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Adaptive Neuro-Fuzzy Inference System Model for Technological Parameters Prediction

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Preliminary note

The main goal of each technologist is the prediction of technological parameters by fulfilling the set design and technological demands. The work of the technologist is made easier by acquired knowledge and previous experience. A plan of input-output data was made by using the hybrid system of modelling ANFIS (Adaptive Neuro-Fuzzy Inference System) based on the results of seam tube production. This plan is the prerequisite for generating the system of fuzzy logic. The generated system can be used to estimate the output (speed of polishing) based on the given input (external tube diameter, oval shaping of the tube after the first phase of production, gradation of belts for grinding or polishing, condition of belts - time of usage, pressure of belts).The more precise predictions of technological time provided by the model 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.

Keywords
Adaptive Neuro-Fuzzy Inference System
Artificial intelligence
Technological parameters

Prilagodljivi neuro-fazi model za predviđanje tehnoloških parametara

Prethodno priopćenje

Procijeniti tehnološke parametre na način da se ispune postavljeni konstrukcijski i tehnološki zahtjevi cilj je i želja svakog tehnologa. Procjenu tehnologu mogu olakšati prikupljena znanja i ranije stečena iskustva. Na temelju sustavno prikupljenih podataka iz proizvodnje šavnih cijevi u radu je primjenom hibridnog sustava za modeliranje ANFIS (Adaptive Neuro-Fuzzy Inference System) oblikovan plan ulazno/izlaznih podataka. Taj je plan pretpostavka za generiranje sustava neizrazitog zaključivanja. Generirani sustav ima mogućnost procjene izlaza (brzine poliranja) na temelju danih ulaza (vanjski promjer cijevi, ovalnost cijevi nakon prve faze proizvodnje, gradacija remenja za brušenje ili poliranje, stanje remenja - vrijeme uporabe remenja, pritisak remenja). Točnije procjene tehnološkog vremena koje daje model upotpunjavaju prethodno definirane tehnološke operacije, zamjenjuje 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.

Ključne riječi
Prilagodljivi Neuro-Fuzzy sustav
Tehnološki parametri
Umjetna inteligencija

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1. Introduction

In manufacturing companies in which emphasis is placed on technological and operational preparation of production i.e. those that keep up to date with technological parameters and the results of technological processes, essential prerequisites are set for improving the activities in the observed sectors. 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 managerial 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.

The technologists must face two major problems within the production enterprises: the prediction of technological parameters in order to achieve the required product quality (according to the technical documentation) and how to maximally use the available production resources [1-2].

Symbols/Oznake

x, y	- inputs of ANFIS - ulazne varijable u ANFIS sustav	ω_i	- the firing strength of a rule - težina pravila
f_{out}	- output from ANFIS - izlazna varijabla iz ANFIS sustava	$Q_{1,i}$	- node function - čvorna funkcija
$\mu(x), \mu(y)$	- membership functions - funkcije pripadnosti	f_1, f_2	- fuzzy IF - THEN rules - neizrazita IF – THEN pravila
a_i, b_i, c_i	- parameter set - parametri neizrazitih skupova	p_i, q_i, r_i	- parameter set, referred to as the consequent parameters - parametri zaključaka
ANFIS	- Adaptive Neuro-Fuzzy Inference System - Prilagodljivi Neuro-Fuzzy sustav zaključivanja	RMSE	- Root mean square error - Korijen srednjeg kvadratnog odstupanja

These problems are very complex and depend on many conflicting factors. Therefore, modelling has a huge influence on solving different problems of production enterprises. Modelling deals with: feature recognition [3-8], operation sequencing, tool path planning and tolerance analysis [9-14], raw material selection [15-17], prediction, determination and optimization of technological parameters [18-24], estimating manufacturing cost [25-28], surface roughness modelling [29-34]. A broad literature survey shows that algorithm modelling, mathematical modelling, regression modelling, simulation modelling or artificial intelligence techniques (genetic algorithms, neural networks, expert systems, fuzzy logic, etc.) are used on empirical and experimental data, or data based on constant measuring. Artificial intelligence techniques (fuzzy logic and neural networks [35-38], fuzzy logic and genetic algorithms [39], and neural networks and genetic algorithms [40-41]) are often combined for technological problems of determination and optimization of technological parameters, and surface roughness. Furthermore, the suggested hybrid models usually show better results than the individual techniques of artificial intelligence and show faster adaptation of the structure to the problem. Therefore, the Adaptive Neuro-Fuzzy Inference System (ANFIS) was used in this paper. It represents a combination of fuzzy logic and neural networks used to estimate speed of polishing of seam tubes in order to achieve the required surface quality (roughness). Speed of seam tube polishing has a direct influence on the technological time. This paper deals with a multidimensional problem where mathematical dependence of the input and output variables cannot be determined easily based on the experimental data.

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 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 neuro-fuzzy model for predicting technological parameters and, indirectly, technological time of the seam tube polishing. 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

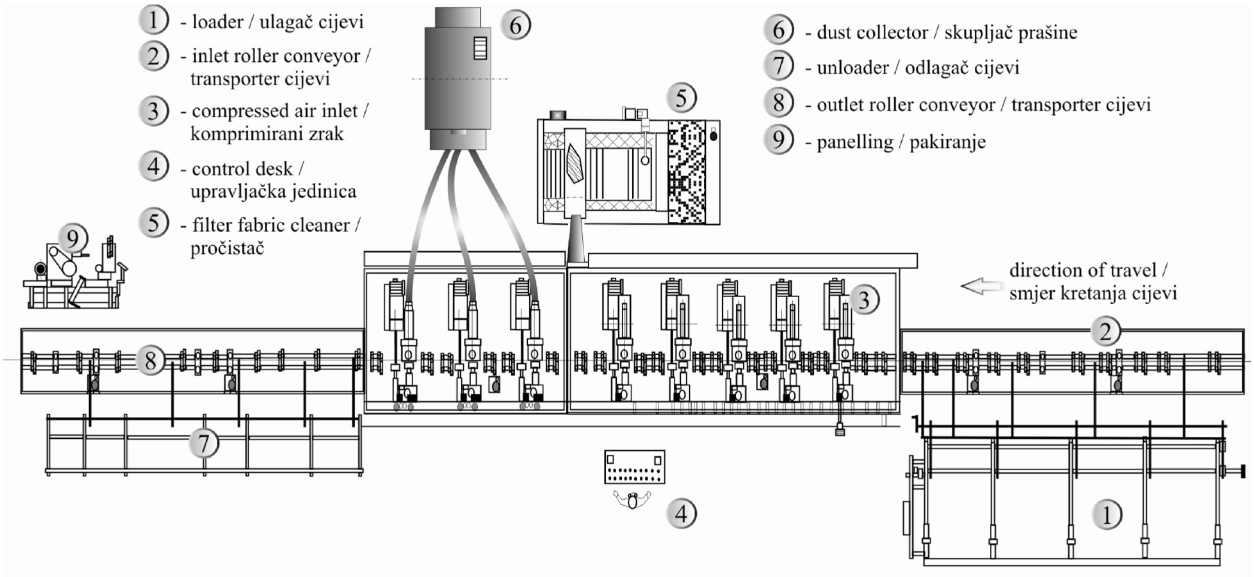

Figure 1. Scheme of the polishing and grinding line

Slika 1. Shema linije za poliranje i brušenje

tubes. In previous articles the process model based on neural networks [29] and mathematical model [42] has been developed by using same or similar data set.

After the papers were published [29, 42] the research and the collection of experimental data continued. Through 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 papers [29, 42] the factors that are not important have been removed.

3. Adaptive neuro-fuzzy inference system (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS) represents a useful neural network approach for the solution of function approximation problems. ANFIS have been successfully applied to classification tasks, rule-based process controls, pattern recognition problems and the like [43]. Both artificial neural network and fuzzy logic are used in ANFIS architecture. An ANFIS gives the mapping relation between the input and output data by using the hybrid learning method to determine the optimal distribution of membership functions. A fuzzy inference system comprises the fuzzy model [44-45] proposed by Takagi, Sugeno and Kang to formalize a systematic approach to generate fuzzy rules from an input output data set.

Basically, five layers are used to construct this inference system (Figure 2). Each ANFIS layer consists of several nodes described by the node function. The inputs of present layers are obtained from the nodes in the previous layers. To illustrate the procedures of an ANFIS, for simplicity, it is assumed those two inputs (*x, y*) and one output (f_{out}) are used in this system.

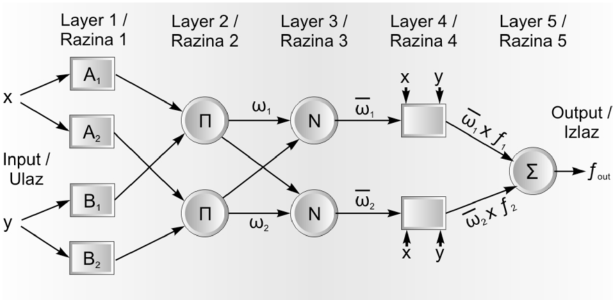

Figure 2. ANFIS structure

Slika 2. Opća arhitektura ANFIS-a

The rule base of ANFIS contains fuzzy IF – THEN rules of Sugeno type. For a first order Sugeno fuzzy inference system, the two rules may be stated as:

Rule 1: IF x *is* A_1 *AND* y *is* B_1 *THEN* z *is* $f_1(x,y)$

Rule 2: IF x *is* A_2 *AND* y *is* B_2 *THEN* z *is* $f_2(x,y)$

where x and y are the inputs of ANFIS, A_i and B_i are the fuzzy sets and $f_i(x,y)$ is a first order polynomial and represents the outputs of the first order Sugeno fuzzy inference system. The architecture of ANFIS is shown in Figure 2, and the node function in each layer is described below. Adaptive nodes, denoted by squares, represent the parameter sets that are adjustable in these nodes, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system.

Layer 1: this layer contains adaptive nodes with node functions described as

$$Q_{1,i} = \mu_{Ai}(x) \quad for \quad i = 1,2,$$
$$Q_{1,i} = \mu_{Bi-2}(y) \quad for \quad i = 3,4, \tag{1}$$

where x and y are the input nodes, A and B are the linguistic labels, $\mu(x)$ and $\mu(y)$ are the membership functions. There are many types of the membership functions that can be used. However, a bell shaped function with maximum and minimum equal to 1 and 0 is usually adopted. It can be written as follows

$$\mu(x) = \frac{1}{1+\left(\frac{x-c_i}{a_i}\right)^{2b_i}} \quad or$$
$$\mu(x) = \exp\left\{-\left(\frac{x-c_i}{a_i}\right)\right\}, \tag{2}$$

where a_i, b_i and c_i are the parameter set. The bell shaped functions vary while the values of this parameter are changing.

Layer 2: Every node in this layer is a fixed node, marked by a circle. The node function has to be multiplied by input signals to serve as output for every node.

$$Q_{2,1} = \omega_1 = \mu_{Ai}(x) \cdot \mu_{Bi}(y) \quad for \quad i = 1,2. \tag{3}$$

The output ω_i represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node, marked by a circle and labelled N, with the node function to normalize the firing strength by calculating the ratio of the ith node firing strength to the sum of all rules' firing strength.

$$Q_{3,i} = \varpi_i = \frac{\omega_i}{\sum \omega_i} \quad for \quad i = 1,2. \tag{4}$$

The output ϖ_i represents the normalized firing strength of a rule.

Layer 4: Every node in this layer is an adaptive node, marked by a square, with node function

$$Q_{4,i} = \varpi_i \cdot f_i \quad for \quad i = 1,2, \tag{5}$$

where f_1 and f_2 are the fuzzy IF – THEN rules as follows:

Rule 1: IF x is A_1 and y is B_1 THEN $f_1=p_1x+q_1y+r_1$

Rule 2: IF x is A_2 and y is B_2 THEN $f_2=p_2x+q_2y+r_2$

where p_i, q_i and r_i are the parameter set, referred to as the consequent parameters.

Layer 5: This layer has only one fixed node, marked by a circle. The node function is to compute the overall output by

$$Q_{5,i} = f_{out} = \sum \varpi_i \cdot f_i = overall \quad output. \tag{6}$$

From the ANFIS structure mentioned above, the overall output can be expressed as linear combination of the consequent parameters. Hence, the final output can be written as

$$f_{out} = \varpi_1 \cdot f_1 + \varpi_2 \cdot f_2 = \frac{\omega_1}{\omega_1+\omega_2} \cdot f_1 + \frac{\omega_2}{\omega_1+\omega_2} \cdot f_2 =$$
$$= (\varpi_1 \cdot x) p_1 + (\varpi_1 \cdot y) q_1 + (\varpi_1) r_1 + (\varpi_2 \cdot x) p_2 + \tag{7}$$
$$+ (\varpi_2 \cdot y) q_2 + (\varpi_2) r_2.$$

The possibility of making a model of fuzzy inference system by using neural networks is used to compute the membership function parameters based on the available input-output data. The model is defined based on the available knowledge of the process under consideration.

There are two approaches:

1. When the model is defined based on the set of language rules formulated by the expert. It is possible to optimize the membership function parameters by using the available input-output data of the process.
2. If there is no previous knowledge of the process, the fuzzy model is designed based only on the input-output data. Such a model could be used to interpret the functioning of a system.

A combination of neural networks and fuzzy logic within the ANFIS system can be found in the programme package Matlab. Matlab Fuzzy Logic Toolbox Software can be used to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data. The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called *anfis*. Using a given input-output data set, the toolbox function *anfis* constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method.

4. Obtained results

Based on the input-output data of the system under consideration, the ANFIS system was used to develop a FIS system for predicting surface roughness after turning. Three parameters (feed rate, number of turns and cutting depth) are the input parameters, while surface roughness represents the output parameter. The set of input-output data is divided in two subsets. One subset is used for generating the FIS system, while the other subset is used for testing the generated FIS system. The basic characteristics of the generated FIS system are shown in Table 1.

Table 1. The basic characteristics of the generated FIS system

Tablica 1. Osnovne karakteristike generiranog FIS sustava

1. Name / Naziv	Polishing speed / Brzina poliranja	12. InLabels / Ulazne varijable	External tube diameter / Vanjski promjer cijevi, mm
2. Type / Tip	Sugeno		Oval shaping of the tube after the first phase of production / Ovalnost cijevi nakon prve faze proizvodnje, μm
3. Inputs/Outputs Ulazi/Izlazi	[5 1]		Gradation of belts for grinding or polishing / Gradacija remenja za brušenje ili poliranje, grit
4. NumInputMFs / Broj ulaznih funkcija pripadnosti	[3 3 3 3 3]		Condition of belts - time of usage / Stanje remenja (vrijeme uporabe remenja), min
5. NumOutputMFs / Broj izlaznih funkcija pripadnosti	243		Pressure of belts / Pritisak remenja, A
6. NumRules / Broj neizrazitih pravila	243	13. OutLabels / Izlazna varijabla	Polishing speed / Brzina poliranja
7. AndMethod / "I" metod	prod	14. InRange / Raspon ulaznih varijabli	[12 42.4]
8. OrMethod / "ILI" metod	max		[4 8]
9. ImpMethodMetoda implikacije	prod		[80 600]
10. AggMethod / Metoga agregacije	max		[8 25]
11. DefuzzMethod / Metoda defazifikacije	wtaver		[45 320]
		15. OutRange / Raspon izlaznih varijable	[45 80]

The main purpose of the ANFIS system (while generating the FIS system) is optimization of the membership function parameters so that membership functions can better connect the input area with the input fuzzy sets and the output fuzzy sets with the output area.

According to [29, 42], the total Root Mean Square error for the neural networks compared to the total Root Mean Square error using the generated FIS system is shown in Table 2.

Figure 3 shows a diagram of estimated polishing speed by using the generated FIS system compared to the real polishing speed.

Figure 4 shows a diagram of 3D surface by using the generated FIS system in the Matlab which represents dependence of the polishing speed on gradation of belts for grinding or polishing and external tube diameter.

Table 2. The total Root Mean Square error

Tablica 2. Ukupno srednje kvadratno odstupanje

Methods / Metode	Neural networks / Neuronske mreže	FIS system/ FIS_sustav
Root mean square error / Srednje kvadratno odstupanje RMSE	4,82 %	2,51 %

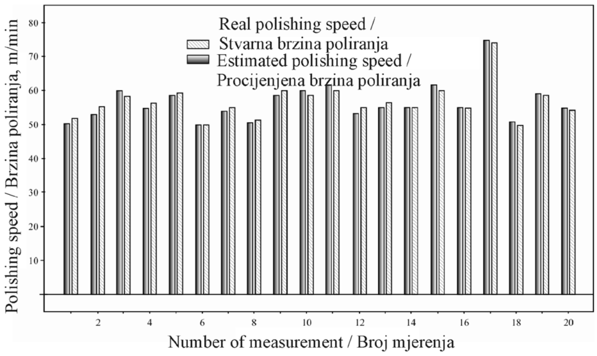

Figure 3. Diagram of estimated polishing speed by using the generated FIS system compared to the real polishing speed

Slika 3. Usporedni dijagram stvarnih i procijenjenih brzina poliranja pomoću generiranog FIS sustava

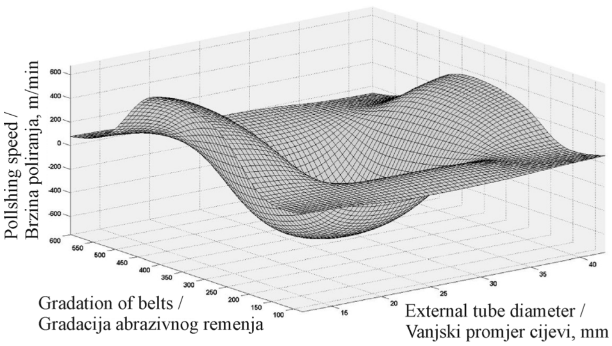

Figure 4. Dependence of the polishing speed on gradation of belts and external tube diameter

Slika 4. Dijagram ovisnosti brzine poliranja o gradaciji abrazivnog remenja i vanjskom promjeru cijevi

5. Conclusion

This paper describes a neuro-fuzzy approach in evaluating the technological parameters and technological time of seam tube polishing. Selection of training data from the entire data set had a major impact on the mean square error. Random selection of data to the training set initially caused a big mean square error. However, through the subsequent impact on the equal representation of characteristic subsets (classes) of data, the error is significantly reduced. The final neuro-fuzzy model gives results with an error of less than 5 %. Namely, the research showed that the young and less experienced engineers commit a 10 % error in process planning when determining the rate of machining and technological time, and the model therefore provides acceptable results.

It can be concluded that the proposed neuro-fuzzy model achieves better results than the model based on neural networks because of faster adaptation to the observed structure of the problem. On the other hand, this model becomes complicated by increasing the number of input parameters, because the number of fuzzy sets and learning rules will be enlarged.

The research will continue and its aim will be to proceed with the collecting of real data in the production of polished seam tubes and to enlarge the amount of sample data. It is to be expected that the results will be even better i.e. smaller error. Therefore the time deviation of actual versus planned time by a working order will be reduced. The aim is also to perform optimization of machining parameters after proposing the rate of polishing. The optimization procedure will incorporate genetic algorithms (GA) so that the combined application of NN and GA should result in obtaining optimal machining parameters considering the ERP system data and condition of the semi products and equipment in the plant.

Model gives results that should form the basis for a more accurate assessment of possible delivery dates and production planning.

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