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Application of Neural Networks to Evaluate Experimental Data of Galvanic Zincing

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***Abstract*—In order to improve corrosion resistance of alloy S355 EN 1025, the relationship between the thickness of zinc coating created during the process of acidic galvanic zincing and factors that influence this process were investigated. Influence of individual factors on thickness of zinc coating for sample area with surface current density of 3 A·dm^{-2} was determined by planned experiment which uses central composite plan. The obtained experimental data were evaluated based on neural network theory using cubic neural unit with Levenberg-Marquardt iterative adaptive algorithm. The influence of number of training data on the reliability of the obtained computational model has been studied. Furthermore, relationship between the amount of training data and reliability of prediction for the thickness of created zinc layer was observed. The relationship between input factors and thickness of layer coating with 88.37 % reliability was reached.**

Keywords*—*neural unit; zincing; thin films; layer thickness

I. Introduction

Electrodeposition of zinc and its alloys has been widely used to create corrosion-resistant coatings on steel [1], non-ferrous alloys and also non-metallic conductive materials [2], for its simplicity and affordability [3], [4]. Electrodepositing of the metal onto a cathode is a fundamental step during the electrolytic processing of zinc in production. The zing coating provides cathodic corrosion protection to steel in almost all environments as a physical barrier [5]. The texture and morphology of electrodeposited zinc can vary greatly depending on parameters such as current density [6], [7], temperature [8], [9], electrolyte composition [6], [10], *pH* [11], additives [12] and impurities [13]. Ultimately, these parameters must be controlled in order to produce a desirable cathode product. The optimum selection of process conditions is an extremely important issue as these determine surface quality of the manufactured components. Previous studies [12], [13], whose prediction models were compiled using classic statistical evaluation methods have established a reliability of prediction model for current density 5 A·dm^{-2} at 58,75 % [12] and for current density 1 A·dm^{-2} at 53,80 % [13], respectively. The mathematical modeling of the process involves several parameters that may lead to difficult analytical solution [14]-[17]. On the other hand, use of artificial intelligence for evaluation of experiments results has its merits [18], [19]. Mainly because of faster and more reliable creation of prediction model for the studied process, compared to classic statistical methods [20], [21]. Also it is possible to achieve maximum output or minimum input or both by usage appropriate type of neural unit order and learning algorithm [22], [23].

II. Materials and Methods

A. Sample Preparation

Samples of material S355 EN 10025 with dimensions 100.00 x 70.00 x 0.50 mm were used for the purposes of the experiment. Before the galvanizing process, each sample was treated as follows:

1) Degreasing in aqueous solution containing 0.6 % sodium carbonate; 0.06 % C18- unsaturated amine ethoxylate; 0.15 % fatty amine ethoxylate; 0.6 % sodium metasilicate pentahydrate; 0.6 % sodium hydroxide, T = 50 °C, t = 3 min.
2) Rinse in distilled water.
3) Pickling in an aqueous solution of HCl 18 %, T = 18 °C, t = 1 min.
4) Rinsing in distilled water.
5) Drying with compressed air.

After drying, sample was immediately submerged into prepared electrolyte and the process of acidic galvanic zincing was started.

B. Electrolyte Preparation

To identify the relationship between thickness of zinc coating and factors that enter the process of galvanic zincing, the planned experiment method was used [24]. The core of the experiment comprised of composite plan that considered six factors which influence the process of zincing. Table I. shows conversion of factor levels between coded scale and natural one. Coded scale is used to prevent influence of the absolute value of the studied factor in evaluating the results of the experiment.

TABLE I. TRANSFER TABLE

Factor		Factor level				
Code scale	***Natural scale***	-2.37	-1.00	0.00	+1.00	+2.37
x_1	Zn [$mol \cdot l^{-1}$]	0.06	0.34	0.54	0.73	1.01
x_2	Cl^- [$mol \cdot l^{-1}$]	0.70	2.26	3.39	4.51	6.07
x_3	H_3BO_4 [$mol \cdot l^{-1}$]	0.10	0.32	0.49	0.65	0.87
x_4	U [V]	1.62	3.00	4.00	5.00	6.38
x_5	T [°C]	-3.78	10.00	20.00	30.00	43.78
x_6	T [min]	3.11	10.00	15.00	20.00	26.89

C. Problem Solution

Higher-order nonlinear neural units (HONU) [25] has been shown as promising polynomial neural architectures to predict chaotic time series [26] and real signals including respiratory time series [27]. Linear predictors, i.e. linear neural units (LNUs) are considered to be the first–order neural units. The second–order neural unit is called the quadratic neural unit (QNU) and the third–order one can be called the cubic neural unit (CNU). Cubic neural unit was used during the evaluation of the experiment, because its resulting mathematical model can cover wide range of measured value variability (training data). This unit has shown highest reliability during the evaluation of experiment results.

Levenberg-Marquardt algorithm, which was used during the training process of neural unit, is described by equations (1) to (7). It is a process of updating individual weights **w** in a predetermined number of steps to achieve a minimum difference between the real (measured) and calculated values [28].

$$u_i = \frac{\partial y_{HONU}}{\partial w_i} \tag{1}$$

$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}, \ \mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \tag{2}$$

$$\mathbf{J} = \begin{bmatrix} \mathbf{u}^T{}_1 \\ \mathbf{u}^T{}_2 \\ \vdots \\ \mathbf{u}^T{}_m \end{bmatrix} = \begin{bmatrix} u_{1;1} & u_{2;1} & \cdots & u_{n;1} \\ u_{1;2} & u_{2;2} & \cdots & u_{n;2} \\ \vdots & \vdots & \ddots & \vdots \\ u_{1;m} & u_{2;m} & \cdots & u_{n;m} \end{bmatrix} \tag{3}$$

$$\mathbf{y}' = \mathbf{w} \cdot \mathbf{u} \tag{4}$$

$$\mathbf{e} = \mathbf{y} - \mathbf{y}' \tag{5}$$

$$\mathbf{\Delta w} = \left(\mathbf{J}^T \cdot \mathbf{J} + \frac{1}{\mu} \cdot \mathbf{I} \right)^{-1} \cdot \mathbf{J}^T \cdot \mathbf{e} \tag{6}$$

$$\mathbf{w}_n = \mathbf{w}_{n-1} + \mathbf{\Delta w} \tag{7}$$

After the learning process of neuron unit is done, we get a computational model that describes the thickness of AAO layer with equations (8) and (9) for surface current density 3 $A \cdot dm^{-2}$.

$$th = \frac{3}{1 + e^{-\alpha}} 3 \cdot \mathrm{std}_y \tag{8}$$

$$\alpha = \sum_{i=1}^{n} (u_i \cdot w_i) \tag{9}$$

where *th* is final thickness of zinc film, α is preliminary thickness of zinc film, u_i is a combination of input factors levels (in coded scale), w is weight of combinations of input factors and std_y is standard deviation of measured thicknesses of all samples. Calculated thickness of zinc film is expressed in $mm \cdot 10^{-3}$. The number of training data was gradually reduced during the neural units learning process from 46 to 30, where the resulting computational model was considered reliable. This gradual decrease in amount of training data was done to increase the reliability of prediction - lesser amount of training data raises the amount of data that is used for verification of compiled prediction model. For this reason, it is possible to consider the compiled prediction model as more reliable.

III. RESULTS AND DISCUSSION

Process of experiment result evaluation using any neural unit is comprised of two parts – neural unit learning process and the verification of obtained computational model. Generally, reliability of computational model that neural unit learning process creates rises with increase in amount of training data. Process of verification is similar in that regard: with rising number of verified values also increases the reliability of prediction for obtained computational model. However, this only applies in cases where verified values were not used as training data.

A problem with arises in case of planned experiment, which uses 46 different combinations of input factors – amount of data for training process and for evaluation process. For this reason, the amount of training data was gradually reduced. Data that were not used during the training process were used to verify the model. Reliability of computational models for different number of training values is shown in Table II. As can be seen from the table, the amount of training data (No.T.D.) decreased from 46 to 30. It was not possible to use lower number of training values due to high prediction error and the associated reliability of resulting model.

Table II shows reliability of computational model in three ways. First case (A.D.) shows models reliability for all measured values of zinc coating thickness. This means, that reliability of the model was calculated from values that were also used during learning process of neural unit. Reliability of model is between 94.72 % (for 46 training data) and 83.30 % (for 30 training data). In second case (W.B.C), boundary conditions were set for a computational model, $x_6 \leq +1$. This means that computational model does not consider the input factor x_6 (zincing time) in case its level is above +1 (20 min). The reason is that after certain time the speed of zinc excretion from cathode changes. Calculation model does not account for this change in excretion speed and the difference between measured and calculated thickness of zinc coating is considerably higher. Again, all values of zinc coating thickness were used during the verification process and the reliability of computational model is between 94.61 % (for 46 training data) and 93.60 % (for 30 training data), which shows 10 % increase in reliability of computational model. In third case (O.U.), only coating thickness values that were not used during training process were used during verification process. In this case, reliability of a model is around 88.37 % (for 30 training data). This means that created model can predict the thickness of zinc coating for any levels of input factors x_1-x_6.

TABLE II. RELIABILITY OF COMPUTATIONAL MODELS

No.T.D.	Adj. [%]		
	A.D.	**W.B.C.**	**O.U.**
46	94.72	94.61	-
45	94.47	94.34	-
44	85.58	99.82	86.13
43	86.26	99.82	82.95
42	85.26	98.41	77.03
41	84.64	97.88	71.04
40	83.73	96.48	94.88
39	82.88	95.20	93.52
38	82.86	95.00	93.01
37	82.90	95.53	92.36
36	82.83	95.78	91.68
35	83.10	96.14	90.67
34	83.34	95.66	90.43
33	82.22	94.06	82.99
32	82.43	94.31	88.92
31	83.34	94.50	89.05
30	83.30	93.60	88.37

Fig. 1 and Fig. 2 show results of neural units training process with 46 (Fig. 1) and 30 (Fig. 2) training data. Line of ideal prediction was plotted in both figures. This means that, the closer the points are to the plotted line, the more accurate the prediction of neural unit is, or the neural unit can learn more accurately from given data. As can be seen in Fig. 1, neural unit was able to learn from 46 training values quite accurately, relatively speaking – thickness values are very close to the line of perfect calculations.

Similar situation arises in case where the neural unit used 30 training values (Fig. 2). However, in this case, all of the plotted values lie on the line of ideal prediction. This means that the neural unit was able to learn from training data with considerably higher accuracy.

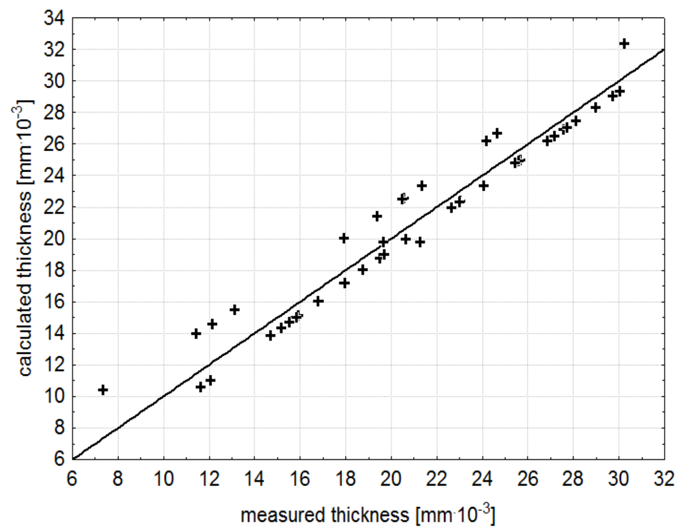

Fig. 1. Result of training process for current density 3 A·dm^{-2} and 46 training data

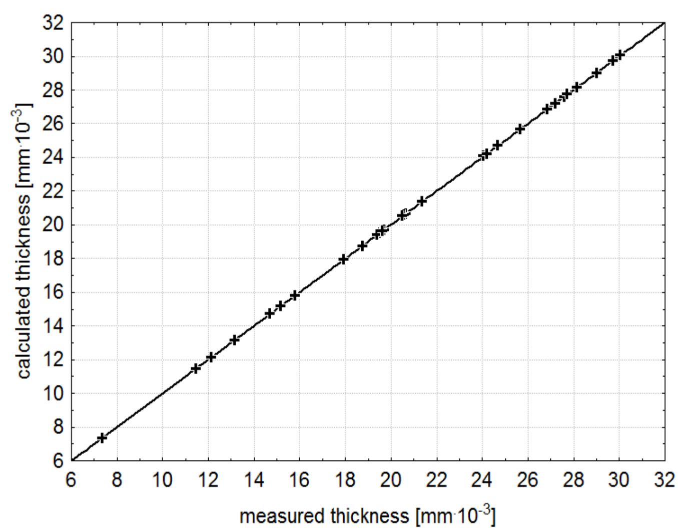

Fig. 2. Result of training process for current density 3 A·dm^{-2} and 30 training data

Results from verification of obtained computational models are shown in Fig. 3 and Fig. 4. Fig. 3 shows calculation error for case where neural unit had access to all 46 training data during the training process. As can be seen from Fig. 3, neural unit predicts the thickness of layer coating with error that ranges from $2.00 \cdot 10^{-3}$ mm to $3.00 \cdot 10^{-3}$ mm for all samples. Fig. 4 shows the case where neural unit had access to 30 training data. As can be seen from Fig. 4, neural unit predicts the thickness of layer coating with error that ranges from $-6.00 \cdot 10^{-3}$ mm to $2.00 \cdot 10^{-3}$ mm. In spite of the fact that the absolute range of error has risen, the model can be considered as more reliable, because the calculation of neural unit could have been verified against an adequate number of values. Data used for verification represent 33 % of total sample number.

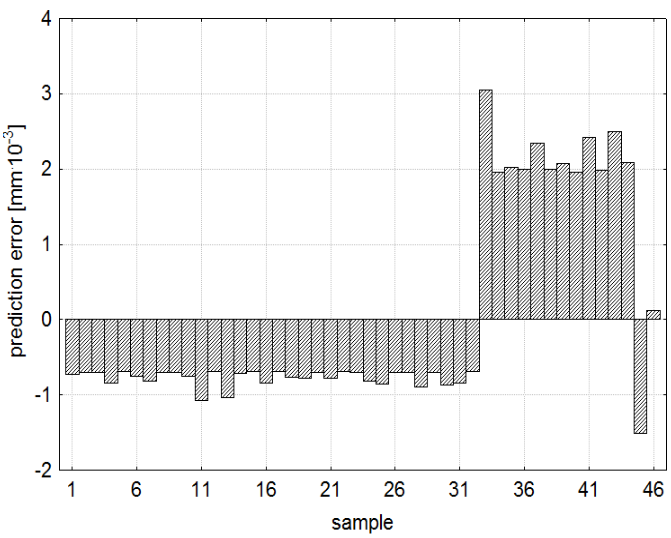

Fig.3. Error of prediction for 46 measured samples and 46 training data for current density 3 $A \cdot dm^{-2}$

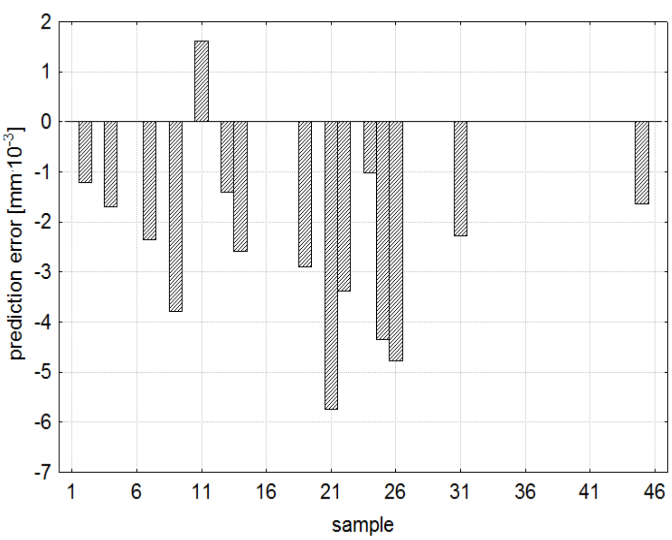

Fig. 4. Error of prediction for 46 measured samples and 30 training data for current density 3 $A \cdot dm^{-2}$

Table III shows weights that were calculated by neural unit for each individual combination of input factors that influence the process of galvanic zincing. These weights were calculated using 30 training data.

TABLE III. INPUT WEIGTHS

input	weight	input	weight	input	weight	input	weight
ABS	-0.57	x_3x_6	0.03	$x_1x_3x_6$	-0.01	$x_2x_6x_6$	-0.02
x_1	0.00	x_4x_4	0.02	$x_1x_4x_4$	-0.01	$x_3x_3x_3$	0.02
x_2	-0.01	x_4x_5	-0.01	$x_1x_4x_5$	0.00	$x_3x_3x_4$	0.01
x_3	0.00	x_4x_6	0.13	$x_1x_4x_6$	-0.02	$x_3x_3x_5$	0.00
x_4	0.01	x_5x_5	-0.05	$x_1x_5x_5$	-0.01	$x_3x_3x_6$	0.05
x_5	0.01	x_5x_6	-0.09	$x_1x_5x_6$	-0.01	$x_3x_4x_4$	-0.01
x_6	0.06	x_6x_6	0.18	$x_1x_6x_6$	-0.01	$x_3x_4x_5$	0.00
x_1x_1	-0.08	$x_1x_1x_1$	0.06	$x_2x_2x_2$	0.01	$x_3x_4x_6$	-0.03
x_1x_2	0.02	$x_1x_1x_2$	-0.02	$x_3x_2x_3$	-0.01	$x_3x_5x_5$	-0.01
x_1x_3	0.00	$x_1x_1x_3$	-0.01	$x_2x_2x_4$	0.01	$x_3x_5x_6$	-0.02
x_1x_4	0.04	$x_1x_1x_4$	0.01	$x_2x_2x_5$	0.00	$x_3x_6x_6$	-0.01
x_1x_5	-0.01	$x_1x_1x_5$	0.00	$x_2x_2x_6$	0.05	$x_4x_4x_4$	0.02
x_1x_6	0.06	$x_1x_1x_6$	0.05	$x_2x_3x_3$	-0.02	$x_4x_4x_5$	0.00
x_2x_2	0.00	$x_1x_2x_2$	-0.01	$x_2x_3x_4$	-0.01	$x_4x_4x_6$	0.05
x_2x_3	0.01	$x_1x_2x_3$	0.04	$x_2x_3x_5$	-0.02	$x_4x_5x_5$	0.01
x_2x_4	0.05	$x_1x_2x_4$	-0.02	$x_2x_3x_6$	0.00	$x_4x_5x_6$	0.04
x_2x_5	0.05	$x_1x_2x_5$	-0.03	$x_2x_4x_4$	-0.02	$x_4x_6x_6$	0.01
x_2x_6	-0.01	$x_1x_2x_6$	0.00	$x_2x_4x_5$	-0.01	$x_5x_5x_5$	0.03
x_3x_3	-0.04	$x_1x_3x_3$	-0.01	$x_2x_4x_6$	-0.01	$x_5x_5x_6$	0.05
x_3x_4	0.02	$x_1x_3x_4$	-0.01	$x_2x_5x_5$	-0.02	$x_5x_6x_6$	0.00
x_3x_5	0.01	$x_1x_3x_5$	-0.01	$x_2x_5x_6$	-0.01	$x_6x_6x_6$	0.12

IV. CONCLUSION

Generally, usage of higher-order neural units has a great potential for evaluation of experiments results in industrial applications. As it has been presented in this paper, the usage of 3rd order neural unit based on the iterative Levenberg-Marquardt (LM) optimization algorithm provides a wide range of options to describe the examined process of galvanic zincing. We have obtained predictive model with almost 90.00 % reliability for surface current density 3 $A \cdot dm^{-2}$. This represents an increase in prediction reliability of resulting zinc layer thickness by 30 to 40 %, as compared to classic statistical evaluation methods. Such high reliability offers some possibilities for optimization of examined technological processes, but more research is still necessary to increase reliability of obtained computational model. Higher reliability of prediction model will allow us to reduce the operating costs and simultaneously create desired value of zinc film thickness.

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