Thermal Stress Prediction within the Contact Surface during Creep Feed Deep Surface Grinding

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Abstract

This paper presents the application of a hybrid approach comprising of Neural Network (NN) and Genetic Algorithm (GA) for modeling and optimization of Creep Feed Deep Surface Grinding (CFDSG) process. Finite Element Method (FEM) has been used to generate data set for NN model to predict the equivalent thermal stress within the contact zone of the workpiece. Subsequently, NN model has been coupled with GA to find optimum input-output parameters of CFDSG. The proposed hybrid approach is well capable to predict thermal stresses in the workpiece quickly and also minimize it with reasonable accuracy during CFDSG process.

Keywords: Creep Feed Deep Surface Grinding, Finite Element Method (FEM), Neural Network, Genetic Algorithm

1 Introduction

Creep Feed Deep Surface Grinding is comparatively a recent development in grinding technology where the operation is performed with high depth of cut, very slow workpiece speed and low wheel speed. Due to high depth of cut, CFDSG is being used in the industries to increase productivity and surface quality simultaneously with a single machining operation rather than using milling and then fine surface grinding. Under such a high depth of cut, much higher material removal rate can be achieved in comparison to shallow cut surface grinding. The major differences between CFDSG and conventional (shallow cut) grinding are the workpiece speed and depth of cut. Conventional grinding is characterized by high workpiece speeds (0.05 to 0.5 m/s), small depths of cut (1-25 µm) and small length of contact between the workpiece and grinding wheel, varying between 1 to 3 mm, whereas CFDSG utilizes low workpiece speeds (0.1 to 20 mm/s) and higher depths of cut (1 to 10 mm) which also leads to higher contact length (Parente et al., 2012).

CFDSG is mainly used for machining difficult to machine materials such as nickel base alloys, tungsten carbide, tool steel and die steels. CFDSG has major applications in the aerospace industry and in particular for the manufacture of turbine blades for aircraft engines made from nickel base alloys. It can also be used to produce broaches, pump rotors, dies and automobile rocker arm etc. (Andrew, 1985). Thermal damage due to high temperature constitutes the major problem when using this process. High contact temperature weakens the bond strength of the wheel, promoting abrasive wheel wear resulting to decrease in the process performance. High heat generated during CFDSG, induces thermal stresses within the workpiece. Therefore, a comprehensive thermal stresses analysis is required not only for better understanding of the process but are also very much useful for simulation, optimization and control of the process. To determine the thermal stresses, a suitable mathematical model in the form of differential equations is required to be developed. These differential equations can be solved using any computational method. Finite element method (FEM) is one of the most widely used computational tool to solve these differential equations.

Major problem in quantitative prediction of output using FEM is the large computational time and dependency of results on meshing related parameters such as type and order of elements, size of elements and their non-uniform distribution in the mesh, connectivity pattern of elements and others. Because of these reasons, the prediction of output for varied operating conditions becomes cumbersome with using FEM. In the present study, an attempt has been made to develop a NN-based model of CFDSG process using the data generated through its thermal FEM-based model to overcome the problem of meshing related time consuming procedure of FEM.

Authors (Tsai and Hocheng, 1996; Gupta et al., 1997; Mahdi and Zhang, 1999a; Mahdi and Zhang, 1999b; Moulik et al., 2001; Xiao et al., 2002; Hamdi et al. 2004; Wang et al., 2011) have attempted for thermal stress modeling of conventional (shallow cut) surface grinding processes but literature related to thermal stress modeling of CFDSG is not available so far. Most of the studies available in shallow cut surface grinding are related to computational determination of thermal stresses considering different shape and quantity of heat flux to the workpiece, energy partition, effect of convection and effect of temperature dependent properties of workpiece material. Parametric studies are also available showing the effect of wheel speed, workpiece
speed, depth of cut on thermal stresses. But authors have not found any analytical or computational model developed for the determination of thermal stresses generated in the workpiece due to CFDSG. Few authors (Sedighi and Afshari, 2010; Joshi and Pande, 2011; Reddy and Pratihar 2011) have attempted for modeling and optimization of manufacturing processes using NNGA coupled approach in the field of CFDSG, electric discharge machining and electron beam welding processes. But most of them are using experimental data set for the training and testing of NN-based model.

Vafaeesefat (2009) developed a NN model to predict the grinding forces during creep feed grinding of nickel based super alloy with aluminium oxide grinding wheel using experimentally measured grinding forces for 19 sets of experiments. They also maximized the material removal rate using nonlinear constrained optimization technique. Sedighi and Afshari (2010) developed a neural network model to predict the surface roughness in creep feed grinding of cobalt based super alloy with aluminium oxide grinding wheel using experimentally measured surface roughness for 16 sets of experiments. They also optimized the process using GA. Joshi and Pande (2011) developed a NN-based model for prediction of output parameters in terms of shape of crater, MRR and TWR during die-sinking EDM process and optimization was done using NSGA II to select the optimum process parameters for roughing and finishing operations using computational dataset generated by FEM. Reddy and Pratihar (2011) developed a NN-based model to predict the temperature during electron beam welding process using input-output data set generated by FEM based temperature model.

In this paper, a back propagation neural network (NN) model has been developed to predict the maximum equivalent thermal stress at the contact surface during CFDSG. For training and testing of the NN-based model, data sets were generated using FEM-based thermal stress model.

2 Modeling of CFDSG

In the present work, first a temperature model has been developed to find the temperature, and then followed by the thermal stress model to calculate the thermal stresses in the workpiece. To make the analysis of temperature and thermal stresses tractable, the following assumptions have been made.

- Workpiece material is homogeneous, isotropic and elastic-perfectly plastic.
- Thermal properties of workpiece material are considered to be independent of temperature.
- Contact between the workpiece and wheel is considered as an inclined flat plane surface but in real situation it is curved with large radius of curvature. Hence, heat flux is assumed to be right angled trially distributed inclined heat source.
- A plane strain conditions are assumed ($\varepsilon_y = 0$).
- Inertia and body force effects are negligible during stress development.

Following governing equation (Cengel, 2005) and boundary conditions for isotropic and homogeneous material and without heat generation can be used to find the temperature variation in the workpiece domain OABCDEO as shown in Fig.1.

$$\frac{\partial}{\partial x} \left(k \frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y} \left(k \frac{\partial T}{\partial y}\right) = \rho C \frac{\partial T}{\partial t}$$

in domain (OABCDEO) \hspace{1cm} (1)

$$T=T_0$$ in the workpiece domain when $t=0$ \hspace{1cm} (2)

where, $T_0$ is the ambient temperature of the workpiece.

$$\begin{bmatrix}
-k \frac{\partial T}{\partial n} = -q_s + h(T-T_0) & \text{on the line BC} \\
-k \frac{\partial T}{\partial y} = h(T-T_0) & \text{on the line AB and CD} \\
\frac{\partial T}{\partial x} = 0 & \text{on OA and DE} \\
T = T_s & \text{on OE}
\end{bmatrix}$$

when $t>0$ \hspace{1cm} (3)

Fig. 1. Discretized domain used for the determination of temperature and thermal stress distribution

The transient temperature distribution in the workpiece, obtained by solving the heat conduction equation (1) along with the initial and boundary conditions, is used as input for the calculation of the thermal stresses. In case of plane strain type thermal stress problem, governing equations (Reddy, 2005) and boundary conditions can be used as follows:

$$\begin{bmatrix}
\frac{\partial \sigma_x}{\partial x} + \frac{\partial \sigma_y}{\partial y} = 0 \\
\frac{\partial \sigma_y}{\partial x} + \frac{\partial \sigma_x}{\partial y} = 0
\end{bmatrix}$$

in the workpiece domain OABCDEO \hspace{1cm} (4)

where, $\sigma_{xx}$ and $\sigma_{yy}$ are the normal stresses and $\sigma_{xy}$ is the shear stress. Here, the body and inertia forces are neglected.

The boundary conditions in terms of displacement and traction can be given as follows.

$$u_e = 0 \hspace{1cm} \text{on OE}$$ \hspace{1cm} (5a)

Because the bottom surface is fixed on the table.

$$t_i = t_r = 0 \hspace{1cm} \text{on OA, AB, BC, CD and DE}$$ \hspace{1cm} (5b)

Because there is no tangential load acting.

The stress-strain relationship due to temperature rise $\Delta T$ can be written as:

$$[\sigma] = [D] \{\varepsilon\} - \Delta T [m]$$

where, $[D]$ is the elasticity matrix, $\{\sigma\}$ is the stress vector,$\{\varepsilon\}$ is the strain vector and $[m]$ is the vector related to properties of the workpiece material. The expression for $\{\sigma\}$, $\{\varepsilon\}$, $[m]$ and $[D]$ are as follows:
\[
\{\sigma\}^T = \{\sigma_n, \sigma_y, \sigma_w\}
\]  \hfill (7)

\[
\{\varepsilon\}^T = \{\varepsilon_n, \varepsilon_y, \varepsilon_w\}
\]  \hfill (8)

\[
[m] = \frac{E\alpha_n}{1-2\nu} \begin{bmatrix}
1 & 0 \\
0 & 1-\nu \\
0 & \nu
\end{bmatrix}
\]  \hfill (9)

\[
[D] = \frac{E}{(1+\nu)(1-2\nu)} \begin{bmatrix}
1-\nu & \nu & 0 \\
\nu & 1-\nu & 0 \\
0 & 0 & \frac{1-2\nu}{2}
\end{bmatrix}
\]  \hfill (10)

Here, \(E\) is Young’s modulus, \(\nu\) is Poisson’s ratio and \(\alpha_n\) is the coefficient of thermal expansion.

To find the plastic zone where the equivalent thermal stress is more than the yield stress of the workpiece material, the following expressions for the deviatoric stress components are used.

\[
s_n = \sigma_n - \frac{1}{3}(\sigma_n + \sigma_y + \sigma_w)
\]  \hfill (11a)

\[
s_y = \sigma_y - \frac{1}{3}(\sigma_n + \sigma_y + \sigma_w)
\]  \hfill (11b)

\[
s_w = \sigma_w
\]  \hfill (11c)

\[
s_{eq} = \sigma - \frac{1}{3}(\sigma_n + \sigma_y + \sigma_w)
\]  \hfill (11d)

The equivalent (or effective) stress, \(\sigma_{eq}\) is given by the following equation.

\[
\sigma_{eq} = J_3^{\frac{1}{3}}
\]  \hfill (12)

where, \(J_3 = \frac{1}{2}(S_n^2 + S_y^2 + S_w^2) + S_z^2\)

A point in plastic zone is identified by the following inequality.

\[
\sigma_{eq} \geq \sigma_y
\]  \hfill (13)

where, \(\sigma_y\) is the yield stress of the workpiece material

### 3 Finite Element Formulation

Galerkin’s FEM is applied to equations (4) and (5) to find the thermal stress distribution. After applying the Galerkin’s method, the following elemental equation is obtained.

\[
[SK]\{\delta\}^e = \{SF\}^e
\]  \hfill (14)

where, \([SK]^e\) is elemental coefficient matrix for stresses, \([\delta]\) is the elemental nodal displacement vector and \([SF]\) is the elemental force vector for stresses. These matrices can be expressed as follows:

\[
[SK]^e = \int [B]^e [D]^e [B]^e d\Omega
\]  \hfill (15)

\[
[SF]^e = \int \Delta T[B]^e [m]^e d\Omega
\]  \hfill (16)

\[
[\delta]^e = \begin{bmatrix}
u_1, u_1, u_2, \ldots, u_k, u_w\end{bmatrix}
\]  \hfill (17)

where, \([B]^e\) is the matrix consisting of derivative of nodal shape functions and it relates the displacement and strain and \(\Delta T\) is the elemental rise in temperature due to grinding. Elemental rise in temperature, \(\Delta T\) can be calculated by the following equation.

\[
\Delta T = \sum_{i=1}^{n} N_i^e \Delta T - T_i
\]  \hfill (18)

where, \(N_i^e\) is the nodal shape function of the typical element, \(T_i\) is the typical elemental nodal temperature which is calculated from the temperature model. When elemental equations of quantity (14) are assembled using assembly rule, the following global equations are obtained.

\[
[SGK][GU] = [SGF]
\]  \hfill (19)

where, \([SGK]\) is the global coefficient matrix, \([GU]\) is the global nodal displacement vector and \([SGF]\) is the global right side vector. After determination of the nodal displacements from the equation (19), strain is calculated using the following equation.

\[
[\varepsilon] = [B]^T [\delta]^e
\]  \hfill (20)

Now, thermal stress is calculated using equation (6). The equivalent stresses are also calculated at each node and compared with the yield stress to identify whether yielding occurs or not.

The primary variable of above FEM based thermal stress model is validated using the literature (Kim et al., 2006). Validation results can be be seen in author’s paper (Narayana and Yadava, 2012). After validation of FEM- based thermal stress model, it is used to generate the data for developing the NN-model. Table 1 shows the operating conditions for generating the data.

| Table 1 Properties of the workpiece (AISI 52100) and grinding wheel (CBN) material and grinding process conditions for prediction of equivalent thermal stress. |
|-----------------|-----------------|
| Entity VALUE | Value |
| Density of the workpiece, \(\rho\) | 7815 kg/m\(^3\) |
| Specific heat of the workpiece, \(c\) | 506 J/kgK |
| Thermal conductivity of the workpiece, \(k\) | 34.3 W/mK |
| Young’s modulus, \(E\) | 1.2x10\(^{10}\) MPa |
| Poisson’s ratio, \(\nu\) | 0.3 |
| Coefficient of thermal expansion, \(\alpha\) | 1.5x10\(^{-5}\) /°K |
| Yield stress, \(\sigma_y\) | 300 MPa |
| Depth of cut, \(d\) | 1-3 mm |
| Workpiece speed, \(v_w\) | 0.5-1.5 mm/s |
| Wheel speed, \(v_r\) | 20-35 m/s |
| Wheel diameter, \(d_r\) | 250-350 mm |
| Convection coefficient of grinding fluid | 15000 W / m\(^2\)K |

### 4 Neural Network Modeling

For the present problem, Back Propagation Neural Network (BPNN) model has been developed to predict the output. The input parameters are workpiece speed, wheel speed, depth of cut and wheel diameter. Maximum equivalent thermal stress is considered as the output parameter. Therefore, the BPNN model consists of four input nodes and one output node. A total of 100 data set were generated using FEM-based thermal stress model. Out of 100 data set, 90 data set were used for NN training purpose and the rest are used for NN testing. Division of the data set is done using the functions available in the neural network tool box in Matlab. The data division is normally performed automatically when the network is trained.
Before training the network, input and output data set were normalized to make the training more efficient. Sigmoidal functions are generally used in multilayer feed forward network like back propagation network, radial basis function network etc. In the present work, tan-sigmoidal function has been used for hidden as well as output neurons. Therefore, input and output data set were normalized from 0.1 to 0.9 which are within the range of tan-sigmoidal values. In this way, the network output always falls into a normalized range. The network output was then reverse transformed back into the units of the original data when the network is put to use in the field.

Scale conjugate gradient algorithm was used to train the network. Various network were formed by varying the number of hidden layers, number of neurons in the hidden layers and number of epochs on the basis of number of input parameters and output parameters and training of networks were performed. After training the networks, prediction error was calculated for each network using computational data. After exhaustive hit and trial method, a network of 4-7-1 is found suitable on the basis of calculated prediction error. Therefore, NN model based on 4-7-1 NN architecture has been finally chosen for the prediction of the output. Figure 2 shows NN-architecture for the present problem. Maximum prediction error is found as 3.4 % and average error is 1.7% for the testing datasets as shown in Fig.3. The testing data set generated by FEM-based model and its comparison with NN-based model is given in Table 2.

After validation of the NN-model, it has been used to predict the equivalent thermal stress at the contact surface of the wheel-workpiece. Effect of different input parameters such as workpiece speed, wheel speed, depth of cut, wheel diameter on maximum equivalent thermal stress have also been studied.

5 Equivalent Thermal Stress Prediction using Neural Network

After training and testing of NN model, it is used to predict the maximum equivalent thermal stress in the contact zone of the wheel-workpiece.

Effect of workpiece speed

Figure 4 shows the variation of maximum equivalent stress within the contact zone for varying workpiece speed at different wheel speed. Peak values of equivalent stresses obtained are 1527, 1613 and 1692 MPa at wheel speeds of 20, 25 and 30 m/s respectively. It is observed that equivalent stress is increasing as the workpiece speed increases. Increase in the equivalent stress may be due to high and non-uniform temperature generated within the contact surface at higher workpiece speed. High and non-uniform temperature generated within the contact zone may be due to high amount of heat appears at higher workpiece speed. Equivalent stress is also increasing with increase in wheel speed but effect is nominal in comparison to workpiece speed.
Effect of wheel speed

Figure 5 shows the variations of the equivalent stress within the contact zone for varying wheel speed at different workpiece speeds. Peak values of equivalent stresses obtained are 608, 1232 and 1779 MPa at workpiece speeds of 0.5, 1.0 and 1.5 mm/s respectively. It is observed that equivalent stress increases as the wheel speed increases from 20 to 35 m/s. But the effect of wheel speed on equivalent stress is again nominal in comparison to the workpiece speed. It is also observed that workpiece speed has the most dominant effect on equivalent stress in comparison to other parameter in case of CFSG.

![Figure 5. Variation of equivalent stress within the contact zone with wheel speed at different workpiece speed (d=2 mm, ds=300 mm).](image)

Effect of depth of cut

Figure 6 shows the variation of equivalent stress within the contact surface for varying depth of cut at different wheel speeds. Peak values of equivalent stresses obtained are 1346, 1387 and 1417 MPa at wheel speeds of 20, 25 and 30 m/s respectively. It is observed that equivalent stress increases as depth of cut and wheel speed increases. It is also observed that the depth of cut has the larger effect on equivalent stress than the wheel speed. When depth of cut increases, more spindle power is required to drive the grinding wheel, consequently, amount of cutting force required in grinding increases resulting increase in the contact surface temperature during CFSG. Due high amount heat generated within the contact zone, temperature and its gradient increases resulting increase in the equivalent stress at higher depth of cut.

![Figure 6. Variation of equivalent stresses with depth of cut at different wheel speed (vs=1 mm/s, ds=300 mm).](image)

Effect of wheel diameter

Figure 7 shows the variation of equivalent stress within the contact surface for varying wheel diameters from 250 to 350 mm at different workpiece speeds. Peak values of equivalent stresses obtained are 613, 1281 and 1882 MPa at workpiece speeds of 0.5, 1.0 and 1.5 mm/s respectively. It is observed that the equivalent stress decreases as wheel diameter increases. But equivalent stress is increasing with increase in workpiece speed. During grinding process, when diameter of the grinding wheel increases, contact length and area of the contact surface increases. Due to large area of contact surface at higher wheel diameter, heat extracted out of the contact surface increases. Consequently, temperature and its gradient decreases within the contact surface at larger wheel diameter. Therefore, lower equivalent stress is observed at larger wheel diameter.

![Figure 7. Variation of equivalent stresses with wheel diameter at different workpiece speed (vs=30 m/s, d=2 mm).](image)

6 GA Based Optimization

Maximum equivalent thermal stress predicted by the NN model has been optimized using GA. For optimization, a function file for objective function (equivalent thermal stress) was created in MATLAB 7.6. Objective function was used for minimization of maximum equivalent thermal stress using Matlab optimization tool box. Number of variables and their ranges were entered in space provided. Number of input parameters and their range are shown in Table 3.

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workpiece speed</td>
<td>0.5-1.5 mm/s</td>
</tr>
<tr>
<td>Wheel speed</td>
<td>20-35 m/s</td>
</tr>
<tr>
<td>Depth of cut</td>
<td>1-3 mm</td>
</tr>
<tr>
<td>Wheel diameter</td>
<td>250-350 mm</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 4</th>
<th>GA parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
<td>Values</td>
</tr>
</tbody>
</table>

Table 3 Input parameters and their ranges.
An extensive study was conducted to determine the appropriate set of GA parameters which are shown in Table 4. After selection of GA parameters, optimization solver was run and optimization terminated after 100 generations. Best fitness value of the function is obtained as 502 MPa during convergence of the solution. Optimum values of the input parameters, are shown in Table 5.

### Table 5 Optimum conditions obtained from GA-NN

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Output Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v_c ) (mm/s)</td>
<td>( \theta_{eq} ) (MPa)</td>
</tr>
<tr>
<td>( v_s ) (m/s)</td>
<td>( d ) (mm)</td>
</tr>
<tr>
<td>0.5</td>
<td>20</td>
</tr>
</tbody>
</table>

### Conclusions

Based on the developed NN model, maximum equivalent thermal stress in the contact zone of wheel-workpiece is predicted by varying the input parameters such as depth of cut, workpiece speed, wheel speed and wheel diameter. Further, maximum equivalent thermal stress predicted by NN model is optimized using genetic algorithm (GA). Following conclusions can be drawn from the present investigation.

(i) The NN-GA hybrid approach has been found capable to optimize process parameter of CFDSG effectively.

(ii) NN-based model is found to show 1.7 % of average prediction accuracy for testing data set during prediction of output performance parameter in very short period of time.

(iii) Result of GA optimization to minimize maximum equivalent thermal stress is found to be 502 MPa.

(iv) Equivalent thermal stress is found increasing with increase in depth of cut, workpiece speed and wheel speed but the workpiece speed has the most dominant effect on equivalent thermal stress. Equivalent thermal stress is found decreasing with increase in wheel diameter.

(v) This hybrid approach can be used for prediction and optimization of process parameter for any cumbersome process based on the dataset generated by FEM.

### References


