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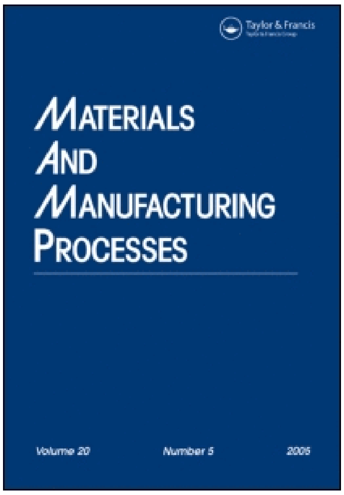

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ELIMINATING FORGING DEFECTS USING GENETIC ALGORITHMS

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In this article, an optimization method for metal forging process designs using finite element-based simulation is presented. Using as entry parameters the specifications of the final product the so-called inverse techniques developed for optimization problems allows the calculation of the optimal solution, the design parameters that produce the required product. An evolutionary genetic algorithm is proposed to calculate optimal shape geometry and temperature. An example demonstrating the efficiency of the developed method is presented considering a two-stage hot forging process. It considers optimization of the process parameters to reduce the difference between the realized and the prescribed final forged shape under minimal energy consumption, restricting the maximum temperature.

Key Words: Finite element method; Genetic algorithms; Hot forging; Metal-forming processes; Optimization; Preform design.

1. INTRODUCTION

Metal forming is one of the most important processes in the manufacturing industry. It can be described as an operation to change the shape and characteristics of a workpiece through plastic deformation without any removal of the material during the process.

Process design in metal forming involves selection of initial billet size, preform shape, design of die shape, ram velocity, etc., among which, the most important are the initial billet shape and the die geometry. It is very difficult to control metal flow during the forging process, so it must be controlled by the initial billet size and/or the die geometry. Therefore, it is necessary to replace experience–oriented technology with a computer-aided approach to reduce or eliminate the trial and error of process design in metal forming.

A metal forming system is composed of all the input variables such as initial billet, tools, conditions at the tool/material interface and finally the plant environment where the process is being conducted. It is time-consuming and difficult

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to consider all these parameters for process planning. Recently, however, new optimization techniques overcome defects, such as folding defects, extensive flash, and underfill, which appear when using an improper initial billet size for a one-stage forging and improper preform shapes for two-stage forging.

Parameter optimization based on the finite element method (FEM) has become an international research interest in the field of metal forming [1, 2]. The optimization methods include mathematical optimization, backward tracing, artificial intelligence, experiment optimization, and an automatic control algorithm. First, the backward tracing method [3] considering a finite element method that simulates metal forming processes in reverse to design the preform die shapes was considered. Then a sensitivity analysis method was developed for large deformation and hyperelastic viscoplastic solids and applied to preform design problems in metal forming [4]. A method to design the preform tools and preform shapes was introduced by using as the objective function to be minimized the distance between the achieved and required part [5, 6]. Furthermore, the optimal design focused on preform die shapes instead of the preform shapes, and an optimization method for preform die shape design in metal forming using forward simulation only was developed [7]. Recently, an optimal design considering shape optimization for both one- and two-step forging operations was developed [8–10]. The shapes were discretized by using cubic B-spline functions. The objective was to reduce the area of the zone where the achieved final forging shape and desired final forging shape do not coincide. B-spline coefficients were considered as the design variables for sensitivity analysis and optimization.

FEM is the basis of parameter optimization in metal forming. The accuracy and efficiency of FEM determine whether the optimization calculation is successful or not and the reliability of the optimal results. In this article, an optimization method is developed by coupling a thermomechanical code with a genetic algorithm. The developed method is applied to forging a preheated billet made of AISI 1018 steel. The optimal solution is not gradient dependent and, consequently, does not have numerical errors resulting from nonaccurate sensitivity calculations. An advantage of genetic algorithms is that shape and process, discrete and continuous variables can be simultaneously handled.

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2. THE THERMOMECHANICAL MODEL

In forging, elastic deformation is usually omitted because it is very small compared with the plastic deformation. Therefore, rigid plastic/viscoplastic FEM is often used to analyze the forming process. Finite element formulation is briefly outlined here because the basic mathematical description of the method as well as the solution techniques are well explained in the literature [1, 11].

The rigid viscoplastic flow capability is based on iteration of the velocity field in an incompressible, non-Newtonian fluid. The normal flow condition for a non-zero strain rate can be expressed as

$$s_{ij} = \frac{2\bar{\sigma}}{3\dot{\bar{\varepsilon}}}\dot{\varepsilon}_{ij} \tag{1}$$

where

$$\dot{\bar{\varepsilon}} = \sqrt{\frac{2}{3}\dot{\varepsilon}_{ij}\dot{\varepsilon}_{ij}} \tag{2}$$

here $\dot{\bar{\varepsilon}}$ is the equivalent strain rate, $\bar{\sigma}$ is the yield stress as a function of strain, strain rate, and temperature, $\dot{\varepsilon}_{ij}$ is the infinitesimal strain rate, and the deviatoric stress is represented by

$$s_{ij} = \sigma_{ij} - \frac{1}{3}\delta_{ij}\sigma_{ij} \tag{3}$$

From the variational principle, the functional Π for rigid plastic material can be written as follows,

$$\Pi = \int_{\Omega} \bar{\sigma}\,\dot{\bar{\varepsilon}}\,dV - \int_{\Gamma_1} t_i\,v_i\,dS \tag{4}$$

where Ω is the region occupied by the deformed body, having volume V and surrounding surface Γ, t_i is the traction specified on the boundary Γ_1, and v_i is the velocity component.

The incompressibility may be imposed in two ways: by means of Lagrange multipliers or penalty functions. In this article, the incompressibility constraint on admissible velocity fields may be removed by introducing a penalty constant, K and modifying the functional given in Eq. (4). Then the solution of the original boundary value problem is obtained from the solution of the dual variational problem, where the first-order variation of the functional vanishes.

$$\delta\Pi = \int_{\Omega} \bar{\sigma}\,\delta\dot{\bar{\varepsilon}}\,dV + K\int_{\Omega} \dot{\varepsilon}_{ii}\,\delta\dot{\varepsilon}_{ii}\,dV - \int_{\Gamma_1} t_i\,\delta v_i\,dS = 0 \tag{5}$$

In Eq. (5), δv_i is the arbitrary variation of the velocity, and $\delta\dot{\bar{\varepsilon}}$ and $\delta\dot{\varepsilon}_{ii}$ are the variations in strain rate from δv_i.

Friction between tool and workpiece is introduced by considering the condition

$$\sigma_{ij}t_j = \sigma_{ti} \tag{6}$$

where t_i is the unit tangential vector to Γ at the point under consideration, and σ_{ti} is the friction stress. The friction stress is tangential to the surface and directed opposite to the relative velocity between the surfaces in contact. According to the Siebel friction law, the value of the friction stress is proportional to the shear stress τ_d at the point under consideration.

$$\sigma_t = m\,\tau_d \tag{7}$$

where m is the friction factor and $\tau_d = \frac{1}{\sqrt{3}}\bar{\sigma}$.

Mechanical properties of metals are temperature dependent. Metal forming processes are characterized by considerable temperature changes because large plastic strains lead to heat generation. During hot forging cooling of the surfaces

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contacting the surroundings takes place. This leads to the necessity of considering a coupled thermoplastic process. The temperature inside the deformed body is determined by the equation

$$\dot{T} = \frac{1}{\rho c_T} \lambda_T T_{ii} + \frac{\dot{Q}}{\rho c_T}, \quad \dot{Q} = k_T \, \bar{\sigma} \, \dot{\bar{\varepsilon}} \tag{8}$$

where λ_T is the conductivity coefficient, c_T is the specific heat supply, ρ is the material density, $\dot{Q}$ is the rate of dissipation during the plastic deformation converted into heat, and k_T is the fraction of the strain rate energy that turns into heat. The remainder fraction of the strain rate energy is expected to cause changes in dislocation density, grain boundaries, and phases and is usually recovered by annealing.

For each material point x_i, at each time t, the temperature boundary conditions are

$$T(x_i, t) = T_S(x_i, t), \quad x_i \in \Gamma_1 \tag{9}$$

$$q_n = \lambda_T \frac{\partial T}{\partial n} = \bar{q}_n, \quad x_i \in \Gamma_2 \tag{10}$$

where T_S is a prescribed temperature on the part Γ_1 of the surface Γ of the body, and $\bar{q}_n$ is the prescribed heat flux on the part Γ_2 of Γ.

A developed finite element code based on the rigid viscoplastic finite element method with an updated Lagrangian formulation [12] has proved to be robust and efficient for numerical simulations of forging processes under different geometric and process input parameters [11–13]. This code is considered in the developed numerical algorithm for optimization of forging processes.

3. INVERSE FORMULATION

3.1. Optimization Problem

Different preform die shapes generate different final forging shapes in a multistage forging process. For metal forming processes, the design goal is to make the achieved final forging as close as possible to the desired final forging shape by designing the proper process planning and optimal preform dies.

Forging is a complex problem due to its non steady nature involving the evolution of boundary conditions. Let us consider the open die forging of a workpiece with a prescribed final shape. The only information known beforehand is the final product shape and material. Starting from an initial bar, the deformation paths are not unique. They will depend on conditions such as the intermediate tool geometries and temperature. Therefore, an inverse problem can be proposed (i.e., find the optimal temperature of the workpiece and the optimal geometry of intermediate tools).

The inverse problem is an optimization problem with an objective function measuring several parameters of the process. Parameters that have to be taken into account in most forging sequences are the total energy of the process and the distance between the current shape at the end of the process and the prescribed shape.

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The distance between the current shape at the end of the process and the prescribed shape can be calculated as

$$\varphi_d(\mathbf{b}) = \int_{\Gamma_{\text{end}}} \|\pi(\mathbf{X}) - \mathbf{X}(\mathbf{b})\|^2 \, dS \tag{11}$$

where **b** are the design variables, and $\pi(\mathbf{X})$ is the projection of a material point **X** of the workpiece boundary Γ_{end} onto the surface of the prescribed shape at the end of the simulation process.

The total energy is a measure of the actual cost of the process and is given by

$$\varphi_e(\mathbf{b}) = \int_0^t \left(\int_\Gamma \mathbf{t} \cdot \mathbf{v} \, dS \right) dt \tag{12}$$

where **t** is the applied traction vector and **v** is the die velocity.

The optimization problem to be solved is stated mathematically as follows.

Find the vector of design variables $\mathbf{b} = \{b_1, \ldots, b_D\} \in R^D$ that minimizes the objective functional

$$\Pi(\mathbf{b}) = \beta_1 \, \varphi_e(\mathbf{b}) \; + \beta_2 \, \varphi_d(\mathbf{b}) \tag{13}$$

subject to

$$\frac{\overline{T}_{\text{end}}(\mathbf{b})}{T_a} \leq 1 \tag{14}$$

$$b_{d^-} \leq b_d \leq b_{d^+} \qquad d = 1, \ldots, D \tag{15}$$

and to the thermal-mechanical problem, Eqs. (5) and (8). The number of design variables is D and b_{d^-}, b_{d^+} are the side constraints for each variable. The parameters β_i are weighting parameters, T_a is the maximum allowed temperature, and $\overline{T}_{\text{end}}$ is the maximum temperature registered in the workpiece along the forging process.

3.2. Evolutionary Search Model

The genetic algorithm (GA) method is a stochastic search method based on evolution and genetics, and exploits the concept of survival of the fittest [14]. For a given problem or design domain of significant complexity, there exists a multitude of possible solutions that form a solution space. In a GA, a highly effective search of the solution space is performed, allowing a population of strings representing possible solutions to evolve through basic genetic operators.

In GA implementation, data codification is very important for further manipulation. The design vector **b** is codified by using the binary code format with a different and independent space design for each variable. Clearly, the dimension of the space design, even for a comparatively small chromosome structure, can be very large. The goal of the genetic operators of the algorithm is to progressively reduce the space design driving the process into more promising regions.

One important step for the evolutionary search is to define the fitness, which is related to the objective function, Eq. (13), and the constraints, Eqs. (14) and (15),

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of the problem. In this work, a hybrid method is adopted based on the basis of a graded penalization of the solutions according to its constraint violation. The genetic algorithm will seek to increase the fitness as it operates. Then the fitness function for the optimization problem, established from Eqs. (13) to (15), is defined as

$$F(\mathbf{b}) = \overline{F} - \Pi(\mathbf{b}) - \Psi_1(\mathbf{b}) \tag{16}$$

with

$$\Psi_1(\mathbf{b}) = \begin{cases} 0, & \text{if } \overline{T}_{end}(\mathbf{b}) \le T_a \\ \xi\left[\dfrac{\overline{T}_{end}(\mathbf{b})}{T_a} - 1\right]^{\eta}, & \text{if } \overline{T}_{end}(\mathbf{b}) > T_a \end{cases} \tag{17}$$

where ξ and η are calculated constants considering two degrees of violation of the constraints, and $\overline{F}$ is a predefined constant to ensure a positive fitness function.

Figure 1 describes the developed genetic algorithm, namely, in the inserted area corresponding to the genetic operators.

It is based on four operators supported by an elitist strategy that always preserves a core of best individuals of the population whose genetic material is transferred into the next generations. A new population of solutions $\mathbf{P}^{t+1}$ is generated from the previous $\mathbf{P}^t$ using the following genetic operators: Selection, Crossover, Elimination/Substitution, and Mutation seeking improvement of the fitness.

After random generation of the initial population, the operators are applied in the following sequence.

3.2.1. Step 1: Selection. Population ranking according to solution fitness. Definition of the elite group that includes individuals highly fitted. Selection of the progenitors: one from the best fitted group (elite) and another from the least fitted one. This selection is done randomly with an equal probability distribution for each solution. Transfer of the whole population $\mathbf{P}^t$ to an intermediate step where they will join the offspring determined by the *Crossover* operator.

3.2.2. Step 2: Crossover. The crossover operator transforms two chromosomes (progenitors) into a new chromosome (offspring) having genes from both progenitors. The offspring genetic material is obtained by using a modification of the *parametrized uniform crossover* technique [15]. This is a multipoint combination technique applied to the binary string of two selected chromosomes. This *Crossover* is applied with a predefined probability $P(c)$ to select the offspring genetic material from the highest fitted chromosome. The new individuals created by *Crossover* will be joined to the original population $\mathbf{P}^t$.

3.2.3. Step 3: Elimination/substitution. New ranking of the enlarged population solutions according to their fitness. Then it follows *Elimination* of solutions with similar genetic properties and subsequent *Substitution* by new randomly generated individuals. Then deletion of the worst solutions with low fitness simulates the natural death of low fitted and old individuals. Now the dimension of the population is smaller than the original one. The original size population will be recovered after including a group of new solutions obtained from the *Mutation* operator.

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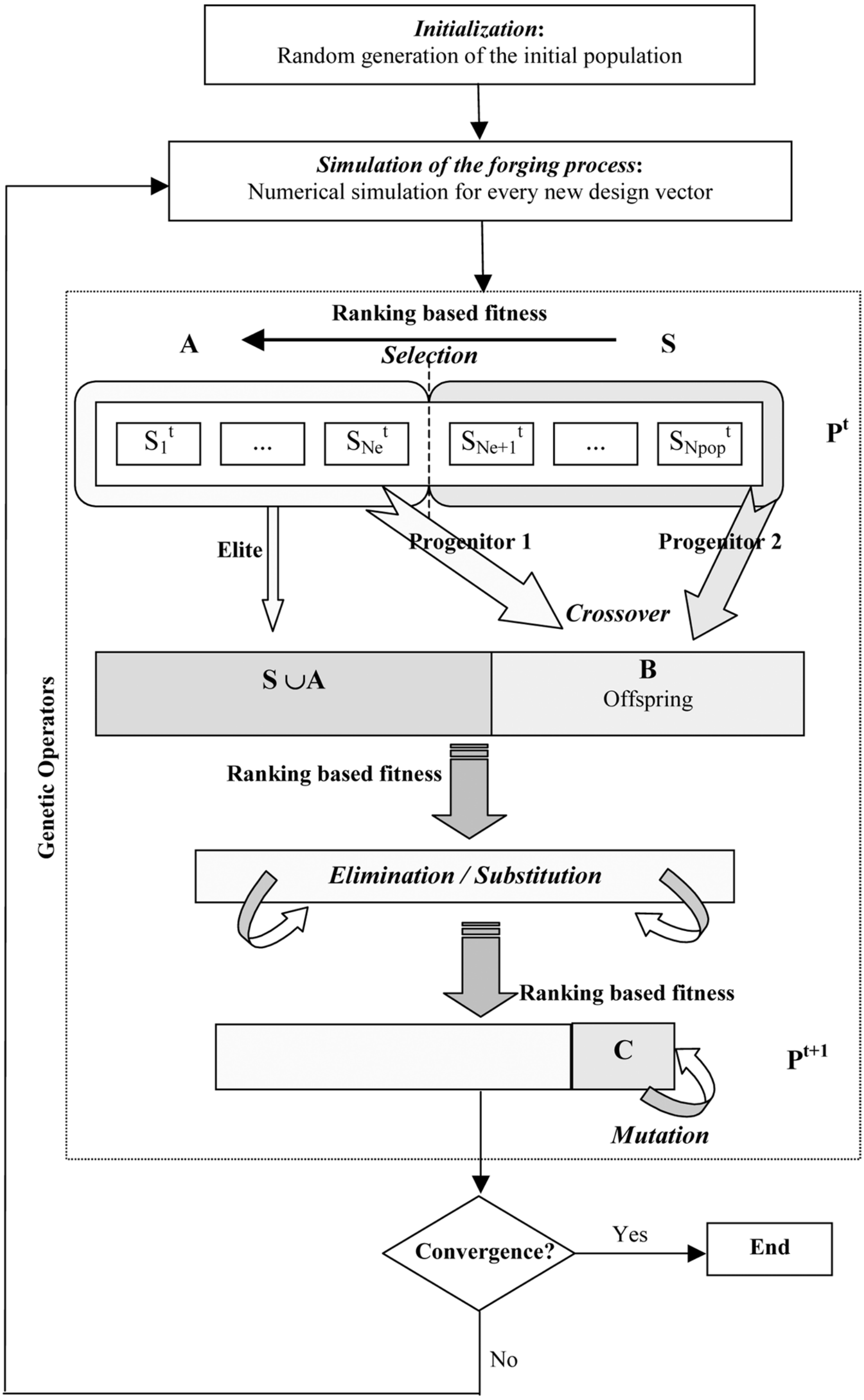

Figure 1 The developed optimization algorithm for the forging sequence.

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3.2.4. Step 4: Mutation. The *Mutation* genetic operator is used to overcome the problem induced by *Selection* and *Crossover* operators where some generated solutions have a large percentage of equal genetic material. The implemented mutation is characterized by changing a set of bits of the binary string corresponding to one variable on a chromosome selected at random from the elite group. The *Mutation* makes possible the exploitation of previously unmapped space design regions and guarantees the diversity of the generated population. After mutation, the new population $\mathbf{P}^{t+1}$ is obtained and the evolutionary process will continue until the stopping criteria are reached.

3.3. Design Optimization Algorithm

An optimization algorithm has been implemented for product quality control of a two-stage forging process with preform and final operations. It is an inverse problem, namely, given a required forged product, the solution will optimize the preform tool geometry and the initial temperature of the workpiece.

After the establishment of a prescribed final product and the corresponding final stage tool shape, a design space is defined by selecting an interval of allowable values for each design variable. Each interval is discretized independently, and the binary code format for each variable is defined. The gathering of the binary encoding of all variables of the design vector **b** will constitute an individual. Then it will be possible to select randomly an individual that will be associated to a particular design vector **b**. The optimization algorithm performs iteratively along $t = 0, 1, 2, \ldots, n$ generations of populations until convergence conditions are reached. The iterative process is described in Fig. 1 as follows.

1. An initial population $\mathbf{P}^0$ is generated by randomly selecting N_{pop} individuals. For each individual of the population, an independent numerical simulation of the two-stage forging direct problem is performed. Each forging simulation will produce a forged piece with an associated fitness value.
2. A new population of solutions $\mathbf{P}^{t+1}$ is generated from the previous $\mathbf{P}^t$ using the described genetic operators: *Selection*, *Crossover*, *Elimination/Substitution* and *Mutation*.
3. The optimization program checks if the stopping criteria are satisfied. The stopping criterion used in the convergence analysis is based on the relative variation of the mean fitness of a reference group during a fixed number of generations and the feasibility of the corresponding solutions. The size for the reference group is predefined. If the constraints of the problem are not satisfied, then the evolutionary process continues. Supposing that there is a feasible solution for the optimization problem, the search is stopped if the mean fitness of the reference group does not evolve after a finite number of generations. Otherwise, the population evolves to the next generation $\mathbf{P}^{t+1}$ and the iterative process continues.

The set of design variables of vector **b** need not have the same units. Two sets of variables will be considered: shape design variables and process variables. The shape of the preform tool geometry can be discretized by using B-spline functions. The displacements of some selected points of the B-splines are the shape design

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parameters defined in the design parameter vector **b**. The considered process variable is the initial temperature of the workpiece, T_0. The temperature of the workpiece will change along the forging process due to shear stress, die velocity, and friction, among others, and its maximum value, T_a, strongly influences the quality of the final product.

4. DESIGN EXAMPLE

In this work, the presented design algorithm is used to optimize a two-stage forging process. The upsetting solution considers a first-stage forging using an optimized preform die shape and a final forging stage with a die shape that matches exactly the required final product. The preform die shape will be optimized by considering different geometries expressed by B-spline curves. The goal of the design example is to search for a preform die shape and a workpiece temperature that will produce after forging a flashless cross-sectional H-shaped axisymmetric product with complete die fill. For H-shaped forging products, two stages should be used to get the final forging. Axisymmetric turbine disks and ribs are examples of H-shaped industrial forging applications.

In practical forging processes, the final forging usually has excessive flash due to the inappropriate design of the preform die shapes. It is important to reduce material waste as flash and excessive die wear to realize a flashless forging process. Elimination of the trimming stage may also be realized for a flashless forging.

The theoretical modeling of the process was performed by using the finite element program [12]. The initial billet is a cylinder of 25 mm diameter by 20 mm height of AISI 1018 steel. The final product prescribes a 29.8 mm equatorial diameter with a height going from 10.1 mm at the inner radius (z-axis) up to 16.7 mm at the highest top of the H-shape and down to 8.3 mm at the outer radius. The simulation considers only one quarter of the process, taking advantage of symmetric conditions. The two-dimensional (2D) computer program models the geometry of the workpiece and dies by a combination of four node and linear friction elements (Fig. 2). The initial workpiece is heated and the dies are considered at room temperature.

AISI 1018 is a low-carbon steel, having higher manganese content than certain other low-carbon steels used in many industrial applications. The temperature-dependent material constitutive relation is given by [16, 17]

$$\begin{aligned} \sigma &= 173.73\,\dot{\varepsilon}^{0.07} \quad [\text{MPa}] \qquad T < 1143\,\text{K} \\ \sigma &= 108.93\,\dot{\varepsilon}^{0.152} \quad [\text{MPa}] \qquad 1143\,\text{K} < T < 1363\,\text{K} \\ \sigma &= 75.83\,\dot{\varepsilon}^{0.192} \quad [\text{MPa}] \qquad T > 1363\,\text{K} \end{aligned} \tag{18}$$

The material properties of the workpiece for the thermal model [16, 17], necessary for the calculation of heat transfer are shown in Table 1 where λ_T is the conductivity, ρ is the density, c_T is the specific heat supply, h_{lub} is the lubricant heat transfer coefficient, h_s is the surface heat transfer coefficient, and *rad* represents the radiation heat flow. The fraction of plastic work transformed into heat is $k_T = 90\%$. The constant shear friction factor m is taken as 0.6.

The die matrix is assumed to be rigid with no internal heat generation with an initial die temperature, $T_{die} = 285\,\text{K}$.

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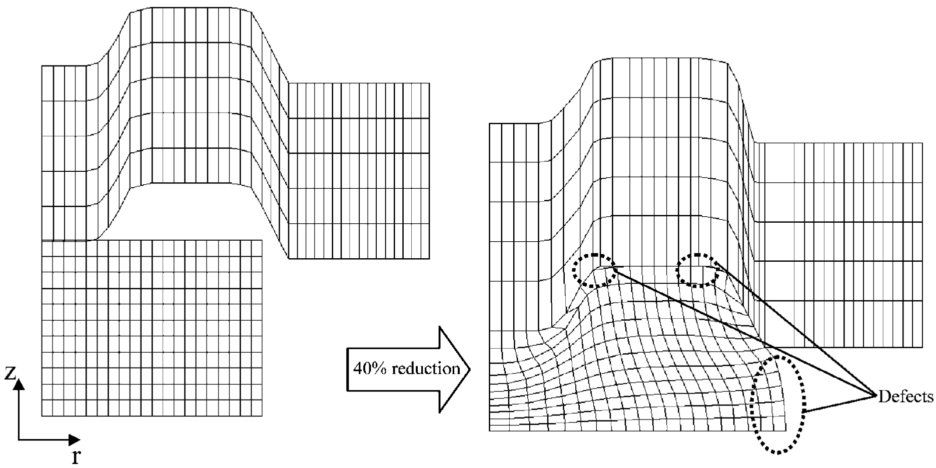

Figure 2 Geometry and finite element mesh for the forging problem.

Figure 2 presents the four-node linear element discretization of the tool and workpiece and the mesh deformation patterns considering only one forging stage. The final forging exhibits defects that have to be discarded by considering the optimization algorithm. The defects are the die underfill and the observable material flash.

Let us consider the shape of the preform die contact zone defined by a cubic B-spline curve. The control points determine the shape of the B-spline curve, and the B-spline curve is bounded by its control polygon. For 2D problems, each control point $P_i, i = 1, \ldots, N$ has two coordinates, $(P_i(r), P_i(z))$. The z displacements (corresponding to the height) of selected active control points of the B-spline function become the geometric design parameters.

In this example, six control points were used to define the B-spline curve representing the preform die shape $(P_i, i = 1, \ldots, 6)$ corresponding to the first six components of the design vector **b**. The seventh component of the design vector **b** is the initial temperature of the workpiece, T_0.

The optimization problem has been solved by applying the developed genetic algorithm. Using acquired experience on the H-shape geometry and considering the usual temperatures for steel hot forging, the problem constraints were

$$\begin{gathered} -2 \leq b_d \leq 2\,\text{mm}, \quad d = 1, \ldots, 6 \\ 1000\,\text{K} \leq T_0 = b_7 \leq 1400\,\text{K} \end{gathered} \tag{19}$$

and the maximum allowed temperature during forging was $T_a = 1450\,\text{K}$.

Table 1 Material properties for the low-carbon steel AISI 1018

λ_T [N/sK]	$0.0469 \times T + 77.467$
ρc_T [N/mm^{2}K]	$4 \times 10^{-8} \times T^3 - 6 \times 10^{-5} \times T^2 + 0.0344 \times T - 2.3977$
h_{lub} [N/s mmK]	4.0
h_s [N/s mmK]	0.00295
rad [N/m s K^4]	$567.0 \times 10^{-13}(1.0 \times 10^{-7} \times T^2 - 9.0 \times 10^{-5} \times T + 0.044)$

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As a compromise between elitist strategy and population diversity, parameters for the genetic algorithm were taken as $N_{pop} = 12$ and $N_e = 5$ for the population and elite group size, respectively. The number of bits in binary codifying for the geometric and temperature design variables was $N_{bit} = 5$. The evolutionary process stops when convergence is achieved (i.e., when the mean fitness of the six best individuals does not change during five consecutive generations). For the objective function defined in Eq. (13), different weights were given to energy and shape fitness components with the weighting parameters $\beta_1 = 10^{-4}$ and $\beta_2 = 10^2$. This way the shape fitness will be the main goal of the optimization problem.

The proposed algorithm is efficient in determining the optimal solution of the numerical example. After 74 generations, the evolutionary process has converged. Figure 3 shows the objective function history over the optimization process represented by the solution with best fitness along each generation of the process.

The evolution of the distance and energy components of the objective function is given by Eqs. (11) and (12). The energy component varies not only with the preform die design but also with the variation of the initial temperature of the workpiece. The compromise between distance and energy components is given by the fitness evolution of the best solution along each generation. The energy required by the optimized process is 10% lower than other processes simulated along the evolutionary process. Consequently, forging load and die wear are significantly reduced.

The optimal solution is shown in Figs. 4 and 5. The optimal design vector is $b^T = [1.73, 0.93, -0.66, 1.73, +0.66, -1.46, 1346.6]$ where the first six components correspond to the z-displacements in mm of the B-spline control points deviating from the highest value $z = 10\,\text{mm}$. The seventh component is the initial temperature of the workpiece, $T_{optimal} = 1347\,\text{K}$. After forging, the barreling effect is minimal and the die is completely filled. The cross section of the resulting disk is almost rectangular so the optimized result is very close to the desired shape. If all material outside the minimum radius were to be trimmed away, this would account for material savings by using the optimized design.

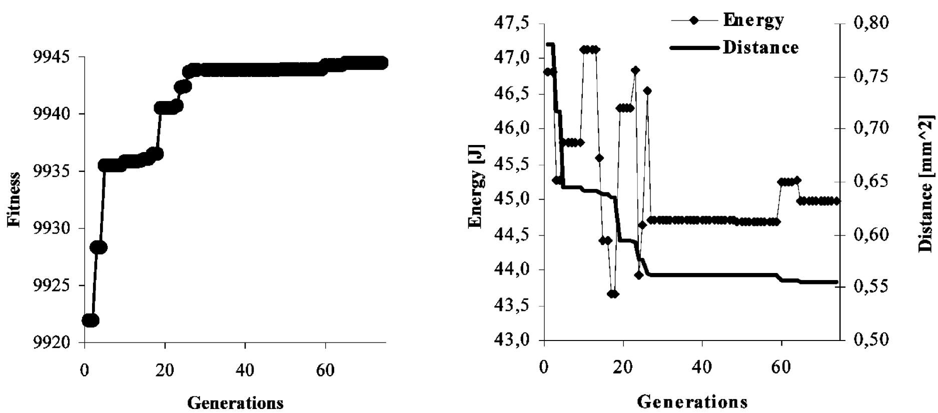

Figure 3 Evolution of the fitness function components.

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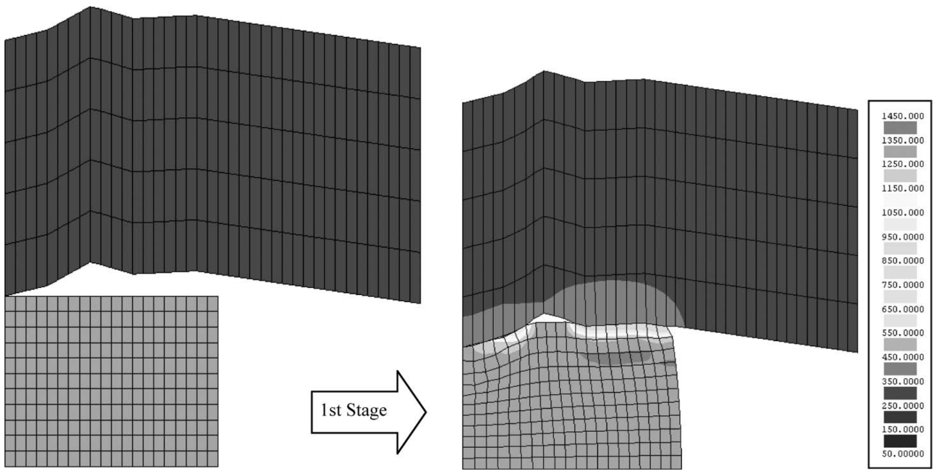

Figure 4 First stage of the optimized forging.

If the objective function would consider only the shape fitness component, $\beta_1 = 0$, one would expect an optimal workpiece solution exhibiting an H-shape for the forged disk cross section. The pursuit of such solution demands too much computer time with oscillating near optimal solutions. So, the introduction of the energy weighting parameter represents a regularization effect.

No violation of the temperature constraint was detected along the two-stage optimal forging. The highest temperature detected during forging was $T_{maximum} = 1360\,K$ at the end of the first forging stage (Fig. 4). The temperature transfer between workpiece and die is observable. Before forging, the die temperature is assumed constant and at room temperature, $T_{die} = 285\,K$, and according to the optimal solution the initial workpiece temperature is $T_{optimal} = 1347\,K$. After forging, the highest achieved temperature in the workpiece is $T_{max} = 1349\,K$ at the

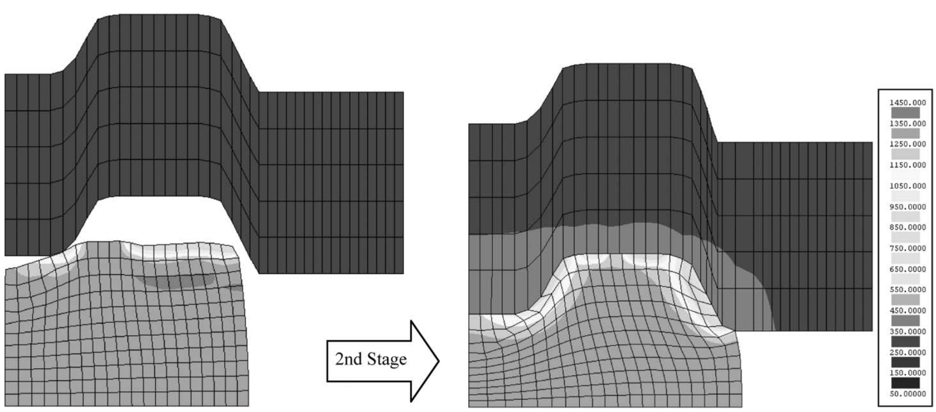

Figure 5 Final stage of the optimized forging.

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equatorial plane and the lowest is $T_{min} = 820\,\text{K}$ at the die/workpiece contact area. The decrease in temperature is due to the heat transfer between die and workpiece.

To simulate one single two-stage forging process using the thermal mechanical code and a Pentium III takes only a couple of minutes. The implemented example took around 24 h to reach the optimal solution. Although time-consuming, the developed genetic algorithm presents some advantages over sensitivity-based methods: the algorithm is not sensitivity dependent, runs well even for discontinuous derivative fields, discrete design variables, and does not introduce iteration-dependent numerical errors.

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5. CONCLUSIONS

This article presents an optimization method to design preform die shapes in forging processes.

The methodology was applied to design the optimal preform die shape of an axisymmetric forming process, the forging of an H-shaped product, starting from a straight cylindrical billet. The material of the billet is AISI 1018 steel. A flashless and completely filled final forging was produced by using the optimized preform die. Due to achieving a flashless forging, the forging load and die wear were significantly reduced, along with the possible elimination of the trimming stage and a reduction in machining costs. These results indicate that the method is very effective in realizing netshape forging.

This work gave special attention to shape optimization, namely, the difference between the desired and achieved final forging shapes. In fact, preform design is related to many process parameters, such as energy requirement, uniform deformation, and die wear. The authors believe that shape design is the most important parameter. Other parameters can be incorporated into the objective function to realize a multiobjective optimization of metal forming processes, such as folding defect, wear of tools, level of effective strain and stress, or uniform distribution of the mechanical properties.

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