Biosci. Biotech. Res. Comm. Special Issue No 1:74-86 (2017)

BBRC
Bioscience Biotechnology
Research Communications

Forging pre-form dies optimization using artificial neural networks and continuous genetic algorithm

H. Hashemzadeh[1], S.A. Eftekhari[2] and M. Loh-Mousavi[3]

[1]*Msc student, Department of Mechanical Engineering, Khomeinishahr branch, Islamic Azad University, Khomeinishahr, Iran*

[2,3]*Assistant Professor, Department of Mechanical Engineering, Khomeinishahr branch, Islamic Azad University, Khomeinishahr, Iran*

ABSTRACT

In forging process of complex parts, the raw material cannot be transformed in one forging stage to the final shape; therefore, using one or several pre-form dies would be necessary. An optimal pre-form die should be capable of meeting several design criteria's. Among such design criteria's one can mention the defect-free parts manufacturing with minimum raw materials, minimum plastic strain, minimum force requirement for fulfilling the process as well as filling completely the final die. In this research, the Genetic Algorithm (GA) is used as a tool for Cartesian path generation. For this reason, at first, several different pre-form dies are produced using random mathematical functions. Then, using finite elements simulation, the optimal die selection criteria's are calculated. An artificial neural network (ANN) is learned by the data obtained from simulation so that it can predict the results of the simulation. The ANN and design criteria's are used as a target function for optimization using continuous GA. Finally, the best pre-form die geometry is calculated using the continuous GA. Also this method is used for H-shape parts to evaluate the method performance. The optimal pre-form die is recommended for the H-shape part and its forging results extracted by the continuous GA. Also, the finite element simulation performed for the optimal die and the obtained results compared to the predicted results of the ANN. The results showed that the obtained optimal model meets the predefined criteria's and this method can be used for optimization of pre-form dies successfully.

KEY WORDS: OPTIMAL PRE-FORM DIE, FINITE ELEMENT SIMULATION, ARTIFICIAL NEURAL NETWORKS, CONTINUOUS GENETIC ALGORITHM, FORGING PROCESS.

ARTICLE INFORMATION:

**Corresponding Author: Hamidreza.hashemzadeh@iaukhsh.ac.ir*

Received 1st Jan, 2017
Accepted after revision 2nd April, 2017
BBRC Print ISSN: 0974-6455
Online ISSN: 2321-4007
Thomson Reuters ISI ESC and Crossref Indexed Journal
NAAS Journal Score 2017: 4.31 Cosmos IF : 4.006

Online Contents Available at: http//www.bbrc.in/

INTRODUCTION

Among manufacturing processes, forging process has a particular importance, since it helps to produce parts with excellent mechanical properties and minimum material wastes. In forging, the raw material has a relatively simple shape. This material is transformed like wax during one or more operations to a product with relatively complex composition. Forging usually needs the relatively expensive instruments. As a result, this process is attractive economically when the manufactured parts are in mass volume or when special mechanical properties are required for the final product. The material's increasing costs, energy and particularly the human force requires that the forging processes and instruments are designed with minimum trial and error and minimum possible time. Therefore, making use of computerized methods, i.e. CAE, CAM, CAD and particularly finite elements analysis-based computerized simulation is an absolute requirement (Altan *et al.* 2006).

For H-shaped parts, considering complexity parameter, if the section height-to-width ratio be high, the part shape would be complex and in order to produce it, the pre-form die is needed. So far, there have been used different methods for pre-form die designing but none of them is suitable for die optimal design.

Lanka *et al.* (1991) proposed a new method for designing the pre-form dies in plane strain forgings. In this method, the number of pre-form stages required for the forging is investigated. The design criteria's also were stress rate and strain rate. Grandhi *et al.* (1993) used design parameters control algorithm in forging process. The mentioned parameters include dies velocity for in-built strain rate control. They performed the analysis on solid and visco-plastic materials in finite elements model. Zhao *et al.* (1995) provided the pre-form die design using a node separation criterion in forging reverse simulation with finite elements model. In this method, the complexity factor which shows the process difficulty is used. Zhao *et al.* (1997) applied sensitivity analysis model with finite elements model for designing pre-form dies in accurate forging. Also, the applicability of this method in plane strain and axisymmetric forging was investigated. Using electrical field theory, Lee *et al.* (2002) proposed a method for manufacturing the axisymmetric parts' pre-form in which the shape complexity parameter is investigated. Then, using neural networks the optimal die was obtained.

Abri Nia *et al.* (2006) obtained the dimensions and coordinate of the part considering the contact time parameters for middle dies of the H-shaped parts using reverse transformation method-based algorithm as well as nonlinear finite elements model. Li *et al.* (2007) presented a novel intelligent optimization approach that integrates machine learning and optimization techniques. An intelligent gradient-based optimization scheme and an intelligent response surface methodology were proposed, respectively. Then optimization algorithms implemented more effectively to find optimal design results. An extrusion forging process and a U channel roll forming process are studied as application samples and the effectiveness of the proposed approach is verified.

Bonte *et al.* (2010) used Sequential Approximate Optimization (SAO) for optimizing forging processes. Three variants of the SAO algorithm which differ by their sequential improvement strategies have been investigated and compared to other optimization algorithms by application to two forging processes. The results showed that SAO provides a very efficient algorithm to optimize forging processes using time-consuming FEM simulations.

Khalili and Fonoudi (2010) investigated hot forging process of AISI-1025 using Deform3D software. They used an artificial neural network to predict forging force and strain based on the initial billet temperature, die velocity, die displacement and friction between billet and dies. The input data gathered using FEM simulations. The obtained results showed that friction and die displacement are the most effective parameters on the forging force respectively.

Hosseinzadeh *et al.* (2010) outlined the Taguchi optimization methodology, to optimize the effective parameters in forming cylindrical cups by the new die set of sheet hydroforming process. It was shown that the Taguchi method is suitable to examine the optimization process. Khalili *et al.* (2011) studied the optimum blank shape design for the deep drawing of Elliptical-shape cups with a uniform trimming allowance at the flange. In this research, a new method for optimum blank shape design using finite element analysis has been proposed. For this reason they applied Response Surface Methodology (RSM) with Reduced Basis Technique (RBT) to assist engineers in the blank optimization in sheet metal forming. The proposed method is found to be very effective in the deep drawing process and can be further applied to other stamping applications. Lu *et al.* (2011a) investigated three direct search algorithms, i.e. a modified simplex, random direction search and enhanced Powell's methods together with a new localized response surface method and applied to solve die shape optimization problems in metal forming processes. Their main motivation is to develop efficient and easy to implement optimization algorithms in metal forming simulations.

The optimization results from the three case problems show that direct search based methods especially the modified simplex and the localized response surface methods are computationally efficient and robust for net-shape forging and extrusion optimization problems. It is also suggested that these methods can be used in more complex forging problems where die shape design and optimization are essential for achieving net-shape accuracy.

Lu *et al.* (2011b) based on the evolutionary structural optimization (ESO) concept, developed a topological optimization method for preform design. In this method, a new criterion for element elimination and addition on the work piece boundary surfaces is proposed to optimize material distribution. Two 2D case problems including forging of an airfoil shape and forging of rail wheel are evaluated using the developed method. The results suggest that the developed topology optimization method is an efficient approach for preform design optimization.

Shamsi-Sarband *et al.* (2012) utilized finite element method and sensitivity analysis for optimizing a preform die shape in the superplastic forming (SPF) process. In their study, the effect of friction coefficient on the optimized preform die shape is investigated. They showed that friction coefficient has an important effect on the optimized preform die shape and thickness distribution.

Naeemi (2013) used the reverse transformation method for designing the pre-form die and ANN for predicting the forging process and finally, among 500 preform dies designed, the optimal die meeting the design criteria's is selected. Shamsi-Sarband *et al.* (2013) used a combination of sensitivity analysis and FEM to design a preform for a two-stage superplastic forming process. The results showed that the geometric parameters have a significant effect on the preform shape. By increasing the height and the cone angle of the final cup, the depth of the preform in the inner cavity decreases and the dome region is approached to the center of the preform cup. By increasing the corner radius of the final-die, only the height of the dome region decreases. Shao *et al.* (2015) presented a recent work on preform design optimization in bulk metal forming process based on a topological approach. In the paper, to obtain a forging preform shape with reduced material consumption but enhanced uniform material deformation, a new element removal and addition criterion has been established with consideration of hydrostatic stress and strain components. They implemented their method to forging of a 3D aero engine blade. Considering the feasibility of producing a preform, different constraints are applied in the optimization process to affect the preform shape. The optimization results suggest that the developed topology optimization method is an efficient approach for 3D preform design and optimization.

In this research, the capability of continuous GA for Cartesian path generation is used as a tool for die shape optimization. At first, several different pre-form dies are produced by random mathematical functions. Assuming that the selected part is axisymmetric, one can simulate it as a 2D die; therefore, a univariate function is used for producing the parts die shape. Then, the optimal die selection criteria are calculated using process simulation in ABAQUS software. The design criteria's considered include final die's filling percentage, maximum force exerted on the final die and the part's maximum plastic strain. The ANN has been taught using the information obtained from simulation so that the relationship between die shape and optimal design criteria's are simulated. These networks can be used as target function in the continuous GA. Finally, the best pre-form die shape is recommended using continuous GA which is a mathematical function and by plotting this function in Cartesian coordination system, the die shape would be obtained. This model is used for H-shaped parts to evaluate the method performance.

MATERIAL AND METHODS

FORGING PROCESS

In forging, a part with primary shape is transformed between 2 instruments (dies) like a wax until it reaches the final desirable shape. Therefore, a simple part geometry becomes complex in this way that the instrument forms the desirable geometry on the part and the pressure is exerted via the contacting surfaces between die and material on the transforming material. Today, the forging process is of significant importance in industry and this is due to its advantages. In the following some of them are mentioned:

- The forging parts are designed in such a form they have the final product's geometry as much as possible. Hence, in this process the material wastes would be minimum relative to the machining one.
- Due to lack of gas bubbles or suck which is observed in other processes such as welding and casting, the parts' mechanical and physical properties would be better in forging.
- Due to the fact that in forging the die walls control the material flow, the part's mechanical properties would improve significantly.

As a consequence, potential economical energy and material use would be resulted from forging; particularly in average-high production quantities in which the instrument cost can be easily depreciated. Forging is a process based on experience. For years, the technical knowledge and experience in this field have been obtained using trial and error methods. However, the forging industry was capable to supply complex products from new alloys with minimum plasticity (Altan *et al.* 2006). Physical phenomena which defines a forging process is hardly explainable using quantitative relations. Metal flow, friction in material and die contacting surface, heat production and transfer during waxy flow as well as process conditions and properties are difficult to predict and analyze. Often, in separate parts manufacturing, several forging processes (pre-forming) are required to transform the simple primary geometry to a complex one without material defect or degradation of properties (Altan *et al.* 2006).

2.2 Optimal pre-form die design using continuous GA and ANN

2.2.1 H-shaped part's properties and geometry

In figure 1 the assumed part is indicated with its dimensions in mm. For modeling this part in ABAQUS, ¼ of the part is considered as indicated in figure 2.

Final die shape and raw material for H-shaped part forging

Considering the part shape, its final die is modeled as curve-shaped as showed in figure 3. The pre-form die for this part is also similar to the curve-shaped final die. Of course, there would be a narrow path in final die for better material flux and the extra materials are extracted as pleated one. The raw part is considered for a cylindrical die with height of 0.9 m and radius of 0.3 m. since the raw part is axisymmetric, for its modeling ¼ of the part is used which is rectangular with height of 450 mm and width of 300 mm.

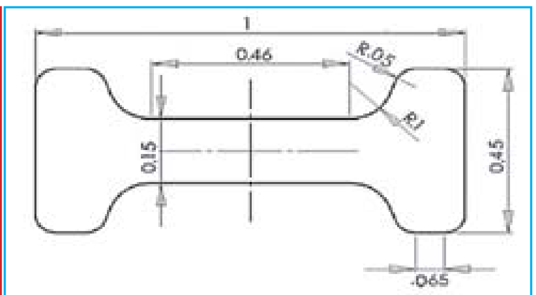

FIGURE 1. H-Shaped part geometry (Abri Nia *et al.* 2006)

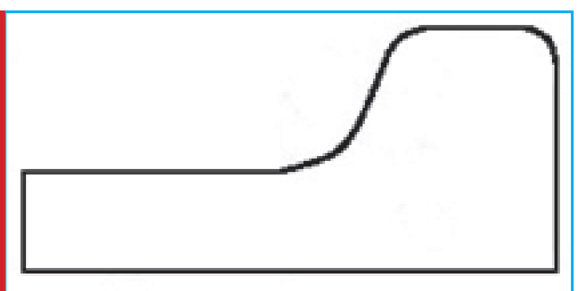

FIGURE 2. Part required geometry for modeling in ABAQUS

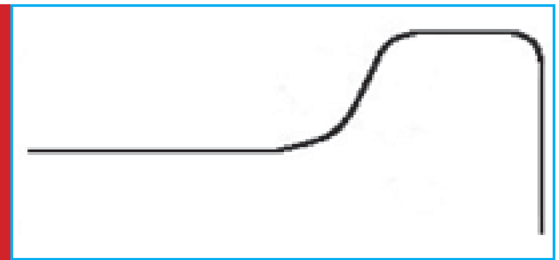

FIGURE 3. Die's final shape

Raw material physical properties

AL2014 is selected as raw material. Since, forging processes are performed in high temperature (400° C), the elastic and plastic properties of this aluminum are required in high temperature. These properties are (Altan *et al.* 1983):

- Primary yield stress=23.7 MPa
- Poisson's coefficient= 0.33
- Elasticity module=27.8 GPa
- Stress-strain relationship in plastic state

$$\sigma_y = max[s, c\varepsilon^m] \tag{1}$$

In this equation, s is the primary yield stress, c is the flow constant and m is the strain-rate hardening which are c=1.02e8 MPa and m=0.11 for aluminum at 400° C.

2.2.4 The required pre-form phases' number

In forging, at first the required number of pre-form phases' has to be determined. For this purpose, one can make use of trial and error method or proposed methods in the previous articles. In this research, considering the H-shaped part for forging, in order to determine the pre-form phases' number, the Thomas' method is used. Considering the part's height-width ratio, the number of phases required is listed in Table 1.

Considering the part's dimensions used in this research, only one pre-form phase is needed. For this reason, the part forging includes 2 stages. At the first phase, pre-form and in the second stage the final die would be applied.

Table 1. Number of required pre-forms based on height-width ratio

required pre-forms	height-width ratio
No need to pre-form	0-2
1 pre-form phase	2-3
2 pre-form phases	3 and more

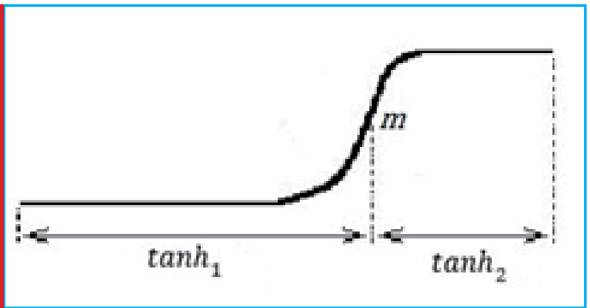

FIGURE 4. Die's shape estimation by mathematical functions

2.2.5 Mathematical function used for the H-shaped part's pre-form

The pre-form's geometry is estimated from mathematical functions and the final die shape. Figure 4 demonstrates the mathematical functions used for pre-form die shape estimation. This curved-shape consists of 2 tangent hyperbolic functions interconnected in point m.

Equation 2 expresses the combination of these 2 functions as a new function.

$$y = \begin{cases} tanh(a_1 \times (x-m)), & x \leq m \\ tanh(a_2 \times (x-m)), & x > m \end{cases} \quad (2)$$

In this relation, x is the pre-form die's width coordinate, y is the pre-form die's height coordinate before mapping, a_1 and a_2 are hyperbolic tangent functions' coefficients and m is the interconnection point of both functions.

The pre-form die's dimensions are selected according with the final part shape and primary part shape. Considering that the part forging process has one pre-form phase, the pre-form die shape is considered a middle shape between final part and primary part's shapes. The curve width formed by equation 2 is selected between the primary part's width (300 mm) and the final part's width (500 mm) which would be 400 mm. also, change of its height equals half of the final part's height change (150 mm). As a result, the pre-form die height would be 75 mm. therefore, the die width and height intervals would be [0, 400] and [0, 75] respectively. Relations 3 indicates the function used in equation 2 which is mapped in to the required width interval.

$$y = \begin{cases} tanh\left(\frac{a_1 \times (x-m)}{m}\right), & 0 \leq x \leq m \\ tanh\left(\frac{a_2 \times (x-m)}{(400-m)}\right), & m < x \leq 400 \end{cases} \quad (3)$$

In equation 3, x is the pre-form die width coordinate; y is the pre-form die height coordinate before mapping, a_1 and a_2 are hyperbolic tangent functions coefficients and m is interconnection point of both functions. Relations 4 indicates the function used in equation 3 which is mapped to the required width interval. This equation is the final problem relation.

$$Y = \frac{75}{y_{max}} \times (y+1) \quad (4)$$

In this equation, y is the pre-form die height coordinates before mapping, Y is the pre-form die height coordinate after mapping and y_{max} is a point of pre-form die with highest height.

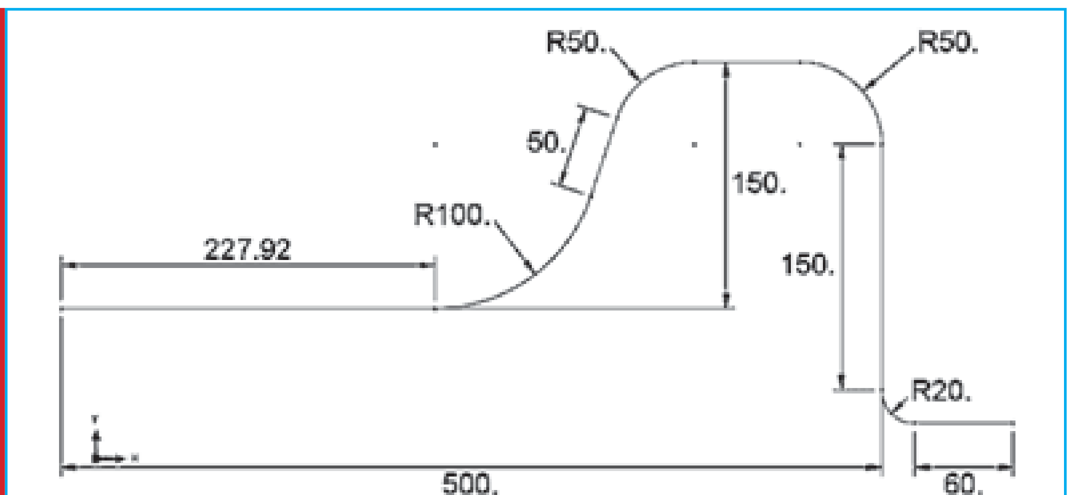

FIGURE 5. Finaldiegeometry

RESULTS AND DISCUSSION

FINITE ELEMENTS SIMULATION AND RESULTS OF FORGING

Required parts formation

The parts required for forging process simulation are raw part, pre-form die and the final die which are modeled in part setting of ABAQUS. All three parts are modeled in axisymmetric form.

In case of pre-form die, the part is modeled in analytic rigid type and wire-shaped. The raw part which is modeled from deformable type and shell-shaped one. In case of final die, similar to pre-form die, the modeling was analytic rigid type and wire-shaped. The final die geometry is indicated in figure 5.

Parts assembly

For parts assembling, the left end of pre-form and final die is places on the top surface of the raw part. Figure 6 indicates the parts assemble.

Loading and boundary conditions definition

In this subsection, motion and the loading as well as parts boundary conditions are determined. In this process, loading condition is applied in the form of die displacement. In the first phase, the pre-form die moves down 187.5 mm and in the second phase the final die moves down 375 mm. The die's motion type is also selected as smooth step.

In case of boundary conditions, for all motion steps, the axis line of the raw part is in horizontal direction and its rotation is about the vertical axis on the surface. The down surface of the raw part is also fixed in the vertical direction.

Part meshing

This section deals with the suitable meshing in order to solve the problem. The pre-form and final dies need no elements due to their final selection as rigid body and the only raw material needs meshing. Element type for raw part is CAX4R. This element is of quadrilateral axisymmetric and 4-node type reduced by integration. The sufficient elements number for part meshing is selected as 2128 to reach convergence.

Problem solving results demonstration

In this research, in order to find filling percentage, the Photoshop software is used. For this reason, at first the simulation result obtained from the ABAQUS with format of PNG is stored with the resolution of 1056×453 pixels. Then, the PNG file is loaded in Photoshop and the pleated zone is removed and using its analysis tool, the number of pixels for the final part is calculated. Comparing this number of pixels with the final die pixels number in completely filled state, the filling percentage of the die is obtained. The next parameter obtained from simulation is the maximum force required for forging. As it is seen in figure 7, plotting the diagram of exerted force on the final die against time, one can obtain this maximum force. Maximum force required for this model is 226 MN.

Simulation validating

In order to validate simulation and results, several check points are implied as follows.

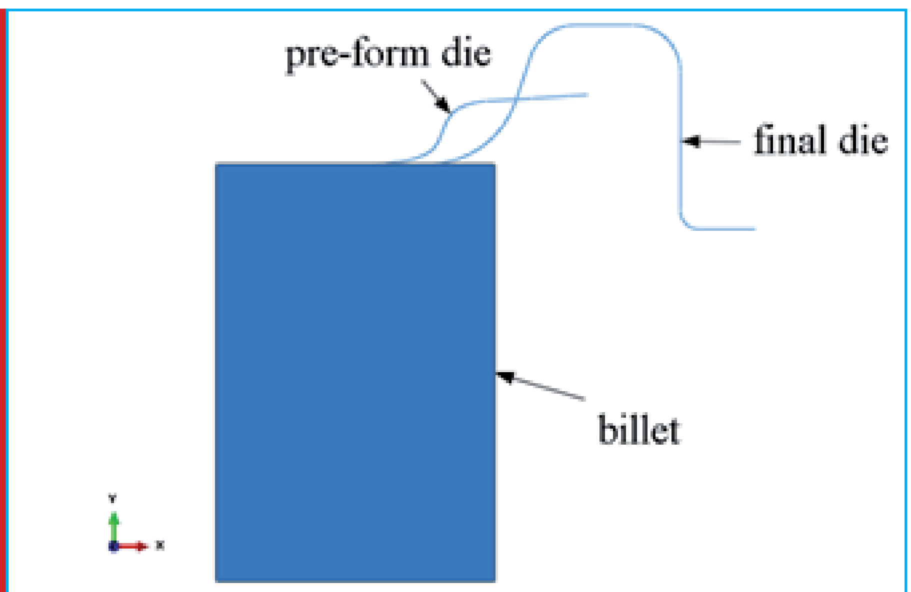

FIGURE 6. Parts assemble

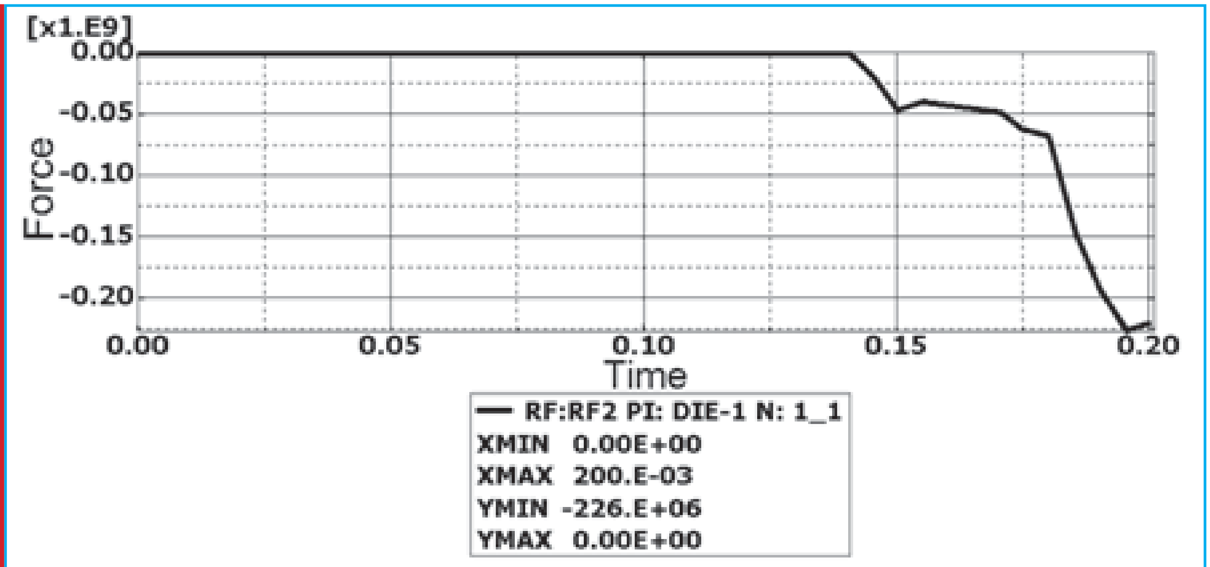

FIGURE 7. Force diagram against time for final die

Kinetic energy-internal energy ratio

In cases the mass scale method is used for problem solving, the energy ratio should be validated. For validating, the maximum kinetic energy-maximum internal energy ratio is used. The value of this proportion should not be more than 0.1. This means that the maximum kinetic energy is 10% of the maximum internal energy. Figure 8 represents the kinetic energy and figure 9 shows internal energy diagram against time. These diagrams can be helpful in calculating the maximum kinetic and internal energy.

As it is observed from figures 8 and 9, the maximum kinetic energy value is 54.4 MN/m and maximum internal energy value is 16.2 GN/m. the ratio of these energies is about 0.34% which is acceptable.

Evaluation of elements' number and results convergence

Making use of sufficient elements in order to make sure the solutions' validity is of significant importance. Lower elements than the necessary level causes wrong solutions. Following, if the elements' number be more than the necessary level, this would not cause large changes

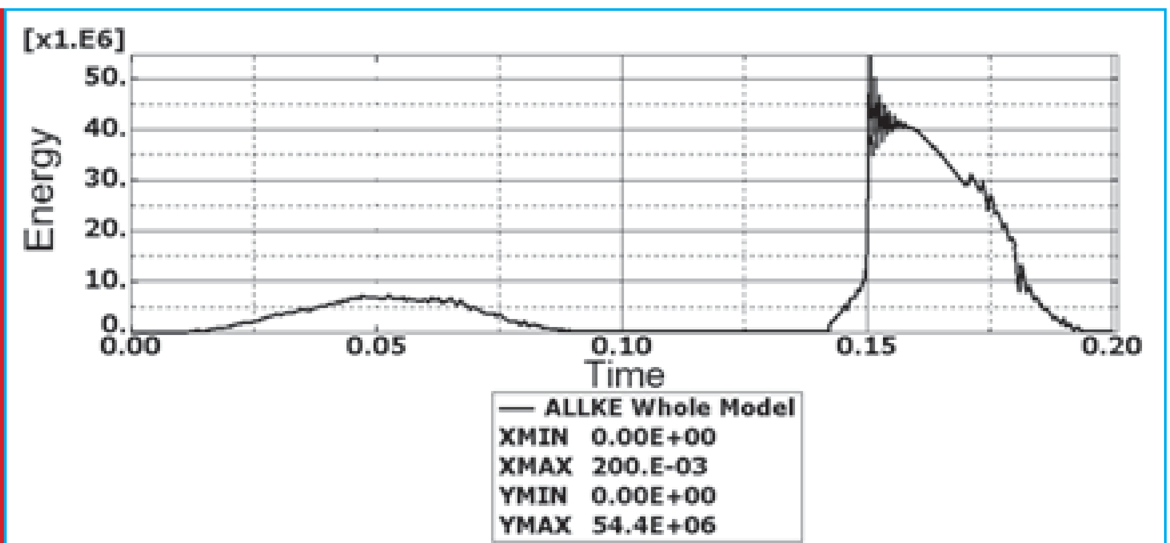

FIGURE 8. Kinetic energy diagram during process

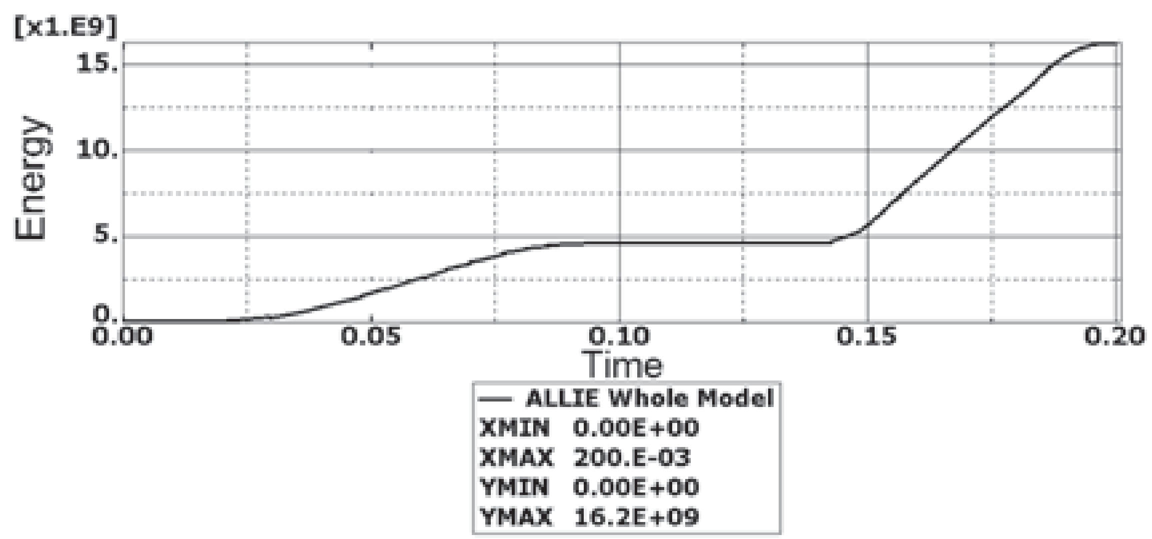

FIGURE 9. Internal energy diagram during process

Table 2. Simulation results for different number of elements

Elements number	Die filling percentage	Maximum plastic strain	Maximum force (MN)	Processing time (s)
150	97.75	3.130	134	11.4
600	98.61	5.145	179	60.50
950	98.94	5.484	190	114.7
1350	98.88	7.525	208	166.4
1734	99.10	7.336	217	139.7
2128	99.36	10.316	226	306.6
2301	99.08	9.253	224	358.0
2400	99.14	11.489	223	385.3

in the solution and only takes more time to solve the problem which is costly. Here, for validating the simulation, the necessary results of the problem for 8 different number of elements are calculated and the results are listed in table 2.

As it is seen from the above table, the output parameters change significantly up to 2128 elements and after that the changes are negligible.

3.1.6.3 Step time

The considered time for solving the problem in step module is effective on the problem results. If the time considered be very low, then the results would be wrong and if the time was very high, then the software would require more time for problem solving which leads an increase in problem processing time.

Table 3 lists the results obtained from applying different times in step module. As it is seen from results, 0.1 s seems sufficient.

It is important to note that due to the fact that the process is isothermal and material properties are considered independent of temperature and strain rate, the step

Table 3. Simulation results by applying different step times

Step time (s)	Die filling percentage	Maximum plastic strain	Maximum force (MN)
0.05	99.31	10.566	222
0.07	99.13	11.257	221
0.10	99.36	10.316	226
0.12	99.97	10.837	220

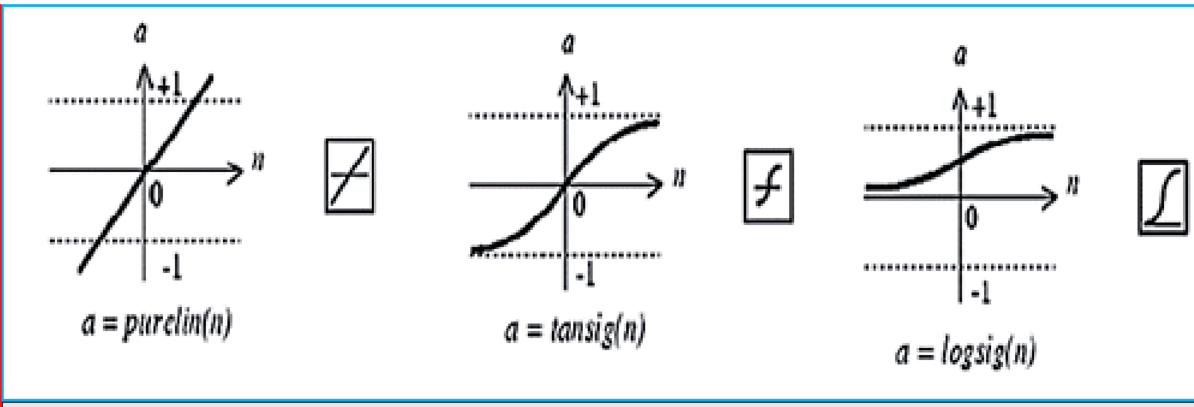

FIGURE 10. Widely used transfer functions in NN (Kia, 2010)

Table 4. Results obtained from networks run with different topologies

Serial	Topology	MSE	Correlation coefficient	Minimum error	Maximum error
1	5,12,3	0.0089	0.87	-0.33	0.47
2	12,15,3	0.0023	0.97	-0.14	0.35
3	18,12,3	0.00021	0.94	-0.21	0.10
4	20,40,3	0.00005	0.99	-0.03	0.05

time doesn't significantly affect the output parameters dramatically.

Finding an optimal pre-form die using ANN and continuous GA

Designing an Artificial Neural Network

Since the FEM simulation is very time consuming, an ANN is used to estimate the forging process results for different settings. A multilayer feed forward Perceptron network is chosen for this reason and the forging process input and output data are used for learning the network parameters. The network parameters include weights and biases which should be adjusted in such a way to optimize the network performance. The network performance is considered the minimum error between network outputs and targets. In order to optimize, one must define a performance index. In this research, mean square error is used as a performance index. MSE is the most common and desirable error function used for multi-layer networks.

Transfer functions selection

Transfer functions are determined based on the requirements of a problem. Considering recent studies and researches for correct results prediction from network as well as making use of the back propagation method in

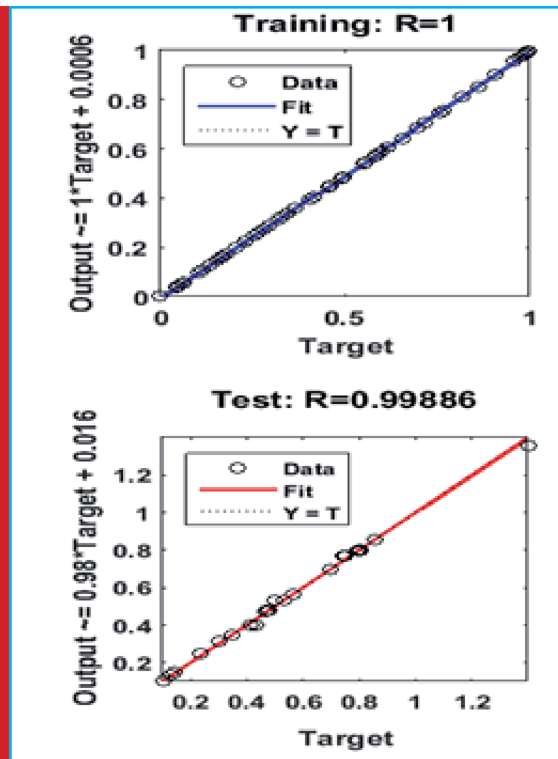

FIGURE 11. Test and training correlation coefficient diagram fortrained network

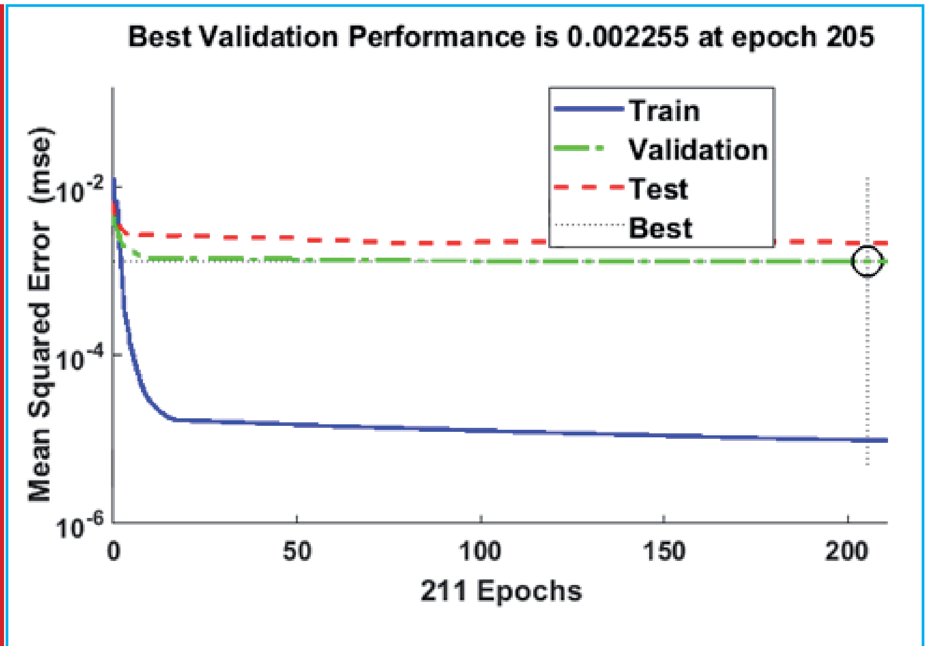

FIGURE 12. Network performance diagram

this research, the only requirement for these functions is that they have to be differentiable in the whole domain, since their differential is used in the learning process. Among most applicable functions, the sigmoid and linear functions are used widely. Figure 10 indicates some of these functions.

In this research, the sigmoid hyperbolic tangent functions in network hidden layers and the linear transfer function in last layer are used.

ANN Optimal topology

In this section, several neural networks are designed with different topologies. Then, these networks are trained and on the basis of performance index, the optimal network is selected for this research. Of course, for training the network, all data has to be normalized.

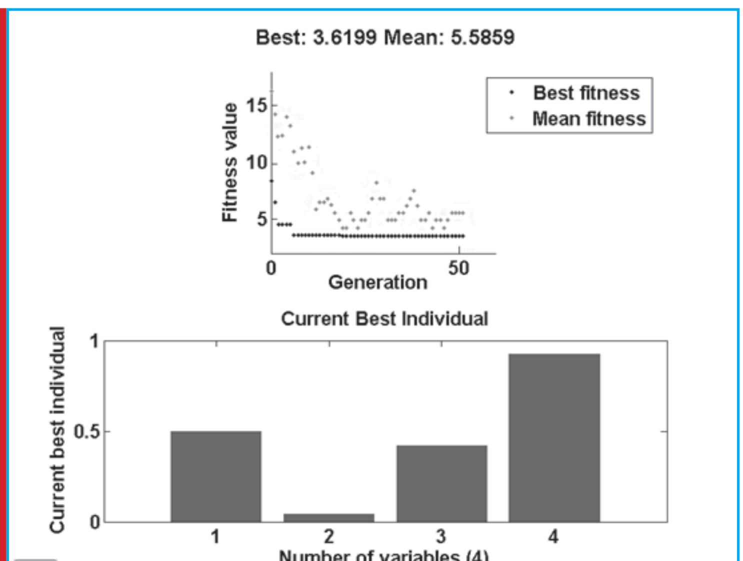

FIGURE 13. Fitness convergence and best generation in normal form

Table 5. Results obtained from normal and real scale

Scale	Raw part's width	m	a1	a2	Die filling percentage	Maximum plastic strain	Maximum force (MN)
Normal	0.5	0.0481	0.4214	0.9214	1.03	0.3038	0.17077
Real	302.5	205.8	9.6	13.9	100.06	8.887	271

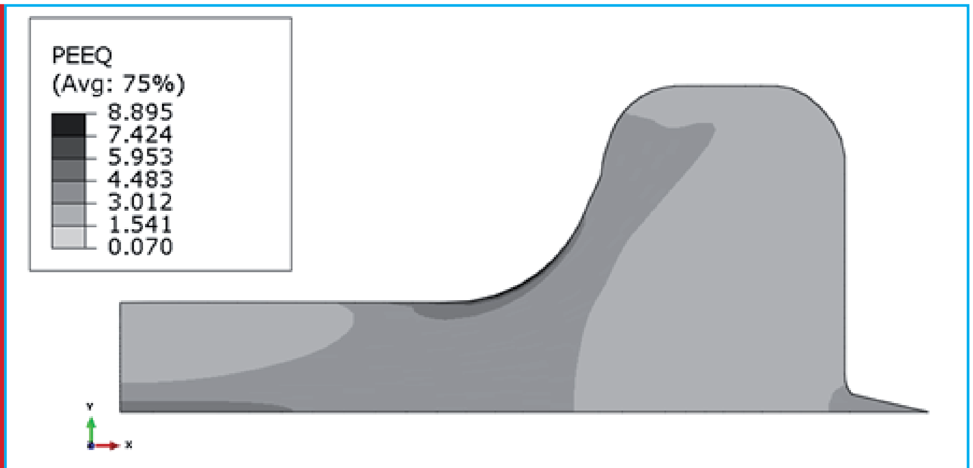

FIGURE 14. Plastic strain contour related to optimal state

Optimal network selection

Table 4 lists the results obtained from network run for several different topologies. In this table, the numbers in the topology column defines the number of neurons in different layers. As it is seen, the last network with three layers containing 20 and 40 neurons in the hidden layers has the best MSE and correlation coefficient.

Figure 11 indicates the correlation coefficient for training and test data and figure 12 indicates the network performance.

These figures show the chosen network capabilities, so this network would be used to simulate the forging process as a fitness function in optimization using GA.

3.2.5 The optimal pre-form die obtained by continuous GA

Figure 13 indicates the fitness convergence diagram and the best generation diagram. It is notable that to make sure the GA results are global minimum, the optimiza-

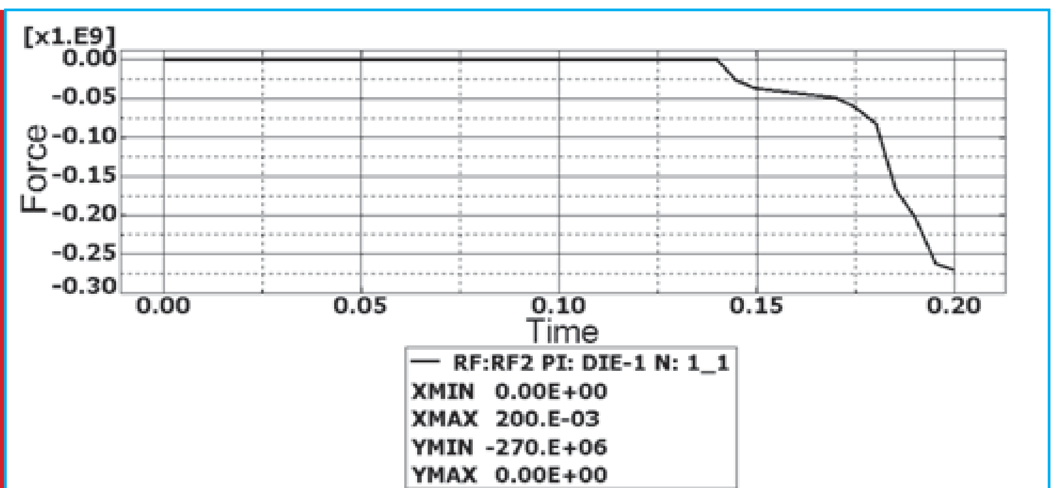

FIGURE 15. Diagram of force exerted on the final die for optimal state

Table 6. Comparison between finite elements and GA results			
Results	Die filling percentage	Maximum plastic strain	Maximum force (MN)
ABAQUS	99.96	8.895	270
GA	100.06	8.887	271

tion process using GA is iterated 20 times and the best result is considered so that its validity was assured.

Following, the best generation values are substituted in neural network and its results were extracted. The results obtained were in normal state; therefore, parameters values returned to their primary scale. Table 5 lists the results obtained in normal and real scale.

3.2.6 Optimal pre-form die finite element simulation and results comparison

Using the optimized parameters obtained from the GA method, the forging process is simulated in ABAQUS and the results obtained would be compared to the results obtained from the GA. Figure 14 demonstrates the plastic strain contour and figure 15 indicates the exerted force on the final die.

Table 6 lists the results of the optimal pre-form die finite element simulation in comparison with the results obtained from the GA. As it is observable from the results, there is very small difference between NN results and ABAQUS results. This means that NN is designed well and can predict the process as well.

To ensure the obtained result is the optimum state of the pre-form die, several random states were simulated and their FEM results are shown in the Table 7 in comparison to best result obtained by the GA method. This table proofs the optimality of GA results versus other states.

In figure 16, the cut section of the optimal state of the part is represented at the end of the final die application.

CONCLUSION

In this paper, necessity of using pre-form dies in forging process declared and pre-form die designing methods were studied. Following, the GA capabilities were out-

Table 7. Comparison of GA result and five random states				
state	Raw part's width	Die filling percentage	Maximum plastic strain	Maximum force (MN)
Random 1	300	99.18	10.254	223
Random 2	301	98.91	9.985	210
Random 3	302.5	99.89	13.834	524
Random 4	305	100	13.779	530
Random 5	304	99.16	13.510	528
best	302.5	99.96	8.895	270

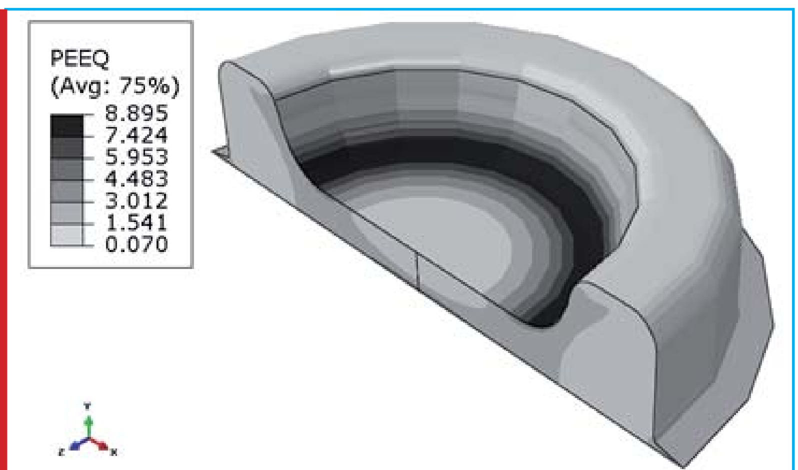

FIGURE 16. Cut section of part for optimal state at the end of final die application

lined such as their application on continuous problems optimization. It was indicated how to make use of mathematical functions in GA. Following, a new method for designing the optimal pre-form dies was proposed. In this method, without simplifying the pre-form die shape and only using different mathematical functions combination, the optimal pre-form die shape was designed. To this end, after selecting the suitable function for pre-form die shape, several random pre-form die shapes were produced and then using finite elements model and ABAQUS software, the pre-form die forging process was simulated and results were extracted. These results were used for training the ANN, a network which can predict the forging process performed in finite elements model due to its time consumption. Finally, using designed ANN and effective parameters on forging, the target function required for GA was formed and following the algorithm running, the optimal pre-form die was obtained. This method was used for an H-shaped part which was axisymmetric to evaluate its performance. The results show that combination of ANN and GA makes a powerful tool for designing complex pre-form dies. Here, the method was used for a part which needs only one step pre-form die, and may be used for more complex parts with several pre-form dies to validate its potential. Also the method can be extended using more parameters including number of pre-form dies, flux stress, friction coefficient and so on. Finally comparison of theoretical optimized results with experimental data is suggested.

REFERENCES

Abri Nia K., M.H. Naie, Y. Taqi Put Lahijani, (2006): Pre-form Forging Cast Design in Reverse Transformation and Finite Elements Method, Technical college magazine, Vol 40, pp 763-769.

Altan T., G. Ngail, G. Shen, M.H. Hojati, (2006): fundamentals of cold and hot forging, Mazandaran University Publication, Babolsar.

Altan T., S. I. Oh, H. L. (1983): Gegel, Metal Forming: Fundamentals and Applications, American Society for Metal, Metals Park.

Bonte M. H. A., L. Fourment, T. T. Do, A. H. Van Den Boogaard, J. Huétink, (2010): Optimization of forging processes using Finite Element simulations Structural and Multidisciplinary Optimization, Structural and Multidisciplinary Optimization, Vol 42, Issue 5, pp 797-810.

Grandhi R. V., H. Cheng, S. S. Kumar, (1993): Optimum Design of Forging Process with Deformation and Temperature Constraints, ASME Advances in Design Automation, Vol 2, pp 583-593.

Hosseinzadeh M., M. Bakhshi-Jooybari, M. Shakeri, H. Mostajeran, H. Gorji, (2010): Application of Taguchi Method in Optimization of New Hydroforming Die Design, Steel Research International, Vol 81, Issue 9, pp 647-650.

Khalili K., Fonoudi H., (2010): Simulation of Hot Forging Process Using FEM and ANN Method to Predict Metal Forming Parameters, the 12th Iranian Conference on Manufactoring Engineering, SMEI University of Tehran, Iran.

Khalili K., P. Kahal, S. Eftekhari, M. S. Khalili, (2011): Blank Optimization in Elliptical-shape Sheet Metal Forming Using Response Surface Model Coupled with Reduced Basis and Finite Element Analysis, Key Engineering Materials, Vol 473, pp 683.

Kia M., (2010): neural networks in MATLAB, Kian Rayaneh Sabz publication.

Lanka S., R. Srinivasan, R. V. Grandhi, (1991): Design Approach for Intermediate Die Shapes in Plane Strain Forgings, Journal of Materials Technology, Vol 9, No 4, pp 193-206.

Lee S. R., Y. K. Lee, C. H. Park, (2002): A New Method of Preform Design in Hot Forging by Using Electric Field Theory, International Journal of Mechanical Sciences, Vol 44, pp 773-792.

Li D.Y., Y.H. Peng, J.L. Yin, (2007): Optimization of metal-forming process via a hybrid intelligent optimization technique, Structural and Multidisciplinary Optimization, Vol 34, Issue 3, pp 229-241.

Lu B., H. Ou, H. Long, (2011a): Die shape optimisation for net-shape accuracy in metal forming using direct search and localised response surface methods, Structural and Multidisciplinary Optimization, Vol 44, Issue 4, pp 529-545.

Lu B., H. Ou, Z.S. Cui, (2011b): Shape optimisation of preform design for precision close-die forging, Structural and Multidisciplinary Optimization, Vol 44, Issue 6, pp 785-796.

Naeemi A., (2013): Design and Optimization of Forging Pre-form Casts in Reverse Transformation and ANN Methods, Msc. Thesis, I.A.U, Khomeini Shahr University.

Shamsi-Sarband A., S. J. Hosseinipour, M. Bakhshi-Jooybari, M. Shakeri, (2012): Study on the Effect of Friction Coefficient on the Optimized Preform Die Shape in a Multistage Superplastic Forming.

Shamsi-Sarband A., S. J. Hosseinipour, M. Bakhshi-Jooybari, M. Shakeri, (2013): The Effect of Geometric Parameters of Conical Cups on the Preform Shape in Two-Stage Superplastic Forming Process, Journal of Materials Engineering and Performance, Vol 22, Issue 12, pp 3601-3611.

Shao Y., B. Lu, H. Ou, J. Chen, (2015): A new approach of preform design for forging of 3D blade based on evolutionary structural optimization, Structural and Multidisciplinary Optimization, Vol 51, Issue 1, pp 199-211.

Zhao G., E.Wright, R. V. Grandhi, (1997): Sensitivity Analysis Based Preform Die Shape Design for Net-Shape Forging, International Journal of Machine Tools and Manufacture, Vol 37, No 9, pp 1251-1271.

Zhao G., E.Wright, R.V. Grandhi, (1995): Forging Preform Design with Shape Complexity Control in Simulating Backward Deformation, International Journal of Machine Tools and Manufacture, Vol 35, pp 1225-1239.