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Modelling Metal cutting Parameters Using Intelligent Techniques

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Cutting temperature, which depends on many factors, has a significant and, mostly negative influence on cutting process parameters. On the other hand, the quality of the machined surface is one of the most important qualitative indicators of a cutting process. Both parameters cannot be omitted in the modeling of metal cutting. Due to the high complexity of the process itself, it is almost impossible to encompass all the relevant factors and their influence within a mathematical formula. In such cases, it is much more efficient to use and process data obtained through experiments. Nowadays, systems that are based on artificial intelligence are often used for this purpose. The paper presents the application of the artificial neural networks and hybrid, neuro-fuzzy model in the prediction of a workpiece temperature and surface roughness. The approach is based on the thermographic method and infra red camera imaging system.

Keywords: metal cutting process, artificial neural networks, neuro-fuzzy model

0 INTRODUCTION

Optimization methods in metal cutting processes, which considered to be vital for a continuous improvement of output quality of products and processes, include the modeling of input–output and in-process parameters relationship and the determination of optimal cutting conditions [1]. Heat generation in the cutting zone occurs as a result of the work done in metal cutting. The total work can be divided into three quantities: work to shear the material to form the chip and the new surface; work to move the chip over the rake surface of the tool; and work necessary to move the freshly cut surface over the flank face of the tool [2]. The heat generated in the chip forming zone directly influences the quality and accuracy of the machined surface and other occurrences in the metal cutting process, such as: built up edge (BUE) formation, work-hardening, plastic deformation of the cutting edge, deformation of the workpiece, etc. [3]. Being aware of the importance of proper temperature monitoring and prediction and, consequently, optimal cutting parameters selection, numerous research projects have been conducted aiming to develop reliable methods. Nowadays these methods, almost inevitably, include soft computing technologies [4]. In the field of metal cutting process monitoring and control numerous approaches consider fuzzy logic systems (FLS), artificial neural networks (ANN) and genetic algorithms (GA), as well as their combinations in the form of hybrid (artificial intelligence) systems [5]. The approaches to monitoring and controlling of the cutting process by soft computing technologies use forces, acoustic emission signals, temperatures, etc. In the research presented in this paper, cutting temperature was monitored and two data modelling approaches, i.e. ANN-based, and ANN-FL-based approach were compared. Also, thermographic imaging by infra red digital camera was used for process monitoring and data gathering.

The following section of the paper provides a brief review of temperature measuring methods in metal cutting, and corresponding influencing factors. The third section explains the setup and the experiment which was conducted in order to obtain the necessary data about the workpiece temperature during cutting and its surface roughness. The experiment and the obtained results are discussed in the fourth section. Sections 4 and 5 explain the basics of the artificial neural networks and neuro-fuzzy systems, which were used for the modeling of the metal cutting process parameters. Section 6

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describes the results of the proposed two data modeling approaches, and provides their comparative analysis. Conclusions summarize the suitability of the proposed models and address future work and applications.

1 MEASURING TEMPERATURE IN METAL CUTTING - A BRIEF REVIEW

The amount of the heat generated in the metal cutting process is expressed through the work done in the process and the mechanical equivalent of heat [6] to [8], in the form:

$$Q = \frac{F_z V}{E} \tag{1}$$

where is : [Q] – amount of the heat generated in the metal cutting process, [$F_z V$] – work done in the process, [E] – mechanical equivalent of the heat.

The heat balance during the metal cutting process can be expressed as follows:

$$Q = Q_1 + Q_2 + Q_3 + Q_4 \tag{2}$$

where: [Q] – total amount of the heat generated in cutting, [Q_1] – amount of the heat carried away in the chips, [Q_2] – amount of the heat remaining in the cutting tool, [Q_3] – amount of the heat absorbed by the workpiece, [Q_4] – amount of the heat radiated to the surrounding air.

According to the findings, 60 to 86% of the heat is carried away in the chips and the percentage increases with cutting speed. For lathe operations this proportion is as follows: 50 to 86% of the total amount is removed in the chip, 10 to 40% remains in the cutting tool, 3 to 9% heats up the workpiece and about 1% radiates into the surrounding air.

Factors which affect the quantity of the generated heat the most, are cutting speed and cutting depth. It has been observed that there is more heat transferred into the workpiece in the finishing turning than in the rough turning. Theoretically, there are three zones of the heat generation that can be identified during turning (Fig. 1(a)):

- cutting zone
- tool-chip contact zone
- tool-workpiece contact zone.

It is obvious that the maximum temperature zone is somewhat distant from the cutting edge, which theoretically, corresponds to the zone of the maximum wear of the tool, i.e. the zone of maximal tool wear coincides with the maximum temperature zone.

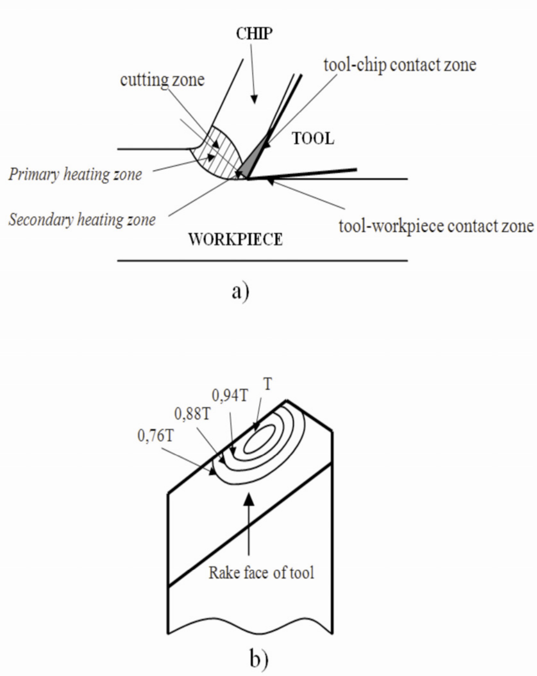

Fig. 1. *a) Heat generation zones during metal cutting process,*
b) Temperature distribution on the cutting tool

1.1 The Influencing Factors on the Cutting Temperature

Factors that have a direct influence on cutting temperature and workpiece temperature during the metal cutting process are: (i) workpiece material, (ii) cutting regimes (cutting speed, feed rate and depth of cut), (iii) dimensions and geometric characteristics of the cutting tool and the type of coolant fluid, etc. Results of many experiments show that cutting temperature depends on a large number of factors, defined by the Eq. (3):

$$T = C_T a^{k_{aT}} f^{k_{fT}} V^{k_{vT}} \tag{3}$$

where is: T [K] – cutting temperature, a [mm] – depth of cut, f [mm/rev] – feed rate, V [m/min] – cutting speed, C_T [] - general coefficient, k_{aT}, k_{fT}, k_{vT} [-] - exponents.

C_T and k_{aT}, k_{fT}, k_{vT} depend on the workpiece and the tool material characteristics, tool geometry, type of coolant, etc.

The nature of each of these factors is elaborated in detail in [3] and [6] to [11].

1.2 Radiation Methods in Temperature Measurements

A large number of temperature measurements methods in the metal cutting have been developed in the past years [3] and [9] to [13]. We will restrict the review only to the radiation methods which play a central role in our research. This category includes methods for measuring temperature in the single point, or measuring temperature field, without a direct contact between the measuring instrument and the object. In the single point temperature measurements an infrared pyrometer is used, while in the measuring temperature field (infrared thermograph) specially made infrared cameras sensitive to radiation of the heated body are used [9]. Radiation methods have a large number of conveniences with respect to conduction methods. The most important are: faster response of the system, i.e. the possibility of measuring rapid variations of temperature, there is no negative influence on the tool and the work material, there is no physical contact between the measuring system and the object, enabled remote temperature measuring for inaccessible objects etc. While temperature is being measured by infrared camera, unwanted hiding of the measuring point with the chip can occur, which can result in faulty data [11]. The other negative feature of this method is the necessary knowledge on the exact value of the coefficient of emission for precise measuring. In order to overcome this problem, the area of interest can be coated by the paint with known coefficient of emission [13]. The coefficient of emission depends on the clarity of the target area, presence of the oxidation covering, the wave length etc. Any of the above mentioned factors have an influence on the measured data.

1.2.4 Metallographic Techniques

The method involves an analysis of microstructure and/or micro hardness of the heat affected zones. It requires calibration curves, which show the level of dependence of the material hardness in terms of known temperatures and the time of heating. The usual accuracy of this method is ±25°. These methods are mainly used for measuring temperatures of cutting tools made from high speed steels as they show structural changes, and/or changes in hardness, in the temperature range of 600 to 1000 °C.

Generally, there are no strictly defined rules as to which method is the most adequate one in a given situation. On the other hand, high complexity of the process itself does not always permit a comparison of the results obtained by different methods. Moreover, even the results obtained by the same method, in identical experiment conditions, may be different, which additionally proves extreme complexity of temperature measurements in the metal cutting process.

2 EXPERIMENT SETUP AND REALIZATION

Fig. 2 shows the scheme of architecture and information flow of the experiment setup and data processing system. The machining (sub)system includes universal lathe, operating in the real industrial environment. Data acquisition (sub)system provides temperature and surface roughness monitoring and measurement. For workpiece temperature measurements the infrared camera (Wohler IK21) was used, and surface roughness is inspected by the measuring machine Surftest SJ-301, as well as the optical microscope, type MBS-9. The infrared camera Wohler IK21 is a hand-driven digital camera, which operates on the basis of non-cooled silica thermoelectric line detector. It forms a thermal image by measuring the infrared radiation of the object.

The software, included in the camera, transforms the signal during the thermal image conversion in an appropriate thermographic image, representing the estimation of the accurate temperature of the scanned object, or the temperature arrangement in the scene (Fig. 3).

The most important temperature from the metal cutting process point of view is the cutting temperature, i.e. the maximum temperature of the cutting tool. This temperature directly affects the cutting characteristics of the tool, tool and workpiece deformation, as well as the quality of the machined surface.

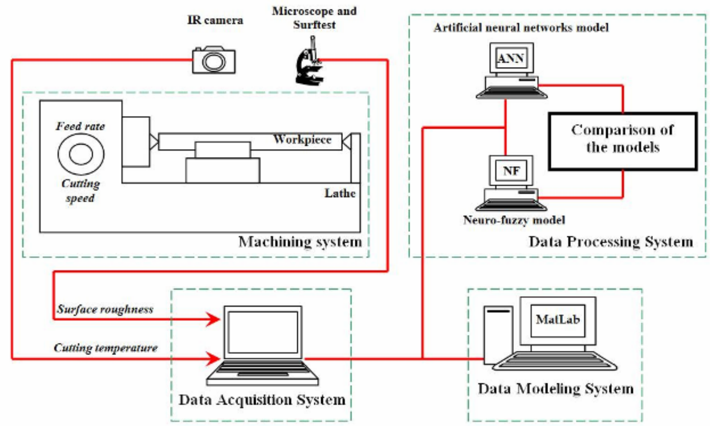

Fig. 2. *Experiment setup and information flow in the system*

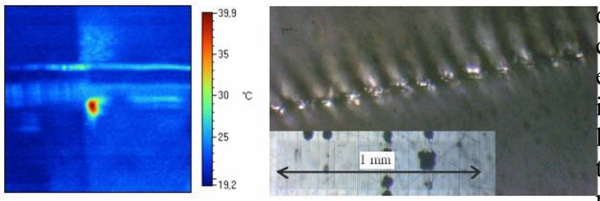

Fig. 3. *Temperature field and magnified profile of the machined surface*

It is obvious that measuring the temperature of the rake face of the tool where the maximum temperature occurs, is not possible by using the mentioned infrared camera because of the constant presence of the chip which covers the area of interest. With known values of the workpiece temperature, the cutting depth and the physical properties of the workpiece it is possible to calculate the cutting tool temperature, using mathematical modelling, FEM analyses, or a similar method. However, the key objective of this work is to explore the possibility of using artificial intelligence methods (artificial neural networks and neuro-fuzzy systems) in the modeling of the cutting process parameters, and not measuring the exact value of maximum cutting temperature. That is the reason why the workpiece temperature and the arithmetic mean deviation are adopted as relevant parameters.

At the beginning of the cutting process temperature increases until it reaches its maximum value. Therefore, measurements should be done shortly after the beginning of the process [14]. The analysis of the results obtained by the infrared camera at the beginning of the process, particularly the results regarding the increase and distribution of temperature, leads to the conclusion that a period of about 60 seconds is enough for stabilizing the temperature. The images (Fig. 3) are sent to a PC memory card, and later additionally analysed. The maximum cutting temperature which occurs on the workpiece is relevant to the measurements included in this experiment.

Providing machine tools with the capability to monitor quality characteristics, such as surface roughness, is an essential component for the ability to create reliable unmanned machining cells [15]. Geometric characteristics of the cutting tool (especially the nose radius) and the feed rate are parameters which, theoretically, define the surface roughness during the metal cutting process, as follows:

$$H = r - \frac{\sqrt{4r^2 - s^2}}{2} \tag{4}$$

where is: H [mm] - height of roughness, r [mm] - nose radius, s [mm] - feed rate.

The real height of roughness is always higher than the theoretic one. The main reasons for this are elastic and plastic deformations of the surface layer of the workpiece. Periodic forming of the built up edge (BUE) has a significant influence on the surface roughness. In addition, continual presence of the friction forces which act between the tool flank and the machined surface also influence the estimation of the real surface roughness. With the increase of the cutting speed this effect is eliminated almost completely, and the real height of roughness approaches its theoretic value. Therefore, the real height of roughness depends on geometric factors, as well as other factors which directly influence the process of chip creation, such as: cutting speed, material characteristics of the workpiece, angles of the cutting tool, coolant fluid, elastic characteristics of the workpiece, state of the cutting insert (sharp or worn), etc. After machining, the surface was inspected using microscope MBS-9, which is connected to the computer, while the arithmetic mean deviation (R_a) was measured with profilometer Surftest SJ-301. The average value of three measurements was adopted as relevant parameter.

The used tool is the cutting tool for turning, with the cross-sectional area of tool holder 16 x 16 mm. The cutting insert is ISO grade K20. The machining is done without a coolant fluid. Between two experiments the system is cooled down to the room temperature.

The workpiece is in the form of a cylindrical bar, ϕ 34 x 250 mm. Work material is brass, UNS designation C85800, with nominal composition: 58% Cu, 1%Sn, 1% Pb and 40% Zn. Its hardness was measured and found to be 113 HV.

3 EXPERIMENT RESULTS AND DISCUSSION

In addition to the recommended data obtained from literature, during the selection of optimal cutting parameters, empirical knowledge has also been taken into an account, since it is significant for optimal machining setup. The adopted variable process parameters are:

- Cutting speed the range of 53 to 150 m/min
- Feed rate 0.135 and 0.224 mm/rev
- Depth of cut 1 and 4 mm

Figs. 4 and 5 show the results of the experiment, together with the power trend lines, which calculate the least squares fit through points by using the formula $y = cx^b$. The workpiece temperature increases with cutting speed, with unchanged values of the feed rate and the depth of cut (Fig. 4). On the other hand, with an increased depth of cut and the other parameters remaining the same, the resistance force of cutting also increases, leading to a change in cutting temperature. For the presented experimental setup, the smallest influence on changes in the cutting temperature has the feed rate (Fig. 5).

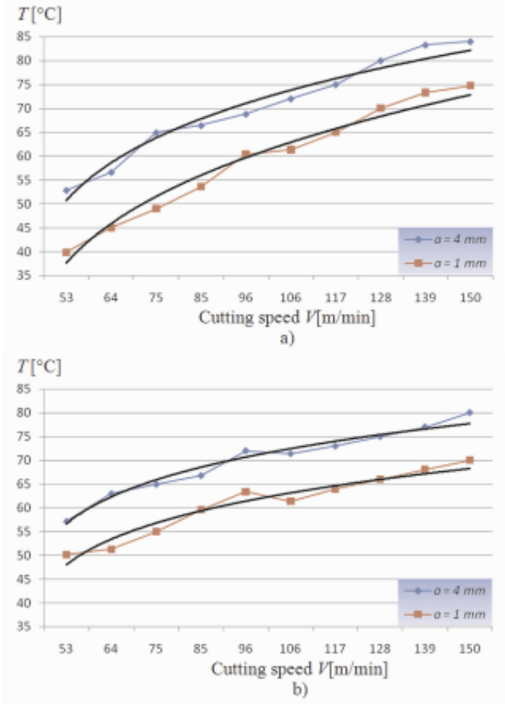

Fig. 4. *Workpiece temperature, feed rate a) 0.224 mm/rev, b) 0.135 mm/rev*

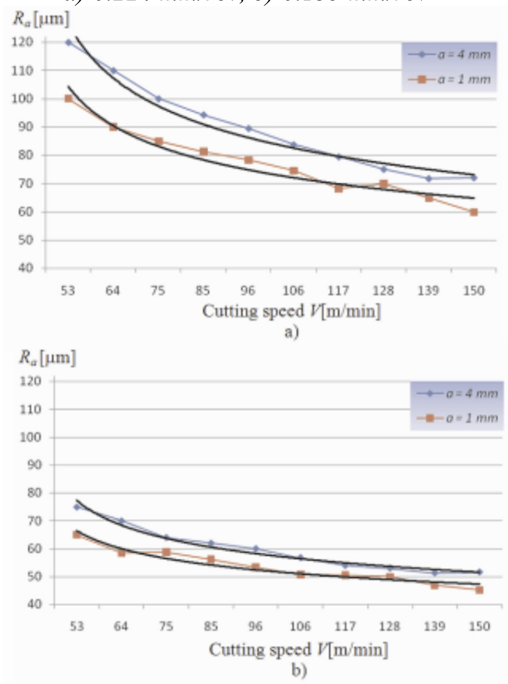

Fig. 5. *Arithmetic mean deviation, feed rate a) 0.224 mm/rev, b) 0.15 mm/rev*

The overall number of experiments is 60, and the obtained values can be used for modeling and simulation by multifactor experiment, FEM analysis [6], etc. In recent years the research has been directed at the use of systems based on artificial intelligence, i.e. artificial neural networks, fuzzy logic systems, genetic algorithms, as well as hybrid systems. In this research work, the results obtained in the first stage are used in the following stage for the modeling of process parameters using artificial neural networks and adaptive neuro-fuzzy systems.

4 DATA MODELING USING ARTIFICIAL NEURAL NETWORKS

An artificial neural networks (ANNs) are massively parallel interconnections of simple neurons that function as a collective system [21]. They are able to receive input vector $I = [\, i_1 \; i_2,...,i_n]$, and generate appropriate output vector $O = [o_1,o_2,...,o_m]$ [22]. Fig. 6 is a schematic representation of an artificial neuron with input vector with r elements, as well as the characteristic structure of the feed forward ANN with k hidden layers.

Each of the input elements $x_1, x_2, ..., x_r$ is multiplied with the corresponding weight of the connection $w_{1,1}, w_{1,2},..., w_{1,r}$. The neuron sums up weighted inputs and adds a bias b_i, which is not present in all networks. In that way, the argument of the transfer function becomes as follows:

$$a_i = x_1 w_{i,1} + x_2 w_{i,2} + ... + x_r w_{i,r} + b_i, \tag{5}$$

and neuron produces output:

$$y_i = f(a_i) = f\left(\sum_{j=1}^{r} x_j w_{i,j} + b_i\right) \tag{6}$$

This output represents an input to the neurons of another layer, or an element of the output vector of the ANN.

The ANNs, can have arbitral number of layers and arbitral number of neurons within. The performance of ANN depends on the number of layers, the number of neurons, transfer function, the presence of a bias and the way the neurons are connected. Unfortunately, there are no regulations regarding a proper choice of the mentioned parameters.

When ANN is created, it has to be trained to produce a desired output vector for a given input vector. During the so called training or learning phase, a large number of input and corresponding target vectors are presented to the ANN. The network modifies its weights and biases (network's "knowledge"), in order to minimize the error, i.e. the difference between the wanted and the obtained outputs, consequently achieving the desired behavior. After this stage, the network is ready for use. One of the most important issues in dealing with the ANN is generalization, i.e. ability to provide the solutions in the situations which were not presented to the network during the training. The ANN can face unknown situations without having an explicit rule for the solution. As mentioned earlier, one of the main drawbacks of the ANN is the fact that defining the optimal architecture of the ANN for a given problem, requires a lot of experimental work.

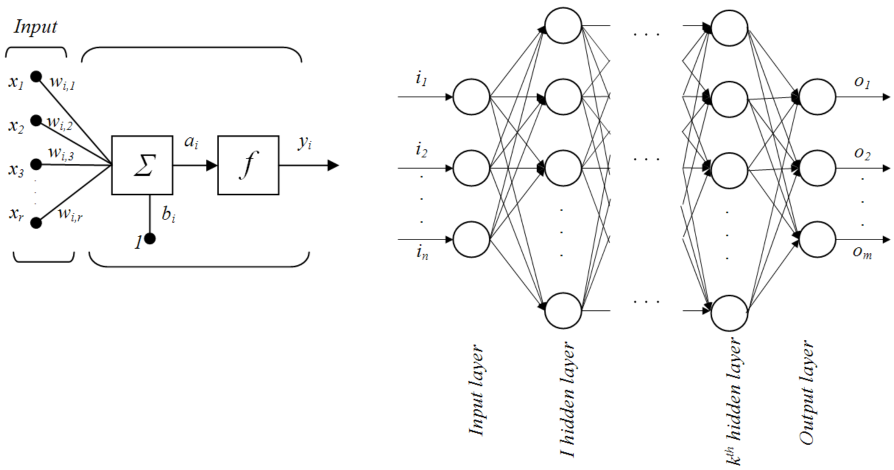

Fig. 6. *Schematic structure of the artificial neuron and artificial neural network*

This includes adjusting the process parameters in order to achieve minimum errors on one hand, and avoiding overfitting, which is the case when the network has a low capability of generalization, on the other.

Two ANNs were created for modeling metal cutting process parameters; the first one for the workpiece temperature prediction and the second one for the prediction of the surface roughness.

The initial step in ANN-based data processing system is determining the inputs of the neural network. The input layer of both ANNs has three neurons: (1) Cutting speed, (2) Feed rate and (3) Depth of cut. The ANN for temperature prediction has just one output neuron for predicting the workpiece temperature, while the other ANN has one output neuron for predicting the surface roughness, i.e. arithmetic mean deviation. In the pre-processing stage the training data are normalized. In the beginning, the number of hidden layers was set to 1, and the number of neurons in the hidden layer was set to 2. After a comprehensive investigation of various networks behavior, ANN architecture with 2 hidden layers of neurons, and 3 and 2 neurons within respectively, was adopted. The training process assumed 40 and 20 data sets are used for testing. The training algorithm used in both cases is Levenberg-Marquardt algorithm which provides the best convergence in the cases of approximation of an unknown function (function prediction). The learning function is a function with decreasing gradient with momentum, which calculates weight change dW depending on the neuron input X, the error E and the momentum mc. The performance function uses mean square error, and the number of training cycles is 1000. The learning rule is created from the data which are used in the neural network training, i.e. measured values. The neurons in the input and hidden layers of ANNs have sigmoid transfer function, while the neurons of the output layer have linear transfer function. This combination of transfer functions enables the desired performances of the networks.

5 DATA MODELLING USING THE NEURO-FUZZY SYSTEM

The adaptive NFSs represent a specific combination of artificial neural networks and fuzzy logic, so they combine the ability of the learning of the artificial neural networks with the logical interpretation of the fuzzy logic systems [16]. The basic rule of the adaptive networks learning is based on a descent gradient method which was proposed in the 1970s by Werbos [17]. The adaptive neuro-fuzzy network consists of many layers of nodes (neurons), where each layer performs a particular function called the node function on the incoming signals as well as on the set of parameters pertaining to this node. The type of the function that the node performs may vary from node to node, and the choice of the node function depends on the overall input-output function that the network simulates [18].

In general, this system represents the way for adjusting the existential base of rules, using the learning algorithm which is based on the assembly of input-output pairs, used for training. Taking into consideration some constraints, the architecture of the adaptive NFS (ANFIS - Adaptive Network Based Fuzzy Inference System), which was proposed by Jang [18] is equivalent to the Radial Basis Function Networks.

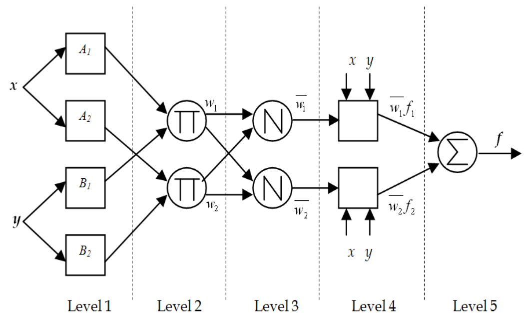

Fig. 7. *Characteristic structure of the neuro-fuzzy system*

For simplicity's sake let us assume that the system has just two input values x and y (Level 1), and one output value z (Level 5). Furthermore, the rule base consists just of two fuzzy **IF-THEN** rules (Takagi-Sugeno type), as shown in Level 2:

Rule 1: **IF** $\underline{x \text{ is } A_1}$ **AND** $\underline{y \text{ is } B_1}$, **THEN** $\underline{f_1 = p_1 x + q_1 y + r_1}$

Rule 2: **IF** $\underline{x \text{ is } A_2}$ **AND** $\underline{y \text{ is } B_2}$, **THEN** $\underline{f_2 = p_2 x + q_2 y + r_2}$

ANFIS system architecture suggests that for the given values of the premise parameters the output value can be presented as a linear combination of the consequent parameters [9]. Mathematically this can be presented as:

$$f=\frac{w_1}{w_1+w_2}f_1+\frac{w_2}{w_1+w_2}f_2=\overline{w}_1f_1+\overline{w}_2f_2=$$
$$=\left(\overline{w}_1x\right)p_1+\left(\overline{w}_1y\right)q_1+\left(\overline{w}_1\right)r_1+\left(\overline{w}_2x\right)p_2+\left(\overline{w}_2y\right)q_2+\left(\overline{w}_2\right)r_2 \quad (7)$$

Operation of the hybrid algorithm is composed from one forward and one backward pass. In the forward pass signals are running until the Level 4, and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and premise parameters are updated by the gradient descent.

During the NFS learning, a large number of input and the corresponding output, in this case measured, values were presented to the NFS. After training, the system is ready for use.

Two NFSs were created: the first one for the workpiece temperature and the second for the surface roughness prediction. Similarly as in the ANN models, the following input parameters are adopted: (1) Cutting speed, (2) Feed rate, and (3) Depth of cut. The output variables are the workpiece temperature, for the first NF, and the arithmetic mean deviation, for the second NF system. Detailed analysis of the various architectures of the NFs, and their suitability for the proposed problem, brought the following parameters for adoption: the number of membership functions of each input is set to 2, the input membership functions are bell shaped, the type of the output membership functions are constant, the optimization method is hybrid and the number of epochs are 300. Also, 40 data sets are used for training and the remaining 20 data sets are used for models testing.

During the learning stage, neuro-fuzzy system accomplishes data generalization, providing a successful prediction of the workpiece temperature and the surface roughness, without any further measurements and calculations.

6 RESULTS AND COMPARATIVE ANALYSIS OF THE ANN AND NFSs

The results of the tentative work of the NF systems, after the training stage and testing, are shown in Figs. 8 to 11. The results show a significant match between the measured and the predicted values, with both, ANN and NF systems.

The error for every single value was calculated. Both, the maximum and the mean errors are calculated for all created systems and the values are shown in Table 1.

The general conclusion is that the measured data are suitable for presentation with the artificial intelligence methods.

Data from Table 1 suggest that the hybrid, NFS has a somewhat better performance. Also, in all situations it was more accurate than the ANN model.

The accuracy and the performances of the artificial neural networks, as well as the n NFSs, can be upgraded by expanding the set of the input and corresponding output data.

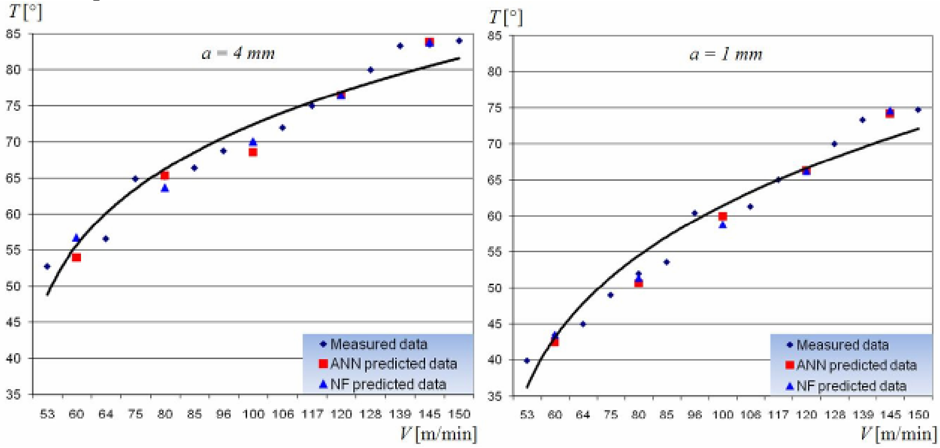

Fig. 8. *Measured, ANN and NF predicted values of the workpiece temperature (f = 0.224 mm/rev)*

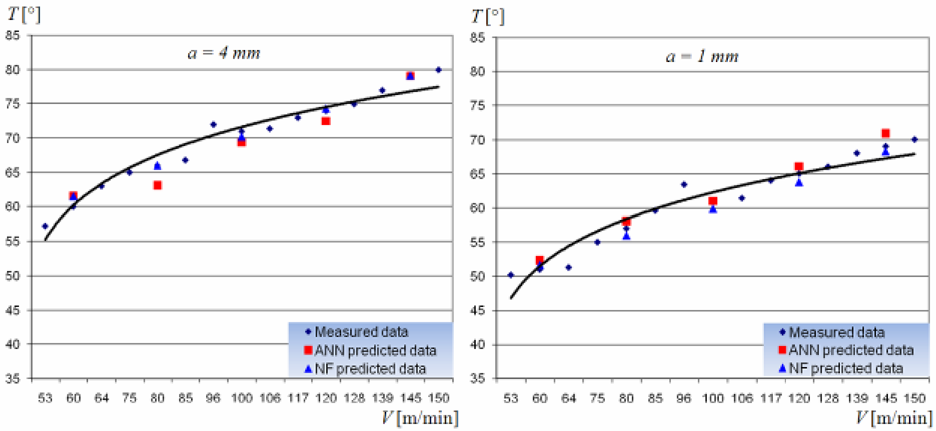

Fig. 9. *Measured, ANN and NF predicted values of the workpiece temperature (f = 0.135 mm/rev)*

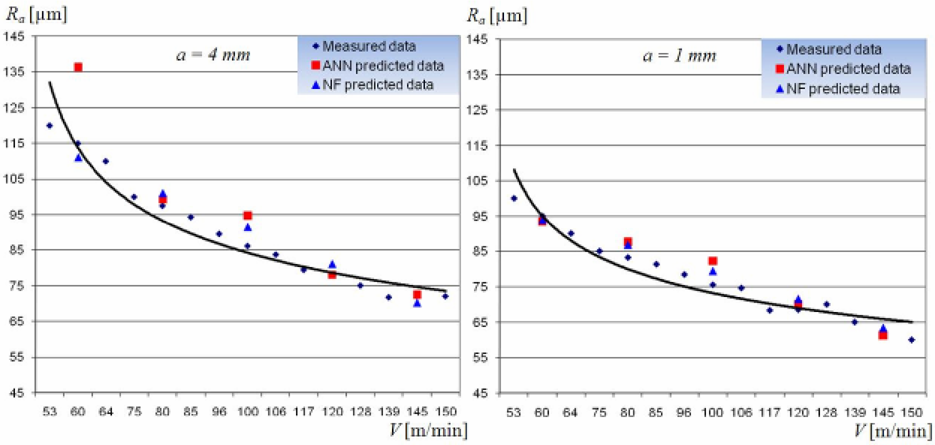

Fig. 10. *Measured, ANN and NF predicted values of the arithmetic mean deviation (f = 0.224 mm/rev)*

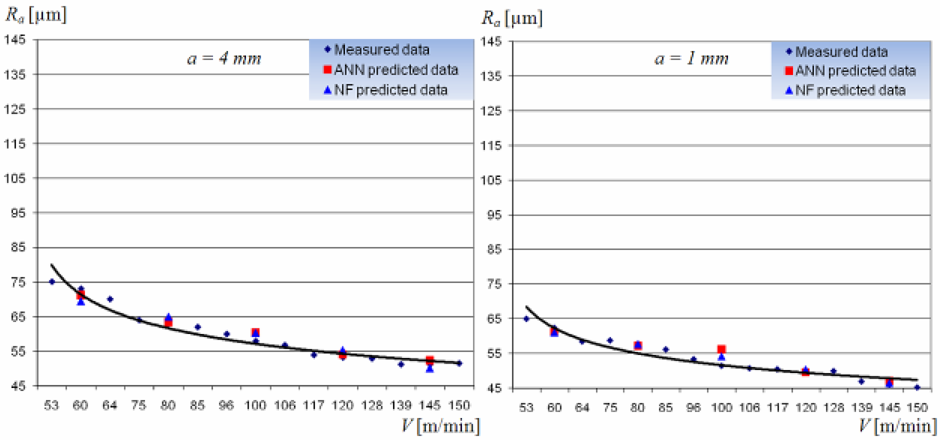

Fig. 11. *Measured, ANN and NF predicted values of the arithmetic mean deviation (f = 0.135 mm/rev)*

Table 1. *Maximum and mean values of errors of the created systems*

Workpiece temperature prediction			**Arithmetic mean deviation prediction**		
Model	Max. error [%]	Mean error [%]	Model	Max. error [%]	Mean error [%]
ANN	4.3488	1.4594	ANN	9.9617	3.8111
NF	4.9908	1.1629	NF	6.1556	3.2526

7 CONCLUSION

Adequate modeling of the metal cutting process parameters is very important from the mechanical and economic point of view. From the mechanical point of view, it is always useful to know which results can be expected before a cutting operation is performed in order to be able to choose the tools, the cutting regimes, the key equipment and the accessories accordingly. From the economic point of view, AI based systems provide the workshops to operate under the optimum conditions which reduces the cost of manufacturing.

The infrared method used in this experiment, gives a relatively good indication of the maximum temperature of the workpiece, while the maximum height of roughness is measured and inspected using a device for surface roughness measurements and a microscope connected to the computer.

The next stage shows the artificial intelligence approach for modelling of the experimentally obtained data in the metal cutting process. Modeling of the workpiece temperature and the surface roughness was done by using the artificial neural networks and the n NFS. The models were tested and the results show a significant agreement with the measured data. The hybrid, NFS, shows better performances and suitability for the proposed setup.

8 ACKNOWLEDGEMENT

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