process. All the data the M_R is minimum value is 96.52 in AFSO its compared to the other technique 97.9% decrease.

The characteristic Figure 4.4.2 illustrates one set of input values of the procedure during the performance technique is carried out in the MATLAB programming indicated on the relative graph. At this juncture, the required constraints cutting speed, feed rate, average feed force and average cutting torque. With the input based on several techniques the drilling parameters are identified. For various testing data values the outputs are achieved in several methods In this process the input data based gesture in LA are producing 87.23% of the GA and DE technique. In this graphical user interface (GUI) based approach, the input values are changed and the corresponding output the gestures are evaluated.

Output															
AFSO				PSO				HS				TS			
d_1	d_2	E_F	M	d_1	d_2	E_F	M	d_1	d_2	E_F	M	d_1	d_2	E_F	M
6.38	5.07	1.17	2082.2	5.47	5.11	1.55	1740.24	7.74	3.5	0.65	1804.9	7.08	5.38	0.7	1990.2
6.27	5.02	1.25	3528.6	5.69	6.15	1.74	3518.4	6.59	5.73	0.4	3522.44	6.04	5.27	0.78	3499.1
6.48	5.06	1.26	9372.7	5.66	5.37	2.14	9372.7	6.66	5.527	0.66	96.95.9	4.60	5.60	0.71	6882.1
6.46	5.10	1.13	10623.2	5.66	5.48	1.62	9378.6	6.50	4.94	0.821	10393.0	4.35	4.28	0.07	10451.5
5.62	5.02	1.20	2132.96	6.14	5.62	2.04	2132.9	6.61	6.072	0.748	1919.3	5.99	3.95	0.71	2004.3

Table 4.3.2 Predicted value of the testing data



(a) Diameter entry

(b) Diameter exit

(c) Ecentricity factor

(d) Material Removal rate

Fig: 4.4.1 Error graph for the Drilling parameters

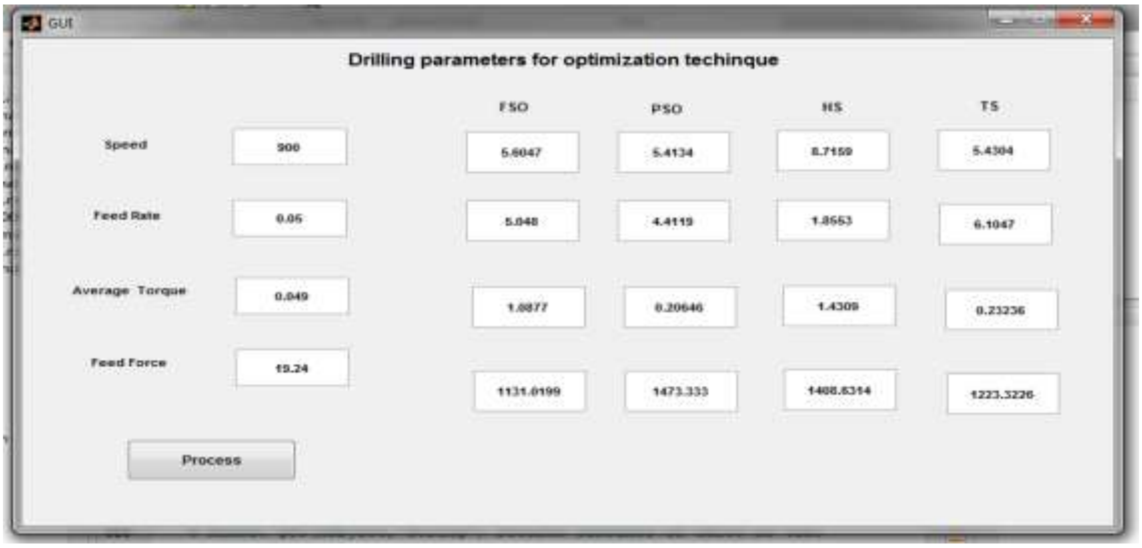


Figure: 4.4.2 Matlab output

5. Conclusion

This paper elegantly explains the mathematical modeling technique crowned with the mighty artificial fish swarm optimization (AFSO) technique which amazingly attains the accurate ideal values of the weights in model. The multivariable optimization issues ushers in the universal optimum solution and illustrates the adaptability to choose the design variables based on the weights.. During the operation of the system the output parameters are assessed with the data sets. The convincing results are observed to be nearly equal to the data set minimum error value achieved in the optimization method. The minimum errors of mathematical modeling with AFSO process in the case of the Diameter of the drill hole entry d_1 and exit d_2, Eccentricity factor (E_f) and material removal rate (M) are 95.7%,98.42%,96.8% and 97.9% respectively. In future the ANN investigators will look towards further unbelievable improvement methodologies for the produce of diminished errors with their excellent techniques for the emission parameters of the drilling process.

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