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GENETIC ALGORITHMS AS AN OPTIMIZATION TOOL OF NEURAL NETWORKS MODELLING FRICTION PHENOMENON

This paper deals with the method of determination of the friction coefficient value by using multilayer artificial neural networks on the basis of experimental data obtained from the strip drawing test. Using genetic algorithm the optimization of number of input variables of artificial neural networks has been done. As an input parameters for training artificial neural networks following parameters has been used: surface parameters of the sheet and working rolls, mechanical parameters of the sheets and clamping force of rolls. The influence of unit penalty value of genetic algorithm on prognosis quality of neural networks has been presented.

Introduction

One of the main factors influencing on frictional resistance is surface topography of deformed sheet. Friction between the sheet and tools is one of the important factors affecting the quality of drawpiece, so that the clarification of the friction is essential for modeling and analysis of sheet metal forming processes. The workpiece surface topography and asperity contact is an important factor controlling the mechanisms of lubrication in metal forming process. Measuring the frictional properties of a material always requires replicating the conditions under which the friction occurs, including the material sliding against test material, the geometry of contact, the conditions of the surfaces, and the speed of relative motion of the sliding bodies. In the deep drawing process a few regions exist, i.e. the wall, bottom and flange of the cup, with different stress state, strain state, sliding speed and friction conditions. In this regard a series of tribological tests modeled friction conditions in different parts of drawpiece were elaborated. In strip drawing test [1] coefficient of friction is determined based on measurement of other factors e.g. friction force and normal force.

The friction tests were carried out for wide range of contact pressures between sheet-tool interface. Considering significant amount of factors influencing frictional resistance during sheet metal forming analytical determination of relationships utilized for calculation of friction coefficient is practically

impossible. For that purpose a multilayer artificial neural networks (ANN) were utilized. An important factor of correct operations of ANN is suitable selection of input variables, often is used methods of experiment optimization in order to reduce number of experiments [2]. The optimization of experimental data set used in researches for ANN training was carried out by using genetic algorithm. The utilization of the ANN enables the behaviour of complicated system to be modeled and predicted based on known experimental data. The ANN can solve complex nonlinear problems, with the ability of using current and historical data [3]. The purpose of the present study is to examine further ability of neural networks to predict accurately the friction coefficient value.

Experimental procedure

Friction tests were carried by strip drawing method placed between two fixed cylindrical rolls with equal radii (Fig. 1). The test was carried out in such a way that a strip of the sheet was clamped with specified force between two cylindrical rolls of equal radii 20 mm. The both clamping F_c and pulling F_p force values were constantly recorded using electric resistance strain gauge technique, 8-channel universal amplifier of HBM's QuantumX data acquisition system and computer PC. The specimens for the friction tests were made of two brass sheet metal M63 with hardening state of r, z4 and z6 as well as M90 with hardening state of z4. Samples were prepared as a strip of 20 mm width and about 200 mm length, cut along transverse directions of the sheet. The rolls were made of cold working tool steel hardened to 58 HRC. The tests were performed under the following conditions: Ra parameter of surface roughness of rolls: 0.32; 0.63; 1.25 and 2.5 μm measured along generating line of rolls, clamping force: 0.4; 0.8; 1.2; 1.6 as well as 2 kN. The sliding velocity was 0.002 m/s, which is relatively high compared with the industrial values.

During the recording of the pulling and clamping forces the sheet was drawn for a distance of about 10 mm. Next the clamping force value was increased simultaneously during tests. To realize dry conditions both rolls and sheet specimens were degreased using acetone. The mean value of the friction coefficient is determined according to (1) for the stabilized range of values of F_p and F_c .

$$\mu = \frac{F_p}{2 \cdot F_c} \quad (1)$$

where: F_p – pulling force,
 F_c – clamping force.

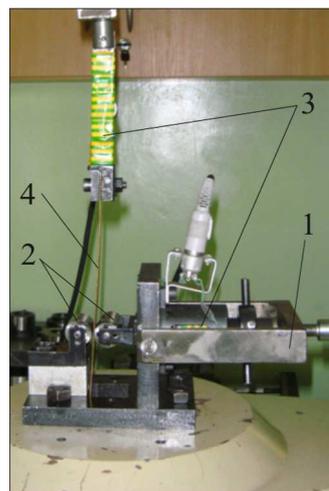


Fig. 1. View of measuring position: 1 – frame, 2 – working rolls, 3 – extensometers, 4 – specimen

Rys. 1. Widok stanowiska pomiarowego: 1 – korpus, 2 – rolki robocze, 3 – tensometry, 4 – próbka

To determine the mechanical properties tensile test in universal testing machine was carried out. Surface roughness 3D parameters were measured by using Taylor Hobson Subtronic 3+ instrument. Table 1 presents the mechanical properties and selected spatial roughness parameters of the sheets. Friction tests were realized for all combinations of grade of brass, roughness of rolls and clamping forces. In this way eighty different data set for training of ANN were obtained.

Table 1. Selected mechanical properties and surface roughness parameters of the sheets

Tabela 1. Wybrane właściwości mechaniczne oraz parametry chropowatości blach

Parameter	Material			
	M63 r	M63 z4	M63 z6	M90 z4
C, MPa	581	570.3	615	400
n	0.365	0.143	0.043	0.040
Sa, μm	0.162	0.151	0.108	0.33
Sq, μm	0.205	0.196	0.137	0.279
Ssk	0.262	0.0371	0.191	0.202
Sz, μm	1.78	2.24	1.34	2.14
Str, mm	0.287	0.153	0.109	0.175
SHTp, μm	0.337	0.309	0.223	0.31
Smmr, mm^3/mm^2	0.00105	0.00103	0.000623	0.000988
Sdq, $\mu\text{m}/\mu\text{m}$	0.0201	0.0183	0.0136	0.0184
Sbi	0.316	0.107	0.172	0.147
Sal, mm	0.074	0.149	0.088	0.123

Artificial neural networks

Neural networks are used particularly to answer the purpose when dependence between inputs and outputs is very complicated. ANN consist of connected together elements named neurons which processing supplied in input information data. In general working of neural networks base on parallel processing idea. Each input signal x_i , where $i = 1, \dots, n$ is loading to neuron by weighted connections w_i . Every neuron has a threshold value specified its activation level. In k th neuron sum of input signal values x_n multiplication by weight factors is calculated. Next this value is increased by external signal value which is refered as a bias term Θ_k . Calculated in this way e value is neuron activation value which is converted by established activation function $f_k(e)$ of k th neuron. Value determined by activation function is output neuron value and specify nonlinear relationship between resultant input signal and output signal y neuron.

A single layer neural networks are characterized by the most simple structure however most often are utilized multilayer networks named multilayer perceptrons. A multilayer perceptron with a suitable number of hidden layers and neurons is theoretically sufficient to approximate any nonlinear function [4].

To determine weighted sum and threshold activation value of separated neurons necessary is preparation training data set consist of input signal values and corresponded values of output signals. As input signals the following input variables set was assigned:

- strength coefficient C [MPa] and strain hardening index n ,
- roughness average parameter R_a of rolls surface [μm],
- surface roughness 3D parameters of the sheets, amplitude: S_a [μm], S_q [μm], S_p [μm], S_v [μm], S_t [μm], S_{sk} , S_{ku} , S_z [μm], superficial and volumetric: S_{HTp} [μm], S_{mmr} [mm^3/mm^2], S_{mvr} [mm^3/mm^2], spatial: S_{ds} [number of vertex/ mm^2], S_{tr} , S_{al} [mm], S_{td} [$^\circ$], S_{fd} , hybrid: S_{dq} [$\mu\text{m}/\mu\text{m}$], S_{sc} [$1/\mu\text{m}$], S_{dr} [%], and functional: S_{bi} , S_{ci} , S_{vi} ,
- clamping force of rolls F_C .

One of the main task necessary to build optimal model of neural network is sufficient selection of input variables which essentially influenced on the output variable value. Too large number of variables may cause information noise whereas do not taking into account even though one variable which essentially influencing output variable may lead to get wrong results. Adding in the input network the next neuron causes excessive expansion of its architecture. Simultaneously, the value of training data is increased. In turn, omission of essential variables in input can cause decreasing quality of the network. There are not universal criteria for selecting an architecture of ANN [5]. Selection of variables essentially influencing the friction coefficient value is difficult because of complex interactions of many factors particularly surface parameters which are additionally correlated each other. Application of genetic algorithms allows

to select input variables without necessity to have knowledge about physical interdependences between individual input variables and output variable.

Genetic algorithms

Genetics algorithm (GA) are based on natural selection mechanisms as well as heredity and operated on population of individuals which are potential solution of the problem. Analogous to natural conditions individuals are subjected to reproduction. Mechanisms of natural selection depend on survive of individuals the most adapted in specified environment. The genetic encoding of a real or artificial organism is contained within their chromosomes. Each chromosome consists of a large number of genes, each uniquely located on the chromosome. Each gene in turn is composed of several alleles. The GA encoded alleles as either zero or one, represented by a single computer bit. A suitable representation of potential results should be resistant to applied genetic operators in order to after evolution can be decoded in order to find solution for input data structure. Set of many chromosomes is called population which is subjected to undergo continuous changes and depends on moment t :

$$P(t) = \{v_1(t), v_2(t), \dots, v_n(t)\} \quad (2)$$

where: n – number of chromosomes,
 v – single chromosome.

Chromosomes consist of genes deciding on hereditary one or more features. Evolution of chromosome population run by reproduction which is composed of crossover, mutation and inversion. Mechanisms of crossover and mutation of genetic information from parents lead to situation in which next generations are average better adapted to environment conditions [6]. In the crossover process genes of chromosomes of parents are joined in one or a few offspring chromosomes. Mutation lead to modification of chain by change one gene or its sequence whereas inversion reverse fragment of chromosome. The task of reproduction is to ensure of output of optimization procedure from local maxima of fitting function by variability of chromosomes. The objective of the GA is finding such solution for which the value of fitting function reaches maximum.

Algorithm worked on the initial population which equals 200 individuals with crossover coefficient $p_k = 0.5$, mutation coefficient $p_m = 0.1$ and with different values of coefficient of unit penalty (Table 2). The unit penalty coefficient is multiplied by a number of chosen in each mask of input variables, and next is added to the value of validation error. For optimization of number of input variables classical Holland's genetic algorithm was used. The evaluation of the population was carried out with the help of mechanism which for each solution sets in order the selection probability to new population with help of roulette selection and to new population is also loaded the best individual so far

found. The task of genetic algorithm was to check the quality of network that realize the generalized regression for given set of input variables resulting from reproduction mechanism of initial population. The collection of the best sets of input data is the result of genetic algorithm rules (Table 2). Results of these analyses were compared with results of network model based on input variables determined by Intelligent Problem Solver (IPS) built-in Statistica Neural Networks.

Increasing value of unit penalty causes the reduction of number of input variables (Fig. 2). With a large number of input variables determined by a small value of unit penalty appears a high value of a genetic algorithm error, which next starts to decrease reaching local minimum for unit penalty value equals 0.001. Further increasing of a unit penalty value causes the increase of an error value. The high error value with a great number of variables can be explained by noise of variables which can be in certain range of value correlated with each other. Then a high value of unit penalty causes that from the quality of algorithm more important occurs the variables numbers [7]. Local increase of the error value corresponding with the value of unit penalty equals 0.0005 can be explained by the fact of appearing a variable that after removing of two variables becomes dominating correlated with other variables. For further analysis the set of 12 input variables characterized by the smallest error value was chosen.

The process of the construction of network on the base of information contained in a chromosome and following it learning of a received model must be done each time by determining of chromosome quality.

Table 2. Influence of unit penalty value on the choice of input variables by genetic algorithm

Tabela 2. Wpływ wartości kary jednostkowej na wybór zmiennych wejściowych przez algorytm genetyczny

	Variable																						Error							
	Unit penalty		C	n	Ra	Sa	Sq	Sp	Sv	St	Ssk	Sku	Sz	SHTp	Smvr	Sds	Str	Sal	Std	Sfd	Sdq	Ssc		Sdr	Sbi	Sci	Svi	Fc		
Genetic algorithm	0.0001		+	+	+	+		+	+	+	+		+	+	+	+	+		+	+	+	+	+	+	+	+	+	+	+	0.01343
	0.0002		+	+	+	+		+	+	+	+		+	+	+	+	+		+	+	+	+	+	+	+	+	+	+	+	0.01244
	0.0005		+	+	+	+		+	+	+	+		+	+	+	+	+		+	+	+	+	+	+	+	+	+	+	+	0.01287
	0.001		+	+	+	+		+	+	+	+		+	+	+	+	+		+	+	+	+	+	+	+	+	+	+	+	0.01232
	0.002		+		+	+		+								+				+			+	+					+	0.01326
	0.004				+	+														+									+	0.01398
IPS			+	+	+	+		+		+	+		+		+				+	+	+	+	+					+	0.01355	

While the operation of the algorithm of genetic optimization the number of evaluated neuron networks is the multiplication of chromosome numbers in the population and number of considered generation.

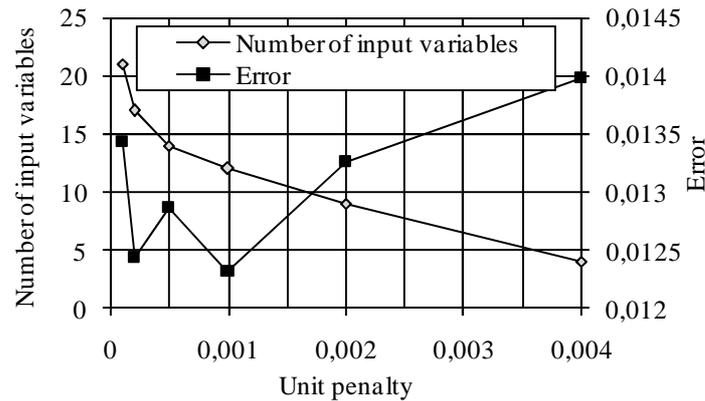


Fig. 2. Influence of unit penalty value on quality of genetic algorithm

Rys. 2. Wpływ wartości kary jednostkowej na jakość algorytmu genetycznego

For early determined by the genetic algorithm set of input variables a series of analyses of different ANN architecture in *Statistica Neural Networks* were investigated. An objective of analysis was to find the network architecture ensured the smallest value of standard deviation ratio in connection with high value of Pearson's correlation coefficient R [8]. On the basis of loading data *Intelligent Problem Solver* determines set of "the best" neural network architecture. In *Statistica* there is not particular information about mathematical nature of input variable selection by using IPS.

Among all experimental set consisted of input data and corresponded with output signal were separated 20% of data which were assigned to testing set (Ts). Data vectors from a testing set did not participate in training process and served to ANN prognostic evaluation purpose. From the remaining set of experimental data belonging to training set (Tr) was separated 10% of data which were assigned to validation set (V). Data from this group were used for independent check of back propagation (BP) training algorithm. The learning rate was equal to 0.1 [9]. To overlearning prevent the learning process braked off when value of verification round mean square error for validation set was stopped dropping [7].

Table 3 shows the regression statistics of „the best” neural networks for input variables determined by genetic algorithm (MLP 12:12-12-1:1, MLP 12:12-14-1:1), Intelligent Problem Solver (MLP 15:15-10-1:1) and using entire variable set do not put to preprocessing process (MLP 25:25-12-1:1). The model with the lowest values of standard deviation ratio in connection with highest value of Pearson-R correlation is network MLP 12:12-14-1:1 which regression statistics are slight better in comparison with network MLP 12:12-12-1:1 and considerably better from MLP 15:15-10-1:1 taking into account all analysed input variables.

Table 3. Regression statistics of MLP neural networks

Tabela 3. Statystyki regresyjne wielowarstwowych sieci neuronowych

Set	MLP 12:12-12-1:1			MLP 12:12-14-1:1			MLP 15:15-10-1:1			MLP 25:25-12-1:1		
	Tr	V	Ts	Tr	V	Ts	Tr	V	Ts	Tr	V	Ts
Error S. D.	0.005	0.005	0.008	0.006	0.007	0.011	0.005	0.010	0.009	0.008	0.900	0.013
Abs error mean	0.0009	0.002	0.0001	0.001	0.008	0.0009	0.003	0.004	0.002	0.009	0.012	0.005
RMS error	0.005	0.006	0.009	0.004	0.005	0.010	0.007	0.009	0.012	0.008	0.013	0.011
S. D. ratio	0.149	0.253	0.250	0.153	0.248	0.170	0.196	0.298	0.171	0.275	0.351	0.285
Correlation R	0.989	0.968	0.973	0.997	0.976	0.996	0.980	0.992	0.993	0.923	0.918	0.937

One of the methods to determine the importance of influence of particular input variables on the value of explained variable is sensitivity analysis (Table 4) which also can be used for choosing input variables. The criterion of sensitivity is the value of the network error after removing this variable. Bigger importance of the variable determines bigger value of the network error. Taking into account the training set clamping force F_C , roughness average parameter R_a of rolls surface and maximum peak height S_p have the biggest influence on the coefficient of friction value.

Table 4. Sensitivity analysis for MLP 12:12-14-1:1

Tabela 4. Analiza wrażliwości sieci MLP 12:12-14-1:1

Variable	Training set		Validation set	
	error	ratio	error	ratio
C	0.0161	1.720	0.0156	1.940
n	0.0184	1.996	0.0180	2.243
R_a	0.0275	2.911	0.0234	2.910
S_a	0.0116	1.227	0.0149	1.851
S_p	0.0252	2.710	0.0305	3.793
St	0.0168	1.784	0.0129	1.612
S _{mv}	0.0152	1.665	0.0124	1.545
Std	0.0241	2.585	0.0201	2.498
S _{fd}	0.0114	1.225	0.0159	1.986
S _{sc}	0.0172	1.880	0.0176	2.197
S _{dr}	0.0151	1.724	0.0120	1.498
F_C	0.0340	3.616	0.0360	4.477

Analyzing the networks with genetic selection of input variables it can be noticed that increase of neurons number in the hidden layer causes the increase of error value on the output of network for each data set.

Less number of neurons in the hidden layer should influence of larger network ability to eliminate the noises coming from input data greater ability of

generalization. Ability of generalization is the quality of generalization of acquired knowledge in the learning process to cases from behind the learning set.

Results of this research shows excellent agreement between experimental data and outcomes of neuron models for all range of input variable used for the training. (Fig. 3). This will allow to reduce or eliminate expensive and time-consuming carrying out of experimental tests in order to determine friction coefficient value. The application of the ANN also allows to eliminate search of complicated dependence between parameters influencing on the friction and the friction coefficient value.

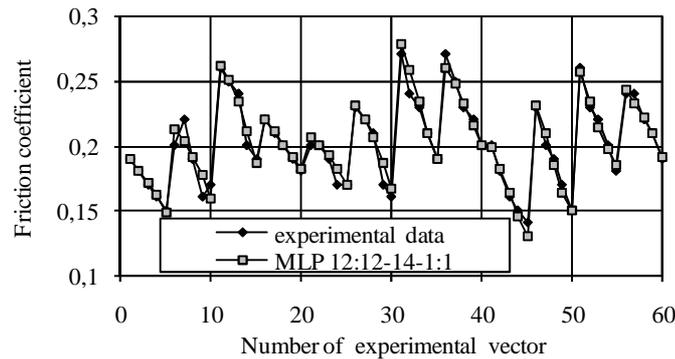


Fig. 3. Comparison of friction coefficient value determined experimentally and using MLP 12:12-14-1:1

Rys. 3. Porównanie wartości współczynnika tarcia otrzymanego eksperymentalnie oraz za pomocą sieci wielowarstwowej o strukturze 12:12-14-1:1

Conclusion

Using of optimization methods of input variables numbers allows to avoid the time-consuming testing of neuron models with different architecture in order to find the optimum network for specific task. Regression statistics of neuron model based on the genetic selection of input variables and using Intelligent Problem Solver are considerably better than models without preprocessing of input data. The most effective in working are neural networks with not extended structure. Proper selection of input variables consisting in rejection of variables which are correlated with each other, influencing in small degree on the explained variable or even rejection of variables that have important information influence on the reduction of network structure. Analyzed network models characterized by unexpectedly good results taking into account that number of input signals and responding to them output signal were limited to eighty.

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ALGORYTMY GENETYCZNE JAKO NARZĘDZIA OPTIMALIZACYJNE SIECI NEURONOWYCH MODELUJĄCYCH ZJAWISKO TARCIA

Streszczenie

Opracowanie dotyczy metody wyznaczania wartości współczynnika tarcia za pomocą wielowarstwowych sieci neuronowych na podstawie danych eksperymentalnych otrzymanych w próbie przeciągania paska blachy. Do optymalizacji liczby zmiennych wejściowych do sieci neuronowych wykorzystano algorytm genetyczny. Jako dane wejściowe do uczenia sieci neuronowych zostały wykorzystane następujące parametry: chropowatości blachy oraz rolek roboczych i mechaniczne blachy oraz siły docisku rolek. Przedstawiono wpływ wartości kary jednostkowej algorytmu genetycznego na jakość prognozowania sieci neuronowej.

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