World Applied Sciences Journal 7 (11): 1464-1473, 2009
ISSN 1818-4952

Optimization of Preform in Close Die Forging by Combination Of Neural Network and Genetic Algorithm

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Abstract: In this essay, a combination of neural network and genetic algorithm has been studied for optimization of the preform in close die forging. Finite Volume Method (FVM) is used as a simulation tool for forging processes. The simulation results have used in the neural network and the genetic algorithm has been employed to optimize the forging force. The neural network was used in three stages for modeling the system. Stage 1 stands for achieving preform shape by open die forging and in stage 2 it has been used to close die forging for attaining the force and in stage 3 for the filling of the die cavity. Geometrical parametric design was used for accelerating the operation. The guideline of simulating operation and optimization has been suggested in a flow chart. An aeronautical forging component has been selected as a case study. Results show a small difference (0.3%) between neural network and direct simulation results. A final reduction of forging force 50% was obtained by optimizing the preform shape.

Key words: Optimization . neural network . genetic algorithm . forging . force

INTRODUCTION

In close die forging, a preform shape will be changed by compressing between two half-dies. In designing this process, perform shape, final shape and material behavior should be contemplated in a way to fill the die cavity completely. Furthermore, the designer should regard the process not causing any defect or undesirable properties. Main purpose of the preform design process can be mentioned as follows:

- Assuring the metal flow without any defect and appropriately filling of the die.
- Minimizing the material wastes in the flash.
- Minimizing the die wear.
- Obtaining the desirable grain flow and suitable mechanical properties.

Thus principal problem in close dies forging of aeroengine component particularly in this case is satisfactory of mentioned request above. Furthermore decreasing forces in close die forging, lead to increasing die life and also decreasing costs widely.

BACKGROUND

Many researchers have studied the optimal designing of the forging process and preform by using classical and finite element methods. Choi [1] introduced a method for the classical design of preform. Park [2] suggested a method namely Backward Tracing for designing preform. Mamali [3] designed the preform related to symmetrical pieces of Bevel gear in precision forging processes. Bramley [4] initiated a reversed method by Upper Bound Elemental Technique (UBET) and has attained the preform shape by reversing the velocity field direction to a minimum amount for whole of the energy distribution rate which optimized by contact conditions. Lee [5] modeled various forms of preform by electrical field theory method and optimized it by neural network. By using Finite Volume Method (FVM) and parametric design, the author [6] introduced a new procedure for designing optimal preform of complex parts. Regarding other aspects of this work, Mok [7] has used the combination of neural network and genetics for optimizing initial parameters of injection moulding.

Reviewing the activities done for designing preform by various procedures, indicate that the majority of the methods in spite of suitable theory-based, encounter with some problems in large plastic deformation. There are two methods for describing the deformation of a continuous environment which are: Lagrange and Euler-methods. Finite Element Method (FEM) is a Lagrange-method and Finite Volume Method (FVM) is an Euler-method [11].

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Lagrange-method is used mostly in metals forming. In this method, the materials are deformed by large scale plastic deformation. Due to element distortion, a time consuming remeshing process is necessary between time steps. In Euler's method, elements are fixed as a grid in the space and material flows through the grid, so no element's fault can be observed. Various FVM software have been produced mostly for fluid dynamics, But in this work a simulation metal forming tool based on FVM method (SuperForge) has been used. Newly Ding and Matthews study on application of neural network techniques for die manufacture. They used neural network for automated cad/cam not in view of stress and other application parameter [17]. Srinivasan and other used backward deformation optimization method (BDOM) in closed-die forging. They improved performance of the preform design using FEM based backward deformation method but their methods appear not able to satisfy all condition of die with complicated design [18]. Zhao *et al*. used an optimization algorithm for preform die shape design in metal-forming processes. Their objective was to reduce the difference between the realized and desired final forging shapes but no consider some parameters [19]. It be seen a gap in researches was done and it is due to some consideration of restricted boundary condition and their effects on each other. But in this essay a new method based on mathematical method investigated that lead to best results that was test by other methods.

THEORIES AND METHODOLOGY

In this analysis, close and open die forging processes have been simulated and its results have been used in a trained neural network model. Finally, the optimal forging force and preform dimensions have been procured by genetic algorithm. Brief discussions of the theories on these methods are as follows:

Neural network: Simulating by neural network procedure is actually the substitution of complex systems performance by continues chains of simple algebraic calculation. This procedure has been established based on human neural network function. The neurons as constituent elements form in tandem layers and create input, output and hidden layers, as shown in Fig. 1. Each neuron comprises the amounts of weight, bias and activation function. The calculation model for each neuron has cited in the equation (1) shown in Fig. 2 [15].

$$a = f(Wp + b) \tag{1}$$

Where: a = output value, p = input value, b = bias value, W = weight function and f = activation function.

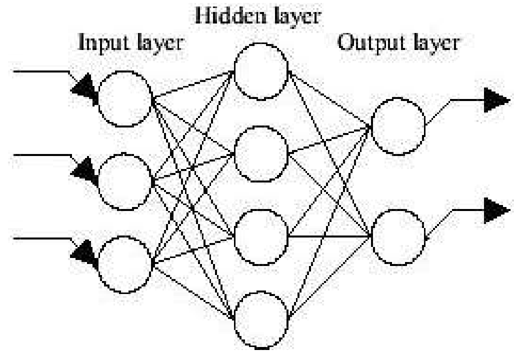

Fig. 1: The structure of the neural networks

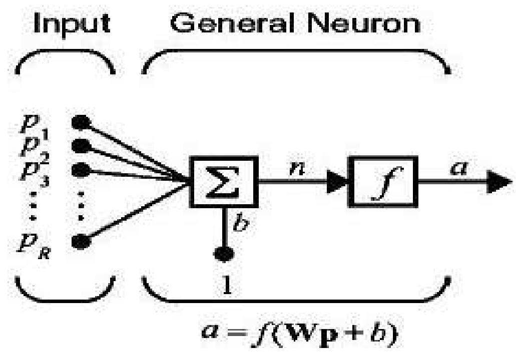

Fig. 2: Calculation model used in neural networks [15]

The amounts of weight related to networks determined by existing data training mentioned in training tables. Training the network performs in two ways:

- Training with supervising.
- Training without supervising.

Each of these training has specific algorithm. The back propagation of error is the most common method of training algorithms, which it uses the maximum slope, conjugate gradient method and Levenberg-Marquardt training method for optimizing the value weight. Generally, different algorithms have different efficiency, but Levenberg-Marquardt training method is the fastest procedure for neural networks. For training the network the data would normalize and it causes an increase in training accuracy and suitable responses. For this reason, equation (2) is used for normalizing data between 1 and-1.

$$P_n = \frac{2(P - P_{min})}{(P_{max} - P_{min})} - 1 \tag{2}$$

And P_n is the normalized value of a certain input.

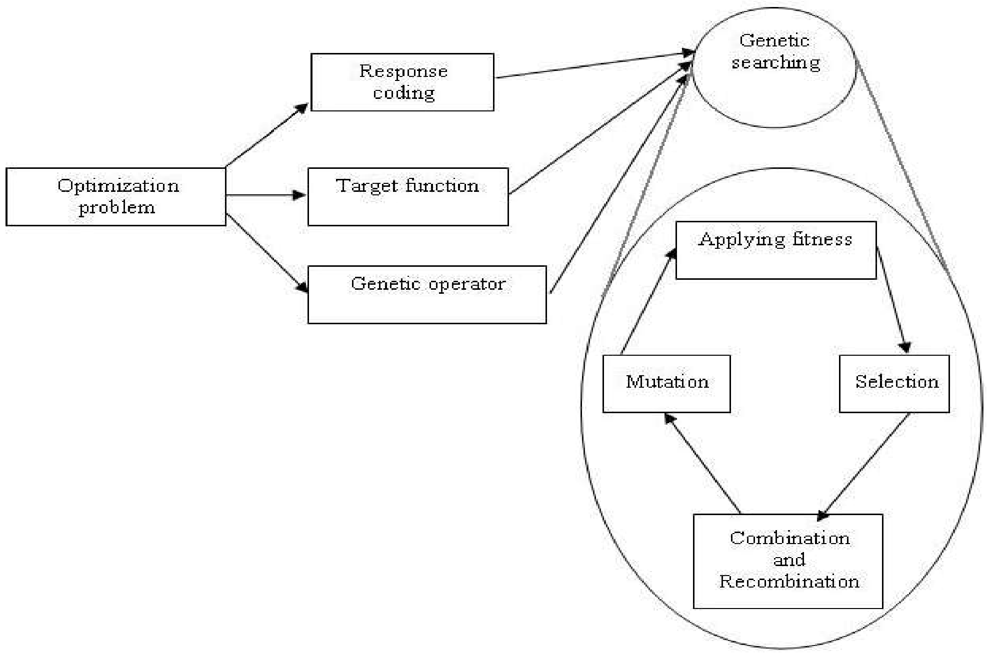

Fig. 3: The process of solving a problem by the genetic algorithm

Genetic algorithm: Genetic algorithm is a searching technique that made of Darvin's theory and an accidental structure of information. Though, this method is usually referred to Holland, but its main idea had been presented by Richenberg's works [16]. Genetic algorithm is an accidental searching method which behaves similar to the biologic gradual evolution process. These algorithms act on a population of responses and applying survival principal of the best responses causing better and suitable answers. Genetic algorithm imitates from the natural process such as selection, recombination and mutation. The process of solving a problem by genetic algorithm is presented in Fig. 3.

Genetic algorithm acts on the population of response in parallel, instead of acting on an individual response. At the beginning of calculation, the initial population is created and then the values of fitness function are determined for initial population. A new production process is initiated. If optimization criterion is obtained, then the fitness values of new generation will be used for preferring and selecting the population. The mutation and recombination occur on parents and then new children are produced. These processes continue until acquiring to the optimal conditions, the more the number of population, the more possibility of accessing to the better answer [16]. In conclusion, the genetic algorithm basically differs from traditional optimization methods. The most important differences are:

- Genetic algorithm works by encoded parameters, but not with parameters itself.
- Genetic algorithm deals with the population of points, not a single point and then optimizes the population in parallel.
- Genetic algorithm uses of probability laws, but not calculating procedures.
- Genetic algorithm does not need the information related to deviation or other additional information, but it is only dependent on the target and fitness that distinguished the movement direction. Various suitable answers can also be obtained for a certain problem.

CASE STUDY

Figure 4 shows an aeronautical forged component selected as a case study for optimization of its perform. It has been made from Al-2014, which should be produced by forging method because of its working conditions and desirable mechanical properties. Figure 5 presents the designed forging half-die. Tetrin and Tarnovski's experimental equation [11] has been used for determining the suitable dimensions of flash land. Die design parameters are shown in Table 1. This method was used for designing of especial workpice in military bell helicopter. This method corrects forces of forging and corrects some properties of workpice.

Table 1: The die design parameters

Gutter width (mm)	Gutter thickness (mm)	Fillet (mm)	Corner (mm)	Draft angle
9	2.6	6.5	3.2	5°

Table 2: The elastic and plastic properties of the alloy Al 2014

	Yield strength 23.7 Mpa Poisson's ratio 0.33 Modulus of elasticity 27.9 Gpa				
		At 400 °c		At 450 °c	
Mechanical properties	Strain Rate	C(Mpa)	M	C(Mpa)	M
Plastic coefficients	0.25	1.02E+08	0.110	3.99E+07	0.126
	0.50	9.10E+07	0.121	3.58E+07	0.121
	0.70	8.62E+07	0.128	3.52E+07	0.119

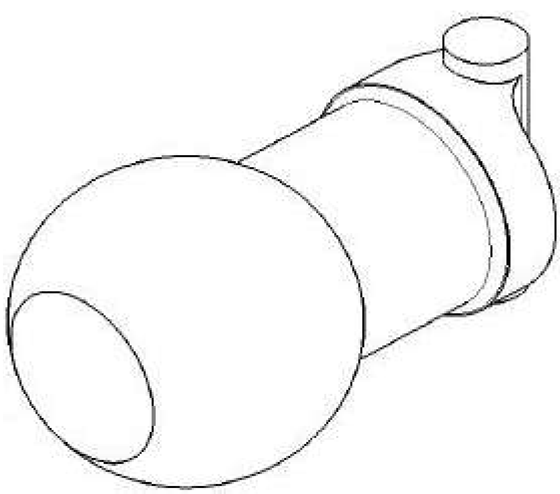

Fig. 4: The final part after forging process

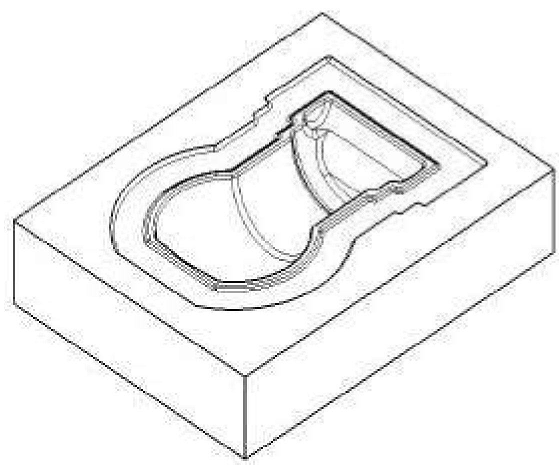

Fig. 5: The geometry of die

Simulation parameters: In the simulating of forging process by FVM, the input parameters play an important role on the results originated from simulation. The material plastic deformation properties were applied using equation (3):

$$\sigma_y = \max[s, c\dot{\varepsilon}^{-M}] \qquad (3)$$

Where s, c and M are minimum yield stress, flow constant and strain-rate hardening, respectively, which are temperature dependent. This alloy applies for hot forging in the ranges of 420-460°C [14]. The parameters related to the material properties between 400°C and 450°C are shown in Table 2.

The die models are assumed rigid for simulation and the friction model is based on equation (4) and m, the friction coefficient of material, according to Ring Test is assumed 0.3 [14].

$$\tau = m\,\tau_{yield} \qquad (4)$$

The stages for complement of the forging process: Simple preforms such as cylinder can not be forged in one step due to the complexity of the final part geometry. Figure 6 shows the mass distribution curve of the part based on Ruller method [1]. Since in aircraft industries, the production quantity is quite limited, then it should be tried to avoid forging processes to be implemented in multi-stages close die forging, which can cause a considerable increase in die making cost. In this case, two stages of forging have been used:

- Stage 1: Open die forging of a cylinder to a rectangular cubic shape (Fig. 7.)
- Stage 2: Close die forging to final shape. Generally, existing of sharp edges in preform can cause defects such as lapping in final parts.

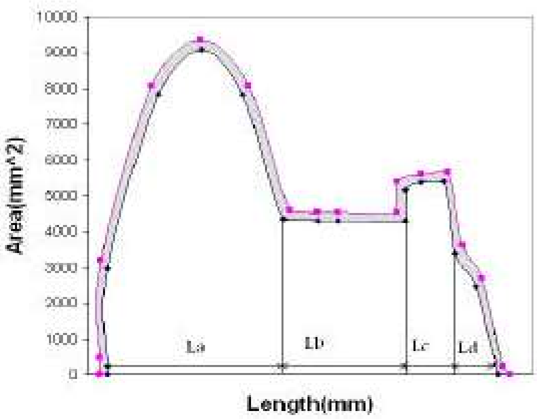

Fig. 6: Mass distribution of the part

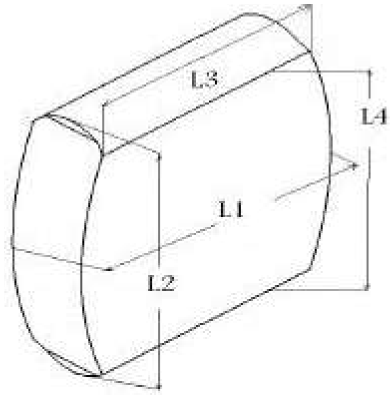

Fig. 7: The preform obtained in open die forging from a cylinder (stage1)

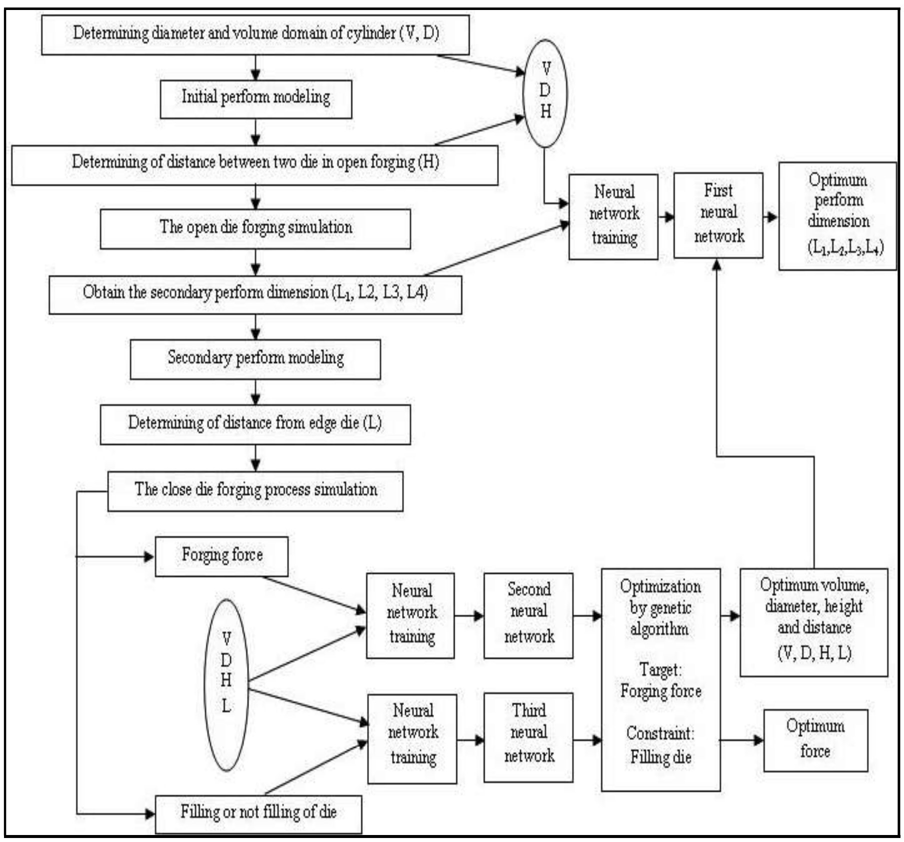

Fig. 8: Flow chart of the process stages for the production of the optimum force and preform dimensions

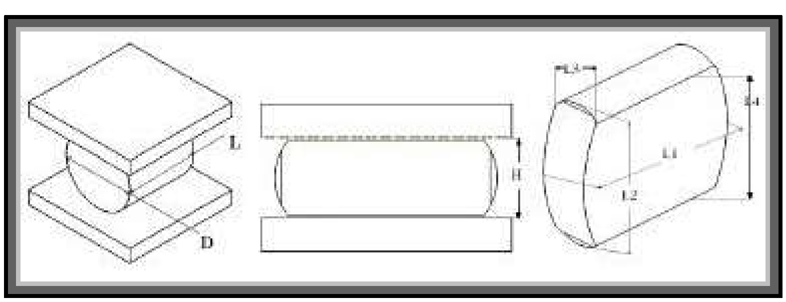

Fig. 9: Open forging and the geometry of the preform for close die forging

This preform (Fig. 7) has also the advantages of the round corners avoiding any lapping in the part. Therefore, open die forging can be used on a cylindrical for removing the sharp edges and better mass distribution. The stages of operation are shown in a flow chart (Fig. 8). The parameters and logic of flow chart will be discussed later. Fig. 9 shows a cylindrical shape with distinct volume (V) and diameter (D) which has been openly forged to a distance equals to H.

It produces different shapes of preform by changing three parameters (V, H and D).

The initial preform volume has been calculated by an extra 10% to the final part volume. The forging was started with this initial 10% extra volume and because of larger size of flash, higher forging was observed.

The next important parameter is the relative location of the preform to close-die edge (L) which should be taken an as input data for optimization process (Fig. 10). Another criterion is the filling of the die cavity, which has been assumed as a 0-1 function. Changing all these dimensional parameters has significant effects on the forging outcomes. The verification of the simulation results have been evaluated [6].

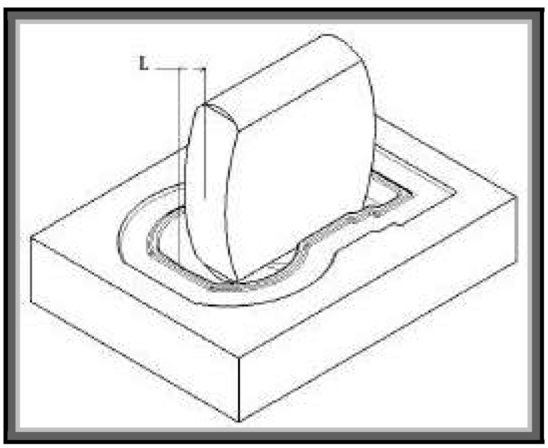

Fig. 10: The geometry of the preform and its relative location to the die

RESULTS AND DISCUSSIONS

The simulation results have been used to train a neural network for obtaining a mathematical model to calculate the forging force. This model was used for optimizing the amount of force in genetic algorithm. The results of neural network and genetic algorithm will be discussed in details.

Results obtained from applying neural network technique: In the modeling of the system, three trained neural networks have used to create nonlinear relations between input and output values in each stage of the forging. These networks are multilayer perceptrons which the back propagation of error algorithm applied for training them. These networks are a static network. Matlab software was used for modeling this system. Tangent Sigmoid and Purelin activation functions are used in the network training.

In the first stage, open die forging modeled by a network with three inputs namely V, D and H, which vary 1.05×106 to 1.06×106 mm3, 45 to 70 mm and 110 to 120 mm, respectively. The output parameters are L1, L2, L3 and L4, indicating the final preform shape. This network has been trained by 36 series of data and 10 series of data have been used for the network verification. According to Fig. 11, the sum of squares of error for training this network is 1.1×10-2 and Fig. 13 shows the differences between the results from simulation and neural network for 10 series of test data. The maximum possible relative error (between Minimum and Maximum) is equal to 8.6%.

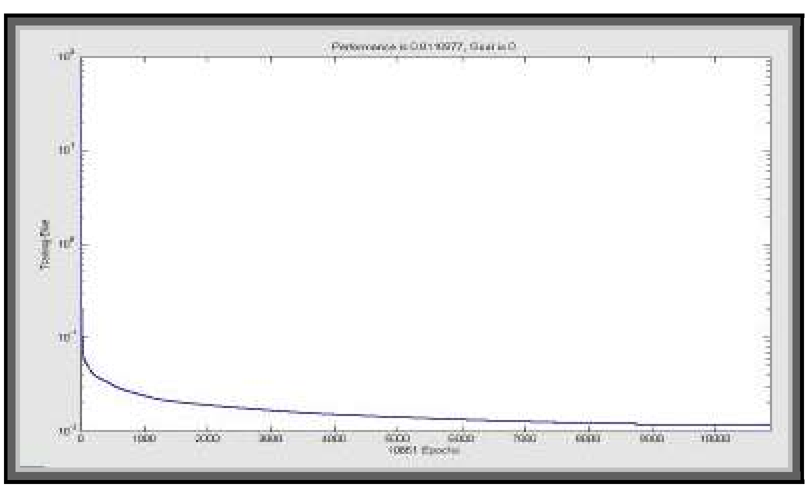

Fig. 11: The sum of squares of error for the first network training

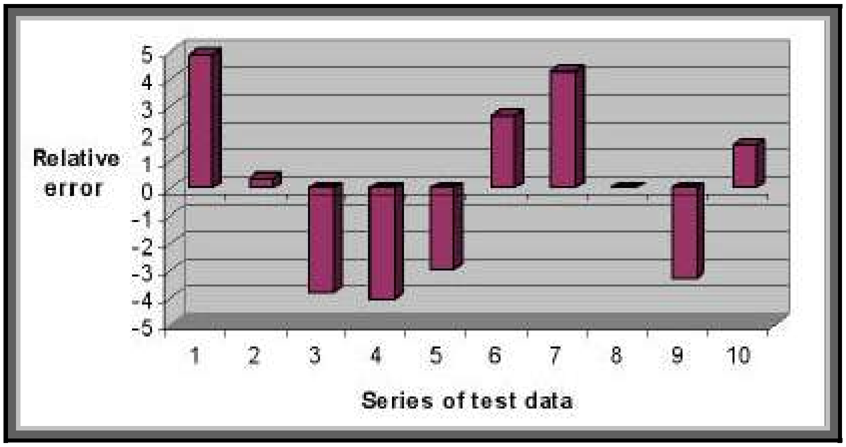

Fig. 12: The first network error values for 10 series of test data

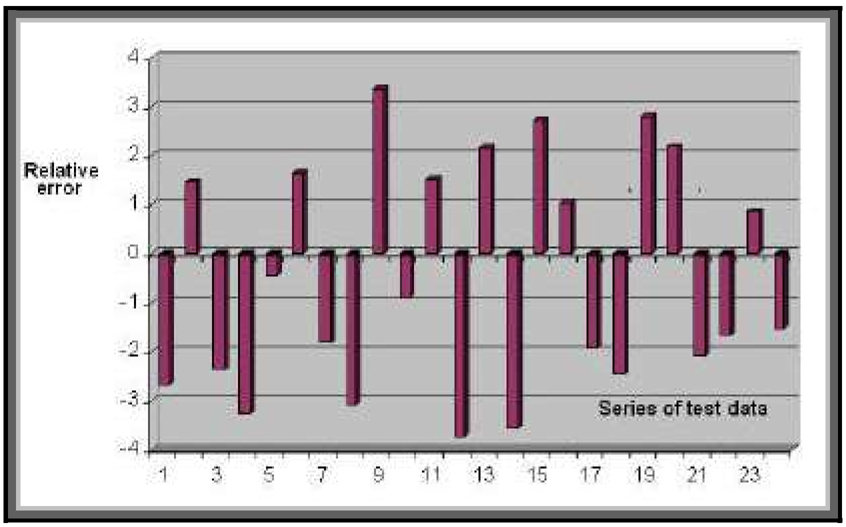

Fig. 13: The second network error values for 24 series of test data

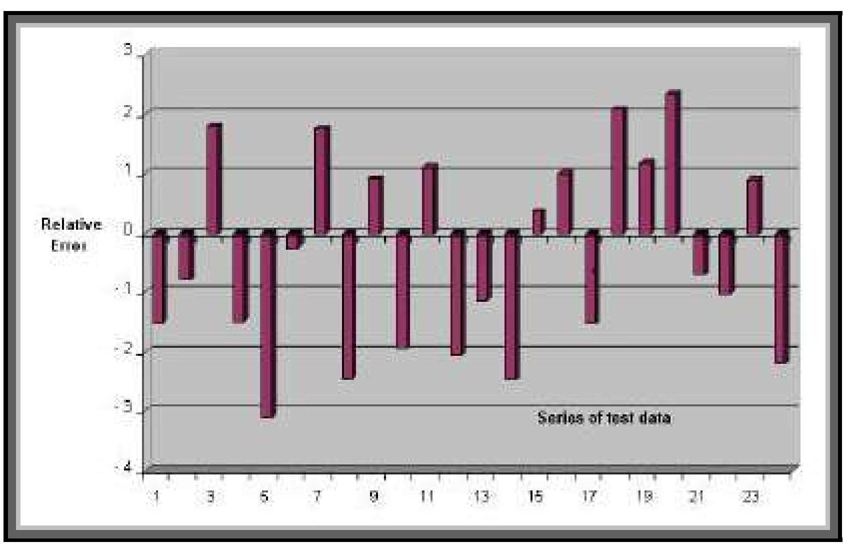

Fig. 14: The third network error values for 24 series of test data

Table 3: A typical training table for the second neural network

Trained input to the neural network				Output
Cylinder volume (mm^3)	Cylinder diameter (mm)	Distance Between two die (mm)	Preform location	Forging force N 10^{6*}
1.06	110	70	10	10.68
1.06	110	70	20	11.03
1.06	110	70	30	10.30
1.06	110	65	10	10.78
1.06	110	65	20	11.04
1.06	110	65	30	10.92
1.06	110	60	10	10.42
1.06	110	60	20	9.23
1.06	110	60	30	10.84
1.06	110	55	10	9.421
1.06	110	55	20	8.92
1.06	110	55	30	11.67
1.06	110	50	10	8.85
1.06	110	50	20	10.64
1.06	110	50	30	8.92

In the second stage, close die forging is modeled by a network with four inputs V, D, H and L and an output which is the forging force. The variation ranges of V, D and H are same as the previous stage and L varied between 10-30 mm. The number of data for training the network is 108 series and 24 series of data were used for verification of the trained network. The sum of squares of error for training this network is equal to 1.5×10-2. The relative error value resulted from simulation and neural network is equal to 6.9% shown in Fig. 13.

Third stage is same as the second stage but the network was trained to check the filling of the die cavity as a vital criterion. The summation of error squares for training this network is equals to 5×10-3. Figure 14 shows the relative error values for 24 series of test's data (5.4%).

The obtained neural networks are used as governing functions in the optimization stage. Table 3 presents a typical data of second neural network. The numbers in the table have not been normalized, but in the training stage, they were normalized by using equation (2).

Results of applying genetic algorithm technique: Genetic algorithm as an optimization tool can usually be converged to an absolute optimal point, because in this method, searching process starts of several different points simultaneously. In this case study, a genetic algorithm was used that supported by elitist strategy. The strings with the best fitness to the environment were directly entered to the next population. The optimization used genetic algorithm operators to produce new population. Rolette Wheel method was used for the selection operator in mating pair members. In these procedure populations were ordered based on the selection probability. These populations were used by combination operator. Another known operator was mutation which an accidental value was assumed for a bit of a member. Then by comparison if the member is smaller, the bit value changed from one to zero or vice versa.

Based on genetic algorithm, the fitness equation which should be optimized is the force equation that has been created by second neural network. The filling of the die is also as a constraint. The final criterion of the optimizations related to two variables: firstly, the minimum convergence of members, secondly, maximum repetition in the optimization, in which minimum convergence value is 0.01 and maximum repetition number is 100.

Genetic algorithm indicates the absolute optimal force is equal to 628* N based on V = 1.05 mm3, D = 112.1 mm, H = 45.8mm, L = 20.1mm. If these values are used as input, then the final optimal preform dimensions will be L1 = 131mm, L2 = 164mm, L3 = 140mm and L4 = 160mm. Figure 15 and 16 present the effective stress, forging force variation and temperature distribution of the final part, respectively.

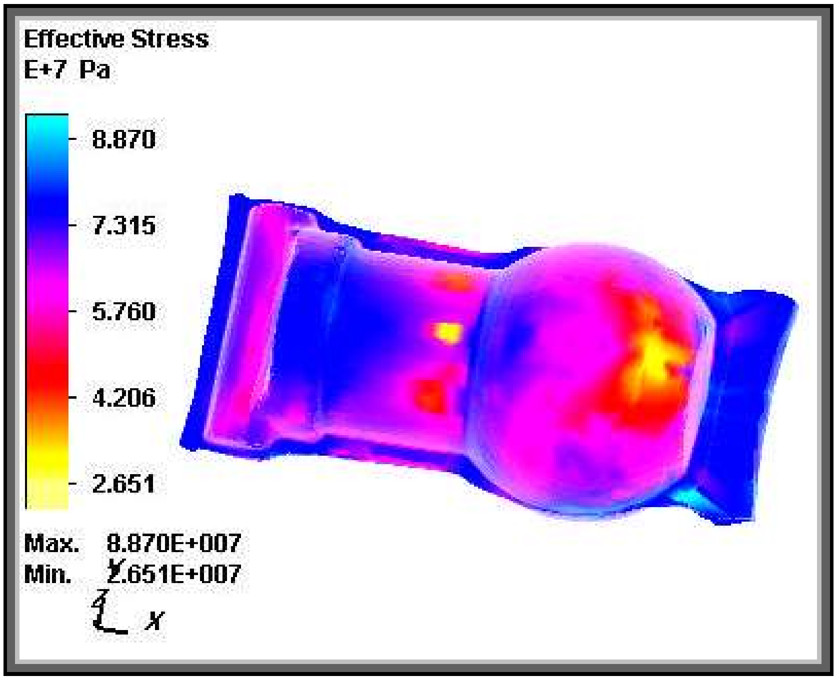

Fig. 15: The distribution simulation of effective stresses on the final part

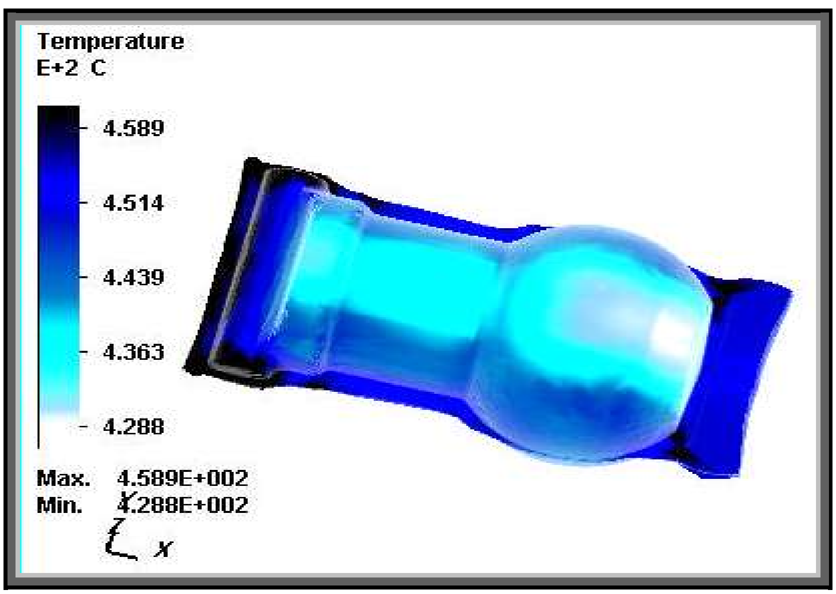

Fig. 16: The temperature simulation distribution on the final part

CONCLUSION

In this work, the methodology for obtaining the optimal shape of preform in forging process of complex part was presented. The optimizing process was mixed up by using simulation tools, neural network and genetic algorithm techniques. A good agreement was shown between the outcome results of optimization procedure and the simulation results presenting an error value for forging force equal to 0.3%. A final reduction in forging force from 1267 to 630* N (50.3%) was achieved. This force reduction is mainly due to reducing the final preform volume. Future work could be applied for creating an integrated system including parametric designing software, a metal forming simulation software and containing neural network and genetic algorithm facilities.

FUTURE WORK

An automated optimization procedure can be recommended to include parametric design tool and simulation software. The effect of flash dimension on material flow can be used as next step. This can include the interaction between preform and gutter dimensions in forging toward an optimization process leading to flashless forging process. Therewith authors try to correct other parameters to design preform bye some new methods.

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