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J. KUSIAK*, A. ŻMUDZKI*, A. DANIELEWSKA-TUŁECKA**

OPTIMIZATION OF MATERIALS PROCESSING USING A HYBRID TECHNIQUE BASED ON ARTIFICIAL NEURAL NETWORKS

OPTYMALIZACJA PROCESÓW OBRÓBKI METALI Z UŻYCIEM TECHNIKI HYBRYDOWEJ OPARTEJ O SZTUCZNE SIECI NEURONOWE

The optimization problems in the field of material processing are very complex. They require a lot of computations, because most of processes are simulated on the base of the Finite Element Method (FEM). In classical optimization approach, every iteration requires time-consuming FEM calculation of the considered problem, which increases the computation time of the optimization procedures. The efficient optimization algorithms of such complex problems should minimize the computation time. The paper presents a new hybrid optimization technique based on the Artificial Neural Network (ANN) modelling. The search of the optimal value is performed not directly on the objective function, but on values predicted by its ANN metamodel. Such approach does not require FEM recalculations of the whole analyzed problem for each optimization iteration. It allows decreasing the computation time of the optimization procedure. The paper presents the description of the proposed method, its algorithm and examples of application to test optimization problems and the inverse analysis of materials properties.

W zagadnieniach dotyczących procesów obróbki materiałów, problemy optymalizacji są bardzo skomplikowane. Wymagają one bowiem wielu obliczeń numerycznych, co wynika z tego iż większość procesów modeluje się za pomocą Metody Elementów Skończonych (MES). W klasycznym podejściu, każda iteracja metody optymalizacji wymaga czasochłonnych symulacji MES rozważanego problemu, co znacząco zwiększa czas obliczeń. Cechą skutecznego algorytmu optymalizacji powinno być zmniejszenie tego czasu. W artykule przedstawiono nową hybrydową technikę optymalizacji opartą o modelowanie z użyciem Sztucznych Sieci Neuronowych (SSN). Poszukiwanie wartości optymalnej nie jest przeprowadzone bezpośrednio za pomocą zdefiniowanej funkcji celu, ale za pomocą jej wartości wskazanej przez metamodel SSN. Zaprezentowane podejście nie wymaga ponownych obliczeń całego analizowanego problemu za pomocą MES w każdej iteracji algorytmu. Pozwala to na zmniejszenie czasu obliczeń procedury optymalizacji. W artykule zaprezentowano opis

* AGH UNIVERSITY OF SCIENCE AND TECHNOLOGY, 30-059 KTAKÓW, AL. MICKIEWICZA 30, POLAND
** NATIONAL — LOUIS UNIVERSITY, 33-300 NOWY SĄCZ, UL. ZIELONA 27, POLAND

proponowanej metodyki, algorytm poszukiwania optimum, oraz przykłady zastosowania do optymalizacji funkcji testowych i do wyznaczania parametrów modelu materiałowego w analizie odwrotnej.

1. Introduction

The common classical iterative optimization procedures (see Figure 1), which are very efficient in case of mathematical problems, fail in case of the optimization of materials processing. It is caused by the fact, that models of these processes are strongly non-linear and associated with the Finite Element Method analysis. The FEM models give good approximation of simulated processes, but usually are time consuming. Therefore, optimization problems of these processes require long calculation time, which often exceeds the acceptable limits and makes the whole optimization procedure useless from the practical point of view.

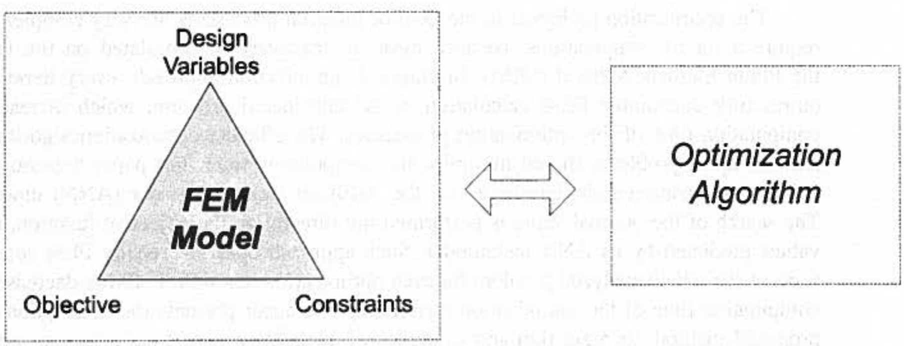

Fig. 1. Flow chart of the classical optimization procedure of real materials processing

Additional difficulties can be faced if the commercial codes (FORGE2/3, DEFORM, ANSYS, etc.) which are used for the simulation of these processes. In such a case, it is difficult to use the efficient optimization gradient-based techniques, because derivatives of the objective function have to be computed numerically. It additionally increases the optimization computation time. Therefore, different efforts towards the decrease of the computation time are being undertaken. The main goal of the work is the presentation of the new hybrid method, which is the modification of the described in [1, 2] approximation-based optimization technique. It combines the Artificial Neural Network approach, used as the metamodel of the considered process, and the Monte Carlo optimization technique. Idea of metamodel application in 'response surface' optimization problems of metal forming processes was widely described in [3, 4].

2. Description of the hybrid optimization method

2.1. General idea

The approximation-based optimization technique is a non-gradient method. The minimum is not searched directly, using the commonly used techniques, but indirectly through the examination of the values of considered objective function, not calculated, but predicted by the ANN metamodel. The hybrid optimization technique consists of the three main stages:

1. **Construction of the Artificial Neural Network model which predicts the objective function values for any input data of design variables.** Such neural network is treated as the metamodel of the considered real process (see Fig. 2). The output of the ANN metamodel is a new objective function, which has to be minimized.
2. **Choosing a training data set for the ANN metamodel.** Selection of the initial design variables vector is crucial. The objective function has to be evaluated for each variable, which requires the time consuming FEM simulation of the considered process. The accuracy of the predictions of the ANN metamodel decreases if the number of training points is not sufficient enough and if they are not properly located. Therefore, the number of points of the training data set and the location of these points is essential for the results and efficiency of the optimization procedure. The initial training data set can be chosen through the Design of Experiment method (DoE), based on statistical principles, used to gain both effectiveness and efficiency in data acquisition [5]. The DoE method can give the minimal number of the initial experimental points and identify the most important ones. Significant reduction in the size of the training set and improvement of the accuracy of the predicted results was observed if the DoE was used for choosing the training set [6].
3. **Iterative search of the minimum of the values predicted by ANN metamodel.** The search for the optimal values of the metamodel can be performed by one of the nonlinear optimization techniques. Monte Carlo method proved to be very useful in cases of the complex form of the objective function. The found minimum is being added to the training data set for the next iteration. The modified design variables data set is used then for the rebuilding the ANN metamodel and the whole procedure of the optimization repeats, until the stop criterion is fulfilled. The most common stop criterion is simply the verification of the difference between the previously found and the actual value of the minimum.

Since the proposed optimization technique does not require as many FEM calculations of considered process, as classical optimization methods, it allows decreasing of the computation time.

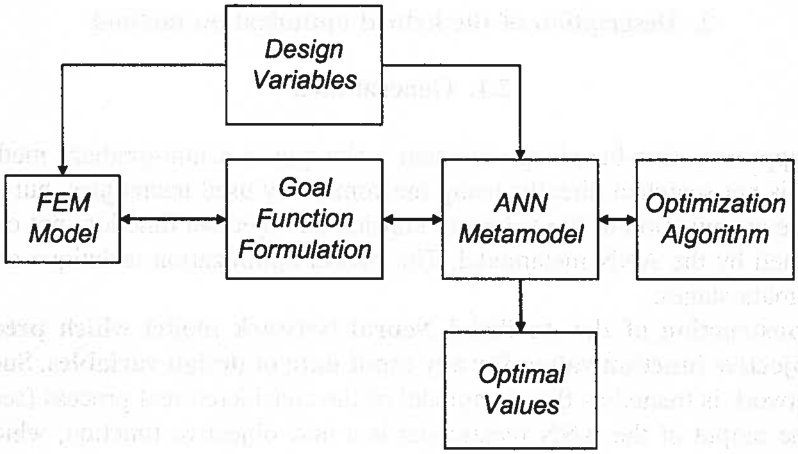

Fig. 2. The basic idea of the hybrid optimization technique

2.2. Algorithm

The algorithm of the hybrid optimization method consists of the following steps:

Step 1.

i) Definition of the objective function F and initial optimization conditions: limits of the search space, the stop criterion, constraints, iteration limits, etc.

ii) Selection of the initial design variable data set according to the Design of Experiment (DoE) rule. The resulting design variable data set can be defined as: $A = \{\mathbf{a}_1, \mathbf{a}_2, ..., \mathbf{a}_n\}$ of n trial vectors $\mathbf{a}_i = [a_1^i, a_2^i, ..., a_N^i]$ of design variables, where N is a number of optimization variables.

Step 2.

i) Computation of the objective function values $\{F(\mathbf{a}_1), F(\mathbf{a}_2), ..., F(\mathbf{a}_n)\}$ corresponding the design variable data set A by FEM simulations of the analyzed process.

Step 3.

i) Construction of the ANN metamodel. Training of the ANN metamodel using the data set consisting of the selected in step 2 objective function values. The output of the metamodel becomes the new optimization objective function named F^*. In consequent iterations the training set is enlarged by the value of objective function in the minimum found in the previous optimization iteration.

Step 4.

i) The search of the minimum $\mathbf{a}^*$ of the objective function F^* using chosen optimization technique. The search of the minimum is performed on the metamodel and does not involve any additional FEM analysis of considered process.

Optimization starting point is chosen randomly only at the first optimization iteration, while in the successive iterations is linked to the previously found optimal value $F^*_{prev}(\mathbf{a}^*)$.

Step 5.

i) Calculation of the minimum value of the objective function $F^*(\mathbf{a}^*)$ (one, single FEM simulation of considered process).

Step 6.

i) If $\left|F^*(\mathbf{a}^*) - F^*_{prev}(\mathbf{a}^*)\right| < \delta$ (δ is a given arbitrary small constant value), then $F^*_{prev}(\mathbf{a}^*) = F^*(\mathbf{a}^*)$, and the program terminates. Otherwise:

(1) $F^*_{prev} = F^*$ and $F^*_{prev}(\mathbf{a}^*) = F^*(\mathbf{a}^*)$; $\mathbf{a}^*$ becomes an additional value of the design variable and $F^*(\mathbf{a}^*)$ becomes an additional point for new training of the ANN model.

(2) The computations return to the ***Step 3***.

The flow chart of the algorithm of the described hybrid optimization technique is presented in Fig. 3. It is seen that the FEM analysis of considered process and optimiza-

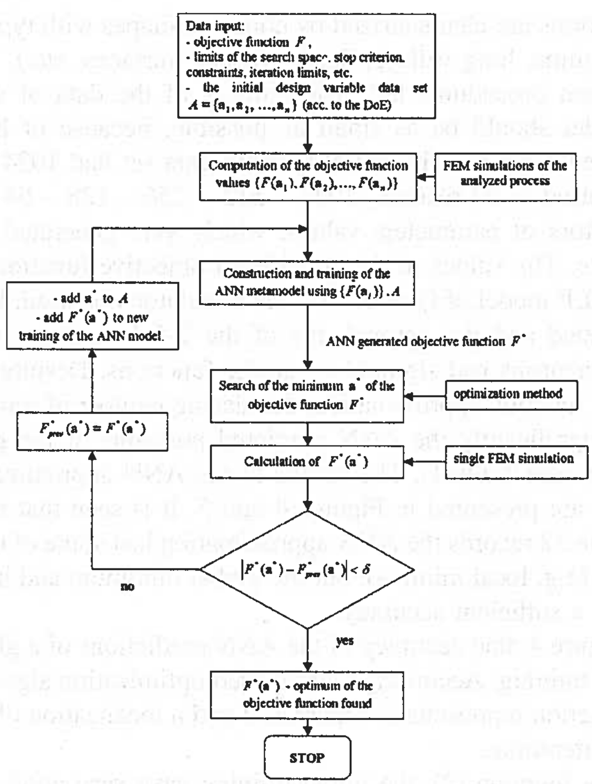

Fig. 3. The flow chart of the algorithm of the hybrid optimization technique

tion procedure are separated. Therefore, no interaction between the FEM simulation program and optimization procedure is needed. In consequence the computation time is much lower than that of the classical optimization approach.

2.3. Examples of the optimization of simple test objective functions

Artificial Neural Networks are able to approximate complex multi-dimensional functions [7]. Two analytical two-dimensional functions of the complex shape were selected to validate approximation ability of the ANN:
Goldstein-Price's function described by equation:

$$f(x,y)=\left[1+(x+y+1)^2\cdot\left(19-14x+3x^2-14y+6xy+3y^2\right)\right]\cdot\left[30+(2x-3y)^2\cdot\left(18-32x+12x^2+48y-36xy+27y^2\right)\right]. \quad (1)$$

Michalewicz's function:

$$f(x,y)=-\left(\sin(y)\sin^{20}\left(\frac{2y^2}{\pi}\right)+\sin(x)\sin^{20}\left(\frac{x^2}{\pi}\right)\right). \quad (2)$$

Analyzed functions are characterized by complex shapes with typical optimization traps (e.g. local minima, long valleys, flat horizontal surfaces, etc.), which cause, the classical optimization procedures fail. The number of the data of a training set for the ANN metamodel should be as small as possible, because of high costs of the objective function evaluations. The initial training data set had 1024 records and was subsequently decreased to 32 records (1024 – 512 – 256 – 128 – 64 – 32). The input data contained vectors of parameters values, which were generated randomly inside limited search space. The values of the considered objective function were calculated analytically. The MLP model of Qnet2000 ANN simulator was used. Different network topologies were tested and the optimal one of the 2-5-1 structure was chosen. The hidden and output neurons had sigmoidal transfer functions. Despite the influence on quality of objective function approximation, decreasing number of training data records did not influence significantly the ANN predicted positions of the global minima in all considered cases (see Table 1). The results of the ANN approximation of analyzed objective functions are presented in Figures 4 and 5. It is seen that in the case of the training based on the 32 records the ANN approximation lost some of the features of the objective functions (e.g. local minima), but the global minimum and its neighbourhood is represented with a sufficient accuracy.

It is seen in Figure 4, that accuracy of the ANN predictions of a global minimum is low after the initial training. According to described optimization algorithm, the quality of the objective function representation increased and a localization of predicted global improved after six iterations.

In case of objective function (2), the initial training gave very good prediction of the localization of the global minimum (see Figure 5). Although there are some discrepancies between the predicted shape of the function, it does not influence the optimization

TABLE 1

Results of the ANN approximation of the test functions

Function	x^*_{NN}	y^*_{NN}	f^*_{NN}	x^*	y^*	f^*	Training error	f^* fitting error	Nb. of trainings
(1)	0.0	-1.03	3.251	0.0	-1.0	3.0	0.012	0.08	6
(2)	2.1	1.57	-1.701	2.198	1.57	-1.8	0.016	0.05	3

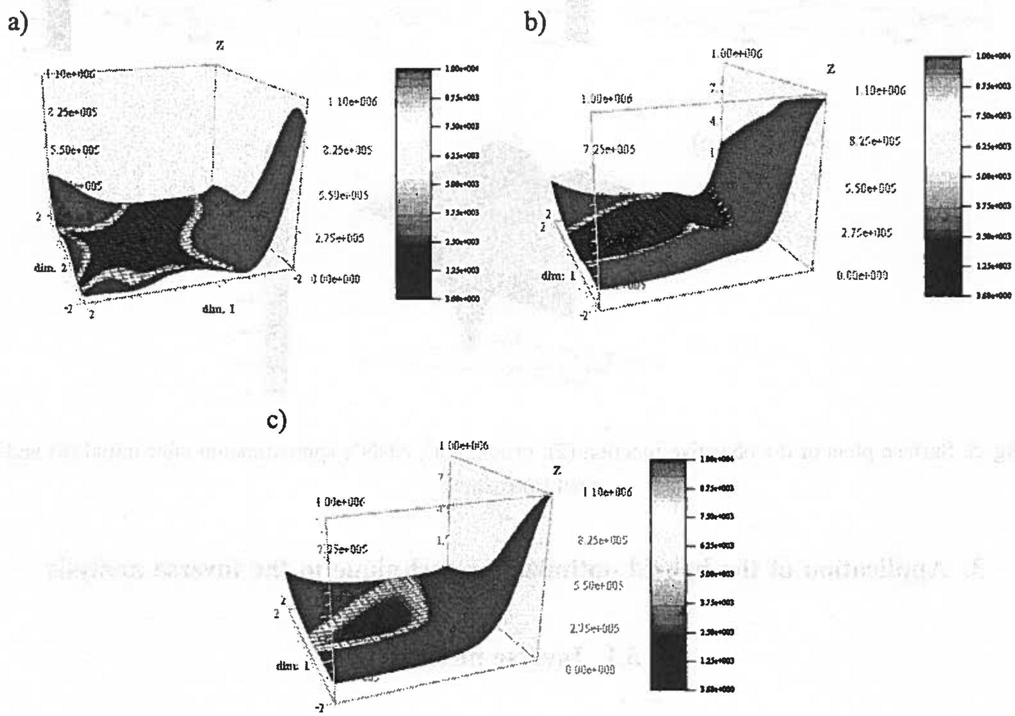

Fig. 4. Surface plots of the objective function (1): original (a), ANN's approximation after initial (b) and final (c) training

procedure. The optimization algorithm converged after 2 retrainings of the ANN meta-model.

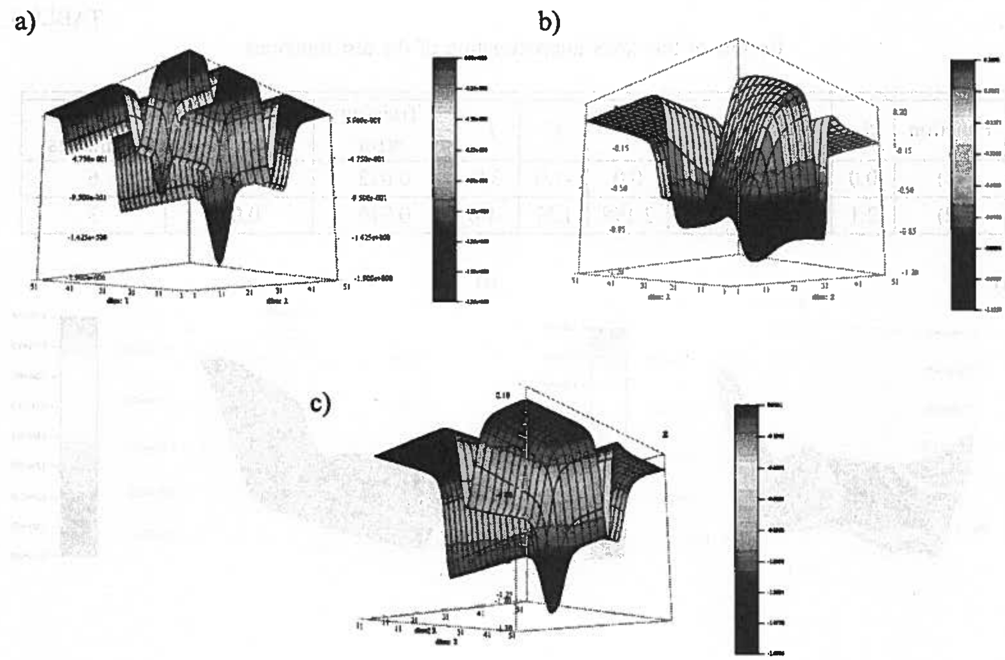

Fig. 5. Surface plots of the objective function (2): original (a), ANN's approximation after initial (b) and final (c) training

3. Application of the hybrid optimization technique to the inverse analysis

3.1. Inverse method

The precise description of the boundary conditions and rheological properties of material is the fundamental point of the simulation of the material processing. Rheological behaviour of deformed materials is usually described by equations with parameters evaluated experimentally in plastometric tests. Due to strong non-linearities and inhomogeneities of the deformation process, the adequate evaluation of parameters of equations describing material rheology and boundary conditions is very difficult. As the result of improper estimation of these parameters, discrepancies between the calculated and measured values of the process output data are observed. The inverse technique [8-14] can improve the evaluation of these parameters. The main part of the inverse method is an optimization technique in which the distance between the measured and calculated values of analysed process features forms the optimization objective function. Obtained optimal values can next be used in the simulation of the forming processes. The algorithm of the inverse analysis is presented in Figure 6. Generally, the inverse analysis requires long computation time and a selection of the best optimization strategy is still a difficult problem. The presented hybrid optimization technique can be very useful in the inverse analysis and can decrease the computation time.

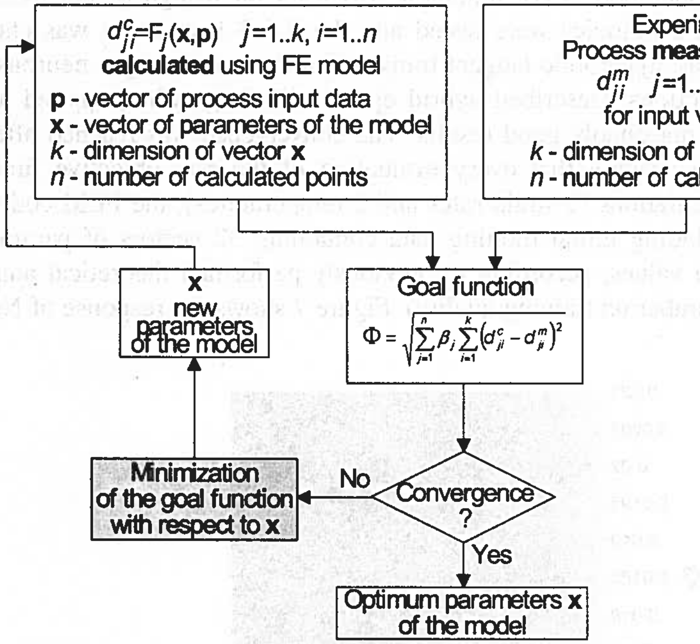

Fig. 6. Algorithm of the inverse analysis [9]

3.2. Results of the optimization problem

Since common Inverse problems are complex (large number of design variables describing materials rheology and boundary conditions, high sensitivity of measured data to process conditions), there are no methods efficient enough for solving optimization problems in reasonably short time and with satisfactory accuracy. Proposed hybrid optimization technique, presented also in [15], was validated in the inverse analysis of rheological parameters describing flow behaviour of microalloyed Nb steel during hot compression test [16]. The chemical composition of analysed material was as follows: 0.17%C, 0.43%Mn, 0.35%Si, 0.03%Cr, 0.03%Nb. A number of compression tests of cylindrical samples (ϕ10mm×12mm) was performed with three strain rates: 0.1, 1 and 10 s^{-1} for the temperature range of 550-650°C (ferritic phase zone). Hot processing of materials requires well parameterized equation for proper description of material behaviour for wide range of temperatures, strains and strain rates. The stress strain curve used in simulations was described by the following equation [7, 13]:

$$\sigma_f = \sqrt{3}\left\{K_0\varepsilon^n \exp(-R_0\varepsilon)\exp\left(\frac{\beta}{T}\right) + [1-\exp(-R_0\varepsilon)]\,K_s\exp\left(\frac{\beta_s}{T}\right)\right\}\left(\sqrt{3}\dot{\varepsilon}\right)^m, \quad (3)$$

where: σ_f — flow stress, MPa; ε — strain; $\dot{\varepsilon}$ — strain rate, s^{-1}; T — temperature, K; m, n, R_0, K_0, K_s, β, β_s — coefficients.

The MLP model of Qnet2000 ANN simulator was used for design of the metamodel. Different network topologies were tested and the 7-5-3-1 structure was chosen. The hidden neurons had hyperbolic tangent transfer functions and output neurons had sigmoidal transfer functions. Described hybrid optimization algorithm, applied to the inverse analysis, gave reasonably good results. The convergence was reached after 27 iterations. Taking into account that every evaluation of the real objective function consists of 9 FEM simulations (3 strain rates and 3 temperatures), the FEM code was called 531 times (including initial training data containing 32 vectors of parameters and objective function values, according to previously performed theoretical analysis of influence of data number on training quality). Figure 7 shows the response of Neural

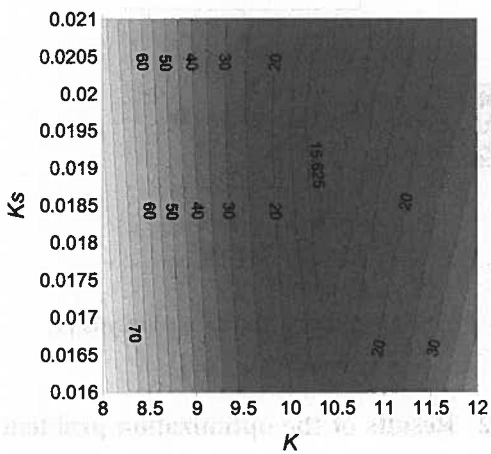

Fig. 7. Surface plot of ANN's response

Network for changes of parameters K and K_s (other parameters remain constant with its optimal values calculated in the last iteration). The search for minimum was based on Monte-Carlo method in which 1024 randomly generated points were distributed at the neighbourhood of previously found minimum.

TABLE 2

Optimal values of the equation (4) parameters

parameter	K_0	n	β	K_s	β	m	R_0
	10.58	0.13	2789	0.019	5950	0.063	0.47

Optimal values of the parameters of equation (4) are gathered in Table 2. Comparison between loads, measured and calcuated with optimal values of flow stress equation (4) parameters, are presented in Figure 8. Very good agreement was observed.

However, small discrepancies are seen for the highest strain rate values. It can be a result of a slight softening phenomenon appearance, caused by high strain rate induced temperature growth.

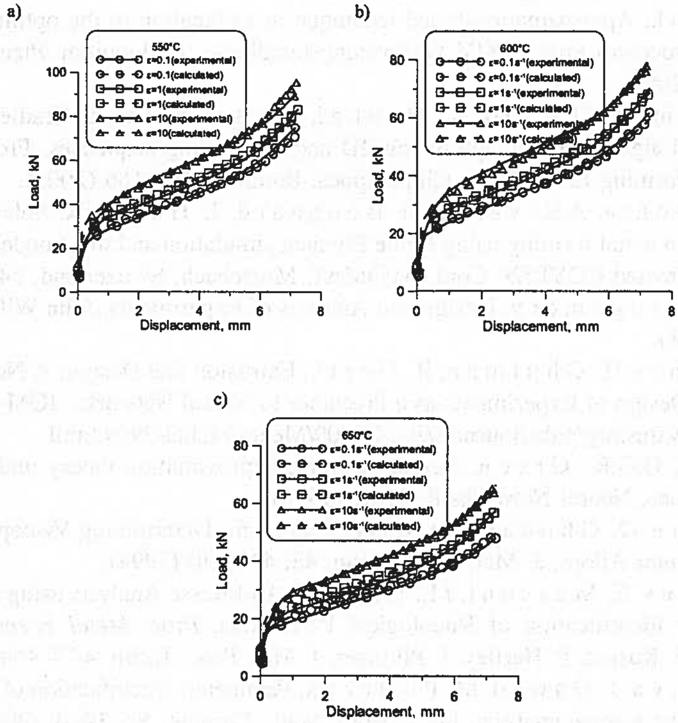

Fig. 8. Comparison of loads monitored during experiment (solid lines) and simulation (dashed lines) for different strain rates and temperatures: 550°C (a), 600°C (b), 650°C (c), respectively

4. Summary

Commonly used classical optimization algorithms are not effective enough in the case of complex inverse analysis, where it is necessary to deal with the objective function of many design variables. They require many objective function evaluations during the optimization procedure, and often do not give a good convergence.

The paper presents the hybrid optimization technique, which can be useful in materials processing applications. The examples of its applications to the inverse analysis are presented. Proposed optimization method allows the significant decrease of the computation time of the inverse analysis without losing the quality of obtained results.

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