# Optimization of the Forging Process of an Aerofoil Blade using the Finite Element Analysis and Response Surface Method

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**Abstract**: Forging of gas turbine blades needs a close control of the process parameters. These parameters require a suitable optimization method to achieve the best process conditions. This paper presents a hybrid method for the optimization of the forging process of an aerofoil blade. Forging process of the aerofoil blade was simulated using 3-dimentional finite element method. Preform shape and die parting-line angle are optimized in order to minimize the volume of the unfilled die cavity, material waste, and forging forces. The overall optimization scheme used in this research work includes a multi-objective approach that is a combination of response surface and finite element methods. The results show that the proposed optimization approach accrued to decrease the flash volume and the forging force of the aerofoil forging process. Therefore the proposed algorithm is a suitable method for the optimization of the gas turbine blade forging processes.

**Keywords:** Blade, Finite Element, Forging, Optimization, Response Surface

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## 1 INTRODUCTION

Compressor blade of gas turbine engines has a complicated shape with low and variable thickness, where stainless steel or titanium alloys are usually used as the material of such blades. However, low machinability of such blade materials and good properties resulted from forging process, has made this process a suitable preference for production. There is a twist in the shape from the root to the end of the blade. Obviously, blade forging is a three-dimensional (3D) process. Therefore, in order to obtain a more realistic deformation and more precise and reliable information, it is necessary to simulate the process using a 3D finite element method (FEM). However, 3D FEM simulation of the blade forging process is still time-consuming [1]. Nowadays, in order to decrease the production cost and improve product quality, its manufacturing process optimization is predominantly important.

Due to the shape complexity and a limited material formability, precise forging of the blade needs close control of process parameters which requires a suitable optimization method for obtaining process conditions. Based on FEM, there are two methods for design of perform and die shape: the backward tracing method in which loading path in forming process is traced backwardly from final shape to perform shape. Other method is based on optimization techniques such as sensitivity analyses and genetic algorithm. Backward tracing method is used only to perform die design but other methods are also used for the optimization of other forging parameters such as temperature and strain rate [2], [3], [4]. These methods have been used for simple parts and few researches have been conducted in complicated shape parts such as blade.

Lu and Balendra have simulated aerofoil dimensional errors due to die elastic deformation, and thermal torsion in unloading and cooling for a temperature region with FEM and predicted forging force and temperature distribution [5]. Lu et al., have presented an error compensation method employing variable weighting factors for the optimization of die shapes by 3D FEM simulation [6]. Kang et al., have presented a systematic procedures for the preform design in forging an aerofoil section blade as a two-dimensional plane-strain problem [7]. They have used forward loading and backward tracing simulations by the FEM for determining the optimal slope angle of the die-parting line and the position of the preform within the die, which satisfy the final design condition of flashless forging.

Tao et al., have simulated precision blade forging by using a backward tracing scheme based on 3D FEM [8], [9]. They have also investigated the influence of dynamic boundary conditions on preform design for deformation uniformity. Boundary conditions in the backward simulation have been controlled by altering the time of boundary node separating from dies. The forging preform shape has principal role on the shape and quality of final workpiece. The filling of the thinner edge of the blade section in the finish forging operation is critical to the quality of final products. Therefore, the correct preform design ensures that the die is properly filled and the workpiece is correctly forged to form the final product.

Up to now, enough research have not been done on the perform shape and die parting line angle in the blade forging process. Therefore, there is a need to study this problem. This paper refers the optimization of the perform shape and die parting-line angle using the response surface and FE methods. Whereas it is very difficult to gain an analytical relation between independent variables and responses in the blade forging process, response surface method can optimize perform shape without any relation using some input and output data.

Although obtaining these data by experimental methods is expensive, however it is possible to achieve these data through FEM simulation of the process. Hence because of the blade shape complexity, a 3-dimensional (3D) finite element analysis is used to achieve a more realistic simulation of forging process. However, 3D simulation of blade forging is time consuming, therefore, the response surface method is a more suitable approach.

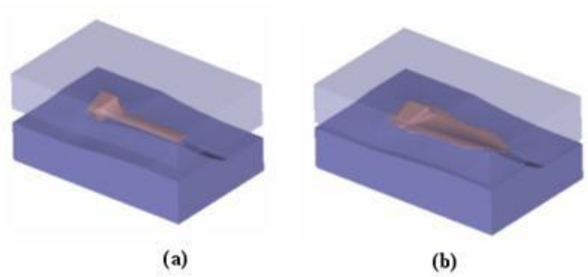


**Fig. 1** FE model a) initial blade forging, b) final forged blade

## 2 FINITE ELEMENT ANALYSIS

Analysis of the blade forging by using analytical methods is very complicated and practically impossible. Therefore the best method for blade forging analysis is the finite element method. In order to obtain more realistic deformation and more precise information to help the optimization of the perform dimensions and the partition line, it is necessary to simulate the blade forging process by using a 3D FEM. Therefore, in the present work, the DEFORM 3D software package was employed to simulate the blade forging process. The material of the workpiece used in the analysis was Ti–6Al–4V, its mechanical behavior was assumed as elasto-visco plastic and used from Ref. [10]. The dies assumed rigid and upper die velocity was 500 mm/s. The friction coefficient between workpiece and dies was applied to be 0.3. Initial workpiece and die temperatures were 930°C and 180°C respectively. FE model of the initial blade forging and final forged blade has been shown in Fig. 1(a) and (b).

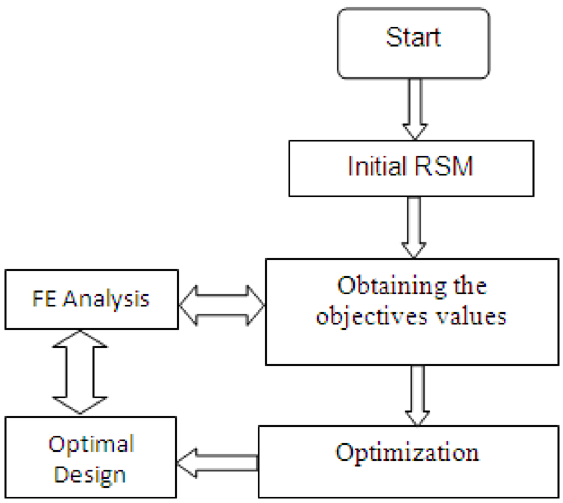


**Fig. 2** Optimization flowchart

## 3 OPTIMIZATION PROCEDURE

The goal of optimization is to obtain the optimal perform dimensions and angle of the die parting line in order to minimize defect volume of the final part, as well as the flash volume, the forging force and the lateral force. Optimization flowchart is shown in Fig. 2. First, procedure of experiments are designed then preform and die shapes are modelled. In the next stage the numerical experiments are performed. Then the simulations outputs are gained and the process is optimized via RSM method. Finally the optimization results are verified.

## 4 RESPONSE SURFACE METHOD

Response surface methodology is a collection of mathematical and statistical techniques that are useful for the modelling and analysis of problems in which a response of interest is influenced by several variables where the objective is to optimize the response [11]. For the first time, RSM was introduced by Box and Wilson in 1951 and then developed by Montgomery and Myers [12]. To date, this method has been used for the optimization of different processes [13-15]. It is possible to separate an optimization study into four stages using the RSM. The first stage is the preliminary work in which the determination of the independent parameters and their levels are carried out. The second stage is the experiments concerning running and collecting data. The third stage is data analysis and the prediction and verification of the model equation (response surface). The last one is the determination of optimum points.

The model equation may be first or higher order for the response function, where usually a low-order polynomial in some regions of the independent variables space is appropriate. If there is curvature in the system, then a polynomial of higher order than one must be used. In many cases, the second-order model that includes the interaction term is required. It is widely used because of its flexibility [17]. The second-order model is quite useful and is easily accommodated via the use of a wide variety of experimental designs [12]. This model is expressed as:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_i \sum_j \beta_{ij} x_i x_j + \varepsilon \qquad (1)$$

where $y$ is the response, $x_i$, and $x_j$, denote the independent variables, $k$ is the number of the independent variables, $\beta_0$, $\beta_i$, $\beta_{ii}$, $\beta_{ij}$ are unknown constant multipliers and finally $\varepsilon$ is the statistical error that represents other sources of variability not accounted for in the model. These sources include the effects such as the measurement error. The coefficients of the model equation are predicted through regression methods. The matrix notation of the regression model is given as follows [13]:

$$\begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ . \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} & . & . & . & x_{1k} \\ 1 & x_{21} & x_{22} & . & . & . & x_{2k} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ 1 & x_{n1} & x_{n2} & . & . & . & x_{nk} \end{bmatrix} . \begin{bmatrix} \beta_0 \\ \beta_1 \\ . \\ . \\ . \\ \beta_k \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ . \\ . \\ \varepsilon_n \end{bmatrix} \qquad (2)$$

The system of equations given above is solved using the method of least squares (MLS). In the MLS, it is assumed that random errors are identically distributed with a zero mean and a common unknown variance and that they are independent of each other. The difference between the observed and the fitted value ( $\hat{y}$ ) for the i[th] observation is called the residual and is an estimate of the corresponding $\varepsilon_i$. Our criterion for choosing the $\beta_j$, $0 \le j \le k$ estimates is that they should minimize the sum of the squares of the residuals, which is often called the sum of squares of the errors and is denoted by SSE. Thus,

$$SSE = \sum_i \varepsilon_i^2 = \sum_i (y_i - \hat{y}_i)^2 \tag{3}$$

The residuals could be written as

$$\varepsilon = y - X\beta \tag{4}$$

and the SSE becomes

$$SSE = \varepsilon^T \varepsilon = (y - X\beta)^T (y - X\beta) \tag{5}$$

By differentiating the SSE with respect to $\beta$, we get a vector of partial derivatives, as follows:

$$\frac{\partial}{\partial\beta}(SSE) = -2X^T(y - X\beta) = 0 \tag{6}$$

These equations could be solved directly to obtain the coefficients of $\beta$ by the following:

$$\beta = (X^T X)^{-1} X^T y \tag{7}$$

The statistical significance of the model equation was evaluated by the F-test analysis of variance [11]. Optimal points are obtained from the response function. Whereas objective function includes multiple response function, there are different methods for the optimization of objective function. One of the beneficial approaches is to use the simultaneous optimization technique popularized by Derringer and Suich (1980). Their procedure makes use of desirability functions. The general approach is to first convert each response $y_i$ into an individual desirability function $d_i$ that varies over the range $-1 \le d_i \le 1$ where, if the response $y_i$ is at its goal or target, then $d_i = 1$, and if the response is outside an acceptable region, $d_i = 0$. Then the design variables are chosen to maximize the overall desirability

$$D = (d_1 d_2 ... d_m)^{1/m} \tag{8}$$

Where there are $m$ responses. If the objective or target $T$ for the response $y$ is a maximum value, when the weight $r = 1$, the desirability function is linear. Choosing $r > 1$ places more emphasis on being close to the target value, and choosing $0 < r < 1$ makes this less important. If the target for the response is a minimum value,

$$d = \begin{cases} 1 & y < T \\ \left(\dfrac{U - y}{U - T}\right)^r & T \le y \le U \\ 0 & y > U \end{cases} \tag{10}$$

If the target is located between the lower $(L)$ and upper $(U)$ limits,

$$d = \begin{cases} 0 & y < L \\ \left(\dfrac{y - L}{T - L}\right)^{r_1} & L \le y \le T \\ \left(\dfrac{U - y}{U - T}\right)^{r_2} & T \le y \le U \\ 0 & y > U \end{cases} \tag{11}$$

When $r_1$ and $r_2$ are weights of the desirability function for ranges $L \le y \le T$ and $T \le y \le U$ respectively. There are some approaches for optimizing the desirability function (D) in Eq. (8) such as reduced gradient approach and direct search methods [12]. In this research reduced gradient method was employed for optimization of the desirability function.

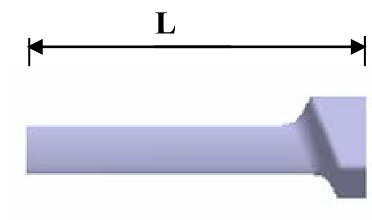


**Fig. 3** Preform [19]

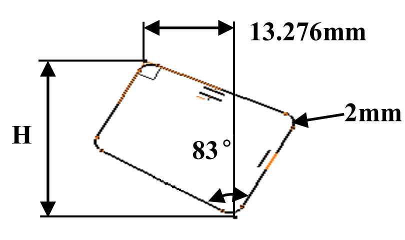


**Fig. 4** Preform root section [18]

## 5 INDEPENDENT VARIABLES AND RESPONSE FUNCTIONS

The major steps for manufacturing the blade include extrusion and forging. The forging preform shown in Fig. 3 is manufactured by extrusion process. Then, this preform transformed to net shape blade forging dies where hot forming process is used to forge the blades. Therefore, the forging preform should be designed in a shape that can be manufactured by the extrusion process. To prevent sliding of the preform inside the die cavity, the root section of the preform is designed according to Fig. 4 [18]. The only variable of the preform root is the distance of a and c apexes (H). Aerofoil region of the preform has a constant section because the manufacturing process of the preform was extrusion. According to Fig. 5, the aerofoil section is assumed as an ellipse. The aerofoil variables are large and small diameters of the ellipse (A and B). The other preform variable is its length (L).

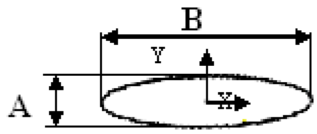


**Fig. 5** Preform aerofoil section [18]

The attitude of the die parting-line would affect material flow and the lateral force, where it is highly dependent on its slop angle (P). That is the rotation angle of the die cavity about the Z axis (Fig 6).

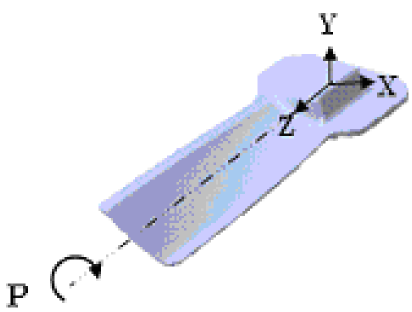


**Fig. 6** Attitude of die parting-line [19]

Therefore, the optimization includes five independent variables: H, A, B, L and P. The goal of optimization is obtaining these variables in order to minimize the following response functions:

1- Flash volume ($V_f$)
2- Volume of the unfilled die cavity or defect volume ($V_{def}$)
3- Maximum distance of the dies from the blade surface at the end of the forging process ($D_{max}$)
4- Forging force ($F_f$)
5- Lateral force ($F_l$)

Geometrical defects such as form-error can be prevented by minimizing the lateral die mismatch which is normally caused by the lateral force. Excessive lateral force can result in deflection of the tool guide-ways and the press elastic deformation.

## 6 RESPONSE FUNCTIONS MODEL

The second order model has been used for the relationship between the response functions and the inputs. There are many design schemes that can be used for fitting a second order model. One of them is the face-centered central composite design. This design locates axial points on the centers of the cube faces. This design scheme is used because it requires only three levels of each factor and, in practice, it is frequently difficult to change the factor levels [11]. From the results of the process simulation in section 3, the domains of the perform shape variables were determined. If the value of the variable P is out of 0°-8°, it causes the side of the die cavity to have a negative slope. Therefore the domains of the variables are determined as:

H: 24-32mm, A: 2.4-6.4mm, B: 11-15mm, L: 92-102mm, P: 0-8°

According to the face-centered central composite design, three levels are considered for any variable. Therefore, the number of experiments is 43 as shown in Table (1). According to the state of any experiment shown in Table (1), the dies and preform shapes were modelled by using the CATIAV5R17 software. Then each preform forging process with its corresponding dies was simulated with the DEFORM 3D software. Other conditions of the analysis are the amounts that were given in section 3.

In the next stage, the amounts of the outputs (response functions) were obtained: the flash volume ($V_f$) is obtained by trimming the forged blade. Defect volume ($V_{def}$) is the difference of the trimmed forged blade with the desirable blade. $D_{max}$ , $F_f$ and $F_l$ is obtained by the simulation software directly. The amount of the outputs is shown in Table (1), where MINITAB R15 was used for the RSM optimization process [19].

By analyzing the variance of each response function, significant variables were specified. Then the regression model was obtained using significant variables. In the next stage, the analysis of the variance was done on the regression model and the significance of the model and its coefficients were investigated and the goodness of the fit of the model was checked. In the analyses of variance, the amount of $\alpha$ in the F-test was assumed to be 0.05 which means that if probability value (P-value) is lower than 0.05, it demonstrates significance for the regression model with a probability more than 95%. By analysis of variance (ANOVA) of the flash volume response function, significant effects were specified and the regression model using those terms was as follows:

**Table 1** Design of experiments and outputs values

| | | Preform (mm) | | | P | Ff | Fl | $V_f$ | Vd | Dmax |
|---|---|---|---|---|---|---|---|---|---|---|
| **Run** | **H** | **L** | **A** | **B** | **(deg.)** | **(tone)** | **(tone)** | **(mm3)** | **(mm3)** | **(mm)** |
| 1 | 24 | 92 | 2.4 | 11 | 0 | 72.5 | 22.7 | 0 | 3577.33 | 4.12 |
| 2 | 32 | 92 | 2.4 | 11 | 0 | 141 | 18.4 | 816 | 909.71 | 1.50 |
| 3 | 24 | 102 | 2.4 | 11 | 0 | 91.1 | 31.4 | 12 | 3396.64 | 4.36 |
| 4 | 32 | 102 | 2.4 | 11 | 0 | 161 | 23.9 | 899 | 802.21 | 1.33 |
| 5 | 24 | 92 | 6.4 | 11 | 0 | 723 | 197 | 1208 | 1678.24 | 3.84 |
| 6 | 32 | 92 | 6.4 | 11 | 0 | 594 | 117 | 3180 | 353.61 | 0.27 |
| 7 | 24 | 102 | 6.4 | 11 | 0 | 655 | 175 | 1616 | 1547.00 | 2.84 |
| 8 | 32 | 102 | 6.4 | 11 | 0 | 689 | 183 | 4118 | 217.80 | 0.22 |
| 9 | 24 | 92 | 2.4 | 15 | 0 | 124 | 37.6 | 59 | 2856.85 | 3.49 |
| 10 | 32 | 92 | 2.4 | 15 | 0 | 200 | 37.7 | 840 | 584.10 | 1.47 |
| 11 | 24 | 102 | 2.4 | 15 | 0 | 124 | 39.1 | 66 | 2601.57 | 3.00 |
| 12 | 32 | 102 | 2.4 | 15 | 0 | 194 | 38.8 | 951 | 435.84 | 0.47 |
| 13 | 24 | 92 | 6.4 | 15 | 0 | 649 | 176 | 2288 | 1303.58 | 2.88 |
| 14 | 32 | 92 | 6.4 | 15 | 0 | 696 | 140 | 4769 | 302.18 | 0.33 |
| 15 | 24 | 102 | 6.4 | 15 | 0 | 560 | 148 | 2963 | 1268.81 | 2.96 |
| 16 | 32 | 102 | 6.4 | 15 | 0 | 756 | 176 | 5760 | 210.64 | 0.11 |
| 17 | 24 | 92 | 2.4 | 11 | 8 | 54.2 | 24 | 0 | 3726.40 | 4.20 |
| 18 | 32 | 92 | 2.4 | 11 | 8 | 125 | 33.6 | 711 | 921.78 | 1.24 |
| 19 | 24 | 102 | 2.4 | 11 | 8 | 72.3 | 36.7 | 16 | 3398.95 | 3.97 |
| 20 | 32 | 102 | 2.4 | 11 | 8 | 130 | 36.4 | 866 | 649.08 | 1.40 |
| 21 | 24 | 92 | 6.4 | 11 | 8 | 556 | 231 | 1206 | 1624.04 | 3.47 |
| 22 | 32 | 92 | 6.4 | 11 | 8 | 740 | 246 | 3423 | 29.35 | 0.00 |
| 23 | 24 | 102 | 6.4 | 11 | 8 | 878 | 367 | 1609 | 1473.16 | 3.03 |
| 24 | 32 | 102 | 6.4 | 11 | 8 | 651 | 239 | 4108 | 81.04 | 0.31 |
| 25 | 24 | 92 | 2.4 | 15 | 8 | 145 | 68.1 | 50 | 2831.14 | 3.38 |
| 26 | 32 | 92 | 2.4 | 15 | 8 | 218 | 66.9 | 863 | 472.75 | 1.47 |
| 27 | 24 | 102 | 2.4 | 15 | 8 | 133 | 60.5 | 136 | 2651.38 | 3.38 |
| 28 | 32 | 102 | 2.4 | 15 | 8 | 215 | 74.4 | 946 | 221.12 | 0.93 |
| 29 | 24 | 92 | 6.4 | 15 | 8 | 706 | 285 | 2257 | 1213.70 | 2.57 |
| 30 | 32 | 92 | 6.4 | 15 | 8 | 538 | 195 | 5080 | 54.49 | 0.18 |
| 31 | 24 | 102 | 6.4 | 15 | 8 | 537 | 220 | 2895 | 1130.15 | 2.64 |
| 32 | 32 | 102 | 6.4 | 15 | 8 | 669 | 233 | 5691 | 0.00 | 0.02 |
| 33 | 24 | 97 | 4.4 | 13 | 4 | 411 | 141 | 780 | 1960.49 | 3.73 |
| 34 | 32 | 97 | 4.4 | 13 | 4 | 507 | 132 | 2618 | 160.46 | 0.32 |
| 35 | 28 | 92 | 4.4 | 13 | 4 | 429 | 119 | 898 | 385.99 | 1.17 |
| 36 | 28 | 102 | 4.4 | 13 | 4 | 384 | 111 | 1138 | 183.86 | 0.78 |
| 37 | 28 | 97 | 2.4 | 13 | 4 | 109 | 35.4 | 39 | 1425.40 | 1.94 |
| 38 | 28 | 97 | 6.4 | 13 | 4 | 744 | 256 | 2638 | 186.52 | 0.17 |
| 39 | 28 | 97 | 4.4 | 11 | 4 | 309 | 94.6 | 545 | 542.17 | 2.04 |
| 40 | 28 | 97 | 4.4 | 15 | 4 | 454 | 139 | 1376 | 337.49 | 2.00 |
| 41 | 28 | 97 | 4.4 | 13 | 0 | 501 | 118 | 1000 | 347.65 | 1.78 |
| 42 | 28 | 97 | 4.4 | 13 | 8 | 464 | 178 | 1018 | 212.84 | 1.71 |
| 43 | 28 | 97 | 4.4 | 13 | 4 | 411 | 127 | 1020 | 284.84 | 1.78 |

$$V_f = 42718.9 - 2424.9H - 84.3L - 3852.5A - 370.1B + 37.8H^2 + 64.1A^2 + 2H.L + 53.6H.A + 6.6H.B + 14.3L.A + 83.7A.B \quad (12)$$

ANOVA results for the regression model of flash volume $V_f$ are shown in Table (2). The low probability value (P<0.001) demonstrates a high significance for the regression model and its coefficients. The goodness of the fit of the model was checked by the determination of the coefficient ($R_2$). In this case, the value of the determination of coefficient obtained was 99.63%, which revealed that this regression is statistically significant and only 0.37% of the total variations are not explained by the model.

**Table 2** ANOVA for $V_f$

| Source | DF | SeqSS | AdjSS | AdjMS | F | P |
|---|---|---|---|---|---|---|
| Regression | 11 | 107075205 | 107075205 | 9734110 | 769.1 | 0 |
| Linear | 4 | 92154551 | 7524055 | 1881014 | 148.62 | 0 |
| Square | 2 | 4652901 | 4652901 | 2326450 | 183.81 | 0 |
| Interaction | 5 | 10267754 | 10267754 | 2053551 | 162.25 | 0 |

For the analysis of cavity filling and dimensional precision of the forged blade, two response functions were corresponded that are the defect volume ($V_{def}$) and the maximum distance of the forged blade surface with die surfaces at the end of the forging process ($D_{max}$). $V_{def}$ is the volume difference of forged blade and desirable blade. By analyzing the variance of the $V_{def}$ response function, significant effects were specified and the regression model using those terms was as follows:

$$V_{def} = 29085.6 - 2983.6H + 578.7L - 2991.2A - 522.9B + 111.9P + 43.6H^2 - 3.1L^2 + 110.6A^2 - 5.2P^2 + 39.3H.A + 11.3H.B - 2.4H.P + 3.4L.A + 25.1A.B - 3.8A.P \quad (13)$$

ANOVA results for the regression model of defect volume $V_{def}$ are shown in Table (3). The low probability value (P<0.001) demonstrates a high significance for the regression model and its coefficients. For the goodness of the fit of the model, the value of the coefficient ($R_2$) was 99.87%, which revealed that this regression is statistically significant and only 0.13% of the total variations are not explained by the model.

**Table 3** ANOVA for $V_{def}$

| Source | DF | SeqSS | AdjSS | AdjMS | F | P |
|---|---|---|---|---|---|---|
| Regression | 15 | 50935253 | 50935253 | 3395684 | 1366 | 0.00 |
| Linear | 5 | 41429386 | 4831798 | 966360 | 389 | 0.00 |
| Square | 4 | 5653225 | 5653225 | 1413306 | 568 | 0.00 |
| Interaction | 6 | 3852642 | 3852642 | 642107 | 258 | 0.00 |

By Analysis the variance of the $D_{max}$ response function, significant effects were specified and the regression model using those terms was as follows:

$$D_{max} = -77.3248 - 2.7868H + 3.1788L + 0.4991A - 4.6756B + 0.0398H^2 - 0.0165L^2 - 0.0831A^2 + 0.1581B^2 + 0.0166H.B \quad (14)$$

The ANOVA results for the regression model of maximum distance of dies from forged blade surface $D_{max}$ are shown in Table (4). The low probability value (P<0.05) demonstrates a high significance for the regression model and its coefficients. The value of coefficient ($R_2$) was 96.45%, which revealed that this regression is statistically significant and only 3.55% of the total variations are not explained by the model.

**Table 4** ANOVA for $D_{max}$

| Source | DF | SeqSS | AdjSS | AdjMS | F | P |
|---|---|---|---|---|---|---|
| Regression | 9 | 76.3351 | 76.335 | 8.48168 | 99.72 | 0 |
| Linear | 4 | 72.1897 | 5.72 | 1.42999 | 16.81 | 0 |
| Square | 4 | 3.5837 | 3.5837 | 0.89592 | 10.53 | 0 |
| Interaction | 1 | 0.5618 | 0.5618 | 0.5618 | 6.6 | 0 |

By analyzing the variance of the forging force response function, significant effects which are just A, B and $B_2$ were specified and the regression model using those terms was as follows:

$$F_f = 129.25A + 326.85B - 12.29B^2 - 2300.0 \quad (15)$$

The ANOVA results for the regression model of forging force $F_f$ are shown in Table (5). The low probability value (P<0.001) demonstrates a high significance for the regression model and its coefficients. The value of coefficient ($R_2$) was 94.2%, which revealed that this regression is statistically significant and only 5.8% of the total variations are not explained by the model.

**Table 5** ANOVA for $F_f$

| Source | DF | Seq SS | Adj SS | AdjMS | F | P |
|---|---|---|---|---|---|---|
| Regression | 3 | 2240168 | 2240168 | 746723 | 205.56 | 0 |
| Linear | 2 | 2223074 | 2225403 | 1112701 | 306.31 | 0 |
| Square | 1 | 17094 | 17094 | 17094 | 4.71 | 0.036 |

By analyzing the variance of the lateral force ($F_l$) response function, significant effects were specified and the regression model using those terms was as follows:

$$F_l = 811.237 - 37.145H - 10.099L + 59.846A + 11.404B - 1.553P + 0.372H.L - 1.981A.B + 1.674A.P \quad (16)$$

The ANOVA results for the regression model of forging lateral force $F_l$ are shown in Table (6). The low probability value ($P<0.05$) demonstrates significance for the regression model and its coefficients. The value of coefficient ($R_2$) was 94.87%, which revealed that this regression is statistically significant and only 5.13% of the total variations are not explained by the model.

**Table 6** ANOVA for $F_l$

| Source | DF | SeqSS | AdjSS | AdjMS | F | P |
|---|---|---|---|---|---|---|
| Regression | 8 | 241358 | 241358 | 30170 | 76.25 | 0 |
| Linear | 5 | 232072 | 21203 | 4241 | 10.72 | 0 |
| Interaction | 3 | 9287 | 9286.5 | 3096 | 7.82 | 0 |

## 7 OPTIMIZATION

For optimization the response functions which should be minimized, first each of them is transformed to desirability function using Eq. (10) then the overall desirability using Eq. (8) is obtained. At last, optimal value of the independent variables are obtained using reduced gradient approach. Whereas the optimal points for the responses may not coincide with each other, it is compromised. For this reason by changing target value, acceptable region and weight of each of the responses, optimal conditions were obtained that desirability of the responses and the overall desirability is maximized. The optimal values and the variation of responses versus independent variables are shown in Fig. 7. The overall desirability value is 95.38%. Variation diagrams show that variable A has more effect on response functions. It is noticeable that if the response functions are optimized separately, the values of the independent variables do not coincide with each other**.** Therefore optimal points were obtained by compromising between the response functions. Optimization results were verified by FEM analysis. According to optimal preform dimensions and die-parting line angle, preform and die shapes were modelled and the forging process was analyzed by FEM according to the conditions introduced in section II. Desirable forged blade shape is shown in Fig. 8(a). Other shapes in Fig. 8 are optimized perform shape (Fig. 8(b)), forged blade with flash (Fig. 8(c)), and forged blade without flash (Fig. 8(d)). Maximum distance of dies to the forged blade in the end of forging process is shown in Fig 9, where it is observed that the maximum distance is zero. Distance that is observed in tip of the blade belongs to the flash. The amount of the flash is 1178.526mm$^3$. Variations of the forging force and lateral force are shown in Figs. 10 and 11. It is observed that force variations are smooth and the amounts of the forces are in the defined acceptable regions.

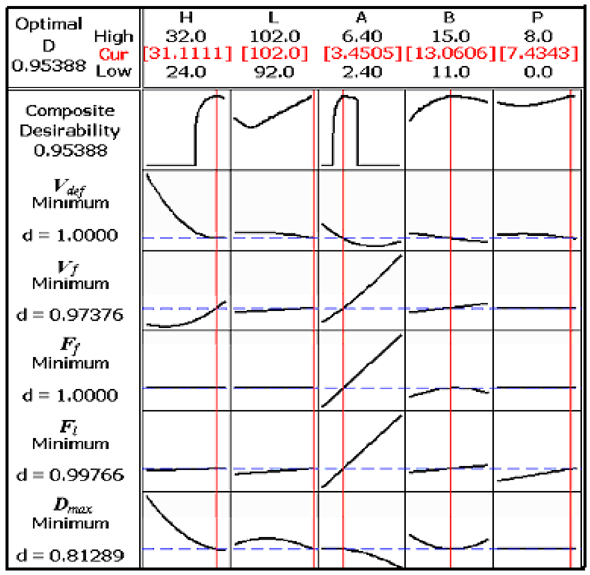


**Fig. 7** Optimization results

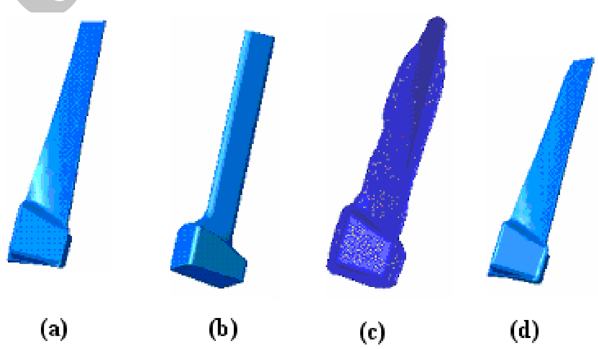


**Fig. 8** (a) Desirable blade shape; (b) optimized perform shape; (c) forged blade with flash; (d) forged blade without flash

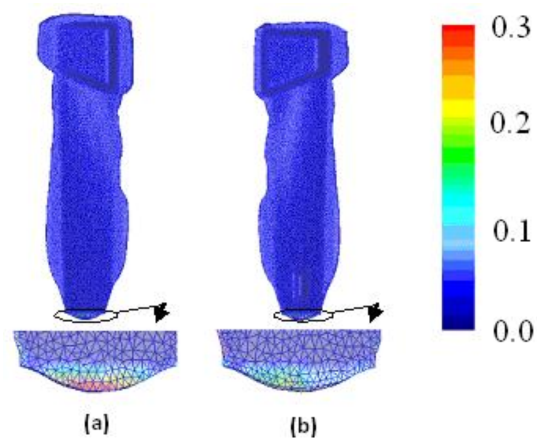


**Fig. 9** Maximum distance of dies to the forged part: (a) upper die; (b) lower die

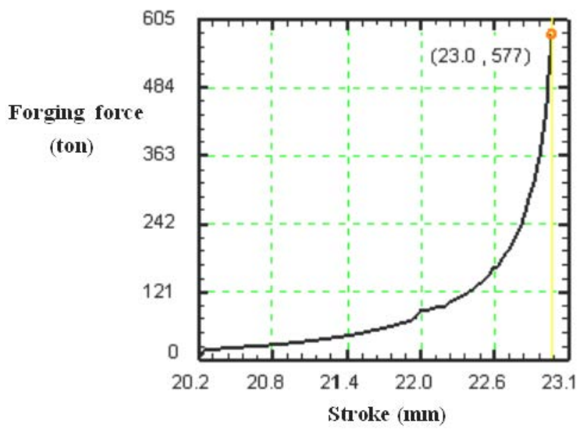


**Fig. 10** Forging force

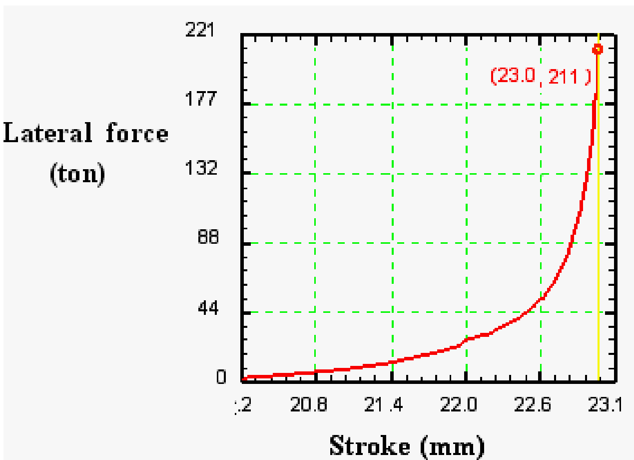


**Fig. 11** Lateral force

The results of the optimization were compared with the results of the conventional method (trial and error using FEA). Table (7) summarizes the values of the response functions including conventional and optimization methods. Results show that in the both methods die cavity is filled and the values of the objectives flash volume and forging force in optimization method are less than the conventional method. But the value of the lateral force is greater because of lower weight of the lateral force function in the compromising between the response functions.

**Table 7** Results of the optimization and conventional methods

| method | Vf ($mm^3$) | Dmax (mm) | Ff (ton) | Fl (ton) |
|---|---|---|---|---|
| **Conventional** | 2679 | 0 | 708 | 112 |
| **Optimization** | 1178.526 | 0 | 577 | 211 |

## CONCLUSION

In this research, a method that is a combination of finite element and response surface methods was presented for the optimization of the preform shape and die-parting line angle in the gas turbine compressor blade forging process. The most important results of this research are:

1-Since empirically executing the forging process of complicated shapes such as compressor blade of gas turbine engines is expensive, simulation and using an optimization approach can be used for the optimization of such process. Because simulation of the forging process is time-consuming, the response surface method which needs fewer runs is a suitable approach.

2-Investigation of the significance and goodness of the fit of the regression models shows that the regression models are significant and have a good coincidence with the data.

3-Whereas the optimization is multi-response, optimal points of response functions did not coincide with each other. Therefore, optimal points were obtained by compromising between response functions.

4- Comparing the optimization results with the conventional method shows that the flash volume and forging force are lower but the lateral force is greater because of lower weight of the lateral force function in the compromising between the response functions.

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