Publishing House
AKAPIT

COMPUTER METHODS IN MATERIALS SCIENCE

Informatyka w Technologii Materiałów

Vol. 11, 2011, No. 4

IDENTIFICATION OF MATERIAL PROPERTIES OF THE DP STEEL BASED ON PLASTOMETRIC TESTS AND ON INDUSTRIAL HOT STRIP ROLLING

ŁUKASZ SZTANGRET*, DANUTA SZELIGA, JAN KUSIAK, MACIEJ PIETRZYK

AGH University of Science and Technology, al. Mickiewicza 30, 30-059 Krakow, Poland
**Corresponding author: szt@agh.edu.pl*

Abstract

The objective of the paper was increasing the efficiency of the material model identification. An attempt to determine the coefficients of the model on the basis of industrial data was made. It is suggested that substituting the FE simulation of the process by a fast metamodel in the inverse analysis should make this analysis much faster. Continuous hot strip rolling process was selected as an object. Artificial neural network was used as a metamodel of this process and good results were obtained in testing the network. Possibility of application of the metamodel of the rolling process for identification of the material model on the basis of measurements of loads during rolling process was the main objective of the paper. The inverse problem was formulated. Due to the lack of the industrial data in a wide range of temperatures and strain rates, in the first approach the experimental data (forces in rolling) were generated by the FE model. The tests of the inverse analysis for the rolling process were performed and good results were obtained. It is shown in the paper that the application of the metamodelling allows for making inverse analysis very fast and, in consequence, any optimization technique can be applied. It is also confirmed that the flow stress model can be identified for the data obtained directly from the industrial rolling process. Possibility of application of the metamodel to the on-line control of the rolling process is demonstrated as well.

Key words: flow stress model, identification, metamodel, DP steel, hot strip rolling

1. INTRODUCTION

Identification of material models is still a challenge for researchers. Inhomogeneity of strains, stresses and temperatures in a majority of experimental tests, which are performed to identify coefficients in material models, is the main reason of difficulties with interpretation of results of these tests. Inverse analysis is commonly used to overcome these difficulties. Application of this analysis to plastometric tests is well researched, eg. Forestier et al. (2002). The authors of the present paper developed an algorithm and computer code (Szeliga et al., 2006) for inverse calculations.

The motivations for the present work are twofold. High computing costs of the inverse analysis is the first inspiration. Searching for the minimum of the objective function requires a large number of runs of the FE code. In consequence, the optimization procedure is often simplified and only certain non-gradient techniques can be used. The costs of the plastometric tests are the second motivation. The tests for identification of rheological models for hot forming require advanced thermomechanical simulator with a precise control of temperature during the test, eg. Gleeble simulator. Preparation of samples and performing the tests is expensive as well. The general objectives of the present work were formulated with the above observations in mind. A sugges-

 ISSN 1641-8581

tion was made that substituting the FE solution by a fast metamodel in the inverse analysis should make this analysis much more efficient. Primary tests of this approach gave promising results (Sztangret et al., 2011a). In the present paper, this approach was used more extensively. The fact that there often exists the necessity for determining the flow stress model without performing plastometric tests was inspiration for the second objective of the present work. The possibility of identification of the material model on the basis of measurements of loads during rolling was evaluated. The metamodel of the strip rolling process was developed and the inverse problem was formulated. In the first approach, the experimental data (forces during rolling) were generated by the model. The results obtained in Szeliga et al. (2011a) from the plastometric tests for the same steel are used for comparison.

2. EXPERIMENT

The material was the DP steel containing 0.11%C, 1.45%Mn, 0.19%Si, 0.27%Cr, 0.04%Cu, 0.042%Al, 0.013%Ti, 0.004%N. This steel has been widely investigated by the Authors as far as phase transformations after rolling were considered (Pietrzyk et al., 2009; Pietrzyk et al., 2010).

2.1. Plastometric tests

Plastometric tests for this steel were made on the Gleeble 3800 simulator in the Institute for Ferrous Metallurgy in Gliwice, Poland. Cylindrical samples measuring Φ10×12 mm were compressed to the strain of 1 with strain rates 1, 10 and 50 s^{-1} and temperatures 950, 1000, 1100, 1200 and 1230°C. Loads and temperatures were monitored during the tests. A selected example of the monitored results for loads is shown in figure 1.

Measurements of the temperature, which are not presented here, show that this temperature varies during the tests. It increases first due to deformation heating. The control system turns off the electric power and temperature starts to drop. All these variations of the temperature, as well as the effect of friction, are considered when inverse analysis is applied to the interpretation of results of plastometric tests.

2.2. Industrial rolling

Measurements of loads during industrial hot strip rolling process were supposed to be the second experiment. The hot strip mill consisted of one reverse roughing mill and 6 continuous finishing stands was considered. Schematic illustration of the finishing train of this mill is shown in figure 2. The main parameters of the mill are: work roll diameter D = 780 mm (stands 1-4) and D = 700 mm (stands 5,6), distance between stands d = 5 m. The model calculates rolling loads and temperatures in all stands. Apart from this, finishing rolling temperature T_f and coiling temperature T_c are calculated. The latter two temperatures were not considered in the present work.

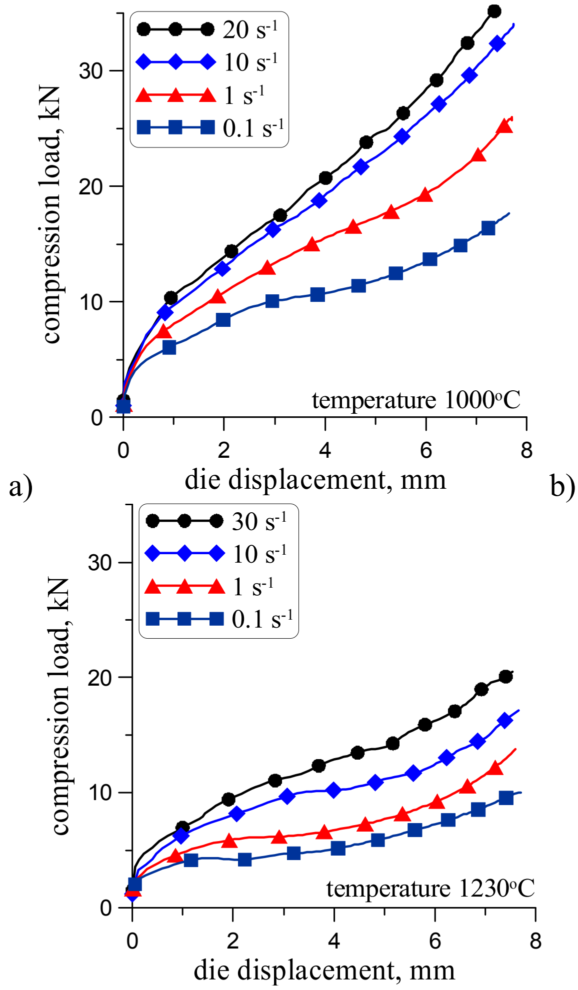

Fig. 1. *Selected example of the load measurements, temperatures 1000°C (a) and 1230°C (b).*

Due to the lack of the access to the industrial data for the DP steel in a wide range of temperatures and strain rates, the experimental results for identifications purposes were generated by the model. These results were used in the inverse analysis. The objective was validation and testing of the inverse algorithm based on the industrial rolling data.

Fig. 2. Schematic illustration of the considered finishing train of the hot strip mill.

3. MODELS

3.1. Flow stress model

The flow stress equation proposed by Hansel and Spittel was used (Hansel & Spittel, 1979):

$$\sigma_p = A\varepsilon^n \exp(-q\varepsilon)\dot{\varepsilon}^m \exp(-BT) \tag{1}$$

where: σ_p – flow stress, ε - strain, $\dot{\varepsilon}$ - strain rate, A, n, q, m and B - coefficients, which have to be determined using inverse analysis.

3.2. Finite element model

Finite element model was used to generate data for development of the metamodel of the hot strip mill. This model is based on the rigid-plastic thermo-mechanical finite element solution proposed in Kobayashi et al. (1989). Detailed description of the algorithm and the program, which was used in this work, is given by Pietrzyk (2000). The solution assumes that the material fulfills Huber-Mises yield criterion and associated Levy-Mises flow rule. The velocity field is calculated by searching for a minimum of the power functional:

$$J = \int_V (\sigma_i \dot{\varepsilon}_i + \lambda \dot{\varepsilon}_V) dV - \int_S \mathbf{f}^T \mathbf{v}_s dS \tag{2}$$

where σ_i - effective stress, which is equal to the flow stress σ_p, $\dot{\varepsilon}_i$ - effective strain rate, V - volume, S - contact surface, $\dot{\varepsilon}_V$ - volumetric strain rate, λ is Lagrange multiplier, $\mathbf{f}$ is vector of boundary tractions, $\mathbf{v}_s$ - vector of slip velocities between the roll and the strip.

In the flow theory of plasticity, strain rates are related to stresses by the Levy-Mises flow rule:

$$\boldsymbol{\sigma} = \frac{2}{3} \frac{\sigma_i}{\dot{\varepsilon}_i} \dot{\boldsymbol{\varepsilon}} \tag{3}$$

where $\boldsymbol{\sigma}$ is vector of stresses, $\dot{\boldsymbol{\varepsilon}}$ is vector of strain rates.

The friction model suggested by Chen and Kobayashi (Chen & Kobayashi 1978; Kobayashi et al., 1989; Lenard et al., 1999) was used in the present work:

$$\tau = \mu \sigma_p \operatorname{arctg} \frac{\Delta v}{c} \tag{4}$$

where μ - friction coefficient, Δv - relative slip velocity, c - constant, few orders smaller than an average slip velocity. The value of $c = 10^{-3}$ was assumed in the present work

The flow formulation, which is the basis of the mechanical model, is coupled with the finite element solution of the Fourier heat transfer equation:

$$\nabla \cdot k \nabla T + Q = c_p \rho \frac{\partial T}{\partial t} \tag{5}$$

where: k - conductivity, Q - heat generation rate due to deformation work, c_p - specific heat, ρ - density, T - temperature, t - time.

The following boundary conditions were used in the thermal solution:

$$k \frac{\partial T}{\partial \mathbf{n}} = q + h(T_a - T) \tag{6}$$

where: h - heat transfer coefficient, T_a - surrounding temperature or tool temperature, q - heat flux due to friction, $\mathbf{n}$ - unit vector normal to the surface.

Discretization of the problem is performed in a typical finite element manner and simulations of hot rolling can be performed. The presented model allows for determining the temperature distribution in the strip, accounting for the deformation heating, heating due to friction and heat transfer to the rolls and to the surrounding atmosphere. Mechanical parameters, including stresses, strains, loads and torques, were calculated by the FE model as well.

A proper definition of the boundary conditions is crucial for the accuracy of the model. The boundary conditions included friction coefficient of 0.25 in the mechanical part and the heat transfer coefficient of 50 kW/m^{2}K (Lenard et al., 1999) for the contact with rolls in the thermal part. Typical convection-radiation equation was used for cooling in the air.

Six stand continuous hot strip rolling mill was selected as an example in the present work.

3.3. Inverse algorithm

Details of the inverse algorithm developed by the Authors are given in Szeliga et al. (2006) and are not repeated here. Briefly, the coefficients in the flow stress equation (1) are determined by searching for a minimum of the objective function defined as Euclid norm between measured and predicted loads in the rolling process:

$$\Phi = \sqrt{\frac{1}{Npt}\sum_{i=1}^{Npt}\left[\frac{1}{Nps}\sum_{j=1}^{Nps}\left(\frac{F_{cji}(\mathbf{x},\mathbf{p}_i)-F_{mji}}{F_{mji}}\right)^2\right]} \quad (7)$$

where: F_{mij}, F_{cij} - measured and calculated loads, Nps – number of stands, Npt - number of tests, $\mathbf{p}$ - vector of process parameters (strain rates, temperatures), $\mathbf{x} = \{A, n, q, m, B\}$ - vector of coefficients in the flow stress model.

The direct problem model is based on the thermal-mechanical finite element program described briefly in section 3.2, see Pietrzyk (2000), Lenard et al. (1999) for details.

3.4. Metamodel

As FE method is commonly used as a direct problem model, long computing times are necessary to determine the values of the objective function. Even if a simple FE model with stationary solution and coarse mesh is used in simulations of metal flow in rolling, the time necessary to calculate one pass is about 2-3 mins. Due to the tact that at least 54 passes have to be calculated to determine one value of the objective function in rolling, the decision was made to search for alternative models which could accelerate optimization. The application of the metamodel is such an alternative. According to Kusiak et al. (2009), metamodel of the considered process or phenomenon is a certain abstraction created on the basis of the lower level model developed using mathematical techniques. Thus, any approximation of the basic model, which gives reasonably realistic description of the process, can be considered a metamodel. Metamodel allows for significant decrease of the computing time.

Various techniques can be used to build metamodels. Artificial intelligence methods, in particular artificial neural networks, are the most commonly used. When the training data set is large enough, the artificial neural network is capable to describe even very complex relationships. The cost of computations for strip rolling is not so high, therefore, application of the ANN is efficient. Contrary, when costs of computations of one set of data are high, other Metamodelling techniques should be searched. Examples of such situation are presented in Sztangret et al. (2011b), where response surface method was used in optimization of forging of crank shafts. Computing costs for that process are about 2 orders of magnitude higher comparing with flat rolling.

The MLP (Multi Layer Perceptron) was used in the present work. This network is built from neurons located in layers. The first layer is called input layer, the last is called output layer, and all remaining are called hidden layers. A single neuron model is composed of summation and activation blocks. Input signals, multiplied by corresponding weight parameters are added together in first block and next transformed by the activation function in the second one. Designing of the artificial neural network consists of the three steps: designing of the structure, training using the training data set and testing using the testing data set. A detailed description of the neural networks can be found in Bishop (2006), Tadeusiewicz (1993).

Assuming certain standardization of the hot rolling process, metamodel of that process based on the artificial neural network was developed. The following input parameters were selected as variables:

- Rolling conditions: entry temperature T, exit velocity v, entry strip thickness h_0 and thickness after all passes $h_1 - h_6$.
- Coefficients in equation (1).

Training and testing data sets should be generated by the FE code (Pietrzyk, 2000; Lenard et al., 1999). To decrease the computation costs, the two step approach to training the network was proposed. In the first step, the part of the rolling process model was considered. This was the relation between the average pressure in rolling and the flow stress of the rolled material. This model follows the idea of Sims (1954), who introduced coefficient Q representing average pressure-to-flow stress ratio ($Q = p_{av}/a\sigma_p$, where $a = 2/\sqrt{3}$, p_{av} – average pressure, σ_p – flow stress). The $\xi = \mu/\Delta$ ratio was introduced as an additional variable, where Δ is the shape factor defined as h_{av}/l_d, h_{av} is an average thickness, l_d is length of the arc of contact. Several FE simulations were made for various process parameters and it was found by Szeliga et al. (2011a) that the relationship between Q and $\xi = \mu/\Delta$ is linear for a wide range of strip thickness and reduction. In consequence, the following equation was obtained by approximation of results of the FE simulations:

$$F = \sigma_p l_d w\left(1 + 0.572\frac{\mu}{\Delta}\right) \quad (8)$$

where: F – rolling force, w – width of the strip.

Thus, the approach based on equation (8) was used as the mechanical part of the rolling model. One dimensional finite element solution was used in calculations of temperatures. This approach was successfully applied in Szeliga et al. (2011b) to the laboratory pilot hot strip mill. The output parameters for this model were values of the rolling forces in all passes. This model was used in the present work to generate training and testing data for the ANN metamodel.

3.5. Training of the metamodel

The metamodel consists of six different artificial neural networks, each one used in prediction of loads at one stand. The typical MLP neural network was trained using the supervised learning methods, which requires an appropriately large training data set. Thus, the data set of 10 000 records was used to train the model. The data set was divided into two separated subsets dedicated to training (90%) and testing (10%). A root mean square error (RMS) was used as a measure of the accuracy of each network. Several tests were performed to adjust optimal topologies of the networks used in metamodel. The topologies as well as errors and activation functions are presented in table 1.

Table 1. *Neural networks metamodels - RMS error values, topologies and activation functions.*

Stand no.	RMS error [%]	Topology	Activation function (input layer – hidden layer)
1	0.26	14-30-1	tansig – tansig
2	0.46	14-28-1	tansig – logsig
3	0.81	14-28-1	tansig – tansig
4	0.46	14-15-1	logsig – logsig
5	0.51	14-11-1	tansig – tansig
6	1.31	14-22-1	logsig – logsig

4. MODEL IDENTIFICATION AND VALIDATION

4.1. conventional inverse analysis based on compression tests

Conventional inverse analysis of plastometric tests with the FE code as direct problem model was performed first. The inverse algorithm described by Szeliga et al. (2006) was used. The results were obtained in the form of a stress-strain relationship given in a tabular form (see figure 3) and as coefficients in equation (1), see table 2.

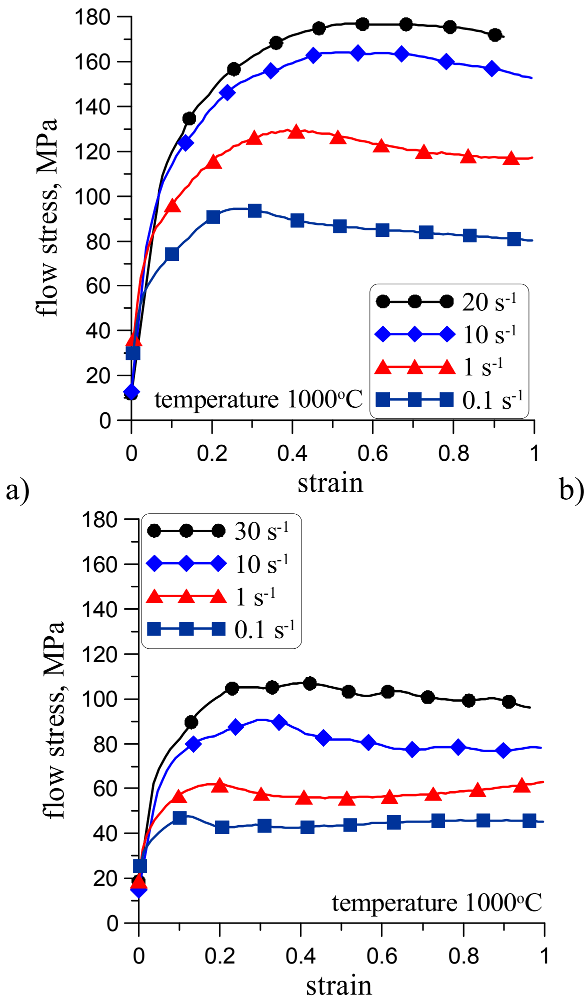

Fig. 3. *Selected plots of the flow stress as a function of strain determined using the inverse analysis of the plastometric tests.*

4.2. Inverse analysis based on hot strip rolling

Schematic illustration of the inverse approach based on the metamodel of the finishing train of the hot strip mill is shown in figure 4. As it has been mentioned, it was not possible to collect the experimental data for the industrial rolling mill in a wide range of temperatures and strain rates. Therefore, these data were generated by the developed model of the hot strip mill. Nine rolling schedules were simulated, with initial temperatures 950°C, 1000°C and 1050°C and with the velocities in the last stand 6, 8 and 10 m/s. Rolling forces in 6 passes in the considered rolling schedule 40 → 19.2 → 12.8 → 9.5 → 7.0 → 5.7 → 4.4 mm were used as the experimental data in the inverse analysis.

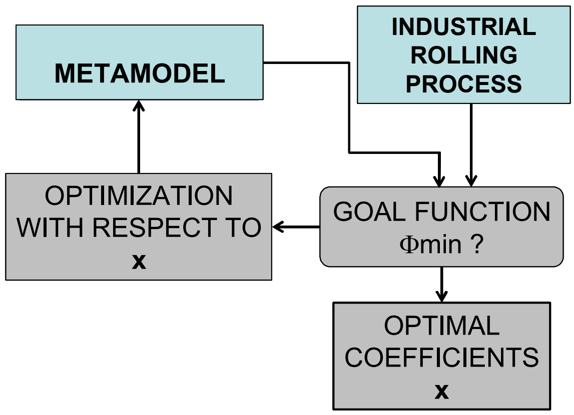

Fig. 4. *Schematic illustration of the inverse analysis based on the metamodel of the finishing train of the hot strip mill.*

The objective function was defined by equation (7). The ANN metamodel was used as a direct problem model, see figure 4. In consequence, time of calculation of the objective function (7) decreased significantly and the application of an arbitrary optimization method was possible. The selection of the method depends on the character of the objective function and on the availability of additional information about this function. Conventional gradient and non-gradient methods are not effective in the case of multimodal objective functions, which have several local minima. They are usually stacked in the first encountered local minimum. Apart from that, the gradient methods require calculation of the derivatives of the objective function. Thus, non-deterministic algorithms were applied in the present work. The bio-inspired methods (Kusiak et al., 2009) were mostly considered. Although they do not guarantee finding the global minimum, they are robust to problems characteristic for the multimodal functions and they search for the minimum using values of the objective function, not derivatives. The following algorithms were used: Genetic Algorithms (GA), Evolutionary Algorithms (EA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Immune System (AIS) and Simulated Annealing (SA) methods. PSO method modified by the Authors was applied, as well. The proposed modification is based on coupling it with the sensitivity analysis, which allows dynamic control of the particles swarm and better convergence of the method.

Performed optimization yielded the values of coefficients in equation (1) given in the second row of table 2. The final (optimal) value of the objective function, which can be treated as the accuracy of the solution was $\Phi = 0.0868$ for plastometric tests and $\Phi = 0.0115$ for the inverse analysis of the rolling process. It should be emphasized again, however, that the experimental data for the rolling process were generated using coefficients obtained in the plastometric tests.

Table 2. *Coefficients of equation (1) obtained using inverse analysis of the plastometric tests and the rolling process.*

test	A	n	q	m	B	Φ
plastometric	3255.3	0.19	0.28335	0.119	3.0067×10^{-3}	0.0868
rolling	3480.2	0.2033	0.2766	0.1142	3.0513×10^{-3}	0.0115

The analysis of the results in table 2 shows that slight differences in the values of coefficients exist between those obtained from the plastometric tests and the rolling process. Therefore, comparison of the plots of function (1) with the two sets of coefficients in table 2 was made and the results are presented in figure 5. It can be seen that the shape of curves is similar.

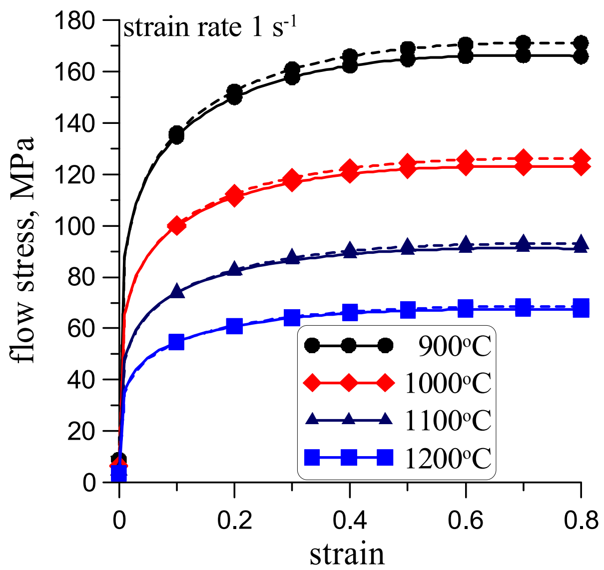

Fig. 5. *Plots of the flow stress calculated from equation (1) with coefficients in table 2, obtained from plastometric tests (solid lines) and from rolling tests (dotted lines).*

Additional evaluation of the accuracy of the identification based on the hot strip rolling process was made by the comparison of rolling loads calculated using the metamodel with the flow stress equation (1) with the two sets of coefficients in table 2. The rolling schedules for the 6 stand finishing train given in table 3 were considered in these tests and the results of the comparison are presented in table 4. The width of the strip was 1500 mm and the roll radius was 390 mm in the stands 1-4 and 350 mm in the last two stands. It is visible that a very good agreement between forces calculated for the two sets of coefficients in table 3 was obtained. It is also well seen in figure 6, where distinction between the two sets of results is difficult.

The results in figure 5 and in table 4 show that very good agreement between the results for the two sets of coefficients in equation (1) was obtained. It questions the uniqueness of the inverse solution, which is probably due to mathematical form of equation (1). This equation allows for obtaining similar results for various combinations of coefficients A, n and q responsible for the strain sensitivity, which is the reason of the lack of uniqueness of the solution. This problem needs a further investigation.

Table 3. *Rolling schedules considered in the numerical tests.*

Test no.	T_0 °C	v_6 m/s	h_0 mm	h_1 mm	h_2 mm	h_3 mm	h_4 mm	h_5 mm	h_6 mm
1	1040	6.3	40	19.2	12.8	9.5	7	5.7	4.4
2	1025	6.8	40	19.2	12	9	7	5.7	4.4
3	980	7.1	40	19.2	13	10	7	5.5	4.4
4	960	8.5	40	19.2	13	9	6.8	5.8	4.4
5	1040	9.1	40	19.2	12.8	9.5	7.1	5.6	4.4
6	1025	9.9	40	19.2	12.2	9	6.9	5.6	4.4
7	980	9.5	40	19.2	12.8	10	6.8	5.5	4.4
8	960	6.5	40	19.2	12.6	9.5	6.8	5.8	4.4

Table 4. *Rolling force (F) calculated using metamodel with the flow stress equation (1) with the sets of coefficients determined from the Gleeble tests (top) and from the rolling tests (bottom).*

Test no.	F_1 MN	F_2 MN	F_3 MN	F_4 MN	F_5 MN	F_6 MN
1	28.29	15.53	11.42	11.42	7.35	9.03
	28.43	15.47	11.33	11.31	7.25	8.91
2	29.89	18.38	11.37	9.87	7.6	9.3
	30.04	18.33	11.27	9.76	7.49	9.17
3	34.47	17.93	12.1	15.39	9.74	8.95
	34.71	17.89	12.02	15.28	9.62	8.82
4	37.45	19.23	17.15	12.84	7.04	11.42
	37.71	19.19	17.05	12.72	6.93	11.27
5	29.57	15.97	11.59	10.98	8.3	8.29
	29.66	15.88	11.48	10.85	8.18	8.15
6	31.27	18.39	12.18	10.43	7.65	8.57
	31.38	18.3	12.06	10.29	7.52	8.43
7	35.7	18.96	11.61	16.58	8.63	8.87
	35.9	18.9	11.51	16.44	8.5	8.73
8	36.25	20.07	13.42	15.11	7.05	11.53
	36.55	20.05	13.34	15	6.96	11.4

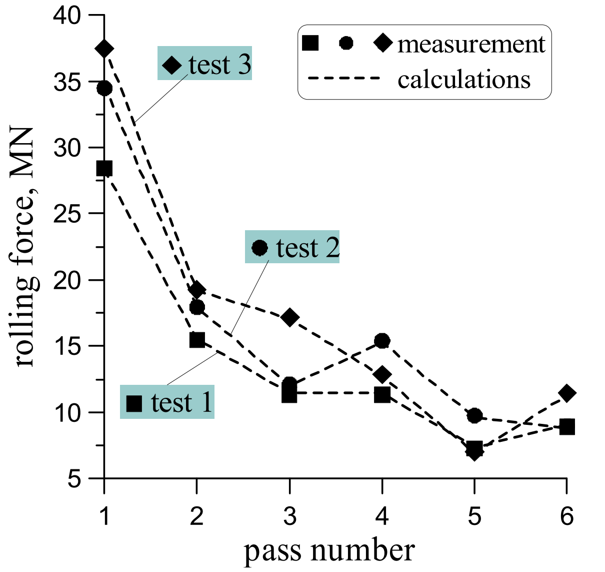

Fig. 6. *Rolling force calculated using metamodel with the flow stress equation (1) with the sets of coefficients determined from the Gleeble tests (filled symbols) and from the rolling tests (dotted lines).*

4.3. Application to the on-line control

The presented method of identification of the flow stress model on the basis of measurements of loads in the rolling process is an alternative for the plastometric tests. Capabilities of this method have been confirmed. Conducted analysis shows that this method has some advantages but also several disadvantages. The solution is very sensitive to errors in temperature calculations. One dimensional FE model, which was used in the present work, is accurate and reasonably fast, calculations of the whole process take less than 20 s. However, this time is too long for the on-line control of the hot strip rolling process. A faster temperature model can be based on artificial neural network, which will be the subject of the future work.

Problems with obtaining data for a wide range of temperatures and velocities are the next disadvantage of the presented approach, which has to be eliminated. The range of strain rates and temperatures in the available industrial experimental data is too narrow. Temperatures in the considered hot strip rolling processes are within the range 1050-850°C, but they are not uniformly distributed in the temperature-strain rate space of the data. Higher temperatures are connected with low strain rates and vice versa. In consequence, there is a lack of the data for certain combinations of the temperature and the strain rate. Finally, due to reasonable low strains in the hot strip rolling, the effect of the dynamic recrystallization on the flow stress is difficult to be evaluated.

Possibility of fast identification of the model during production, without performing plastometric tests, is the main advantage of the presented approach. Apart from this, the approach can be used for adaptive updating of the flow stress model in the on-line control of the strip rolling process (Szeliga et al., 2011a). The application of the adaptive procedure is an efficient method of improvement of the accuracy of the process control. The coefficients in the flow stress equation are corrected during the on-line work, basing on the current measurements of the loads, see for example Svietlichnyj and Pietrzyk (1999). Such an adaptation can be based on the coefficients determined using the inverse method, which is described above. In this approach, the parameters in equation (1) are substituted by their new values, using the digital filter rule:

$$\mathbf{x}_{av,i} = (1-\varsigma)\mathbf{x}_{av,i-1} + \varsigma \mathbf{x}_i \tag{9}$$

where: $\mathbf{x}_{av}$ - current, average values of parameters $\{A, n, q, m, B\}$, $\mathbf{x}$ - values of these parameters calculated using inverse analysis for the recent measurements, i - iteration number, ζ - inertia coefficient ($0 < \zeta < 1$).

5. CONCLUSIONS

Metamodel of the hot strip rolling process was developed. The tests of the inverse analysis with the metamodel for the hot strip rolling process were performed in the paper and very good results were obtained when experimental data were generated by the model. The following conclusions were drawn:

- Identification of the flow stress model on the basis of the hot strip rolling data is possible, but, due to narrow range of temperatures and strain rates, the inverse analysis based on these data would be probably difficult.
- The agreement between flow stresses and rolling forces calculated for the two sets of coefficients in the flow stress model was very good. One set was obtained from the Gleeble tests and the second from the rolling tests. It has to be remembered that, due to the lack of the experimental data for strip rolling, this data was generated by the model.
- Values of the coefficients responsible for the strain sensitivity in the flow stress equation were different in the two sets. It questions the uniqueness of the inverse solution, which is due to the mathematical form of the flow stress equation proposed by Hansel and Spittel (1979).
- Developed technique can be useful as an adaptive model in the on-line control of the hot strip rolling process.

Summarizing this work, it was shown that application of metamodelling and inverse analysis allows for fast identification of the coefficients in the flow stress equation on the basis of the data for the industrial process.

ACKNOWLEDGEMENT

Financial assistance of the NCN, project no. N508 590 139, is acknowledged.

REFERENCES

Bishop, C. M., 2006, *Pattern Recognition and Machine Learning*, Springer, New York.

Chen, C.C., Kobayashi, S., 1978, Rigid Plastic Finite Element Analysis of Ring Compression, In: *Application of Numerical Methods to Forming Processes*, ASME, ADM 28, 163-174.

Forestier, R., Massoni, E., Chastel, Y., 2002, Estimation of constitutive parameters using an inverse method coupled to a 3D finite element software, *J. Mat. Proc. Techn.*, 125, 594-601.

Hansel, A., Spittel, T., 1979, *Kraft- und Arbeitsbedarf Bildsamer Formgebungs-verfahren*, VEB Deutscher Verlag fur Grundstoffindustrie, Leipzig.

Kobayashi, S., Oh, S.I., Altan, T., 1989, *Metal Forming and the Finite Element Method*, Oxford University Press, New York, Oxford.

Kusiak, J., Danielewska–Tułecka, A., Oprycha, P., 2009, *Optymalizacja: wybrane metody z przykładami zastosowań*, PWN, Warszawa, (in Polish).

Lenard, J.G., Pietrzyk, M., Cser, L., 1999, *Mathematical and physical simulation of the properties of hot rolled products*, Elsevier, Amsterdam.

Pietrzyk, M., 2000, Finite element simulation of large plastic deformation, *J. Mat. Proc. Techn.*, 106, 223-229.

Pietrzyk, M., Kusiak, J., Kuziak, R., Zalecki, W., 2009, Optimization of laminar cooling of hot rolled DP steels, *Proc. XXVIII Verformungskundliches Kolloquium*, Planneralm, 285-294.

Pietrzyk, M., Madej, Ł., Rauch, Ł., Gołąb, R., 2010, Multiscale modelling of microstructure evolution during laminar cooling of hot rolled DP steel, *Archives of Civil and Mechanical Engineering*, 10, 57-67.

Sims, R.B., 1954, The calculation of roll force and torque in hot rolling mills, *Proc. Inst. Mech. Eng.*, 168, 191-200.

Svietlichnyj, D., Pietrzyk, M., 1999, On-line model for control of hot plate rolling, eds, Beynon, J.H., Clark, M.T., Ingham, P., Kern, P., *Proc. Modelling of Metal Rolling Processes 3*, Waterson, K., London, 62-71.

Szeliga, D., Gawąd, J., Pietrzyk, M., 2006, Inverse analysis for identification of rheological and friction models in metal forming, *Comp. Meth. Appl. Mech. Eng.*, 195, 6778-6798.

Szeliga, D., Sztangret, Ł., Kusiak, J., Pietrzyk, M., 2011a, Two approaches to identification of the flow stress model – application of the metamodel, *Proc. XXX Verformungskundliches Kolloquium*, Planneralm, 109-114.

Szeliga, D., Graf, M., Kawalla, R., Pietrzyk, M., 2011b, Identification of material properties based on rolling process at 4-stand laboratory mill, *Proc. 14th ESAFORM Conf.*, Belfast (CD ROM).

Sztangret, Ł., Szeliga, D., Kusiak, J., Pietrzyk, M., 2011a, Identyfikacja modelu materiału w prawie konstytutywnym w oparciu o rozwiązanie odwrotne z metamodelem, *Mechanik*, 84, 32-36 (in Polish).

Sztangret, Ł., Milenin, A., Sztangret, M., Walczyk, W., Pietrzyk, M., Kusiak, J., 2011b, Computer aided design of the best TR forging technology for crank shafts, *Computer Methods in Materials Science*, 11, 237-242.

Tadeusiewicz, R., 1993, *Sieci neuronowe*, Akademicka Oficyna Wydawnicza RM, Warszawa, (in Polish).

IDENTYFIKACJA WŁASNOŚCI MATERIAŁOWYCH STALI DP W OPARCIU O PRÓBY PLASTOMETRYCZNE ORAZ WALCOWANIE BLACH NA GORĄCO

Streszczenie

Celem pracy była poprawa dokładności i skrócenie czasu identyfikacji parametrów modelu materiału. W pracy podjęta również została próba wyznaczenia współczynników modelu materiału w oparciu o dane przemysłowe. Zmodyfikowano algorytm obliczeń odwrotnych zastępując model MES znacznie szybszym metamodelem i redukując w ten sposób znacząco czas obliczeń. Jako proces przemysłowy wybrano walcowanie ciągłe blach na gorąco, natomiast metamodel został zbudowany w oparciu o sztuczne sieci neuronowe. Głównym celem pracy było sprawdzenie możliwości zastosowania metamodelu procesu walcowania do wyznaczania wartości sił występujących w tym procesie. Ze względu na brak pomiarów przemysłowych dla szerokiego zakresu zmian temperatury i prędkości walcowania, dane eksperymentalne zostały wygenerowane za pomocą modelu MES. Wyniki uzyskane z przeprowadzonej analizy odwrotnej procesu walcowania były bardzo zadawalające. Wykazano, że zastosowanie metamodelu pozawala na znaczne skrócenie czasu obliczeń odwrotnych, przez co możliwe jest stosowanie dowolnych metod optymalizacji. Potwierdzono, że parametry modelu płynięcia materiału można identyfikować w oparciu a dane przemysłowe uzyskane wprost z procesu walcowania. Przedstawiono również możliwość zastosowania aplikacji opartych o metamodel w sterowaniu on-line.

Submitted: December 05, 2011
Submitted in a revised form: December 12, 2011
Accepted: December 19, 2011