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PREDICTING THE ABRASION RESISTANCE OF TOOL STEELS BY MEANS OF NEUROFUZZY MODEL

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ABSTRACT

This work considers use neurofuzzy set theory for estimate abrasion wear resistance of steels based on chemical composition, heat treatment (austenitising temperature, quenchant and tempering temperature), hardness after hardening and different tempering temperature and volume loss of materials according to ASTM G 65-94. Testing of volume loss for the following group of materials as fuzzy data set was taken: carbon tool steels, cold work tool steels, hot work tools steels, high-speed steels. Modelled adaptive neuro fuzzy inference system (ANFIS) is compared to statistical model of multivariable non-linear regression (MNLR). From the results it could be concluded that it is possible well estimate abrasion wear resistance for steel whose volume loss is unknown and thus eliminate unnecessary testing.

KEY WORDS

abrasion resistance, tool steels, modelling, neurofuzzy

CLASSIFICATION

JEL: Z19

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INTRODUCTION

The good wear resistance, especially against abrasion, is the most important property of tool materials. The main influence factors, which determine the abrasion resistance of steel, are: chemical composition (carbide forming elements), microstructure (type, form, distribution and contents of carbides) and hardness (macro and micro) [1, 2]. It is well known, that the abrasion wear resistance mostly depends on the types (hardness) and contents of carbides in martensite matrix (Fig. 1). Additionally, the microstructure constituents change own form, size and distribution during the tempering, e.g. depend on tempering condition (Fig. 2). The determination of the form, distribution and portion of carbides by quantitative image analysis for each heat treatment condition of certain steel require a long time. Additional problem is the identification the type of carbides in a microstructure. In this paper an easier way for predicting the abrasion wear resistance of different tool steels by means of neural network and fuzzy method is investigated. The input data were not the microstructure parameters but the known chemical composition of steel and hardness in the hardened and tempered conditions. The learning data set for neural network contains chemical composition, heat treatment parameters, hardness and volume loss of different tool steels and high speed steels in different heat treatment conditions (Table 1).

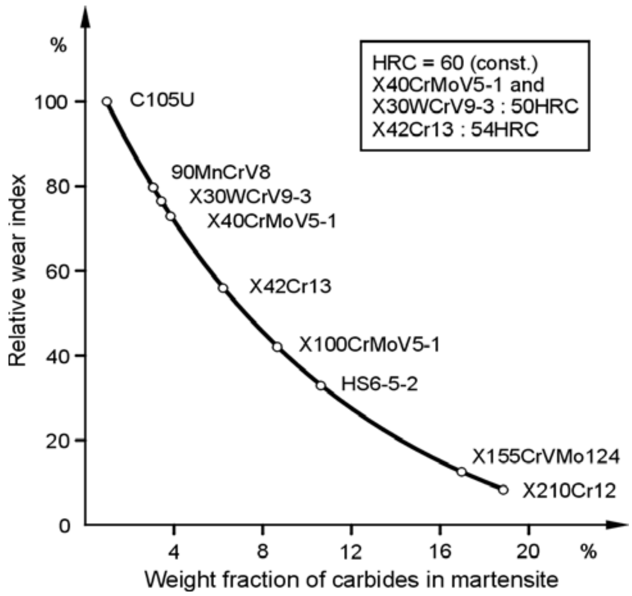

Figure 1. Relative wear of different tool steels vs. weight portion of carbides [1].

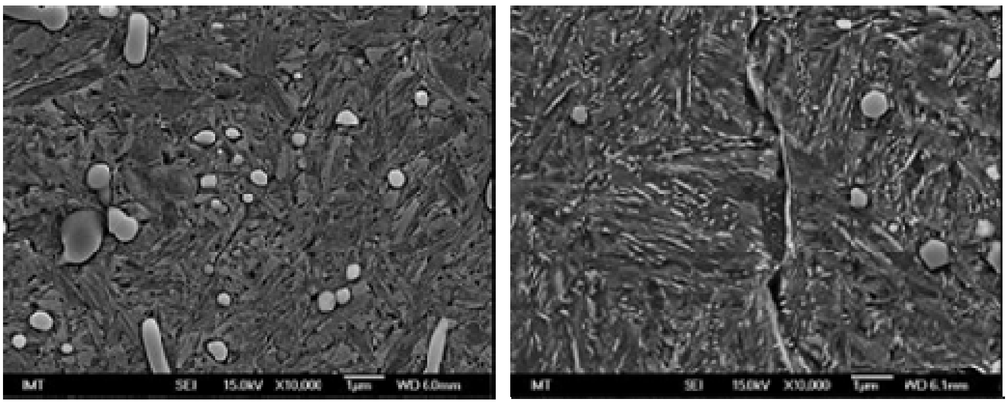

Figure 2. Microstructure of sample steel X160CrMoV12-1 (Scanning Electron Microscope micrograph's – secondary electron image). Left: tempering temperature 160 ºC and hardness 61,5 HRC, right: tempering temperature 515 ºC and hardness 60,5 HRC [1].

RESULTS OF ABRASION WEAR RESISTANCE

Different tool and high speed steel (10 types) have been austenitised and quenched applying specified temperatures and quenching media. After hardening, each sample has been tempered applying several different temperatures, and subsequently hardness (HRC) and volume loss (GV, mm^3) were measured.

The measure for abrasion wear resistance were data for volume loss after testing of steels in different heat treatment conditions using a method dry sand(SiO2)/rubber wheel – ASTM G65-94 (Fig. 3**.**).

Table 1. The data for investigated steels [3, 4].

Steel designation EN AISI	Composition – element*, %								Hardening		Temp., °C	Hardness, HRC	GV, mm^3
	C	Si	Mn	Cr	Ni	Mo	W	V	T_a, ºC	Quench			
CT105W110 W1	0,95 **1,00** 1,05	0,29 **0,31** 0,32	0,29 **0,31** 0,32	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	760	water	20	68	61,05
											150	67	64,35
											180	65	66,55
											320	56	93,20
											370	50	104,60
											440	44	116,60
90MnCrV8 O2	0,86 **0,91** 0,95	0,24 **0,25** 0,26	1,90 **2,00** 2,10	0,33 **0,35** 0,37	**0,00**	**0,00**	**0,00**	0,09 **0,09** 0,10	800	oil	20	65	59,50
											200	61	70,60
											320	58	98,55
											370	56	104,60
											470	50	118,65
X210Cr12 D3	1,96 **2,09** 2,21	0,29 **0,31** 0,32	0,29 **0,31** 0,32	11,4 **12,0** 12,6	**0,00**	**0,00**	**0,00**	0,09 **0,10** 0,10	980	oil	20	66	24,65
											150	65	23,95
											200	63	28,95
											320	59	30,15
											480	54	31,70
											550	49	39,10
											590	43	48,25
											650	38	64,35
X40CrMoV5-1 H13	0,38 **0,40** 0,42	0,95 **1,00** 1,05	0,38 **0,40** 0,42	4,75 **5,00** 5,25	**0,00**	1,43 **1,51** 1,58	**0,00**	0,95 **1,00** 1,05	1040	oil	20	54	128,40
											590	52	127,00
											540	54	136,05
											630	48	144,70
											650	44	186,05
X100CrMoV5-1 A2	0,95 **1,00** 1,05	0,29 **0,31** 0,32	0,57 **1,20** 0,63	4,75 **5,00** 5,25	**0,00**	0,95 **1,00** 1,05	**0,00**	0,24 **0,25** 0,26	960	oil	20	64	57,75
											200	62	61,25
											230	61	62,25
											550	56	75,75
											590	51	83,40
											650	44	107,70
X160CrMoV12-1 D2	1,43 **1,51** 1,58	0,29 **0,31** 0,32	0,29 **0,31** 0,32	11,4 **12,0** 12,6	**0,00**	0,86 **0,91** 0,95	**0,00**	0,95 **1,00** 1,05	1040	oil	20	63	59,90
HS6-5-2611 M2	0,86 **0,91** 0,95	0,23 **0,34** 0,45	0,20 **0,30** 0,40	3,80 **4,00** 4,20	**0,00**	4,75 **5,00** 5,25	6,18 **6,51** 6,83	1,81 **1,91** 2,00	1260	salt bath	150	66	23,30
											550	65	25,80
											520	65	27,95
											660	57	41,55
											680	55	66,70
											690	51	77,75

Table 1. continuation from p.336.

Steel designation EN AISI	Composition – element*, %								Hardening		Temp., °C	Hardness, HRC	GV, mm³
	C	Si	Mn	Cr	Ni	Mo	W	V	T_a, °C	Quench			
-F2	1,20 **1,30** 1,40	0,10 **0,30** 0,50	0,10 **0,30** 0,50	0,20 **0,30** 0,40	0,00 **0,75** 0,75	0,00 **0,15** 0,15	3,00 **3,75** 4,50	0,00 **0,10** 0,10	800	water	20	67	39,35
											180	65	36,15
											330	59	47,25
											370	55	56,85
											450	50	57,40
											430	52	57,80
-A6	0,65 **0,70** 0,75	0,10 **0,40** 0,70	1,80 **2,15** 2,50	0,90 **1,15** 1,40	0,00 **0,75** 0,75	0,90 **1,15** 1,40	0,00 **0,10** 0,10	0,00 **0,10** 0,10	840	air	20	62	73,80
											180	60	75,23
											340	55	106,30
											480	50	118,10
											590	45	130,75
-S2	0,40 **0,48** 0,55	0,90 **2,10** 1,20	0,30 **0,40** 0,50	0,00 **0,30** 0,30	0,00 **0,75** 0,75	0,30 **0,45** 0,60	0,00 **0,10** 0,10	0,00 **0,50** 0,50	880	oil	20	63	81,70
											150	62	81,30
											290	59	113,75
											430	53	137,30

*numbers within a cell represent minimal, average and maximal value, respectively from the uppermost to the lowest row.

EXPERIMENT

Schematic representation of the standardised experiment is whosn in Figure 3. The diagrams in Figure 4 show the characteristic depending of hardness and volume loss vs. tempering temperatures for two steel types.

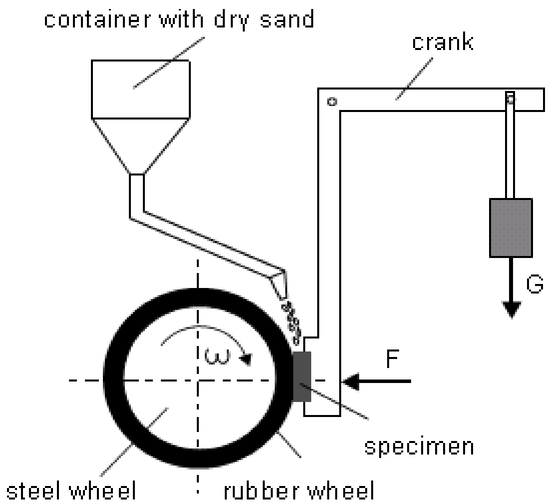

Figure 3. Sketch of a testing method of abrasion wear resistance according to ASTM G65-94 [2].

Based on the measured data for hardness and volume loss after abrasion test of all investigated steel types in different tempering condition, listed in Table 1, regression analysis resulted with a following linear relation between hardness (HRC) and volume loss GV in mm^3:

$$GV = -2{,}8146 \times HRC + 235{,}53 \quad (1)$$

The coefficient of determination is relatively low (R^2 = 0,312) what indicate that about of 70 % the influence factors on the abrasion resistance are not included or have not been known but could be significant e.g. carbide content or chemical composition as one group of input variable for formation of the carbides.

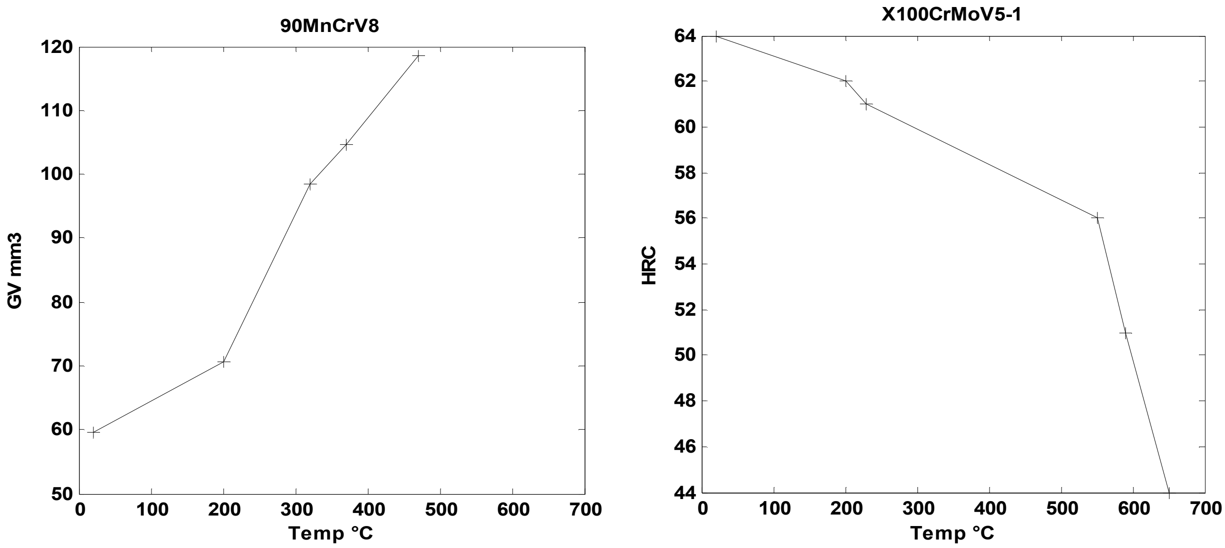

Figure 4. Abrasive volume loss and hardness vs. tempering temperature for two steel types.

NEUROFUZZY MODEL

The key benefit of fuzzy logic is, that it lets you describe desired system behaviour with simple "if-then" relations (Figure 5). In many applications, this gets a simpler solution in less design time. In addition, we can use all available engineering know-how to optimize the performance directly.

While this is certainly the beauty of fuzzy logic, it at the same time is its major limitation. In many applications, knowledge that describes desired system behavior is contained in data sets. Here, the designer has to derive the "if-then" rules from the data sets manually, which requires a major effort with large data sets.

When data sets contain knowledge about the system to be designed, a neural net promises a solution as it can train itself from the data sets. The sparse use of neural nets in applications is due to a number of reasons. First, neural net solutions remain a "black box". We can neither interpret what causes a certain behavior or we can modify a neural net manually to change a certain behavior. Second, neural nets require prohibitive computational effort for most mass-market products. Third, selection of the appropriate net model and setting the parameters of the learning

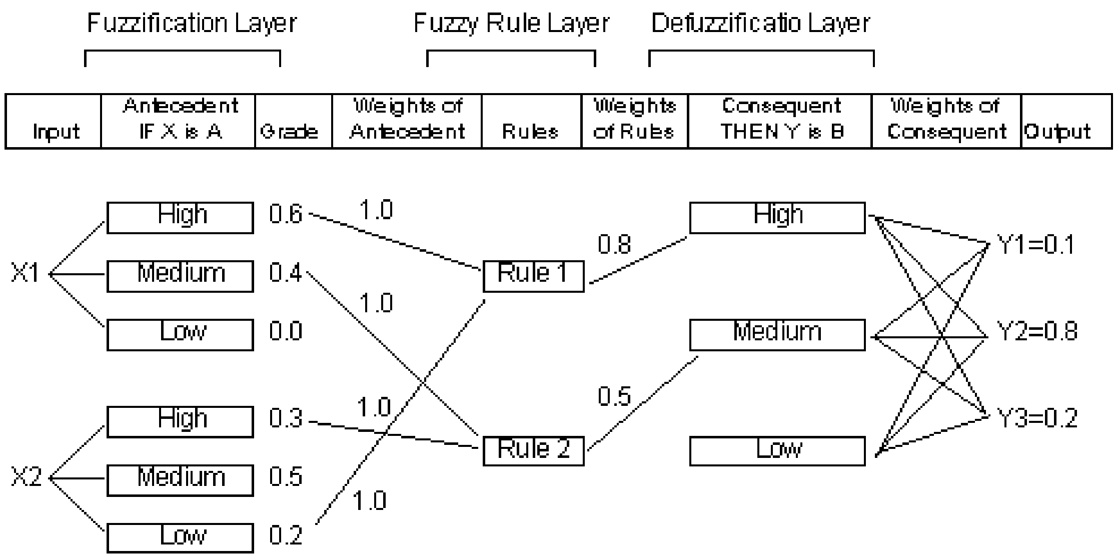

Figure 5. Layers of fuzzy system [6].

algorithm is still a "black art" and requires long experience. Of the aforementioned reasons, the lack of an easy way to verify and optimize a neural net solution is probably the mayor limitation.

In simple words, both neural nets and fuzzy logic are powerful design techniques that have its strengths and weaknesses. Neural nets can learn from data sets while fuzzy logic solutions are easy to verify and optimize. If we look at these properties in a portfolio, the idea becomes obvious, that a clever combination of the two technologies delivers best of both worlds. Combine the explicit knowledge representation of fuzzy logic with the learning power of neural nets, and we get NeuroFuzzy.

One major milestone in the development of neural net technology was the invention of the so-called error back propagation algorithm about ten years ago. The error back propagation algorithm soon became the standard for most neural net implementation due to its high performance. First, it selects one of the examples of the training data set. Second, it computes the neural net output values for the current training examples' inputs. Then, it compares these output values to the desired output value of the training example. The difference, called error, determines which neuron in the net shall be modified and how. The mathematical mapping of the error back into the neurons of the net is called error back propagation.

If the error back propagation algorithm is so powerful, why not use it to train fuzzy logic systems too? But this is not straightforward. To determine which neuron has what influence, the error back propagation algorithm differentiates the transfer functions of the neurons. One problem here is that the standard fuzzy logic inference cannot be differentiated.

To solve these problems, some neuro-fuzzy development tools use extended fuzzy logic inference methods. The most common approach is to use so-called Fuzzy Associative Memories (FAM). A FAM is a fuzzy logic rule with an associated weight. A mathematical framework exists that maps FAMs to neurons in a neural net. This enables the use of a modified error back propagation algorithm with fuzzy logic. Modern NeuroFuzzy tools work as an "intelligent" assistant with our design. They help us to generate and optimize membership functions and rule bases from sample data.

When experimental data exists, fuzzy systems can be trained to represent an input-output relationship. By using gradient descent techniques, fuzzy system parameters, such as membership function (LHS or RHS), and the connectives between layers in an adaptive network, can be optimised. Adaptation of fuzzy systems using neural network training methods has been proposed by various researchers [4, 5]. Regardless of the method or the parameter of the fuzzy system chosen for adaptation, an objective error function E must be chosen. Commonly, the squared error *E* is chosen:

$$E=\frac{(y-y')^2}{2}, \tag{2}$$

where *y*' is the target output, and *y* is the fuzzy system output. Consider the i-th rule of the zero-order Sugeno fuzzy system consisting of n rules (i = 1, ..., *n*). The Figure 6 shows the zero-order Sugeno system with *m* inputs and *n* rules.

Mathematically, zero-order Sugeno systems is represented by the following equations

$$w_i=\prod_{j=1}^{m}\mu_{A_j}(x_j), \tag{3}$$

where $\mu_A(x)$ is the membership of x_j to the fuzzy set A and w_i is the degree of fulfilment of the i-th rule. The normalized degree of fulfilment is given by

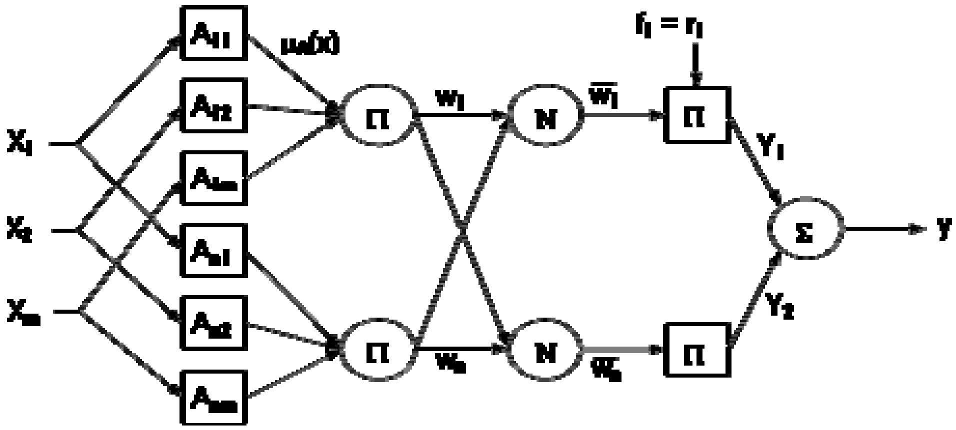

Figure 6. Model of a zero-order adaptive neurofuzzy inference system (ANFIS) [6]. Here x is the input vector, A is an antecedent membership function (LHS), $\mu_A(x)$ is the membership of x to set A, w_i is the degree of fulfilment of the i-th rule, $\hat{w}_i$ is the normalized degree of fulfilment of the i-th rule, r_i is a constant singleton membership function of the i-th rule (RHS), while y_i is the output of the i-th rule.

$$\overline{w_i} = \frac{w_i}{\sum_{i=1}^{n} w_i}, \tag{4}$$

The output y of a fuzzy system with n rules can be calculated as:

$$y = \sum_{i=1}^{n} \overline{w_i} f_i = \sum_{i=1}^{n} y_i \,. \tag{5}$$

In this case, the system is a zero-order Sugeno system and f_i is defined as:

$$f_i = r_i. \tag{6}$$

RESULTS AND DISCUSSION

Standard designations of steel grades whose wear resistance has been evaluated applying neourofuzzy model of conclusion making mechanism are listed in Table 1. For each of grades the mean values of content have been calculated from minimum and maximum values for each of eight chemical elements. Input data for ANFIS modelling according Table 1 contain mean values of chemical composition and HRC hardness, while output data contain value of mass loss. Available set contains total of 52 records. Out of this total, 50 percent of records have been randomly selected for training (learning) data set, while remaining records are assigned to checking (25 %) and testing set (25 %). Method of subtractive clustering [8] has been applied for optimisation of ANFIS, i.e. for number and shape of membership functions and their location within universe of discourse. For the applied method, parameter *radii* of 0,995 was selected, where *radii* is a vector that specified a cluster center's range of influence in each of the data dimension. Other parameters for ANFIS learning were as follows: *training epoch number* equaled 10; *training error goal* was set to 0; *initial step size* was set to 0,07; *step size decrease rate* equaled 0,7 while *step size increase rate* equaled 1,05. Volume loss GV_{MNLR} was estimated applying Multivariable Non-linear Regression (MNLR) and Hougen-Watson model [9] with shape fitting curve:

$$GV_{MNLR} = c + b_1x_1 + b_2x_2^2 + b_3x_3^3 + b_4x_4^4 + b_5x_5^5 + b_6x_6^6 + b_7x_7 + b_8x_8 + b_9x_9 \,. \tag{7}$$

and parameters c = 5, b_1 = 159,4153, b_2 = 5,3485, b_3 = 2,5476, b_4 = –0,0108, b_5 = 149, 4353, b_6 = –0,0056, b_7 = –30,3958, b_8 = 146,8483 and b_9 = –1,7242.

Independent variables X_i (i = 1, ..., 8) represent chemical composition in percentages: X_1 represents percentage of carbon, X_2 of silicon, X_3 of manganese, X_4 of chromium, X_5 of nickel, X_6 of molybdenum, X_7 of tungsten, X_8 of vanadium. Along with these, X_9 represents hardness as measured in HRC.

Results of investigation and comparison of volume loss evaluations applying neurofuzzy and MNLR model to experimental data are plotted in diagrams for generalization of training and testing data sets (Figs. 7 and 8). Statistical parameters R-correlation coefficient, SSE-sum square error, MSE-mean square error, RMSE-root mean square error, NRMSE-normalized root mean square error are given in Tables 2 and 3.

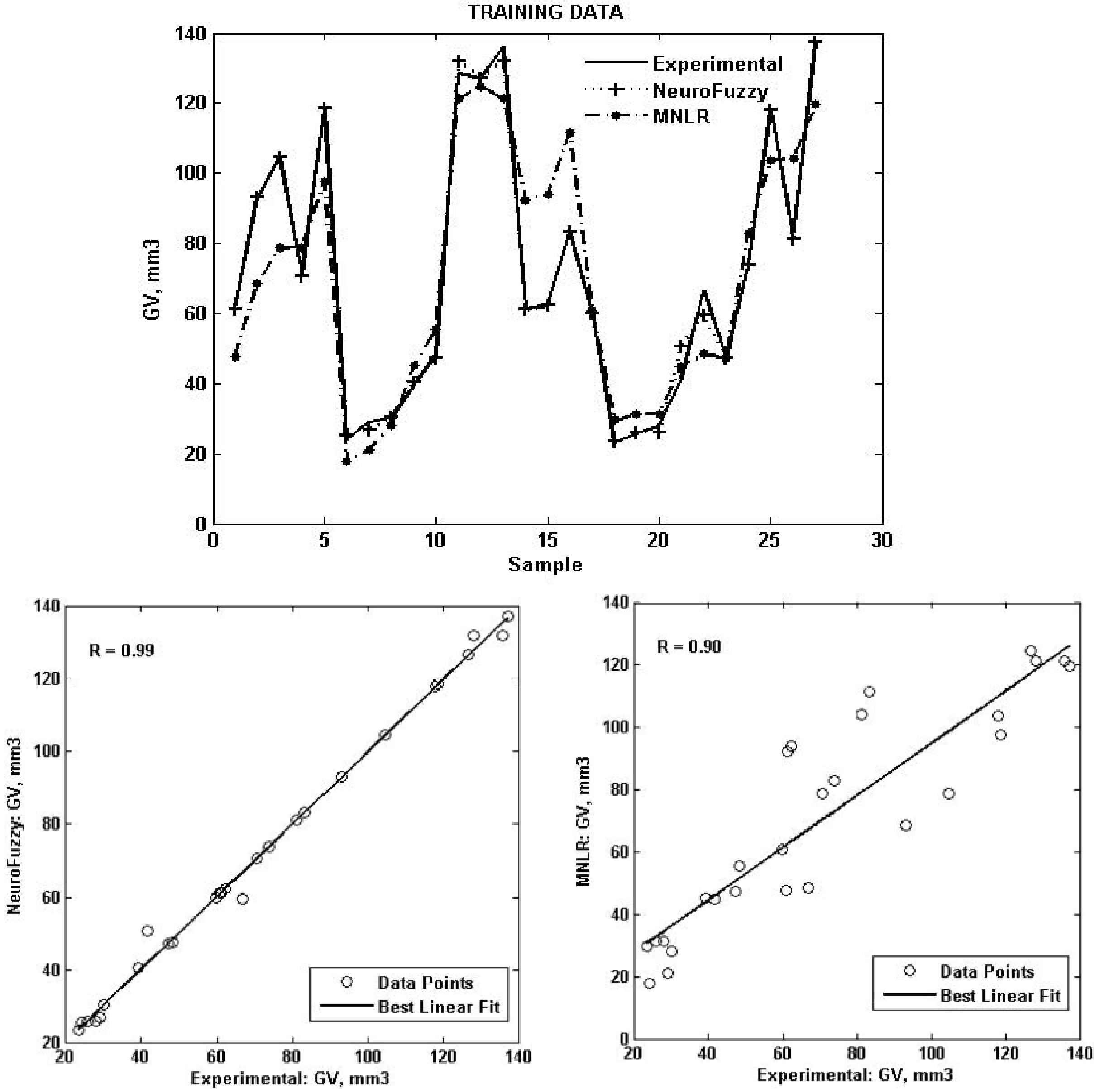

Figure 7. Generalization of data set used for training.

Table 2. Statistic parameters of data set used for training.

Method	**GV, mm^3**					**Statistical parameters**				
	min	max	mean	median	std	R	SSE	MSE	RMSE	NRMSE
NeuroFuzzy	23,30	137,30	71,10	62,25	37,53	0,99	179,53	6,64	2,57	0,26
MNLR						0,90	6750,60	250,02	15,81	0,42

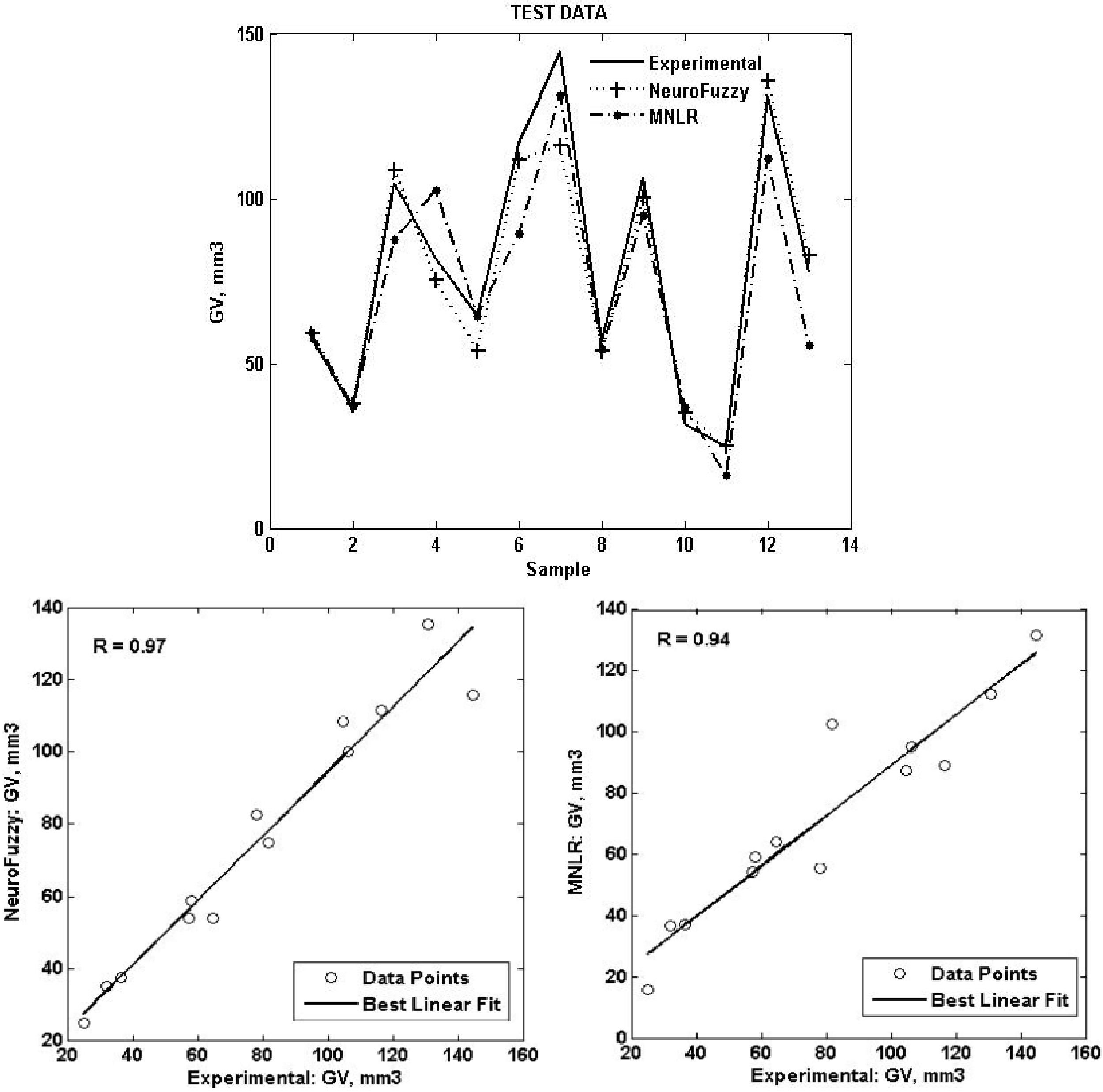

Figure 8. Generalization of data set used for testing.

Table 3. Statistical parameters of data set used for testing.

Method	**GV, mm^3**					**Statistical parameters**				
	min	max	mean	median	std	R	SSE	MSE	RMSE	NRMSE
NeuroFuzzy	24,65	144,70	79,53	77,75	38,72	0,97	1122,8	86,36	9,29	0,24
MNLR						0,94	2735,8	210,44	14,50	0,37

CONCLUSIONS

Considering rather limited collection of available data, adaptive neurofuzzy inference engine (ANFIS) providing estimation of volume loss (GV, mm^3) for the abrasion wear was successfully modelled.

Optimisation of ANFIS, i.e. number, shape and position of membership functions within universe of discourse has been made applying substractive clustering method. In this manner, combinatory explosion of rules is avoided. Suitability of neurofuzzy model has been confirmed through comparison with statistical model of multivariable non-linear regression.

Though advanced algorithm for multivariable non-linear regression was used for experimental work, registered results were inferior to those obtained by neurofuzzy model. NRMSE-normalized root mean square error index has been used as a measure for the model fitness. As presented in Tables 2 and3. For training and testing data sets, NRMSE indexes are smaller for neurofuzzy model than for MNLR model. Somewhat lower NRMSE index value for the checking data set might be explained by the fact that these data have not been included in the learning process. For selecting appropriate model for evaluation of abrasion volume loss (GV, mm^3), relevant information is NRMSE index obtained from testing data set. From Table 4 it can be noted that neurofuzzy model is more appropriate. The more accurate results could be done by working out with more homogenous data what means analysis inside the group of similar steel grades. Further research will be directed to modelling of ANFIS that will include effects of type and content of carbides and their microhardness, content of retained austenite upon the wear resistance.

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PROCJENA OTPORNOSTI ABRAZIJI ALATNIH ČELIKA PRIMJENOM *NEUROFUZZY* MODELA

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SAŽETAK

U radu se razmatra primjena *neurofuzzy* modela za procjenu otpornosti na trošenje čelika na temelju kemijskog sastava, sprovedene toplinske obrade (temperatura austenitizacije, temperatura kaljenja temperatura popuštanja), izmjerene tvrdoće nakon kaljenja s različitih temperatura kaljenja, te ispitivanja gubitka volumena materijala propisano prema standardu ASTM G 65-94. Ispitivanje gubitka volumena provedeno je za sljedeće skupine materijala: ugljični alatni čelici, alatni čelici za hladni rad, alatni čelici za topli rad i brzorezni čelici. Rezultati *neurofuzzy* adaptivnog modela također su uspoređeni u odnosu na statističko modeliranje multi-varijabilnom nelinearnom regresijom. Iz rezultata se može zaključiti da je moguća procjena otpornosti abrazivnog trošenja čelika primjenom *neurofuzzy* modela, te se predloženim modelom izbjegava dugotrajno laboratorijsko ispitivanje, a troškovi budućih ispitivanja mogu se značajno smanjiti.

KLJUČNE RIJEČI

otpornost abraziji, alatni čelici, modeliranje, *neurofuzzy*