Optimization of Process Parameters That Affects hole Quality Characteristics in Drilling Of Syntactic Foams Using Artificial Neural Network Model And Particle Swarm Optimization

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Abstract. The drilling is known popular and common mechanical operation which is performed frequently during manufacturing of automotive and aerospace related parts, it is important to study the manufacturability of any novel engineering materials developed and subjected for machining more often as drilling a hole which is required for the purpose of assembly. In this regard the proposed work aims at study of drilling process parameters on newly developed class of polymer based composites. Cenosphere or fly ash acts as a filler material which is a by-product of coal combustion used along with epoxy to produce syntactic foam. The preparation of cenosphere based epoxy composites is done using hand layup technique. The controllable factors in the presented study identified such as cutting speed, feed rate and drill diameter are suspected to have effect on drilled hole quality characters, such as surface roughness and delamination factor. Syntactic foams of 40\% by weight are fabricated. A complete factorial design has been selected to perform drilling experiments and recommended drilling quality aspects are analyzed using RSM based quadratic relationships. The relationship of RSM revealed that $Ra$ and $Fd$ are varying non-linearly for selected input variables. The optimization of selected parameters is performed and it is seen that $Ra$ of 0.2 microns and $F_d$ 0.99 are achieved at cutting speed of 55m/min, feed rate of 0.05mm/rev and using drilling tool of diameter 16mm.

1. INTRODUCTION

Drilling operation is the most common operations performed till today. Drilling operations on laminated composites which is essential for fastening with other materials to obtain useful articles as outcomes. The fastening efficiency and excellence is relied mainly on the quality of drilled hole. Producing error free précised holes is desired to ensure high joint strength during assembling of materials by riveting or bolting.
The new engineering materials with an added advantage of having less in weight brought a greater interest especially in locomotive applications. Reduction in structural weights is beneficial towards savings in fuel consumption. The hollow particle filled porous material is called syntactic foam, which consists of silica and alumina (Scott, W D et al., 2005). The syntactic foams are well known form of particulates type reinforced polymer composites. The porosity of these foams being enclosed with resin form a less thick and strong exterior that helps to achieve low densities in syntactic foams without compromising on important mechanical properties. Cenosphere based composites possess excellent properties when subjecting to compressive loads. Correlating the structure with properties of reinforced syntactic foams will offer provision to develop lighter composites for structural requirements that enables to reduce the cost and weight of developed composites; cenosphere is used as filler material in polymer composites and hence that meets more structural attributes in the components (Axen N et al., 2001). Machining engages a vital part in the fabrication process which will lead to an intended application. As a result, the development of powerful machining method leads to reduction in cutting forces. The Cenosphere reinforced epoxy composites are superior in comparison with traditional materials in terms of obtaining nearly expected physical, mechanical, thermal and tribological properties. The machining of composites is different from that of homogeneous counterparts. The superior outcomes relating towards machining operation are considerably depends on work the material and its properties.

The study of machinability depicts the relative easiness through metal cutting by employing appropriate tools and important machining parameters. power, specific cutting pressure, tool life, surface roughness and Forces are some of the criteria that are recommended to assess machinability (Groover M P et al., 1996). In a drilling process the quality aspect of a drilled hole can be identified in terms by the measurement of the delamination factor that occurs often during the process. The quality of holes is determined by the cutting efficiency of drill in the drilling process (Gaitonde et al., 2012).It is necessary to chose appropriate process parameters when drilling component. The drilled holes quality on features can be enhanced by appropriate choice of cutting parameters (Redouane et al., 2010). There is work which has reported that 60 to 70% of rejections in industries is because of drilling associated delamination at the time of assembly (Stone R et al., 1996). Therefore there is a need to study to delamination occurred after drilling as it counts the wear of the material. Syntactic foam is composed of hollow particles; it’s a composite which satisfies low weight sustainable strength application. Composite materials are class of materials which are fabricated with a combination of two or more materials that are chemically and physically diverse and are assorted by a prominent interface. Drilling experiments are performed in order to form a machining system which would avoids delamination near entry and tool exit. This attempt to control feed rates the drill bit makes contact work material, thereby reducing delamination. Experimental approaches are employed for investigating optimal cutting conditions or tools and those required for improving the machining processes. (Dharan and Won et al., 2000).

2 LITERATURE REVIEW

In today’s scenario Composite materials play major role in serving as material for most of the parts manufactured. They are adapted because of the versatile nature of the particles and the matrix which provides adequate strength and stiffness. The need for high tensile strength low density, light weight
material has given rise to composite material. Composites are heterogeneous in nature as they are made of more than one component along with fillers and a matrix. The matrix gives the composite a required shape, surface appearance and an overall durability. Thus, study on drilling of syntactic foam is required. The quality of holes is determined by the cutting efficiency of drill in the drilling process. The sharp cutting edges performed efficient cutting action, generates lower heat flux and good hole quality (Zaffar et al., 1991). With the increase in depth of cut and feed rate the surface finish decreases. The optimal way to determine combination of cutting parameters for surface finish is Taguchi parameter design (Pang et al., 2013).

To perform machinability studies of specimen prepared out of syntactic foam proper cutting parameters are to be selected. The feed rate, point angle and cutting speed vary the quality of hole produced and the delamination also varies with these parameters (Ashish et al., 2016) (Gaitonde V N et al., 2014). The response surface methodology (RSM) as applied for statistically planned experiments has revealed that is efficient process-modeling tool (Montgomery, D.C., 1997). The methodology that aims at reducing the machining expenditures, time and also provides information about individual and combined effects of controllable factors on chosen responses in entire design matrix.

Taguchi’s parameter design strategy evolved as a popular tool for getting more improved results on intended responses. With continuous reduction in cost, that accomplished with the number of experiments (Phadke, 1989; Ross, 1996). From the earlier works on composites drilling, the research information on low cost and lighter weight materials, as a potential structural component having greater hole quality is scarcely existing. Additionally, the correlation amongst the controllable variables and their influence on hole quality are not known. Thus, in present research an attempt is made to fill the space through carrying out the investigations based on experiments on cenosphere reinforced epoxy composites drilling on hole quality such as drilled hole surface roughness and delamination factor.

The composites are prepared with 40% weight percentages of cenosphere in epoxy matrix. The RSM based models for Ra and Fd are built-in with least number of experiments using complete factorial designs (Montgomery, 2003; Myers, 2009). The significances of cutting speed, feed and % filler content on proposed hole quality have been analyzed.

3. ARTIFICIAL NEURAL NETWORK MODELING (ANN)

The artificial neural network (ANN) being a modeling tool that allows to understand relationship map between input and output process variables (Schalkoff, R. B., 1997). The ANN model development attempts towards imitating a human brain with the association functions, generalization & self-organization. The biological configurations of nerve system obtained through ANN are in turn computer model represents various processes and mechanisms. The ANN models in their attractive view of higher processing speed with moderately adopted computer hardware's which are in adjusting nature and ability in solving non-linear and complex problems.

In this investigation, the EBPTA training algorithm is adapted which is a feed forward multi layer ANN and is being supervised learning algorithm (Schalkoff, R. B., 1997), which requires a set of inputs to
obtain certain expected outputs, which are called as training patterns. The EBPTA uses a gradient search technique, the MSE error between output pattern which is the actual and the desired output pattern is minimized. the neurons are subdivided into input layers, output layers and hidden layers, hence this feed forward ANN is multilayered network. The following is the activation input for neuron which is \( i^{th} \) position (Schalkoff, R. B., 1997).

\[
net_i = \sum_{j=1}^{a} w_{lm} x_j
\]  

Where, \( w_{lm} \) = link weights of connection neuron from \( i \) to \( j \); \( x_i \) = neuron at output of \( i^{th} \). which is a unipolar transfer function of sigmoid (Schalkoff, R. B., 1997):

\[
o_i = \frac{1}{1 + e^{\eta net_i}}
\]  

Where, \( \eta \) is scaling factor. The training algorithm is formed to minimize, MSE on the basis of weight updates for \( L \) no. of neurons.

If \( L \) is the number of neurons in layer of output and an algorithm is formulated based of weights is presented below (Schalkoff, R. B., 1997).

\[
E = \frac{1}{2} \sum_{L=0}^{L} (d_{L,p} - o_{L,p})^2
\]  

Where, \( d_{L,p} \) = desired output for \( p^{th} \) pattern.

\[
w_{lm(n+1)} = w_{lm(n)} + \alpha \delta_{pq} o_{pi} + \beta \Delta w_{lm(n)}
\]  

Where, \( n \) is a step for learning, \( \alpha \) represents rate of learning and \( \beta \) denotes constant for momentum. The residue term \( \delta_{ql} \) in Eq. 4 is given by (Schalkoff, R. B., 1997):

For output layer: \( \delta_{ql} = (d_{L,p} - o_{L,p})(1-o_{L,p}) \); \( L=1, \ldots L \)  

\[
(5)
\]

For hidden layer: \( \delta_{pm} = o_{pm}(1-o_{pm}) \sum \delta_{pl} w_{lm} \); \( m=1, \ldots J \)  

\[
(6)
\]

Where, \( m \) neurons to be in hidden layer

The ANN training pattern involving following steps:

The initialization of weights for random values

By increasing weights at every time the following will presents the input/output pairs
The MSE for MN number of patterns is obtained using,

\[
MSE = \frac{1}{MN} \sum_{N=1}^{MN} \sum_{L=1}^{L} (d_{Lp} - o_{Lp})^2
\]  
(7)

If MSE is lesser than tolerance

Termiate.

Else, repeat second step.

4 PARTICLE SWARM OPTIMIZATION (PSO)

The particle swarm optimization (PSO), is a relatively recent heuristic search method, here mechanics is inspired by collaborative populations behaviour. The fitness values tested using fitness testing relation which is then optimized, in turn helps to attain at fitted velocities, which in turn direct the particles flying. Considering the search space is \(D\)-dimensional, then the \(i^{th}\) particle within population, a swarm, is represented by a \(D\)-dimensional vector \(m = (m_1, m_2, \ldots, m_D)\).

The particle velocity is represented using other \(D\)-dimensional vector \(q = (q_1, q_2, \ldots, q_D)\). The best position of the \(i^{th}\) particle is designated as \(t_{best} = (t_1, t_2, \ldots, t_D)\). If \(L\) is the best particle index of a swarm \(L_{best}\) and superscripts denotes number of iteration, then the manipulated swarm is obtained in the following equations:

\[
q_i^{k+1} = w^k q_i^k + b_1 u_1^k (t_{i}^k - m_i^k) + b_2 u_2^k (t_{i}^k - m_i^k)
\]  
(8)

\[
s_i^{k+1} = s_i^k + v_i^{k+1}
\]  
(9)

Where, \(w\) is the inertia weight; \(b_1\) and \(b_2\) are the social and cognitive parameters; \(u_1\) and \(u_2\) are distributed uniformly within a range of \([-1, 1]\); \(i = 1, 2, \ldots, N\), where \(N\) is the swarm size and \(k = 1, 2, \ldots\) is the presented iteration. The higher weight gives the understanding of global search which is an exploration, The finner-tuning of \(b_1\) and \(b_2\) factors results from convergence of algorithm. Further, parameters \(u_1\) and \(u_2\) are used to maintain diversity of the population which are distributed uniformly in the range \([0, 1]\).

5. SPECIMEN PREPARATION

Syntactic foams of epoxy resin and cenosphere combinations are prepared with variation of cenosphere percentages of 20, 30 and 40% in medium viscosity epoxy resin (LAPOX L-12), mixed with K-6 and allowed to solidify at room temperature. The cenosphere is an inert hollow spherical shaped filler (hardness 5-6.5 MOH). The chemical composition of cenosphere used in the current investigation is: SiO2-55%; Al2O3- 34%; Fe2O3-1.5%; TiO2-1.2%; CaO - 0.3%; MgO-1.8%; Na2O-0.5%. Hardener is
measured in 10% of epoxy weight and stirred with the mixture of cenosphere/epoxy syntactic foam for 10mins.

Hand-layup technique was employed for preparing the specimens. The mixed content is poured into a rectangular mould of size 110 x 110 x 20 mm³, which is covered with aluminum foil for easy removal and stored in conditioned environment in such a way that the external factors like temperature and dust do not affect the quality of the specimens. Wax is applied gently applied for ensuring easy removal of the cast sample. The cured composite slabs are taken out from the mould and test specimens prepared through cutting to an appropriate dimensions i.e., 35 x 35 x 15 mm³ to conduct drilling tests.

6 EXPERIMENTAL DESIGN PLAN

The statistically planned experimenting tool such as DOE is used to build the mathematical models using artificial neural network (ANN) and particle swarm optimization (PSO). In the current research work, a study on hole quality of cenosphere/epoxy syntactic foams is carried out, the input variables considered are cutting speed (v), feed (f) and drilling tool diameter (d) are selected, these are the variables that are suspected to have affect on the hole quality characteristics such as drilled hole surface roughness (Ra) and delamination factor (Fd).

The ranges for the input variables are selected on the basis of preliminary experiments and three levels for each of the input variables are identified. The important controllable parameters and respective treatment levels presented in Table 1.0. The influence of input variables on hole quality parameters were tested through full factorial design (FFD) and accordingly, 27 trials based on FFD are conducted; the plan for performing experiments is given in Table 1.2.

6.1 EXPERIMENTATION AND HOLE QUALITY MEASUREMENT

The experiments involving drilling are performed as per FFD without any coolant on ‘Maxmill plus vertical machining centre’. 8 mm diameter of K20 grade tungsten carbide twist drill was used throughout the drilling experimentation.

| Table 1.0 Input variable with their treatments setting |
|------------------------------------------------------|
| Parameter                                             | Code | Unit      | Levels   |
|                                                      |      |           | 1        | 2     | 3     |
| Cutting speed                                         | V     | m/min     | 25       | 75    | 125   |
| Feed                                                  | F     | mm/rev    | 0.04     | 0.08  | 0.12  |
| Drilling tool diameter                                | D     | mm        | 8        | 12    | 16    |
Table 1.2 Investigation plan and drill quality parameters

| Trial No. | Parameter settings | Hole quality parameters |
|-----------|--------------------|------------------------|
|           | v (m/min) | f (mm/rev) | d (mm) | R_a (microns) | F_d |
| 1         | 25       | 0.04       | 8      | 3.23         | 1.0028 |
| 2         | 25       | 0.08       | 12     | 4.6          | 1.00408 |
| 3         | 25       | 0.12       | 16     | 1.81         | 1.00062 |
| 4         | 75       | 0.04       | 8      | 2.82         | 1.0127 |
| 5         | 75       | 0.08       | 12     | 3.95         | 1.015 |
| 6         | 75       | 0.12       | 16     | 1.35         | 1.01187 |
| 7         | 125      | 0.04       | 8      | 3.3          | 1.00287 |
| 8         | 125      | 0.08       | 12     | 2.76         | 1.0025 |
| 9         | 125      | 0.12       | 16     | 1.01         | 1.00087 |
| 10        | 25       | 0.04       | 8      | 2.47         | 1.00324 |
| 11        | 25       | 0.08       | 12     | 4.72         | 1.00215 |
| 12        | 25       | 0.12       | 16     | 2.35         | 1.00132 |
| 13        | 75       | 0.04       | 8      | 3.21         | 1.00217 |
| 14        | 75       | 0.08       | 12     | 2.91         | 1.00208 |
| 15        | 75       | 0.12       | 16     | 2           | 1.00668 |
| 16        | 125      | 0.04       | 8      | 5.83         | 1.00312 |
| 17        | 125      | 0.08       | 12     | 2.99         | 1.009 |
| 18        | 125      | 0.12       | 16     | 1.91         | 1.00141 |
| 19        | 25       | 0.04       | 8      | 2.37         | 1.016 |
| 20        | 25       | 0.08       | 12     | 5.01         | 1.0291 |

| Trial No. | Parameter settings | Hole quality parameters |
|-----------|--------------------|------------------------|
|           | v (m/min) | f (mm/rev) | d (mm) | R_a (microns) | F_d |
| 21        | 25       | 0.12       | 16     | 3.09         | 1.0125 |
| 22        | 75       | 0.04       | 8      | 4.04         | 1.0246 |
| 23        | 75       | 0.08       | 12     | 4.19         | 1.0078 |
| 24        | 75       | 0.12       | 16     | 1.77         | 1.0085 |
| 25        | 125      | 0.04       | 8      | 3.89         | 1.0105 |
| 26        | 125      | 0.08       | 12     | 3.49         | 1.0142 |
| 27        | 125      | 0.12       | 16     | 3.06         | 1.0175 |

The Talysurf surface tester is used to estimate centerline average surface roughness (R_a) of the drilled surface. A ‘Faro’ metrological instrument is used to measure the maximum diameter (D_max) of the drilled hole at the entry. The delamination factor (F_d) is determined by:

\[ F_d = \frac{D_{\text{max}}}{D} \]  \hspace{1cm} (10)

Where, \( D \) = Nominal diameter of the drill in mm.

CAM Smart Inspect is a metrology software package specifically designed to conduct the precise measurements and inspections of complex features simply by inputting the 3D measurements. Faro gauge is having a measuring ball, which is calibrated. Later, it is checked for the flatness of measuring specimen by clamping it on the surface plate. Faro gauge is connected to the computer system with the installed package of CAM, which records measured values of the desired hole quality specifications.
The measured values (response) of average surface roughness ($R_a$) from drilled surface and computed values of delamination factor ($F_d$) for 27 trials are presented in Table 3.2.

The following equation showing all inputs involved and outputs:

$$\frac{2(Y - Y_{\text{min}})}{(Y_{\text{max}} - Y_{\text{min}})} - 1$$

where, $Y_{\text{min}}$ = least value in the matrix arrangement for Y; $Y_{\text{max}}$ = highest value in the matrix of pattern for Y. All inputs and outputs are distributed normally between the range from -1 to +1. The input layer consists of 3 neurons for simulated architecture of ANN which is a multi-layer that corresponding to five input parameters, $v$, $f$, and $d$, 1 neuron in the output layer. ANN simulation is performed using variable learning rates procedures for learning (Math Works Incorporation., 2005). Optimization hidden layer is performed to obtain required set of neurons on trial and error basis. There are 22 number of training has been performed until the mean squared error (MSE) reaches 1500 epochs. After successful training, single hidden layer having 14 neurons in the ANN structure with rate of learning 0.05 and a momentum constant of 0.9 are found to be suitable for $R_a$ and $F_d$.

Fig 1.1 Mean squared error (MSE)

7 RESULTS AND DISCUSSIONS

7.1 ANN MODEL TESTING

Over 22 inputs in a training pattern of ANN is tested. For individual input training pattern, the ANN estimated $R_a$ in comparision with those of experimentally obtained values and similiary the comarision is made for the ANN predicted delamination factor ($F_d$) and are found to be very close for each of the training patterns. to validate results, further drilling experiments are performed for 5 combinations of input process variables, which are not considered in earlier training data set. The Table 1.2 summarizes details of experimental settings along with the measured values $R_a$ and $F_d$. A comparative outcome of ANN predicted and the measured values of $R_a$ and $F_d$ for the validation data set is tabulated in Table 1.3 and Fig 1.2 and Fig 1.3. It is observed that the ANN estimated values from model following almost nearest to that of measured responses through experiments, which validates developed model for ANN for $R_a$ and $F_d$. 

![Mean squared error (MSE)](image_url)
### Table 1.3 Experimental and predicted values of Ra and Fd

| Sr. No | v  | F  | D  | Ra (exp) | Ra (prd) | Fd(exp) | Fd(prd) |
|--------|----|----|----|----------|----------|---------|---------|
|        |    |    |    | Training patterns |         |         |         |
| 1      | 25 | 0.04| 8  | 3.23      | 3.231207 | 1.0028  | 1.002853|
| 2      | 25 | 0.04| 12 | 4.6       | 4.608629 | 1.00408 | 1.003915|
| 3      | 25 | 0.08| 8  | 2.82      | 2.799584 | 1.0127  | 1.012667|
| 4      | 25 | 0.04| 16 | 1.81      | 1.794763 | 1.00062 | 1.000724|
| 5      | 25 | 0.08| 16 | 1.35      | 1.358269 | 1.01187 | 1.011903|
| 6      | 25 | 0.12| 12 | 2.76      | 2.796827 | 1.0025  | 1.002578|
| 7      | 25 | 0.12| 16 | 1.01      | 1.014352 | 1.00087 | 1.000851|
| 8      | 25 | 0.12| 8  | 3.3       | 3.31783  | 1.00287 | 1.003063|
| 9      | 75 | 0.04| 12 | 4.72      | 4.717918 | 1.00215 | 1.002187|
| 10     | 75 | 0.04| 16 | 2.35      | 2.359484 | 1.00132 | 1.001332|
| 11     | 75 | 0.08| 12 | 2.91      | 2.8728   | 1.00208 | 1.002226|
| 12     | 75 | 0.08| 8  | 3.21      | 3.201241 | 1.0017  | 1.001909|
| 13     | 75 | 0.12| 8  | 5.83      | 5.835877 | 1.00312 | 1.003158|
| 14     | 75 | 0.12| 12 | 2.99      | 2.964935 | 1.009   | 1.008983|
| 15     | 75 | 0.12| 16 | 1.91      | 1.920206 | 1.00141 | 1.001413|
| 16     | 125| 0.04| 8  | 2.37      | 2.36211  | 1.016   | 1.016073|
| 17     | 125| 0.04| 12 | 5.01      | 4.992528 | 1.0291  | 1.029101|
| 18     | 125| 0.04| 16 | 3.09      | 3.084752 | 1.0125  | 1.012485|
| 19     | 125| 0.08| 12 | 4.19      | 4.205137 | 1.0078  | 1.007826|
| 20     | 125| 0.08| 16 | 1.77      | 1.847196 | 1.0085  | 1.008533|
| 21     | 125| 0.12| 12 | 3.49      | 3.484341 | 1.0142  | 1.014186|
| 22     | 125| 0.12| 16 | 3.06      | 3.050986 | 1.0175  | 1.017497|

| Sr. No | v  | F  | D  | Ra (exp) | Ra (prd) | Fd(exp) | Fd(prd) |
|--------|----|----|----|----------|----------|---------|---------|
|        |    |    |    | Testing patterns |         |         |         |
| 1      | 25 | 0.08| 12 | 3.95      | 3.950025 | 1.015   | 1.014979|
| 2      | 75 | 0.08| 16 | 2        | 1.9436   | 1.00668 | 1.006476|
| 3      | 125| 0.08| 8  | 4.04      | 4.057823 | 1.0246  | 1.024568|
| 4      | 75 | 0.04| 8  | 2.47      | 2.478098 | 1.00327 | 1.003226|
| 5      | 125| 0.12| 8  | 3.89      | 3.877709 | 1.0105  | 1.010508|
Fig 1.2 Experimentally obtained responses and estimated responses of $R_s$ from ANN model

Fig 1.2 Experimentally obtained responses and estimated responses of $F_d$ from ANN model
Fig 1.3 The interaction effect plots for feed rate and drill diameter on Ra.

The interaction effect plots of Fig 1.3. Has revealed that the combined effects of parameters such as feed rate (f) and the drill diameter (d) at a constant cutting speed (v) will minimizes the surface roughness. The parameters from their low level to high levels there is a decrement trend of surface roughness value is observed. However at higher cutting speeds the surface roughness is observed on higher side in its magnitude, this increase roughness happens at higher values of selected parameters characterized by localized heat formation due to abrasion causes intern variations in the surface patterns. There for this is a clear understanding that can be made that higher feed rate of 0.12mm/rev and drill diameter of 16mm can be recommended by keeping the cutting speed at lower side 25 m/min towards achieving minimization in surface roughness.

Fig 1.4 The combined effects plots for feed rate and drill diameter on Fz.
The interaction effect from Fig 1.4 is describing the combined effects of factors where the other factor kept at constant level. The graph is clearly indicates that there is a statistically significant variation identified in terms of mean delamination factor, it is observed that the delamination is found minimum in its value when drilling is performed at higher feed rate and using drill bit of 16 mm at lower cutting speed of 25m/min. the on the other side it is also observed there is an indication of non linearity in terms of delamination factor i.e. the delamination increases initially from 8mm drill diameter t up to 12mm and there afterwards there is a reduction in delamination factor for 16mm drill size. Also there is an indication of anti synergistic interaction found at higher cutting speed, this is as a result of increased plastic deformation and temperature effects at tool and work interface leads to variation in drilled hole size, thereby delamination will be on the higher side. It is recommended in this study that minimal in delamination could be achieved at lower cutting speeds as well as feed rate with using higher drill size.

7.2 PSO OPTIMIZATION RESULTS

PSO simulation are results obtained using MATLAB software (Math Works Incorporation 2009) with highest number of 100 generations ($k_{\text{max}}$) every individual drilling tool diameter ($d$) that is in the range between 8-16 mm, optimal combination of cutting speed ($v$), feed ($f$) and drill diameter ($d$) and corresponding optimal $R_a$ and $F_d$ are recorded. In PSO the number of particles is typically selected between 20 and 50, therefore the swarm size is chosen as 50. The values of the learning factors, $c_1$ and $c_2$ are taken as 2.0. Firstly, a large value of inertia weight ($w_{\text{max}}$) considered for global search. Reduction in weights on iterations and attaining at exploiting specific fields the algorithm is built in and the following equation is used.

$$w^k = w_{\text{max}} - \left[ \frac{(w_{\text{max}} - w_{\text{min}})k}{k_{\text{max}}} \right]$$

(13)

Here $w_{\text{max}} = 0.80$ & $w_{\text{min}} = 0.01$. The convergence characteristic from PSO for a drill diameter of 8 mm is depicted in Fig 1.6.
The optimal values of surface roughness ($R_a$) and delamination factor ($F_d$) for different drilling tool diameters ranging from 8-16 mm are displayed in Fig. 1.8 and Table 1.4. As observed from this figure, that optimal surface roughness decreases as there is increase in drilling tool diameter up to 16 mm. The optimal delamination factor also decreases as there is increase in drilling tool diameter up to 16 mm.

### Table 1.4 Optimal control factors and response variables

| D  | Optimal control factors | Optimal responses |
|----|------------------------|-------------------|
| 8  | 60.072                 | 0.0559            | 1.2857 | 0.9962 |
| 9  | 54.520                 | 0.0523            | 2.5755 | 0.996  |
| 10 | 61.730                 | 0.0916            | 2.6544 | 1.0    |
| 11 | 61.796                 | 0.0941            | 1.7855 | 0.9982 |
| 12 | 60.364                 | 0.0968            | 1.292  | 0.9945 |
| 13 | 55.950                 | 0.0964            | 0.986  | 0.9925 |
| 14 | 55.820                 | 0.0929            | 0.879  | 0.9918 |
| 15 | 32.70                  | 0.1088            | 0.5596 | 0.9986 |
| 16 | 54.660                 | 0.0570            | 0.206  | 0.9961 |

From the convergence plots Fig 1.6 and Fig 1.7 for optimal cutting speed ($v$) and optimal feed rates depicted the decreasing trend in $R_a$ and $F_d$ increase in drill diameter. Graph also clearly reveals that higher drill diameter has reduced significantly the surface roughness and delamination.
The optimization results that for minimizing surface roughness, the optimum cutting speed requirement is high i.e. 54 m/min and drill diameter of 16mm. Alternatively, as depicted in Table 1.4, Fig 1.7 and Fig 1.8 the expected optimum feed in middle level range i.e. 0.04-0.06 mm/rev. This results in minimum surface roughness.

From optimization results, Fig 1.9 it is noticed that delamination factor reduces with increase in drill diameter, drill diameter 14mm is found optimum drill size which results in minimum delamination. The optimal results also revealed that cutting speed 55m/min and the 0.1mm/rev will results in less delamination.

Through optimization results, also viewed that combined effect of optimal cutting speed, feed rate and selection of drill diameter has shown reduction in surface roughness. The drilling tool diameter available generally in the range 16-28 mm. However, both of these parameters are having direct relationship in achieving minimum surface roughness and delamination factors involved in drilling process.

8 CONCLUSION

The multilayer feed forward artificial neural network (ANN) architecture of EBPTA and Particle Swarm Optimization (PSO) are developed to analyze the effects of drilling factors on R$_a$ and F$_d$ of syntactic foams. The input-output patterns required for ANN training are recorded through drilling
experiments planned as per full factorial design (FFD). A statistical correlation is observed between the ANN predicted and the experimental values of $R_a$ and $F_d$. The results after simulation have showed effectiveness of advanced modeling techniques in realizing a non-linear relationship between $R_a$ and $F_d$.

The optimal parameters for both selected responses are determined using PSO optimization technique. In this regard the supporting findings are drawn as conclusions from the analysis:

- The analytical models showed non-linear relationship between surface roughness ($R_a$) under varying drilling factors individually.
- It is observed experimentally that there is decrement in $R_a$ for every increment in feed and is more delicate at high levels of cutting speed and feed. The minimum roughness results with lower values of cutting speed and feed combination.
- The delamination also found decreases with increase in feed and is however at appropriate feed rate and cutting speed combination delamination can be minimized.
- For minimizing the surface roughness and delamination lower values of cutting speed can be recommended for the selected drill diameters.
- The cutting speed 55m/min, feed rate of 0.05mm/rev and the drill diameter of 16mm settings has shown with minimum $R_a$ of 0.2 microns and 0.99 as delamination factor.
- The ANN and PSO methods of optimizations are found suitable techniques for extracting non-linearity effects and optimization of multiple parameters involved.

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