R. TURK, I. PERUŠ, M. KOVAČIČ, G. KUGLER, M. TERČELJ

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# GENETIC PROGRAMMING AND CAE NEURAL NETWORKS APPROACH FOR PREDICTION OF THE BENDING CAPABILITY OF ZnTiCu SHEETS

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Genetic programming (GP) and CAE NN analysis have been applied for the prediction of bending capability of rolled ZnTiCu alloy sheet. Investigation revealed that an analysis with CAE NN is faster than GP but less accurate for lower amount of data. Both methods enable good assessment of separate influencing parameters in the complex system.

*Key words:* rolling, ZnTiCu alloy, bending, genetic programming, CAE neural networks

**Primjena genetskog programiranja u CAE neuronskih mreža za prognozu izdržljivosti kod savijanja ZnTiCu traka.** Metode genetskog programiranja (GP) i CAE NN bile su upotrebljene za studij utjecaja izdržljivosti savijanja tankih ploča slitine ZnTiCu. Istraživanje je pokazalo da je CAE NN metoda brža od GP metode a istovremeno je manje precizna pri manjoj bazi podataka. Obje primenjene metode dobro vrednuju utjecaj parcijalnih komponenata kompleksnog sistema.

*Ključne riječi:* valjanje, ZnTiCu legure, savijanje, genetsko programiranje, CAE neuralne mreže

## INTRODUCTION

ZnTiCu (zinc-titan) sheets with approximately 0,1% Cu and 0,1% Ti content are very widely used in the construction industry for roof covering, gutters, drain pipes, facing linings, connections, window shelves, decorative elements on roofs, art products, etc. Data on the production technology of zinc-titan alloy sheet and on its forming properties are very scarce and unreliable. Therefore they must be checked for each individual technological step and the conditions under which the metal sheet is formed. Their forming properties are influenced by many parameters, e.g. chemical composition, technological parameters of rolling, etc. Due to large number of influential parameters the desired mechanical properties of the metal sheet (e.g. bending capability) are difficult to monitor and to keep within acceptable technological limits. Rolling mills usually collect data on an individual batch (e.g. alloy composition, conditions in which the sheet metal has been rolled etc.) but in most cases the general approach assuring achievement of the desired forming properties based on the influential parameters of metal sheet production cannot be traced. Often it is not known which parameters are of importance. In such cases linear regressions methods are not efficient since the abundance of input parameters and their mutual influences make the determination of an adequately precise model impossible [1].

In the present work two different approaches based on experimental data on ZnCuTi alloy composition and on technological parameters of hot and cold rolling have been used to predict the metal sheet bending capability. The first one is the GP which belongs to the class of the methods of evolutionary computation [2-7], and the second one is the CAE neural network, which has been successfully applied for solving many engineering problems [e.g. 8-16].

## EXPERIMENTAL SET-UP

The process of manufacture of rolled ZnTiCu metal sheet may be divided into three main steps: (i) casting of alloy, (ii) hot rolling of metal ingots, (iii) cold rolling into stripes. In rolling mill the ZnTiCu ingots were first cast according to the technology of semi-continuous vertical casting. The content of alloying elements in the alloy was limited to 0,13±0,02% and 0,10±0,02% for Cu and Ti, respectively. The permissible impurities amounted to 0,005%. The capacity of the net frequency electro-inductive furnace for melting and alloying of zinc into the final ZnTiCu alloy was 10000kg (4 ingots). The required inlet temperature was 460 (+5, -0) °C.

The zinc-titan plates were formed from ZnTiCu ingots on a Siemag roll stand by with the hot rolling pro-

R. Turk, G. Kugler, M. Terčelj, Faculty of Natural Sciences, Ljubljana, Slovenia, I. Peruš, Faculty of Civil and Geodetic Engineering, Ljubljana, Slovenia, M. Kovačič, Štore steel, Ltd, Štore, Slovenia

cess. Prior to hot rolling the ZnTiCu ingot was heated in a Junker block furnace to the hot rolling temperature of 305°C±10°C. The micro blowholes and gas bubbles formed during casting were welded (rolled) during hot rolling. The recrystallization temperature represents the limit distinguishing hot rolling from cold rolling. The re-crystallization temperature for ZnTiCu alloy is approximately 300°C. For re-crystallization a critical degree of deformation (2-5%) is also necessary. Therefore the heated titanzinc ingot was rolled from 118 mm thickness by 14 passes through the mill to dimension of 14000 mm length and 1055 mm width (mass approximately 1800 kg). The process of hot rolling of one ingot took 10 to 15 minutes. The plate temperature after hot rolling amounted to 285°C±10°C. Cooling took 40 to 120 minutes.

From the ZnTiCu plate ZnTiCu sheet (strip) of 0,7 mm thickness was formed on a Schmitz rolling machine by the cold rolling process. Prior to cold rolling the plate was heated to about 170°C in a Küppersbusch furnace. Cold rolling took about 40 minutes at a temperature of 140°C to 170°C. Finally the strips were wound into a coil of about 300m length.

In the present study nine input parameters, denoted as *X1*, *X2*, …, *X9,* which influences the bending capability of rolled zinc-titan metal sheet have been selected. According to the three main steps of the manufacturing process they can be described as: *(i) alloy casting:* the percentage of Cu (*X1*), percentage of Ti (*X2*) , and percentage of Fe (*X3*), *(ii) hot rolling:* the temperature of the ingot before rolling (*X4*), time of rolling (*X5*), temperature of plate after rolling (*X6*), time of cooling (*X7*), *(iii) cold rolling:* the temperature of the plate before rolling (*X8*), temperature of sheet after rolling (*X9*).

As the aim of this research was to establish the influence of the technological parameters of metal sheet manufacture on its bending capability, a bending test was executed for each coil of zinc-titan sheet in accordance with DIN 1781. In our study standard test pieces were cut from the middle of each coil. 34 coils were available and 5 test pieces were cut from each coil. Thus altogether 170 test pieces were subject to the bending test. If all 5 test pieces underwent the test without destruction (i.e. the test piece did not break), the bending capability was evaluated as 100%; if one of them broke, as 80%; if two of them broke, as 60%, etc. If all 5 test pieces failed the bending test (i.e. all test pieces broke), the bending capability was evaluated as 0%. Detailed description about forming the database, which includes data on input parameters (*X1*, *X*2, …, *X*9) and the coil bending properties (*Y*), can be found in [11]

## GENETIC PROGRAMMING

GP is probably the most general evolutionary optimization method [2]. The organisms that undergo adaptation are in fact more or less complicated computer programs. The computer programs have different meaning depending on the type of problem dealt with and can be mathematical expressions, control strategies, decision trees, Boolean expressions, etc. In order to solve the problem adequate genes must be available. First, the generation of random computer programs (organisms) is needed from the available genes. Then, evaluation of the generation follows. Afterwards, genetic operations (usually reproduction, crossover and mutation) are used to create descendants of the new generation. The new generation is evaluated again. Iterations are repeated until the termination condition is fulfilled. The latter can be the prescribed maximum number of generations or an adequate quality of the solution.

The organisms in the presented research are basically mathematical expressions, i.e. models for the determination of metal sheet bending capability. They consist of terminal and functional genes. The terminal genes used were simply the input variables: percentage of Cu (*X1*), percentage of Ti (*X2*), percentage of Fe (*X3*), ingot temperature before hot rolling (*X4*), time of hot rolling (*X5*), temperature of plate after hot rolling (*X6*), cooling time (*X7*), plate temperature before cold rolling (*X8*) and temperature of sheet after rolling (*X9*). The function genes connect the terminal genes by mathematical expressions. Arithmetic operations of addition (+), subtraction (-), multiplication (*), and division (/) taking two arguments each were used as function genes. The arithmetic operation of division / is protected against extreme values: thus the result of division by 0 is equal to 1.

As mentioned above, the organisms have the nature of mathematical models for prediction of sheet bending capability. The following agreement was accepted: if the raw calculated values of the model are smaller than 0, from 0 to 20, from 20 to 40, from 40 to 60, from 60 to 80 and higher than 80, the discrete values 0%, 20%, 40%, 60%, 80%, and 100%, respectively, are taken into consideration for the values of the model. Therefore, each model returns a value which falls into one of the six classes. For example, if the model returns the raw value of bending capability of 36, a 40% bending capability is taken.

For the fitness function the average of the sum of the absolute differences between the discrete experimental values and the discrete values of bending capability returned by the model is selected. The fitness measure is defined as follows:

$$\Delta = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - P_i\right|, \tag{1}$$

where $n$ is the number of measurements, $i$ is the measurement index, $Y_i$ and $P_i$ are the actual bending capability and the predicted bending capability calculated by a prediction model, respectively. It is assumed in this study that the problem is solved successfully if the average absolute deviation Δ of the model is lower than 10% (i.e., lower than 0,5 of a class). This means that an average absolute deviation of one half of a class is allowed.

In the study the following evolutionary parameters were used: population size 1000, maximum number of generations to be run 1000, probability of reproduction 0,1, probability of crossover 0,9, maximal depth of organisms after crossover 15, and tournament selection with a group size of 7. More detailed description of the procedure may be found in [5, 11].

## CAE NEURAL NETWORK

CAE neural network was first presented by Grabec and Sachse [12]. According to the theory, the bending capability of metal sheet can be characterized by a sample of experiments on $N = N_t/5$ test metal sheet specimens ($N_t$ =170, $N$ = 34 test specimens). The problem now is how bending capability can be estimated from known input parameters and available data in the data base. By using the conditional probability function the optimal estimator for the given problem can be expressed as i.e. [10, 12, 13-16]:

$$\hat{Y} = \sum_{n=1}^{N} A_n \cdot Y_n \qquad (2)$$

where $A_n = a_n / \sum_{i=1}^{N} a_i$, and

$$a_n = \frac{1}{(2\pi)^{d/2} w^D} \exp\left[\frac{-\sum_{l=1}^{D}(x_1 - x_{nl})^2}{2w^2}\right] \qquad (3)$$

$\hat{Y}$ is the estimation of the bending capability, $Y_n$ is the same output variable corresponding to the $n$-th model vector in the data base, $N$ is the number of model vectors in the data base, $b_{nl}$ is the $l$-th input parameter of the $n$-th model vector in the data base (e.g. $b_{n1}, b_{n2}, b_{n3}, ..., b_{nL}$), $b_l$ is the $l$-th input parameter corresponding to the model vector under consideration, and $D$ is the number of input parameters. The "smoothing" parameter $w$ is the width of the Gaussian function. However, in some applications, a non-constant value of $w$ yields more reasonable results than a constant value. When using non-constant $w$ values (regarding input parameters and/or position of model vectors in the sample space), Eq. (2) can still be used, but proper, locally estimated values of $w$ should be taken into account. The formula for $a_n$ (see Eq. (3)) can be rewritten as

$$a_n = \frac{1}{(2\pi)^{D/2} w_1 \cdot \ldots \cdot w_D} \cdot \exp\left[-\sum_{l=1}^{D} \frac{(b_1 - b_{nl})^2}{2w_l^2}\right] \qquad (4)$$

where different values of $w_l$ correspond to different input variables (index $l$).

In determining an appropriate value of the smoothing parameter $w$, a measure to calculate the average error in the bending capability predictions is defined as:

$$E_1 = \frac{1}{\overline{Y}} \sqrt{\frac{1}{N} \sum_{n=1}^{N} (Y_n - \hat{Y}_n)^2}, \qquad (5)$$

where $Y_n$ and $\hat{Y}_n$ are measured and predicted bending capability of the $n$-th metal sheet specimen from the database, respectively. $\overline{Y}$ is the mean value of the bending capability of the metal sheet specimens from the database, and $N$ is the number of metal sheet specimens in the database.

## RESULTS AND DISCUSSION

### Analysis of the influence of individual parameters by GP

One hundred independent runs of the GP system were performed. Among these runs the criterion of success (i.e. an average absolute deviation lower than 10%) was reached 21 times.

Since the models developed by simulated evolution are based on probability, there is no guarantee that the models will contain all independent available variables (i.e. terminal and function genes). During previous studies it was established experimentally that for building GP, models usually uses only ingredients leading to successful solutions, whereas ingredients having the nature of disturbances or not having decisive influence on the description of the system are on the average more frequently eliminated by evolution [7]. Thus in our case, by analyzing the ingredients present (i.e. remaining) in the final models, the influence of the individual ingredient (parameter) on the sheet bending capability can be indirectly estimated. Of course, among other factors the precision of execution of the measurements can influence the presence of ingredients in the final model. Thus the greater the number of runs where individual parameter is not present in the final modes, the more probable is it that such parameter does not decisively influence the sheet bending capability. Figure 1.a shows the number of runs (out of 100) in which it happened that an individual input parameter was not present in the final model.

It can be seen that evolution most frequently eliminated the input parameter of percentage Ti (X2 is not present in 53 final models out of 100), the input parameter of percentage Fe (X3 is not present in 52 final models out of 100), and the coil temperature during cold rolling (X9 is not present in 45 final models out of 100). The time of hot rolling X5 and the cooling time X7 are least frequently omitted, since evolution did not incorporate them into the final model only 22 times and 25 times, respectively. A similar trend appears in the 21 successful runs (Figure 1.b). Also in this case evolution least frequently eliminated the two input parameters rolling time in hot rolling *X5* and cooling time in hot rolling *X7* - they were not present in the final model only once and twice, re-

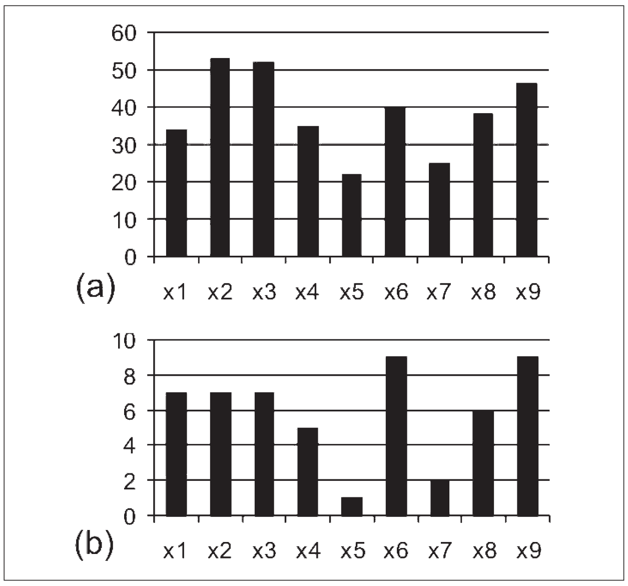


**Figure 1.** Number of runs in which it happened that an individual input parameter was not present in the final model: (a) out of 100 runs, and (b) out of 21 runs.

spectively. These results indicate that these two parameters decisively influence the sheet bending capability.

## The model obtained by GP

The best mathematical model for prediction of the bending capability is shown in Figure 2. Note that, when evaluating the model it must be strictly taken into consideration that the result of division by 0 is 1 as this is the protection against non-defined values. The average absolute deviation of prediction of the model from the actual experimental values is 2,35% (i.e., 0,12 of the class). In practice that means that in the case of 10 measurements (each of them made with 5 test pieces) the model would give only one incorrect prediction of the bending test. It would either incorrectly predict destruction the test piece or it would incorrectly predict that the test piece would survive.

The comparison of the prediction of the best GP model and the experimental ("learning") data is shown in Figure 3.a.

It can be seen that small deviations appears (only about one class – 20%). In order to verify the prediction capability of the genetically developed model, ten additional measurements were carried out, where each measurement was performed with 5 test pieces. Then the prediction capability of the best model was tested with the values of the input parameters of the test data.

The results are indicated in Figure 3.b. Again, it can be seen small deviations of about one class in some cases. The average absolute deviation of the test data $(4 \cdot 20\%/10) = 8\%$ (i.e., 0.4 of a class). Although the deviation is greater that in the case of the data used for the development of the model, the prediction capability is nevertheless very good.

## The CAE neural network model

For the application of the CAE method the same "training" database of 34 metal sheet specimens with the same nine input parameters as in case of GP was used. By trial and error procedure the "best" constant value of smoothing parameter was determined as $w$ = 0,25. Fig-

$$
\begin{aligned}
&\frac{1}{X5}\Bigg(X6+X7-\frac{2\,X9}{-X5+\frac{X9}{X5}}+\frac{X9}{X5\left(-2\,X3+X5-X9+\frac{X9}{X2\;X3}+\frac{X9}{X2\;X5}\right)}+\frac{2\,X3+X5+\frac{1}{X2\left(-\frac{1}{X2^2}+X5\right)}+2\,X9+\frac{X3+X9}{X5}}{-X9+\frac{X9}{(X2+2\,X3)\;X5}}+\\
&\frac{X9}{7\,X3+X5+X9-\frac{X9}{X5}-\frac{X9}{X2\;X5}-\frac{X9}{\frac{X2}{X3+X5}-X9}-\frac{2\,X3+X9}{X5}}+\frac{-X3+X9+\frac{X3+X9}{X5}}{-X9+\frac{X9}{X2\;X5}-\frac{X9}{-X9+\frac{X9}{X2\;X5}}}+\frac{1+\frac{1}{X2^2}+X5+\frac{X9}{X2\left(X5+\frac{X9}{X3}\right)}}{-X3+X5+\frac{X3+X5+X9}{-X3-X9+\frac{X9}{X2\;X5}}}+\\
&\frac{X9}{-1-\frac{1}{X2}-X3-X9-\frac{X9}{X5}-\frac{X9}{X2\left(X3+\frac{X9}{X3}\right)}+\frac{2\,X9}{-X5+\frac{X9}{X3+X5}}}+\frac{X3-X5+X9+\frac{X9}{X2\;X5}}{X3+\frac{X9}{X5}+\frac{X9}{X3+X9}-\frac{X9}{-X3-X5+\frac{X9}{X5}}+\frac{X9+\frac{X3+X9}{X5-X9}}{X2\;X5}}\Bigg)+\\
&\frac{\left(-X3+X5+X9+\frac{-2\,X3+X5+X9+\frac{X9}{X2\;X5}+\frac{1}{X2\left(-X9+\frac{X9}{X5}\right)}-\frac{-X3-X9+\frac{X9}{2\,X3+X5}}{-X3+\frac{X9}{X2\;X5}}}{1.+X2+X3-\frac{X9}{X2\;X5}+\frac{(X3+X9)}{(X2+2\,X3)\;X5}-\frac{2\,X3+X9+\frac{X9}{X5}}{-X9+\frac{X9}{X2\;X5}}}+\frac{X9}{-X3-X9-\frac{X9}{-X9+\frac{X9}{X2\;X5}}+\frac{X9+\frac{X3+X5+X9}{X3+X5-X9}}{X2\;X5}}\right)}{-2\,X3-X5-\frac{X9}{X3+2\,X5+X9-\frac{X9}{X2\;X5}-\frac{X9}{X3+X9}-\frac{X3+X9}{X5}-\frac{X3+X9}{X2\;(X3+X5)}}+\frac{X9+\frac{X3+X9}{X5+X9-\frac{2\,X3+X9}{(X2+X3)\;X5}}}{-X5+\frac{X9}{X5}}}
\end{aligned}
$$

**Figure 2.** The best GP mathematical model for prediction of the bending capability.

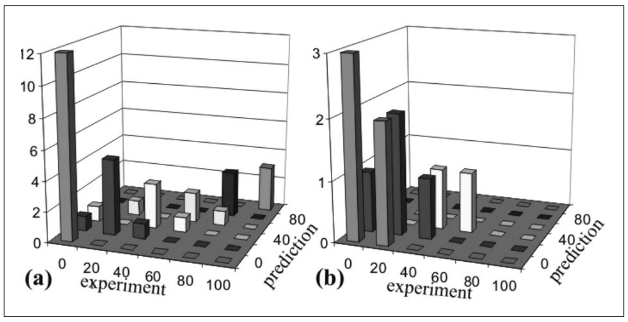


**Figure 3**. Comparison of the predicted and experimental data (a) The histogram chart for the best GP model for the experimental ("training") database (n=34), and (b) The histogram chart for the best GP model for the test database (n=10).

ure 4 indicates that the results predicted by CAE neural network model are worse than that predicted by the "best" GP model. Even if weights are added to input parameters according to Figure 1, prediction was not improved. It seems that problem is highly non-linear and CAE neural network is not capable to model it. The problem lies also in the size of the database. Figure 4.a shows typical averaging effect which indicates (too) small database. However, past results proved that by increasing the size of the database the CAE neural network model performance increases as well.

Prediction capability of the CAE model was tested on the same test data as the "best" GP model. The results are shown in Figure 4.b. It can be seen that the average absolute deviation of the test data that amounts to 18% is better than that of the training data. Again, as expected according to the results from Figure 4.a, the "best" GP

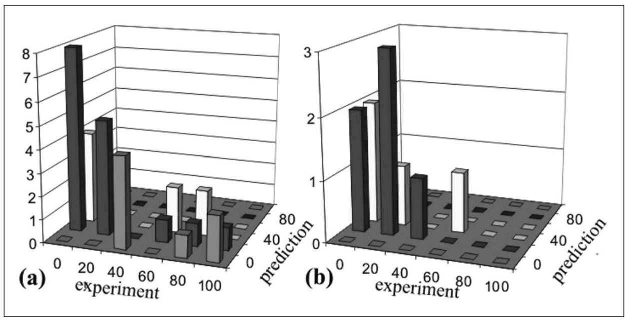


**Figure 4.** Comparison of the predicted and experimental data a) The histogram chart for the CAE model for the experimental ("training") database (n=34), and (b) The histogram chart for the CAE model for the test database (n=10).

model gives better results than CAE NN model.

## CONCLUSIONS

In this paper the bending capability of rolled ZnCuTi metal sheet was studied by GP and CAE NN approaches. Prediction models were developed on the basis of experimental data on the chemical composition of the ZnCuTi alloy and the technological parameters of hot and cold rolling.

Thirty four measurements were performed for establishing the database for the prediction model. A large number of successful prediction models differing in prediction accuracy and complexity were developed by GP. One model was developed also by CAE NN, using the same data. The best GP model gives the most precise prediction of the bending capability of titanzinc metal sheet and the CAE NN model were additionally verified on the basis of a test data set obtained by 10 measurements.

The main findings of the presented research can be summarized as follows: (i) on the average, the evolutionary process more often eliminates those ingredients (input parameters) having a smaller influence on the bending capability, (ii) for the existing experimental data and working conditions it was proved that two technological parameters have the highest influence on the bending capability of the metal sheet: the rolling time of hot rolling X5 and the cooling time of hot rolling X7, (iii) the influence of the plate temperature after hot rolling X6 and the coil temperature in the case of cold rolling X9 is relatively small. The influence of Cu, Ti, and Fe content on the bending capability was not decisive; (iv) compared to the CAE NN model, GP model gives better predictions. By increasing the database, better predictions could be obtained also by CAE NN.

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**Note:** The responsible translator for English language is the author G. Kugler.