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Comparison of the Technological Time Prediction Models

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The paper sets out to describe the results obtained by investigating the prediction of technological parameters and, indirectly, of technological time needed for seam tube polishing. The results of experimental investigations were used to define, analyse and compare two models. One is a mathematical i.e. statistical model obtained by the application of the least squares method and the least absolute deviation method. The other is a model based on the application of neural networks. To define the model based on the application of neural networks various structures of the back-propagation neural network with one hidden layer were analysed and the optimal one with the minimum RMS error was selected.
The more precise predictions of technological time provided by the models supplement the previously defined manufacturing operations, replace the predictions based on the technologists' experience and form the basis on which to plan production and control delivery times. The work of technologists is thus made easier and the production preparation technological time shorter.

Usporedba modela za procjenu tehnološkog vremena

Izvornoznanstveni članak

U radu su opisani rezultati istraživanja vezani uz procjenjivanje tehnoloških parametara i, neizravno, tehnološkog vremena poliranja šavnih cijevi. Prikupljeni su rezultati eksperimentalnih istraživanja koji su poslužili za definiranje, analizu i usporedbu dvaju modela: matematičkog, odnosno statističkog modela, za čije je postavljanje primijenjena metoda najmanjih kvadrata i metoda najmanjih apsolutnih odstupanja, i modela temeljenog na primjeni neuronskih mreža. Za definiranje modela temeljenog na primjeni neuronskih mreža analizirane su različite strukture neuronske mreže širenja unazad s jednim skrivenim slojem, te je izabrana optimalna s najmanjom razinom RMS greške.
Točnije procjene tehnološkog vremena koje daju modeli upotpunjavaju prethodno definirane tehnološke operacije, zamjenjuju iskustvene procjene tehnologa i predstavljaju osnovu za planiranje proizvodnje i kontrolu rokova isporuke. Na ovaj se način olakšava rad tehnologa i skraćuje vrijeme tehnološke pripreme proizvodnje.

1. Introduction

The application of new scientific approaches that will improve the level of knowledge and organisation in production preparation sectors has a considerable impact upon the final characteristics of products and an indirect effect on production costs and times of delivery. Integration of computers i.e. computer systems into the preparation, manufacturing and managing process has exerted a great influence on increasing the level of automation, productivity and flexibility in manufacturing companies. In this way the human involvement in production has been significantly reduced while at the same time the human factor's importance in production preparation has remained exceptionally great.

In manufacturing companies in which emphasis is placed on technological and operational preparation of production i.e. those that keep up to date with the technological parameters and the results of technological processes, essential prerequisites are set for improving the activities in the observed sectors. By the application of the systems based on artificial intelligence attempts are made to integrate and make commonly accessible the accumulated individual knowledge and experience of the people working in the production preparation sectors. Some authors today deal with the way of collecting the technological knowledge, its presentation and application to intelligent systems. They use the acquired expert knowledge in the Computer Aided Process Planning (CAPP) system for the identification (classification)

Symbols/Oznake

α	– vector of unknown parameters – vektor nepoznatih parametara
$\mathcal{P}$	– parameter space – prostor parametara
(ω_i, ζ_i, y_i)	– experimental data – eksperimentalni podaci
ω_i	– weights of data – težine podataka
ε_i	– unknown additive errors – nepoznate aditivne greške
σ^2	– variance – varijanca
F_p	– functional – funkcional
$\varnothing_1, \cdots, \varnothing_n$	– known real functions – poznate realne funkcije
s	– given positive vector – zadani pozitivan vektor
D_i	– outside diameter of tube, mm – vanjski promjer cijevi
o_i	– oval shape of the tube after the first phase of production, µm – ovalnost cijevi nakon prve faze proizvodnje
g_i	– gradation of belts for grinding and polishing, grit – gradacija remenja za brušenje ili poliranje
t_i	– condition of belts (time usage of belts), min – stanje remenja (vrijeme uporabe remenja)
p_i	– pressure of belts, A – pritisak remenja
E	– global error – globalna greška
$\Delta w_{ji}^{[s]}$	– network weighted connections – prirast težina veza u mreži
α	– learning coefficient – stopa učenja
$x_j^{[s]}$	– output state of j-th of this neuron in the s-th layer – izlazno stanje j-tog neurona u s-tom sloju
$e_j^{[s]}$	– parameter that represents the learning error – parametar koji predstavlja grešku učenja
RMS	– Root Mean Square error – korijen srednjeg kvadratnog odstupanja
MS	– Mean Square error – srednje kvadratno odstupanje
N	– number of pairs of the training set input-output values – broj parova ulazno-izlaznih vrijednosti skupa za učenje
y_n	– neural network n-th output – n-ti izlaz neuronske mreže
d_n	– desired value of a neural network n-th output – željena vrijednost n-tog izlaza neuronske mreže
Δw_{ji}	– value of the difference in the weights of neuron j and neuron i realized in two steps (k-th and k-1) – vrijednost razlike težina neurona j prema neuronu i ostvarene u dva koraka (k-tom i k-1)
y_{di}	– actual (desired) output – stvarni (željeni) izlaz
G	– function increment – prirast funkcije
T	– function threshold – prag funkcije

of work pieces, selection of a manufacturing process, machines and machining parameters in order to shorten the time and minimize the errors in the process planning of the machining process [1-3] and some other processes like forging [4]. The technological knowledge is necessary for determination of the basic material, sequence of manufacturing operations, selection of tools etc [5-6]. The problem of optimization in the mentioned activities is quite important in manufacturing industries. One of the up-to-date techniques in the optimization procedure is the application of genetic algorithms (GA). This optimization technique, which is more efficient than the traditional ones (geometric programming, dynamic programming, ..) is described and implemented in the works of many authors [7-10]. The authors [7] and [8] use genetic algorithms in the optimization of cutting parameters in turning processes. They consider a great number of constraints such as cutting force, machine power, tool reliability, cutting zone temperature etc. in order to shorten the time and reduce the operating costs. Attempts are made to achieve the same goals by a continuous improvement of cutting conditions i.e. by the development and application of an on-line intelligent system for the monitoring and optimization of cutting conditions based on genetic algorithms [9-10]. Besides the GA the neural networks (NN) [11-14] are also often combined in the procedures of the machining parameters optimization. Thus for the selection of optimal machining parameters, based on experimental data, when the analytical and empirical mathematical models are not available, Genetically Optimized Neural Network System (GONNS) [12] is proposed. In this paper the NN represents the relationship between the cutting conditions and machining-related variables, and Genetic Algorithm (GA) obtains the optimal operational condition. The paper [13] presents the use of neural network and genetic algorithm for modelling and optimal selection of input parameters of abrasive flow machining process. For a multi-criteria optimization of the cutting parameters in a turning process the hybrid analytical-neural network approach [14-15] is also proposed. Neural networks are also used for evaluation of the machined surface roughness [16] i.e. of the tool wear in the machining process [17]. The authors [16-17] compare the results obtained by the application of neural networks with the results obtained by analytical models. In the multi-dimensional problems in which the mathematical dependence of the input and output variables cannot be easily established, the application of neural networks is of considerable importance.

Mathematical modelling is also widely applied in prediction of surface roughness [18-19], in prediction of cutting forces [20] and in prediction of technological time [21].

This work therefore deals with the problem of prediction of the seam tube polishing technological time by the application of two approaches for the model definition: mathematical, i.e. statistical and the other, based on neural networks. Based on experimental research results the models are set up, analysed and compared.

2. The problem and investigating goal definition

There are two phases in the production of stainless steel seam tubes: rolling phase and grinding and polishing phase. In the initial phase a stainless steel band of diverse width and thickness, depending on the required external diameter of the tube, is rolled over a number of vertical and horizontal rollers and formed into a tube. Then the edges of the rolled tube are heated and prepared for the TIG welding in a protective chamber. This is followed by the grinding of the raised edges of the weld and calibrating of the tube according to the required tolerance of external diameter and the required oval shaping. After the weld is tested by a non-destructive method and occasional technological trials, the tube is rough ground, marked, cut to the specified length and taken to a store for the semi-manufactured products. A planned minimal quantity of the tubes of various dimensions is kept in the store.

In most cases (about 95 %) these stainless steel seam tubes need additional grinding and polishing. The scheme of the grinding and polishing line is given in Figure 1. Depending on the customers' orders the tubes are taken from the storage place and the second phase (grinding and polishing) follows. Passage through abrasive belts and polishing heads and rotation around axis give the required cleanliness and polish to the external surface. If the required quality is to be reached the worn out abrasive belts should be replaced in time. If this is not the case the tubes will be sent back for additional treatment (II or III phase of polishing) which results not only in the loss of time but in the increase of the working order costs too. Machining parameters and the time necessary for the second phase of production are mostly assessed based on experience. The machining time can be calculated on the basis of the polishing rate and the polishing rate depends on a great number of other parameters of influence.

Therefore one of the goals of this paper is to develop a mathematical model for predicting technological parameters and, indirectly, technological time of the seam tube polishing. Along with this model a processing model is developed based on the application of neural networks. To establish the model, mathematical approach and neural networks have been selected since the knowledge about the problem is available in the form of a set of discrete values of the state vector element and the process output values. Actual data for setting up the model have been collected from 172 work orders over a longer period of time in the company Đuro Đaković Welded Vessels Ltd. in the production of stainless steel seam tubes.

After the paper was published [21] the research and the collection of experimental data continued. By the analysis of the experiment data variance a conclusion was reached on the importance of factors and factor interactions. Therefore, with regard to the model published in the paper [21] the factors that are not important have been removed.

3. Least squares method modelling

In setting up the model the linear least squares problem was applied i.e. the moving least squares method described in the text that follows. The problem is reduced to the prediction of parameters in mathematical model. Assuming that the given model function is $f : \mathbb{R}^d \to \mathbb{R}$,

$$\xi \to f(\xi;\alpha), \tag{1}$$

which depends on the vector of unknown parameters $\alpha = [\alpha_1,\ldots,\alpha_n]^T \in \mathcal{P} \subseteq \mathbb{R}^n$. The unknown parameters vector $\alpha \in \mathcal{P}$ is to be determined based on experimental data $(\omega_i, \xi_i, \gamma_i)$, i=1,…,m, m>>n. In the process $\xi_i \in \mathbb{R}^d$ are the values of independent variable and $\gamma_i \in \mathbb{R}$ the values of dependent variable, while $\omega_i > 0$ denote the corresponding data weights. Weights ω_i usually depend on ξ_i and γ_i. In literature such problem is known as the parameters prediction problem in a mathematical model [22-25].

If assumed that the dependent variables γ_i contain unknown additive errors ε_i i.e.

$$\gamma_i = f(\xi_i;\alpha) + \varepsilon_i, \quad i=1,\ldots,m, \tag{2}$$

the unknown parameters vector $\alpha \in \mathcal{P}$ is normally to be predicted by the minimization of the weighted sum of the p-th power $1 \le p \le \infty$ of additive errors ε_i absolute values, i.e. by the minimization of the functional

$$F_p(\alpha) = \sum_{i=1}^{m} \omega_i \left| f(\xi_i;\alpha) - y_i \right|^p, \tag{3}$$

in the parameters $\mathcal{P} \subseteq \mathbb{R}^n$ space [23-26].

Assuming that the additive errors ε_i are normally distributed anticipating zero and with variance σ^2, it is usual to predict the unknown parameters vector $\alpha \in \mathcal{P}$ by the minimization of derivable functional

$$F_2(\alpha) = \sum_{i=1}^{m} \omega_i \left(f(\xi_i;\alpha) - y_i \right)^2, \tag{4}$$

in the parameters $\mathcal{P} \subseteq \mathbb{R}^n$ space. What is dealt with in this case is the least squares method [22-27].

If the model – function is linear in parameters i.e. if it is in the form of

$$f(\xi, a) = \alpha_1 \phi_1(\xi) + \ldots + \alpha_n \phi_n(\xi),\ a = [\alpha_1, \ldots, \alpha_n]^T, \tag{5}$$

where $\phi_1, \ldots, \phi_n$ are known real functions $\phi_i : \mathbb{R}^d \to \mathbb{R}$, $i = 1,\ldots,n$ the functional F_p can be written in the form

$$F_p(a) = \left\| W^{\frac{1}{p}} (Xa - y) \right\|_p^p = \sum_{i=1}^{m} \omega_i \left| x_i^T a - y \right|^p, \tag{6}$$

where

$$X := \begin{bmatrix} \phi_1(\xi_1) & \phi_2(\xi_1) & \cdots & \phi_n(\xi_1) \\ \phi_1(\xi_2) & \phi_2(\xi_2) & \cdots & \phi_n(\xi_2) \\ \vdots & \vdots & \vdots & \vdots \\ \phi_1(\xi_m) & \phi_2(\xi_m) & \cdots & \phi_n(\xi_m) \end{bmatrix} = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_m^T \end{bmatrix} \tag{7}$$

and

$$W := \begin{bmatrix} \omega_1 & 0 & \cdots & 0 \\ 0 & \omega_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \omega_m \end{bmatrix},\ y := [y_1, \ldots, y_m]^T. \tag{8}$$

Because the functional F_p, $1 \le p \le \infty$ is convex, in general, the sub-gradient methods, that unfortunately converge very slowly, are used for its minimization.

This paper treats the problem of the functional (p) minimization in case $p = 2$. The case $p = 2$ is known under the name linear least squares problem or the linear LS problem for short. The linear LS problem has been well studied in literature so that the stable numerical methods based on QR or SVD decomposition of the matrix X are used for its solution.

In the paper the moving linear LAD i.e. the linear LS method is applied for modelling. In this method point $P = (u, v), u \in \mathbb{R}^d, v \in \mathbb{R}$, experimental data $(\omega_i, \xi_i, y_i), i = 1,\ldots,m, \xi_i \in \mathbb{R}^d, \xi_i \in \mathbb{R}^d, \omega_i > 0$ and function $\phi_i : \mathbb{R}^d \to \mathbb{R}, i = 1,\ldots,n.$ are given. It is assumed that the aim is to solve the linear LS and the linear LAD problem (p) around the point P. At the same time the data that are closer to point P are to have stronger impact on optimal parameters with regard to the data that are further away. For this purpose each datum (ξ_i, y_i), $i = 1,\ldots, m$ with regard to point $P = (u, v)$ is assigned the weights $\omega_i(u, v) = e^{-s^T(u-\xi_i)}$, $i = 1,\ldots, m$ where $s \in \mathbb{R}^d$ is the given positive vector.

The minimization problem of the functional is considered given by the following expression:

$$F_{2,(u,v)}(\alpha) = \sum_{i=1}^{m} \omega_i(u, v) \left(x_i^T \alpha - y_i \right)^2 \to \min_{\alpha}. \tag{9}$$

Before establishing the function model it is essential to predict the form of the function dependence. This is particularly important in multi-dimensional problems. Thus it is advisable to present the results of the measuring in the three-dimensional coordinate system i.e. try to "reduce" it to the three-dimensional one. Upon examination of the graph showing research (experiment) results some essential predictions can be made for setting up the function model. For the case studied in this paper it has been found (according to Figure 1) that linear members only in the function model will not suffice to obtain the prediction function.

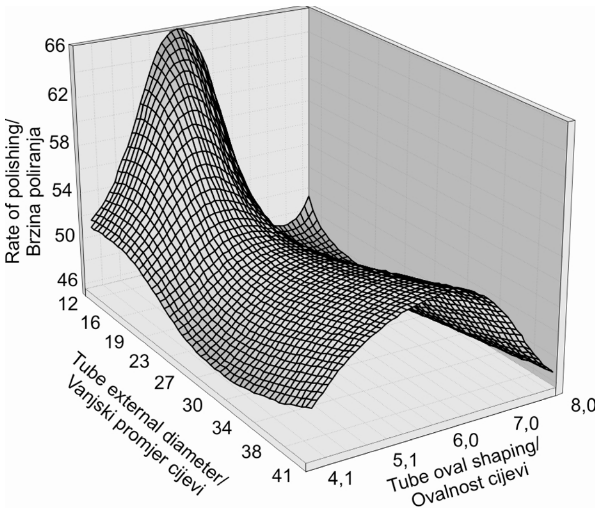

Figure 1. Functional dependence of the rate of polishing on outside diameter and oval shape of the tube

Slika 1. Funkcijska ovisnost brzine poliranja o vanjskom promjeru i ovalnosti cijevi

The model-function which is linear in parameters has the following general form

$$f(\xi, a) = \alpha_1 \phi_1(\xi) + \ldots + \alpha_n \phi_n(\xi),\ a = [\alpha_1, \ldots, \alpha_n]^T, \qquad (1)$$

As mentioned earlier, based on experimental data, dependent variable $\mathsf{y}_i \in \mathbb{R}$ is defined as the polishing rate υ_i, while the outside diameter of tube D_i, oval shape of the tube after the first phase of production o_i, gradation of belts for grinding and polishing g_i, condition of belts (time of usage of belts) t_i and pressure of belts p_i are defined as independent variables. Therefore:

$$\mathsf{y} := [v_1, \ldots, v_m]^T,$$

$$\xi := \begin{bmatrix} D_1 & o_1 & g_1 & t_1 & p_1 \\ D_2 & o_2 & g_2 & t_2 & p_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ D_m & o_m & g_m & t_m & p_m \end{bmatrix} = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_m \end{bmatrix}, \qquad (11)$$

where the real functions $\phi_1, \ldots, \phi_n$ are defined in the following way:

$$X := \begin{bmatrix} \phi_1(\xi_1) & \phi_2(\xi_1) & \cdots & \phi_n(\xi_1) \\ \phi_1(\xi_2) & \phi_2(\xi_2) & \cdots & \phi_n(\xi_2) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_1(\xi_m) & \phi_2(\xi_m) & \cdots & \phi_n(\xi_m) \end{bmatrix} = \qquad (12)$$

$$= \begin{bmatrix} 1 & D_1^2 & o_1^2 & g_1^2 & t_1^2 & p_1^2 & D_1 o_1 & D_1 g_1 & D_1 t_1 & D_1 p_1 & o_1 g_1 & o_1 t_1 & o_1 p_1 & g_1 t_1 & g_1 p_1 & t_1 p_1 \\ 1 & D_2^2 & o_2^2 & g_2^2 & t_2^2 & p_2^2 & D_2 o_2 & D_2 g_2 & D_2 t_2 & D_2 p_2 & o_2 g_2 & o_2 t_2 & o_2 p_2 & g_2 t_2 & g_2 p_2 & t_2 p_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & D_m^2 & o_m^2 & g_m^2 & t_m^2 & p_m^2 & D_m o_m & D_m g_m & D_m t_m & D_m p_m & o_m g_m & o_m t_m & o_m p_m & g_m t_m & g_m p_m & t_m p_m \end{bmatrix}$$

so finally according to

$$y_i = f(\xi_i; \alpha) + \varepsilon_i,\ i = 1, \ldots, m \qquad (13)$$

it is possible to write

$$y_i = \alpha_1 \phi_1(\xi_i) + \ldots + \alpha_n \phi_n(\xi_i) + \varepsilon_i,\ i = 1, \ldots, m \qquad (14)$$

It follows that the polishing rate can be written by the regression model obtained on the basis of experimental results:

$$\begin{aligned} H_i &= \alpha_1 + \alpha_2 D_i^2 + \alpha_3 o_i^2 + \alpha_4 g_i^2 + \alpha_5 t_i^2 + \alpha_6 p_i^2 \\ &+ \alpha_7 D_i o_i + \alpha_8 D_i g_i + \alpha_9 D_i t_i + \alpha_{10} D_i p_i + \alpha_{11} o_i g_i \\ &+ \alpha_{12} o_i t_i + \alpha_{13} o_i p_i + \alpha_{14} g_i t_i + \alpha_{15} g_i p_i + \alpha_{16} t_i p_i + \varepsilon_i. \end{aligned} \qquad (15)$$

The values of coefficients were obtained from the program package Mathematics and are shown in Table 1. The overall relative error for the weighted LS is 5.98%.

Table 1. Model (15) values of coefficients

Tablica 1. Vrijednosti koeficijenata u modelu (15)

Values of coefficients / Vrijednosti koeficijenata	Values of coefficients / Vrijednosti koeficijenata
α_1 = 56.949700	α_1 = 0.008406
α_1 = 0.087596	α_1 = 0.000036
α_1 = -0.000134	α_1 = 0.014040
α_1 = -0.114694	α_1 = 0.000976
α_1 = -0.001127	α_1 = -0.008527
α_1 = 0.003533	α_1 = 0.020593
α_1 = -0.020795	α_1 = -0.000070
α_1 = -0.002485	α_1 = -0.000818

Figure 2 shows the actual and predicted (by a mathematical model (15) values of the rate of polishing.

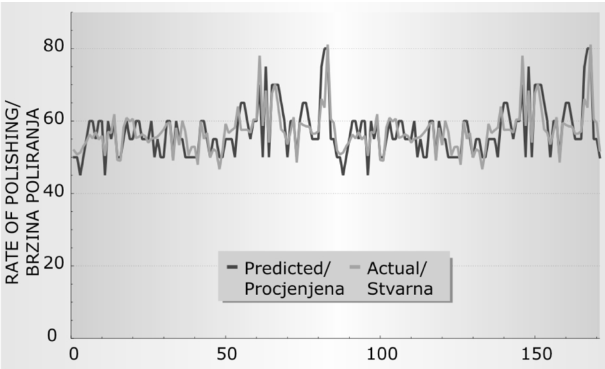

Figure 2. The rate of polishing actual and predicted (by a mathematical model (15)) values

Slika 2. Stvarna i procijenjena vrijednost brzina poliranja (matematičkim modelom (15))

4. Modelling by the application of the "back-propagation" neural network

4.1. Selection of the type of neural network – general model

The observed research belongs to the problems dealing with continuous input and output values i.e. problems connected with prediction, thus the back-propagation network is applied.

During the process of learning the aim is to enable fast convergence and reduce global error given by (16).

$$E = 0,5 \cdot \sum \left(d_k - x_k\right)^2. \tag{16}$$

In this type of network global error propagates backwards through the network all the way to the input layer. During the backward pass all weighted connections are adjusted in accordance with the desired neural network output values. Increase or decrease of the actual values of the weights $w_{ij}^{[s]}$ affects the decrease of global error.

By the application of the gradient descent rules the increase in the network weighted connections $\Delta w_{ji}^{[s]}$ can be given as:

$$\Delta w_{ji}^{[s]} = -\alpha \cdot \left(\frac{\partial E}{\partial w_{ji}^{[s]}} \right), \tag{17}$$

where α is the learning coefficient.

Derivations given above can be calculated as:

$$\frac{\partial E}{\partial w_{ji}^{[s]}} = \left(\frac{\partial E}{\partial I_j^{[s]}} \right) \cdot \left(\frac{\partial I_j^{[s]}}{\partial w_j^{[s]}} \right) = -e_j^{[s]} \cdot x_i^{[s-1]}. \tag{18}$$

The value of the weighted connections increase in the network $\Delta w_{ji}^{[s]}$ is now:

$$\Delta w_{ji}^{[s]} = \alpha \cdot e_j^{[s]} \cdot x_i^{[s-1]}, \tag{19}$$

where α is the learning coefficient, $x_j^{[s]}$ represents output state of the j-th of this neuron in the s–th layer, and the parameter $e_j^{[s]}$ that represents the error and propagates backwards through all the layers of the network is defined as:

$$e_j^{[s]} = \frac{-\partial E}{\partial I_j^{[s]}}. \tag{20}$$

The learning coefficient should be kept law to avoid divergence although this could result in very slow learning. This situation is solved by including a momentum term into expression (19):

$$\Delta w_{ji}^{[s]} = \alpha \cdot e_j^{[s]} \cdot x_i^{[s-1]} + momentum \cdot \Delta w_{ji}^{[s]}. \tag{21}$$

The weights in the network can be updated for each learning vector separately or else cumulatively, which considerably speeds up the rate of learning (convergence).

Therefore the objective of the learning process in a neural network is to achieve the lowest possible level of error between the outputs obtained by training the network and the actual (desired) results. This is realized by adjusting the weights of the neurons, and by accepting the objective function, defined below through the minimization of the mean square error.

General form vector of the model applicable for a neural network input is as follows:

$$X_i = \left\{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}\right\} \Rightarrow \\ Y_o = \left\{y_{o1}, y_{o2}, y_{o3}, \ldots, y_{on}\right\}, \tag{22}$$

where vector $X_i = \left\{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}\right\}$ represents input variables, and vector $Y_o = \left\{y_{o1}, y_{o2}, y_{o3}, \ldots, y_{on}\right\}$ output variables.

4.2. Setting up of the model and the obtained results

In the given problem the model vector has one output variable – the rate of polishing. The machining technological time is calculated from the rate of polishing. Input variables are: tube external diameter, tube oval shaping after first phase of production, gradation of the belts used for grinding or polishing adjusted on machine (conveyor), condition of belts (time of usage) and pressure of belts (Table 2).

The RMS error (Root Mean Square error) is taken as a criterion for network validation. It is defined as:

$$RMS = \sqrt{MS} = \sqrt{\frac{\sum_{n=1}^{N} \left(d_n - y_n\right)^2}{N}}, \tag{23}$$

where:

MS	-	Mean Square error,
N	-	Number of pairs of the training set input-output values
y_n	-	Neural network n-th output
d_n	-	Desired value of a neural network n-th output

The Delta rule is applied for network training. This rule is also called Widrow/Hoff rule or the minimum mean square rule which has become one of the basic rules in the training process of most neural networks.

Table 2. Variables with a value range for the proposed model

Tablica 2. Varijable s vrijednostima protezanja za predloženi model istraživanja

No	Variable / Naziv varijable	Minimum value / Minimalna vrijednost	Maximum value / Maksimalna vrijednost
1.	Tube external diameter / Vanjski promjer cijevi, mm	10	50
2.	Tube oval shaping after first phase of production / Ovalnost cijevi nakon prve faze proizvodnje, μm	0,04	0.1
3.	Gradation of belts for grinding or polishing / Gradacija remenja za brušenje ili poliranje, grit	80	700
4.	Condition of belts (time of usage) / Stanje remenja (vrijeme uporabe remenja), min	0	1200
5.	Pressure of belts / Pritisak remenja, A	0.8	2.5

In expression (24) the formula for the Delta rule is given:

$$\Delta w_{ji} = \alpha \cdot y_{cj} \cdot \varepsilon_i, \tag{24}$$

where Δw_{ij} is the value of the difference in the weights of neuron j and neuron i realized in two steps (k-th and k-1), mathematically described by (25):

$$\Delta w_{ji} = \Delta w_{ji}^{k} - \Delta w_{ji}^{k-1}, \tag{25}$$

α is the rate (coefficient) of learning, y_{cj} is the output value of neuron j calculated according to transfer function, ε_i is the error given as:

$$\varepsilon_i = y_{cj} - y_{di} \tag{26}$$

where y_{di} is the actual (desired) output. The error given by the expression (26) returns to the network only rarely, other forms of error are used instead depending on the kind of network.

For most actual problems various rates of learning are used for various layers with a low rate of learning for the output layer. It is usual for the rate of learning to be set at a value anywhere in the interval between 0,05 and 0,5, the value decreasing during the learning process. While using the Delta rule algorithm the used data are to be selected from the training set at a random basis. Otherwise frequent oscillations and errors in the convergence of results can be expected.

The transfer function used in this study is the Sigmoid function calculated according to expression (27).

$$Output_i = \frac{1}{1 + e^{-G \cdot input_i}}, \tag{27}$$

where G – is the function increment. It is calculated as G=1/T. T is the function threshold. This function is often used when neural networks are created or investigated. The function graph is continuously monotonous. The values of this transmission function are in the interval [0,1].

The study of the application of the back-propagation network was carried out for a defined data model. By alternating the attributes diverse architectures of neural networks were studied. The network with the best architecture generated the network output with 3,46 % rate of RMS error in the training phase and 5,01 % in the validation phase. The graph in Figure 3 shows the results obtained by this network structure with regard to experimental results.

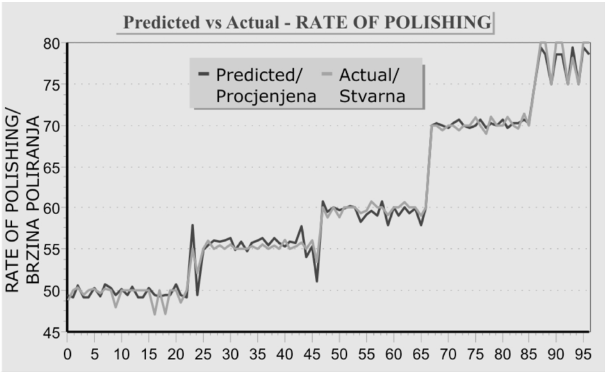

Figure 3. Presentation of actual and predicted values given by NN for the rate of polishing

Slika 3. Prikaz stvarnih i neuronskom mrežom procijenjenih vrijednosti brzine poliranja

5. Conclusion

The paper deals with the comparison of the technological time prediction models. In the mathematical (regression) model, based on experimental results, the relative error for the weighted LS is 5.98 %. The prediction model, based on neural networks, gives the result with the 3.46 % level of RMS error in learning phase and 5.01 % in validation phase. The error of prediction of technological parameters and technological time of seam tube polishing in both models is within permitted limits. Namely, the models are acceptable if the percentage of prediction does not exceed 10 % since according to some earlier research the young and less experienced engineers as a rule commit about 10 % error in technological process planning when determining the rate of machining and technological time.

The results obtained by the models should be used as a starting point for a more precise prediction of the possible delivery times and production planning. The models will upgrade the activities in technological scheduling of production and make the production planning jobs easier.

In future research the aim is to proceed with collecting actual data in the production of polished seam tubes and thus enlarge the amount of sample data. It is to be expected that after learning and training and the application of different transmission functions the network will give even better results i.e. smaller error and that the time deviation of the actual versus planned time by a working order will be reduced. It is of course also possible to include various models of neural networks into the research and through adaptation of their architecture and by adjusting network parameters try to find an optimal solution.

Further research should also aim at optimizing the technological process parameters by the application of response surface methodology.

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