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APPLICATION OF GENETIC ALGORITHMS FOR IDENTIFICATION OF RHEOLOGICAL AND FRICTION PARAMETERS IN COPPER DEFORMATION PROCESSES

ZASTOSOWANIE ALGORYTMÓW GENETYCZNYCH DO IDENTYFIKACJI PARAMETRÓW REOLOGICZNYCH I TARCIA DLA MIEDZI

The objective of the paper is an evaluation of optimization technique based on genetic algorithm, concerning an applicability of the method to the inverse analysis. The general principles of the inverse analysis are discussed in the paper and short description of the direct model based on the finite element solution is given. Genetic algorithm is presented next and an implementation of the method into the inverse analysis is shown. Practical application of the algorithm is investigated for copper rings compressed on the Gleeble 3800 simulator. Load-displacement data and shape of the ring after compression were used as input to the inverse analysis. Three optimization methods are compared in this analysis: genetic algorithm, Hooke-Jeeves and simplex. The parameters of the analysis were selected taking into account a similar number of callings of the finite element solver for all methods. Comparison of the results has shown that genetic algorithm is an efficient optimization technique for the inverse method applications. It confirmed good accuracy and convergence as well as avoiding of local minima during the optimization process.

Celem pracy jest ocena przydatności metody optymalizacji opartej o algorytmy genetyczne, do analizy odwrotnej procesów plastycznej przeróbki metali. W pracy przedstawiono ogólne zasady analizy odwrotnej i opisano model zadania bezpośredniego wykorzystujący sztywno-plastyczne rozwiązanie metodą elementów skończonych. Zaprezentowano algorytmy genetyczne w aspekcie ich implementacji do rozwiązania problemu odwrotnego oraz zbadano skuteczność metody dla pierścieni spęczanych w symulatorze Gleeble 3800. Wyniki pomiarów siły w funkcji przemieszczenia stempla oraz kształt pierścienia po odkształceniu stanowiły dane wejściowe do analizy odwrotnej. Ponadto algorytmy genetyczne zostały porównane z klasycznymi metodami optymalizacji: algorytmem Hooke'a-Jeevesa i metodą sympleksów, przy czym kryterium porównawczym była liczba wywołań programu metody elementów skończonych niezbędna do osiągnięcia minimum. Wyniki analizy odwrotnej dla różnych metod optymalizacji pokazały, że algorytmy genetyczne są przydatne w zastosowaniach do analizy odwrotnej. Procedura wykazuje zarówno dobrą dokładność i zbieżność jak też skuteczność w omijaniu minimów lokalnych.

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1. Introduction

The accuracy of simulation of metal forming processes depends on correctness of the description of the boundary conditions and the properties of the deformed material. The parameters in models describing friction, heat exchange with a surrounding and flow stress are determined from the results of various tests, among others the plane strain compression, the axisymmetrical compression and the ring compression are the most popular. All the tests involve large inhomogeneities of deformation, therefore, an interpretation of the results of these tests presents difficulties. An inverse analysis, combined with the finite element solution of the direct problem, has been commonly used to account for the inhomogeneities and to obtain the values of the coefficients in the models independently of the test conditions. Numerous successful applications of this method are described in the scientific literature, see for example [1–4]. Analysis of some results has shown that, usually, the phenomena investigated in the inverse analysis are mutually dependent. For example, friction coefficient has to be known for evaluation of rheological parameters while, vice versa, constitutive model has to be known for evaluation of friction parameters. This inspired a search for the techniques, which allow for evaluation of coefficients in various types of models from one type of tests. In consequence, the propositions of evaluation of both rheological and friction parameters from one set of ring compression tests have been suggested in [5–7].

Long computing time is the main obstacle preventing common applications of the inverse technique. In situations, when the cost function is built on the basis of the results of several experiments, the gradient optimization techniques cannot be applied directly. Non-gradient methods require a large number of finite element simulations to be performed what leads to very long computing times. Improvement of this situation can be obtained by selection of the starting point as close as possible to the global minimum and by an application of more efficient optimization methods. The former problem is discussed in publication [8]. The general objective of this work is looking for the optimization technique, which allows for fast and efficient searching for the minimum in the inverse analysis. The particular emphasis is put on an investigation of the capabilities of the genetic algorithms.

2. Inverse analysis

The aim of the inverse analysis is an estimation of coefficients in the models describing boundary conditions and materials properties in various processes. The subject of the present work is an application of this analysis to the evaluation of both friction and rheological parameters in metal forming on the basis of results of compression tests. The idea of the inverse approach is presented in Fig. 1. The analysis is composed of three parts:

- experiment, which supplies results of measurements in the form of load-displacement data and shapes of samples after compression,

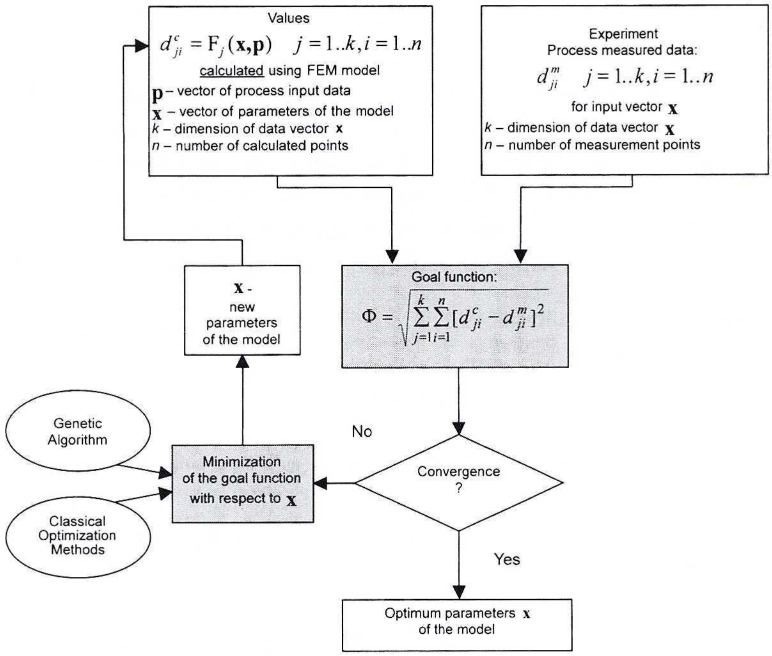


Fig. 1. The flow-chart showing the inverse method

- solution of direct problem, which uses the finite element model of the considered test,
- optimization procedure, which determines unknown parameters from the condition of minimum of the cost function.

Direct model calculates process output parameters (**d**) as a function of process conditions (**p**) and coefficients in the rheological and friction models (**x**):

$$\mathbf{d} = \mathrm{F}(\mathbf{p}, \mathbf{x}). \tag{1}$$

In the inverse analysis the vector of coefficients **x** is not known but two vectors **d** are available. One is obtained from measurements during the tests and one from the predictions using the direct model. Thus, the coefficients **x** are determined using optimization techniques with the cost function defined as a difference between measured and predicted vectors **d**.

Various approaches to the solution of the inverse problem are presented in the literature. The inverse algorithm developed in [5] is considered in the present work. In this algorithm the rheological and friction parameters are evaluated simultaneously on the basis of results of ring compression tests. The ring compression is simulated using the finite element code. The goal function of the form:

$$\Phi = \left\langle \frac{1}{Nt}\left\{\frac{1}{Npl}\sum_{i=1}^{Nt}\sum_{j=1}^{Npl}\left(\frac{F_{cij}-F_{mij}}{F_{mij}}\right)^2 + \frac{1}{Npr}\sum_{i=1}^{Nt}\sum_{j=1}^{Npr}\left[\left(\frac{R^{in}_{cij}-R^{in}_{mij}}{R^{in}_{mij}}\right)^2 + \left(\frac{R^{out}_{cij}-R^{out}_{mij}}{R^{out}_{mij}}\right)^2\right]\right\rangle^{\frac{1}{2}}, \tag{2}$$

where: F – compression load, R – inner or outer diameter, Nt – number of tests, Npl – number of measured loads during one test, Npr – number of the co-ordinates of the ring surface (outer or inner) used in an analysis, is minimized with respect to rheological and friction parameters, index c refers to computed values, index m – to measured values.

The optimization usually requires long computing time and problem of avoiding local minima remains open. Therefore, the objective of the current work is testing of various optimization methods and evaluation of their applicability to the inverse analysis. The genetic algorithm (GA) was selected as a new possibility and its efficiency was tested and compared to other methods.

3. Direct model

The finite element simulation of the investigated tests was applied in the direct model. The finite element code used in the calculations is based on the rigid-plastic approach coupled with the solution of the heat transport equation. Detailed description of the model is given in [9]. Briefly, the mechanical part of the approach is based on an the extremum principle, which states that for a plastically deforming body of volume V, under the tractions $\underline{s}$ prescribed on the part of the surface S_t and the velocity $\underline{v}$ prescribed on the remainder of the surface S_v, under the constraint $\dot{\varepsilon}_V = 0$, the actual solution minimizes the functional:

$$J = \int_V (\sigma_i \dot{\varepsilon}_i + \lambda \dot{\varepsilon}_V)\, dV - \int_{S_t} \underline{s}^T \underline{v}\, dS_t, \tag{3}$$

where: λ – Lagrange multiplier, σ_i – effective stress which, according to the Huber-Mises yield criterion is equal to the flow stress σ_p, $\dot{\varepsilon}_i$ – effective strain rate, $\dot{\varepsilon}_V$ – volumetric strain rate, $\underline{\mathbf{s}} = \{\tau_x, \tau_y\}^T$ – vector of boundary traction, $\underline{\mathbf{v}} = \{v_x, v_y\}^T$ – vector of velocities, v_x, v_y – components of the velocity vector, τ_x, τ_y – components of the external stress, which in metal forming processes is a friction stress or stress caused by external tension (for example back and front tension in rolling).

In the flow theory of plasticity, strain rates $\underline{\dot{\varepsilon}}$ are related to stresses $\underline{\sigma}$ by the Levy-Mises flow rule:

$$\underline{\sigma} = \frac{\sigma_p}{3\dot{\varepsilon}_i} \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \underline{\dot{\varepsilon}}. \tag{4}$$

The flow stress σ_p in equation (4) was introduced as a function of strain rate, strain and temperature. The evaluation of coefficients in this function is an objective of the inverse analysis.

The friction model proposed by Chen and Kobayashi and described in [5,9] is used in this approach. Discretization of equation (3) and differentiation with respect to the nodal velocities and to the Lagrange multiplier yields a set of non-linear equations usually solved by the Newton-Raphson linearization method. The mechanical part of the model is coupled with the finite element solution of the heat transport equation:

$$\nabla k(T)\nabla T + Q(T) = c_p(T)\varrho(T)\frac{\partial T}{\partial t}, \tag{5}$$

where: $k(T)$ – conductivity, $Q(T)$ – heat generation rate due to deformation work during compression, $c_p(T)$ – specific heat, $\varrho(T)$ – density, T – temperature, t – time.

The following boundary conditions were used in the solution:

$$k(T)\frac{\partial T}{\partial \mathbf{n}} = q + \alpha(T)(T_0 - T), \tag{6}$$

where: α – heat transfer coefficient, T_0 – surrounding temperature or tool temperature, q – heat flux due to friction, **n** -unit vector normal to the surface.

The finite element model described by equations (3) – (6) was used as the direct model in the present work.

4. Optimization

As mentioned earlier, testing of various optimization methods regarding their applicability to the inverse analysis was an objective of the work. Three optimization methods were investigated. The genetic algorithm, a method newly implemented into the inverse algorithm, was tested and compared to the two classical methods: Hooke-Jeeves and simplex. Detailed description of the genetic algorithm and an application to the inverse analysis is given below.

4.1. Genetic algorithms

Evolutionary Algorithms (EA) belong to the methods of Artificial Intelligence (AI) and are used to solve optimization problems. AI methods include several separate approaches, such as **Genetic Algorithms (GA)**, Evolution Strategies (ES), Genetic Programming (GP) and Evolutionary Programming (EP) [10].

Genetic algorithm is a search technique based on ideas from the science of genetics and the process of natural selection. GAs have proved to be useful in difficult optimization problems [11,12,13] and their advantages comparing to classical optimization methods are due to the following features:

- genetic algorithms do not search from one single point, but from a population of points,
- use only goal function instead of derivatives or other auxiliary knowledge,
- use stochastic reproduction instead of deterministic rules.

A schematic illustration of a simple genetic algorithm is presented in Fig. 2. Genetic algorithm uses vocabulary borrowed from natural genetics [14]. GA starts searching from the initial *population* of chromosomes usually generated randomly from the population of feasible solutions. GA is based on the population:

$$P(n) = \{x_1^n, x_2^n, ..., x_L^n\}, \tag{7}$$

where: n – generation number, L – size of population, x_i^n – chromosome.

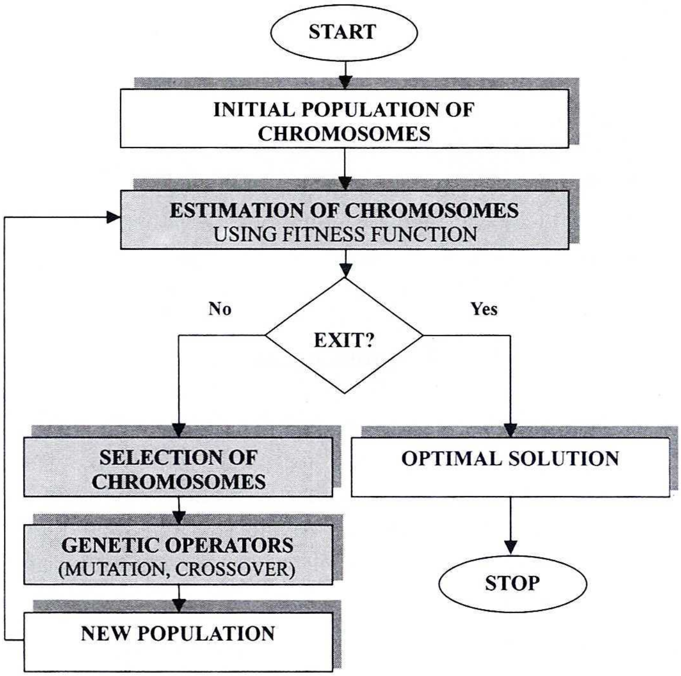


Fig. 2. The flow chart of the genetic algorithm

Each chromosome x_i^n, $i = 1, 2, ..., L$, represents one potential solution. Usually a chromosome is a string of bits representing optimizing parameters. The number of bits used to encode each parameter will depend on the required precision.

Chromosomes are estimated using the fitness function $F(x_i^n)$ corresponding to the goal function in the optimization problem (see equation (8)). The fitness function describes the 'quality' of the solution (individual of population). At the stage of *selection* the part of chromosomes is taken into the next population. Then genetic operators, *mutation* and *crossover*, are applied at the selection stage. The procedure is repeated until the optimal solution is reached.

There are many modifications of the classical genetic algorithm because of several variations of:

- encoding parameters (in binary format or in floating-point format),
- selection (selection by stochastic universal sampling, roulette wheel selection, truncation selection, tournament selection, local selection),
- crossover (single point crossover, double point crossover, shuffle point crossover, single point crossover with reduced surrogate, double point crossover with reduced surrogate) and mutation [10,14].

4.2. Application of genetic algorithm for identification of rheological and friction parameters

Genetic representation of potential solutions. Each chromosome in population (feasible solution) is represented as a vector of rheological and friction parameters encoded in a binary format. The initial population is created randomly.

Fitness function. Evaluation of chromosomes in population is done using fitness function. In the conventional optimization method the mean square error function (2) is chosen as the goal function Φ for identification problem of stress-strain curves parameters. Search for a minimum of this function yields the solution. In the genetic algorithm the goal function is transformed into the fitness function F, because the genetic methods search for maximum. Thus:

$$\mathrm{F} = \frac{1}{\Phi + \chi}, \tag{8}$$

where χ is a very small number.

Genetic operators. Three genetic operators are applied to chromosomes: selection, crossover and mutation.

A roulette wheel **selection** is used as follows:

- calculate the fitness value $\mathrm{F}(x_i^n)$ for each chromosome x_i^n, $i = 1, 2, \ldots, L$, where L is the size of population,
- find the total fitness of the population $\mathrm{TF} = \sum_{i=1}^{L} \mathrm{F}(x_i^n)$,
- calculate the probability of the selection p_i for each chromosome x_i^n, $i = 1, 2, \ldots, L$, $p_i = \mathrm{F}(x_i^n)/\mathrm{TF}$,
- calculate the cumulative probability q_i for each chromosome x_i^n, $i = 1, 2, \ldots, L$, $q_i = \sum_{j=1}^{i} p_j$,
- generate a random number r from the range $[0,1]$,
- if $r < q_1$ then select the first chromosome x_1^n, otherwise select the i^{th} chromosome x_1^n, $2 \le i \le L$, such that $q_{i-1} \le r \le q_i$.

Selection represents a very important aspect of the genetic algorithm. Chromosomes with the highest values of the fitness function have more chance to get into the new population.

The single point **crossover** is applied. Mixing features of two chromosomes of previous generation creates new chromosomes. The probability of crossover *pc* determines the expected number of chromosomes, which undergo the crossover operation. The following steps are performed for each chromosome in population:

- generate a random number *r* from the range [0,1],
- if $r<pc$ chromosome is destined for crossover.

For each pair of individuals a random integer number pos (crossing point) from the range [1... $m-1$] is generated, where m is the total length of chromosome (number of bits). Two chromosomes: $(b_1b_2 \ldots b_{pos}b_{pos+1} \ldots b_m)$ and $(c_1c_2 \ldots c_{pos}c_{pos+1} \ldots c_m)$ are replaced by a pair of their offspring: $(b_1b_2 \ldots b_{pos}c_{pos+1} \ldots c_m)$ and $(c_1c_2 \ldots c_{pos}b_{pos+1} \ldots b_m)$.

Mutation operation introduces random changes to chromosomes. Probability of mutation *pm* gives the expected number of mutated bits. The following steps are performed for each chromosome in population and for each bit within the chromosome:

- generate a random number *r* from the range [0,1],
- if $r<pm$ bit is mutated (change from 0 to 1 or vice versa).

The simple genetic algorithm is stopped after an assumed number of iterations.

5. Experiment

Ring compression test was selected for supplying the data for the inverse analysis. Schematic illustration of the test is shown in Fig. 3. The tested material was technically pure copper. Initial dimensions of the ring were: outer diameter 14 mm, inner diameter 7 mm, height 4.69 mm, what gives the standard ratio for this test 6 : 3 : 2. The tests were performed in the room temperature. Strain rate of 1.0 s^{-1} and homogeneous logarithmic strain of 0.361 were the remaining process parameters. Experiment was performed on the Gleeble thermomechanical simulator at the Institute for Ferrous Metallurgy in Gliwice.

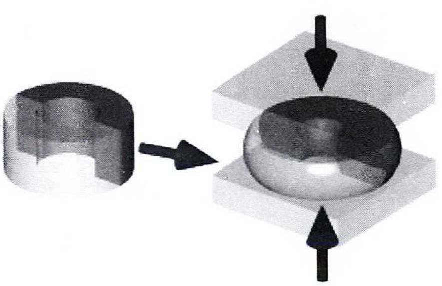


Fig. 3. Schematic illustration of the ring compression test

6. Results

Evaluation of various optimization methods with respect to their applicability to the inverse analysis was the main objective of the work. The maximum number of FEM solver callings for n optimized parameters in one step of the optimization was evaluated for each investigated method:

- Hooke-Jeeves: $1+2*n$
- Simplex: $n+5$
- AG: L – size of population.

These data are for the analysis based on one compression process only. They should be multiplied by a number of tests used in the analysis.

Selection of the starting point is the main difference between the genetic algorithm and the conventional methods. The starting values of components of **x** vector in the Hooke-Jeeves and simplex methods are chosen by the user, therefore, endeavors are made to select the starting point as close to the final minimum as possible [8]. This point is selected randomly in the genetic algorithm method. In order to make the comparison more convincing, the starting point for the conventional methods in this work was chosen reasonably far from the expected minimum.

Since the tests were performed in the room temperature, the strain rate sensitivity of copper was negligible and the following flow stress function was defined:

$$\sigma_p = a_1 + a_2 \varepsilon^{a_3}. \tag{13}$$

The constant friction factor m was assumed and, in consequence, the optimized vector x contained four components: $\mathbf{x} = \{a_1, a_2, a_3, m\}$.

In this work the optimization procedures, which include 50 iterations using Hooke-Jeeves or 60 iterations using simplex methods or 20 iterations using GA are considered. The number of runs of the FEM solver is similar for these three cases, namely 371 for Hooke-Jeeves, 416 for simplex and 400 for GA. The results, which were obtained after these optimization schedules, are presented below. The following constraints were imposed on the variables for the genetic algorithm: $a_1 \in \{1,100\}$, $a_2 \in \{100,900\}$, $a_3 \in \{0.1,0.9\}$, $m \in \{0.01,0.4\}$, and the parameters of the method were: size of population $L = 20$, probability of crossover $pc = 0.9$ and probability of mutation $pm = 0.09$. These parameters are established in testing processes. Each of four coefficients was coded on 5 bits, thus the total length of the chromosome was equal $n = 5*4 = 20$, and the calculation accuracies were: $a_1 \pm 3.1$, $a_2 \pm 25$, $a_3 \pm 0.025$ and $m \pm 0.012$.

Starting coefficients **x** for the Hooke-Jeeves and simplex methods and the cost function Φ calculated for these coefficients were:

$$\mathbf{x} = \{90.0,\ 110.0,\ 0.21,\ 0.19\} \qquad \Phi = 1.003.$$

Comparison of measured and calculated loads and shape of ring predicted for starting coefficients **x** is shown in Fig. 4. Results of the optimizations are presented below in the Table.

a)

b)

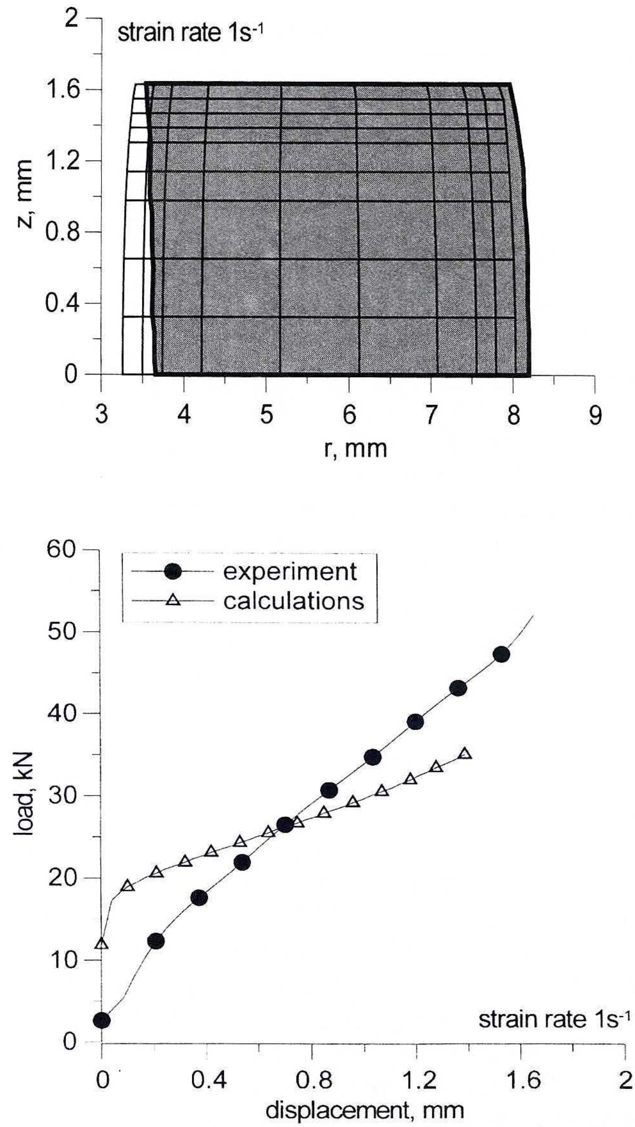


Fig. 4. Comparison of loads (*a*) and ring shapes (*b*) obtained from measurements and from finite element calculations using staring values of coefficients **x**. Measured ring shape is represented by the gray area (thick line) and predicted by the mesh (thin line).

Fig. 5 shows compression loads as a function of die displacements calculated for coefficients x obtained from the optimization schedule. These loads are compared with the experimental data. It is seen in Fig. 5 that, in the considered case, the genetic algorithm appeared to be more efficient and accurate than the simplex methods and comparable with the Hooke-Jeeves method. The coefficients **x** and the values of the goal function obtained for various methods are given in Table.

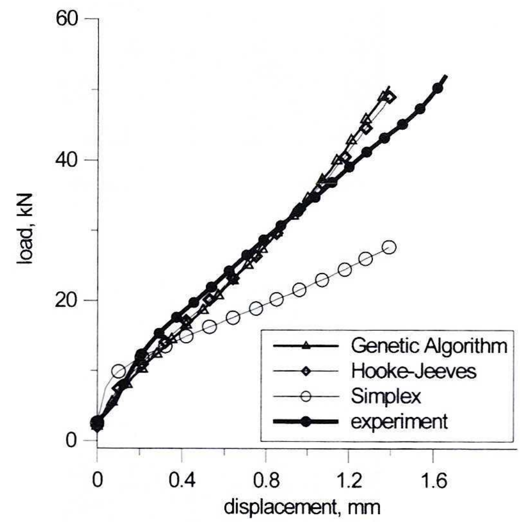


Fig. 5. Comparison between loads measured in the test and predicted by various optimization methods

TABLE

Results of optimization

Optimization method	a_1	a_2	a_3	m	Goal function Φ
Genetic Algorithm (20 iter.)	16.47	525.0	0.7	0.095	0.109
Hooke – Jeeves (50 iter.)	16.3	472.5	0.643	0.107	0.1
Simplex (60 iter.)	18.99	162.1	0.298	0.213	0.367

Comparison between the shape of the ring measured in the experiment (gray area) and predicted by the direct model with coefficients **x** determined by the AG method (mesh) is shown in Fig. 6. Due to two axes of symmetry a quarter of the ring cross section is presented. Very good agreement between measurements and predictions confirms good optimization capabilities of the genetic algorithm.

Fig. 7 shows comparison between the shape of the ring measured in the experiment (gray area) and predicted by the direct model with coefficients **x** determined by the Hooke-Jeeves and simplex methods (mesh). It is seen in this figure that the former method performed very well and good agreement between measured and predicted shapes of the ring was obtained after 50 iterations. 60 iterations of simplex method were not satisfactory.

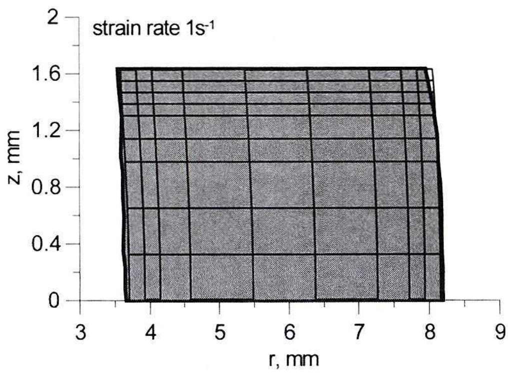
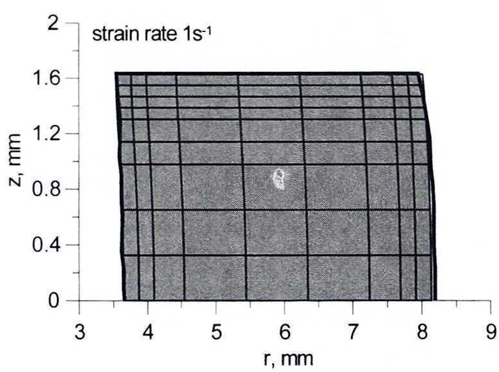


Fig. 6. Comparison between shapes of the ring predicted by the FEM simulation with coefficients **x** determined by the AG method (mesh) and measured in the test (gray area)



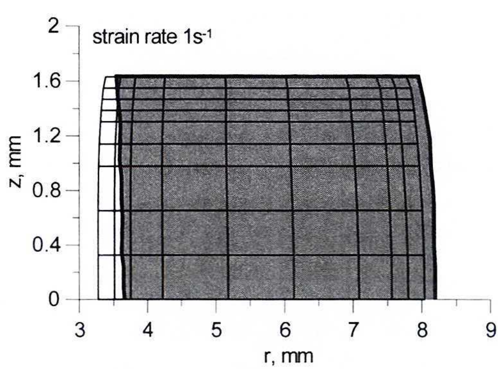


Fig. 7. Comparison between shapes of the ring predicted by the FEM simulation with coefficients **x** determined by the Hooke-Jeeves method (a) and simplex method (b) (mesh) and measured in the test (gray area)

Further assessment and comparison of the optimization methods were performed by analysis of changes of the goal function in subsequent iterations. It is seen in Fig. 8 that the goal function drops rapidly at the beginning of the procedure and, after several iterations, the decrease becomes much slower. The Hooke-Jeeves method and the GA converge well to a reasonably low value of the goal function. The simplex method stacked at an unacceptable level.

a)

b)

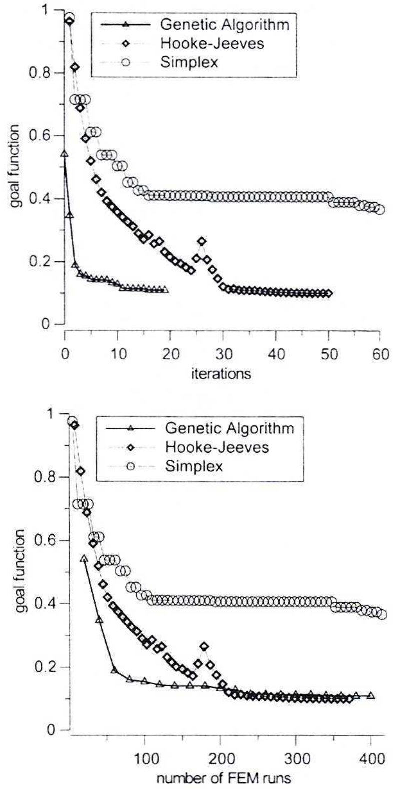


Fig. 8. Changes of the goal function in subsequent iterations (*a*) and with number of runs of the FEM code (*b*) for various optimization methods

7. Discussion

An analysis was performed on the basis of one experiment and reasonably low number of optimization variables. In general, all previous observations concerning performance of the Hooke-Jeeves and the simplex methods have been confirmed. These methods have a tendency to stack in the local minima and selection of the starting point is of major importance. Evaluation of the genetic algorithm method comparing to the conventional ones allowed the following conclusions:

- Conventional genetic algorithm shows good applicability to solving optimization problems in the inverse analysis of rheological and friction parameters.
- GA method shows similar or better convergence than classical methods for an approximately the same number of callings of the FEM solver.
- The computing time for the GA was decreased by proper selection of number of bites in the chromosome (the length of the chromosome depends on the range of the search and on the required accuracy).
- Simplicity of implementation and lack of sensitivity of the algorithm's complexity on the goal function are the main advantages of this method. The GA transforms the population of solutions instead of a single solution.
- GA is efficient in avoiding local minima of the goal function, what is due to the mutation mechanism.

Further investigation concerning genetic algorithms should include more complex problems, such as analysis of materials with strain rate and temperature sensitivity. Beyond this, the research should focus on applications of other methods of encoding parameters and genetic operators (selection, crossover, mutation) to improve the results of genetic algorithms and to reduce the calculation time.

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