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ESTIMATION OF MACHINING TIME FOR CNC MANUFACTURING USING NEURAL COMPUTING

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Abstract
An approach to solving the problem of machining time estimation in production of complex products within CNC machining systems is presented in the paper. Heuristic analysis of the process is used to define the attributes of influence to machining time. For the problem of estimating machining time the following „Neural Computing techniques“ are used: Back-Propagation Neural Network, Modular Neural Network, Radial Basis Function Neural Network, General Regression Neural Network and Self-Organizing Map Neural Network. Real data from the technological process obtained by measuring are used to design the model used in investigation. The established model is used to carry out the investigation aimed at learning and testing different algorithms of neural networks and the results are given by the RMS error. The best results in the validation phase were achieved by Modular Neural Network (*RMSE*: 1.89 %) and Back-Propagation Neural Network (*RMSE*: 2.03 %) while the worst results were achieved by Self-Organizing Map Neural Network (*RMSE*: 10.05 %).
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Key Words: Process Planning, Machining Time, Neural Networks, Estimation, CNC Manufacturing

1. INTRODUCTION

Ensuring the effectiveness and viability of manufacturing enterprises in the market is reflected among other things in the application of scientific approaches that can raise the level of knowledge and organization in departments of production and operating sequences preparation. The imperative of modern production is to respond to all demands of the market at affordable costs. The persistence on the market is provided by products and services that have and maintain a high level of product quality, observe delivery times, and are designed and carried out by technological processes with acceptable costs. To respond to this set of requirements represents a serious challenge for the management of manufacturing enterprises. One possible approach to a rational and efficient business of a production enterprise is certainly the integration of computer systems. This integration allows raising the level of automation, flexibility and productivity, and certainly the decision-making process and management of the production system. This approach reduces direct participation of a human in production, while at the same time the importance of the human factor in the preparation and the operative process of production is still significant. There are basic preconditions for improvement of activities in the departments of technological and operational preparation of production in which a systematic monitoring is provided of technological and operational parameters and results of the manufacturing process. Trials are made to consolidate and make universally accessible the individual skills and experience of employees acquired during many years in the departments of production preparation by using systems based on neural computing techniques i.e. artificial intelligence. By analyzing the literature and the application of artificial neural networks, various application areas can be given: modelling and prediction of process parameters, status monitoring and tool wear, optimization of cutting parameters and surface roughness, prediction - estimate of time, job classification etc. Some authors deal with the method of calculation and estimation of machining time. Estimating and

determining machining time plays an important role in the production process planning and scheduling. Usually authors calculate machining time based on technological parameters in case of conventional approaches to machining, designed CNC programs and features of machining systems (machines). For the estimation and determination of machining time authors also use other approaches such as: feature-based method for NC machining time estimation [1]; method based on the photographs of machined parts using texture features of the photographs [2]; estimation model that uses several factors such as distribution of NC blocks, angle between the blocks, feed rates, acceleration and deceleration constants, classifying tool feed rate patterns into four types based on the acceleration and deceleration profile, NC block length, and minimum feed rate [3]; neural computing system that can forecast the tool path in the process of milling [4] and others. Authors use Artificial Neural Networks (ANN) as the main or one of the methods in different investigations. An important group of papers dealing with the application of ANN consists of the models in which prediction of machining parameters is investigated, usually in hard turning or milling. The usually used input parameters for the processes modelled in this way are: speed and depth of cut, feed rate, tool edge radius, cutting forces, tool wear, material removal volume, coolant pressure, etc., while one or more parameters are used as output, such as: surface roughness, spindle motor power consumption, machining time, tool wear, tangential force (cutting force), axial force (feed force) etc. For design of experiments and process modelling Taguchi's Design of Experiments [5] and Differential Evolution algorithm [6] are often used. Paper [7] uses „multilayer feed-forward artificial neural network (ANN)“ to study the effect of „cutting speed, feed rate, and machining time on machinability aspects such as specific cutting force, surface roughness, and tool wear in AISI D2 cold work tool steel hard turning with three different ceramic inserts, namely, CC650, CC650WG, and GC6050WH“. Along with ANN, in development of empiric model for surface roughness prediction, tool wear and energy needed for hard turning operations, author [8] uses Response Surface Methodology (RSM) and Support Vector Regression (SVR).

The applied methodologies showed successful with experimental data but compared to RSM, ANN and SVR they achieved significantly better results. Tool service life and technological conditions in the machining process are, among others, important for economic aspects of production. As the cost-efficient production is imperative, the state of the tool is monitored and it is modelled accordingly [9-11]. Drilling operations are often used as preliminary operations followed by various technological operations such as boring, reaming and tapping. As the process of drilling is also a complex operation, authors [9] experimentally investigated and modelled the impact of tool wear (as output variable) on the process parameters (input variables: drill size, feed, spindle speed, torque, machining time and thrust force) using various structures of ANN and statistical analysis. In paper [10] an on-line scheme for tool wear monitoring using ANN is proposed with the following input variables of the model: cutting speed, feed, cutting force and machining time. These are used as output variables in the function of tool wear analysis. Paper [11] also models and investigates the ANN architecture subsequently used as the methodology for tool wear estimation in hard turning. For the ANN architecture modelling data are used that were obtained from experimental model in which input variables were the conditions (parameters) of the machining process and machining time while tool flank wear was used as output variable. Authors [12] use ANN for analysis and prediction of modelling the complex relations between cutting conditions and process parameters in metal-cutting operations and the cutting process optimization for efficient and economic production.

The created model is complex, using the following as input variables: speed, feed rate, depth of cut, cutting time and coolant pressure while measuring seven output variables: tangential force (cutting force), axial force (feed force), spindle motor power consumption,

machined surface roughness, average flank wear, maximum flank wear and nose wear. Application of ANN in the machining process, tool wear and surface roughness process (parameters) optimization along with other approaches such as Genetic Algorithm (GA), Pareto, Grey-Taguchi methodology and Gravitational Search algorithm are given in papers [13-19]. The paper [20] presents a research on inventory ABC classification using various multi-criteria methods (AHP and cluster analysis) and neural networks. The applied methods' obtained results have been used to evaluate their usage possibilities in real manufacturing environment. The paper [21] presents new iso-parametric tool path planning for machining trimmed free-form surfaces. Researchers use ANN (various algorithms of neural networks) and other approaches to study a wide range of problems. The paper [22] gives problem of frequent production plan change in an environment where manufacturing systems are constantly varying, an improved hybrid rescheduling strategy is proposed. Disturbance factors are classified according to their origin and influence, and their disturbance degree is determined using a fuzzy-neural network. Authors in paper [23] use new model to analyse the interaction between urban densities and travel mode split. A feedback simulation model based on radial basis function neural networks is developed in this research.

Using the various ANN algorithms can be reduced to the denominator „neural computing techniques" (Multi-Layer Perceptron – MLP, Radial Basis Neural Networks – RBNN, and Generalized Regression Neural Networks – GRNN). For the temperature of soil modelling authors in paper [24] use three different neural computing techniques (Multi-Layer Perceptron, Radial Basis Neural Networks, and Generalized Regression Neural Networks). In studying the problem of flood forecasting [25] the three neural computing techniques approach was also used (Multi-Layer Perceptron–Neural Networks Model – MLP-NNM, Generalized Regression Neural Networks Model – GRNNM, and Kohonen Self-Organizing Feature Maps–Neural Networks Model – KSOFM-NNM). Use of Neural Computing for 3D modelling of Virtualized Reality Objects is demonstrated in paper [26], and three neural architectures are applied for research in the paper: Multilayer Feed–Forward Neural Network (MLFFNN), Self-Organizing Maps (SOM) and Neural Gas Network (NGN).

In all of the described papers conclusions mostly confirm justification of the application of neural computing techniques i.e. ANN for solving concrete technological problems. In complex problems in which modelling mathematical dependance of input and output variables is difficult, application of ANN is surely valid. Therefore, this paper deals with the problem of estimation (evaluation) of machining (technological) time in the production process using CNC machining systems by the application of neural computing techniques (ANN). The collected results of experimental investigations from the technological process are used for setting, analysing and evaluating the model.

2. DEFINITION OF PROBLEM AND AIM OF INVESTIGATION

Analysing the features of production realization in an enterprise of engineering industry, deviations were identified of the calculated in relation to the realised (effectuated) machining time. The process planning on CNC machining systems includes the process of calculation of the necessary machining time. Upon completion of activities in the technological preparation of production and provision of all necessary resources (material, CNC machine operator, tool, CNC program, technological documentation, etc.), realization (machining) can begin of production elements through production orders under the guidance and supervision of operational preparation department. By monitoring production, deviations were observed between the calculated and the realised machining times. The production is organized in three shifts during the week. After a complete analysis of the production orders (for a selected group of series of production elements) whose implementation cumulatively needed the planned 7160 hours (298.33 working days), significant deviations of time were observed.

Table I: Time series efficiency analysis.

Operative efficiency analysis of vertical CNC machining centre performance				
	Amount		Amount	
Planned:	7160.00	hours	298.33	days
Realised:	8317.21	hours	346.55	days
Lost:	**-1157.21**	hours	**-48.22**	days

After the implementation of the planned production orders, 8317.21 hours were realised (346.55 working days) which makes a difference of 1157.21 working hours (48.22 working days). Time series analysis of the efficiency of the vertical CNC machining centre is shown in Table I. The previously given and observed deviations of machining times directed the authors towards investigation of the features of the technological process that affect deviations. Rational analysis and heuristic approach were used to define the features of influence to the technological process and to design the model for investigation.

3. DEFINITION AND DESCRIPTION OF MODEL FEATURES BY THE SELECTED METHODOLOGY OF INVESTIGATION

Rational and detailed analysis of the vertical CNC machining centre (MAG FTV-850/2500) technological process and the realised production orders on selected production elements (see Fig. 1) have shown the features of influence to the correction of machining time. Expert knowledge of technologists and operatives in technological process has been used in analysing and setting up the model. The model is defined by the following features of the process (input vector): complexity of production element, number of procedures, number of pieces in a series, operator implementing the activities, stopping of activities and machine stoppage. The analysed production elements (see Fig. 1) represent one of the main parts of the complex product.

Heuristic approach has been used to define the study model with the realised machining time as output variable and the following input variables:

1) *Production element* (*Prod_elem*) – four production elements are used for analysis;
2) *Complexity of production element* (*Complex_pe*) – variable is defined at four levels;
3) *Number of procedures in CNC machining of production element* (*Number_pe*) – due to the characteristics of the selected machine, production elements must be turned two to four times and gripped so as to be completely machined;
4) *Number of pieces in a series* (*Number_ps*) – this variable considers losses of time that are in the function of the number of production elements in a series. In piece production losses of time not sufficient for manufacturing have been observed while with production of a greater number of pieces the calculated time has been longer than the realised time;
5) *Operator preparing and realizing activities of manufacturing* (*Operator_am*) – this is also a very important variable as one production element can require up to three operators in a shift for its manufacturing. Thus four levels of this variant are defined in view of the operator experience (more than 10 years experience in jobs of CNC operator, more than 5 years, more than 2 years, less than 2 years experience);
6) *Shift of starting the activities* (*Shift_activity*) – this variable is connected with the working condition of the worker, and is in the function of the shift the worker is in. Monitoring and analysis of production process have shown that the workers' productivity is the best in the first shift. There are three values of this variable (first, second and third shift);

7) *Errors on CNC machining centre* (*Error_CNCmc*) – the operator may or may not have personal effect on this variable. Conditions in manufacturing can be various and most often they can be defined as the following: no stoppages, cleaning and preventive maintenance of the machine, tool breakage, adaptation and adjustment of new CNC program, stoppage of production order;
8) *Machining time calculat* (*Machining_time_calculat*) – (machining time that the technologist calculates for manufacturing of a production element) – this variable adopts four values in the function of production element: first production element330 minutes, second production element 450 minutes, third production element 360 minutes and fourth production element 650 minutes.

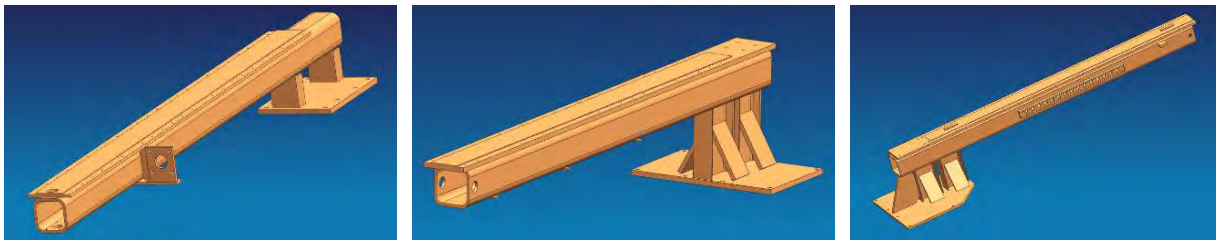

Figure 1: Review of production elements for the analysis of machining times.

The problems with the definition of process parameters limit the development of mathematical models so today the methods are used in scientific and engineering approaches that enable the development of processing models without the knowledge of natural patterns of process development. These methods developed as the field of so called Artificial Intelligence (expert systems, fuzzy systems and neural networks). The knowledge about the problem being unstructured and the values of input vector, conditions and output values from the process numerical, the selection of neural networks as the method for modelling, analysis and study of established problem is a logical decision.

4. ESTIMATE OF MACHINING TIME BY USING NEURAL COMPUTING

4.1 Neural Computing – general approach

Studying the way our brain functions and the way to solve problems, a number of investigators were trying to design an abstract model that would imitate functioning of the brain. As a result neural computing was created. The neuron is the basic cell unit of the neural system. Its structure is relatively simple and represents a micro processing unit that receives and combines the other neurons' signals through input processes (dendrites). If the combined signal is strong enough and activates the neuron, it generates output signal (axon). The output (axon) connects the neuron with the inputs (dendrites) of other neurons by way of synapses. Transfer of information is realised by way of chemical compounds in nature, and the amount of transferred signals is in the function of the amount of chemical compounds (neurotransmitters) output by axons and received by dendrites. This efficiency of synapses (or „force“ of the realised connections of neurons) is what changes when the brain is learning. In general, by neurons' connecting, artificial neural network is being formed. Neurons are grouped in layers. Multilayer neural networks are composed of minimally three basic layers: input, hidden and output layer. The input layer is responsible for acceptance of input data from environment and their transfer to the hidden layer (input vector). There may be several hidden layers. The information travels (is being processed) through the hidden layer(s) and is passed on to the output layer (output vector). The process of adjusting the weights of the

neurons' connections within the network is called learning. The learning process is realised in the defined architecture (topology, structure) of the network. The neuron's body takes over the role of a summator, while the role of dendrites is taken over by the inputs into the summator. The layer of the biological neuron sensibility activation is taken over by the transfer function and it defines the moment of sending (launching) the impulse to the neuron output. The transfer function can be either linear or nonlinear. Most of the problems investigated by neural networks are prediction problems, there are only several cases belonging to classification problems. Different algorithms are used for neural networks design but the most often used one is the back propagation algorithm. The review of available literature reveals that investigators use different algorithms as well as terms for neural networks. Different neural networks are used and modelled for different problems so that it is difficult to claim that a certain kind of problems is solved by a definite kind of neural networks (algorithms). For solving a given problem (defined research) five kinds of neural networks are determined: Back-Propagation Neural Network, Modular Neural Network, Radial Basis Function Neural Network, General Regression Neural Network and Self-Organizing Map Neural Network. They are used for designing, modelling and investigating the architectures of neural networks.

4.2 Preparation of data and investigation model design

By setting up the model for investigating estimation of machining time on vertical CNC machining centre a general form of the model vector for the neural network input can be given according to the defined Eq. (1).

$$X_i = \{x_{i1}, x_{i2}, x_{i3}, ..., x_{in}\} \Rightarrow Y_o = \{y_{o1}, y_{o2}, y_{o3}, ..., y_{on}\} \tag{1}$$

where X_i represents input vector (input variables) and Y_o output vector (output variables).

Analysing the process of manufacturing production elements on vertical CNC machining centre, based on experience in the process and heuristic approach, the investigation model is defined. The model is defined by selecting input variables – vector X_i = *{Prod_elem; Complex_pe; Number_pe; Number_ps; Operator_am; Shift_activity; Error_CNCmc; Machin_time_calculat}* and their influence on output variable is investigated – vector Y_o = *{Machin_time_realised}*. For the selected input and output variables the data from production process were collected (from department for technological and operative preparation of production). Each of the variables was defined with maximum and minimum values (Table II) and the design and experimental work with the architecture of neural networks could begin. The collected data for experimental work are prepared and devided into the data for neural network training and the data for testing. The set of data is composed of real data from 960 cases from production process. The data sample is devided into 5 groups according to the output variable and the groups are determined so that each one has the same number of data.

Table II: Min-Max values of model variables.

Variables of model		Variable value	
		Min	Max
X_i	*Prod_elem*	1	4
	Complex_pe	1	4
	Number_pe	1	2
	Number_ps	1	3
	Operator_am	1	4
	Shift_activity	1	3
	Error_CNCmc	1	5
	Machin_time_calculat	330	650
Y_o	*Machin_time_realised*	284	1014

Each group has the data as follows: 60 % for learning, 20 % for testing and 20 % for validation. Each group has 115 cases for training and 38 cases for testing and validation.

When the preparation of data ended, design of the neural networks' architecture began (defining and adjusting of the best attributes). After the network architecture was designed, the network training for the selected machining process could start. The procedure of neural networks training was conducted on an arbitrary number of iterations by adjusting the network attributes. The criterion of RMS error (Root Mean Square Error) was adopted as a criterion of validation for the neural network architecture design, given by Eq. (2).

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

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.

4.3 Short review of selected neural networks with achieved results

A short review is given of the neural networks five selected algorithms and achieved results. The results were achieved during experimental work on the design of each particular architecture, i.e. adjusting the attributes (learning rules, transfer function, coefficient of learning, momentum, size of epoch) of neural networks.

Back-Propagation Neural Network (BPNN) is one of the very popular and often used neural networks. The set problem of Perceptron network served as inspiration for design of this network. The problem consisted in distribution of connection weights in the network and adaptation of other attributes in the network. Solution to the problem was defined through the error localisation so that after calculation in output layer it returns backwards through hidden layers and serves for adjusting connection weights in the network. Characteristics of this network architecture are: input layer, one or more hidden layers and one output layer. The number of hidden layers is theoretically unlimited but usually it is one or two. Each layer is completely connected with the following which refers to a great number of synapses. The neuron model used in this network has a nonlinear, smooth, output characteristic.

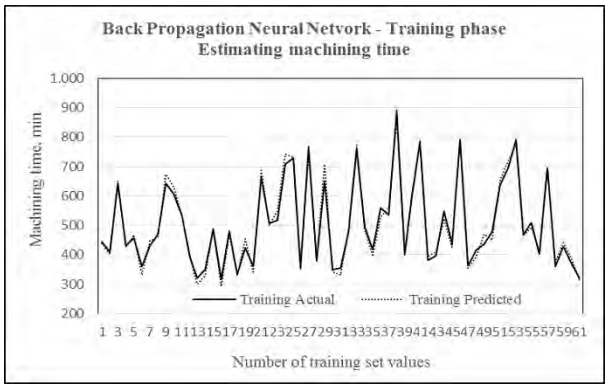

Figure 2: Presentation of realised BPNN values in the training phase.

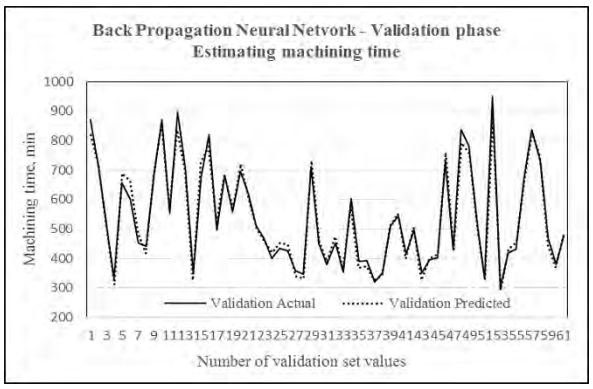

Figure 3: Presentation of realised BPNN values in the validation phase.

After design of a significant number of the neural networks' architectures by varying various attributes, the neural network with the smallest root mean square error 0.0121 (1.21 %) in the phase of learning (training) was selected. The selected neural network gave the result of 0.0203 (2.03 %) in the phase of validation. Analysis of results relating to the processes of training and validation is graphically presented in Figs. 2 and 3.

Modular Neural Network (MNN) is presented as „adaptive mixture of local experts“. It consists of a group of neural networks represented as local experts that compete for learning of different aspects of the set problem. Local experts can consist, for example, of a backward propagation group of networks and in that case the results obtained by the backward propagation network can be improved. Transitory network controls competition and learning and through its outputs it affects the definition of different fields of data for different local experts of a network. In case only one network is suitable for solving the set problem, the transitory network will direct to it and will give preference to only one neural network out of a set of local experts. The transitory network and the local experts network are fully connected with input layer. These networks process input data and send them to the transitory layer. Training of the modular neural network is performed simultaneously for the transitory network and the local experts. Training rules are created so as to encourage competition between the local experts assigned to input vector and the transitory network that will certainly rather be directed to the selection of one local expert than to their combination. By design and experimental work with this network, after adjusting the network attributes (varying transfer functions and rules of training and other attributes), the results are achieved with the lowest root mean square error 0.0139 (1.39 %) in the neural network training phase. On a new set of data for validation the obtained network gave the result of 0.0189 (1.89 %). The results achieved by the Modular Neural Network being very similar (close) to the results achieved by the Back-Propagation Neural Network, they will not be presented graphically in this part of the paper.

The term **Radial Basis Function Neural Networks** (RBFNN) can in most cases refer to every network that has a radially symmetric transfer function within the neuron in the hidden layer. For the sample unit (hidden layer neuron) to be radially symmetric it must consist of three elements: *Centre*, the input domain vector which is usually deposited in the output layer weights vector in the sample unit; *Measure of distance*, the measures that define how distant the input vector is from the centre (usually the standard Euclid measure of distance); *Transfer function*, the one variable function that defines the neuron's output with functional mapping of the distance from the centre. A common transfer function is the Gaussian function that reinforces output values of variables in case of small distance. In the radial basis functions the networks' training can be defined by layers. In input layer the training starts according to the principle „without a trainer“ that results in defining the centre position.

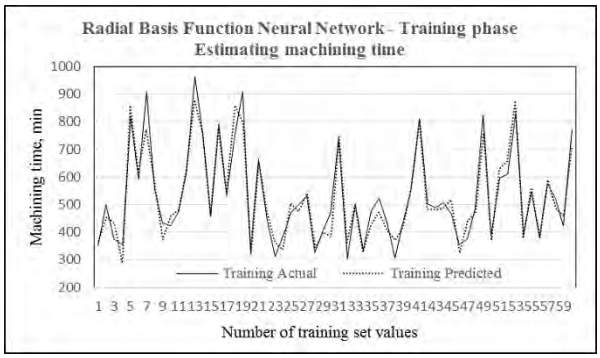

Figure 4: Presentation of realised RBFNN values in the training phase.

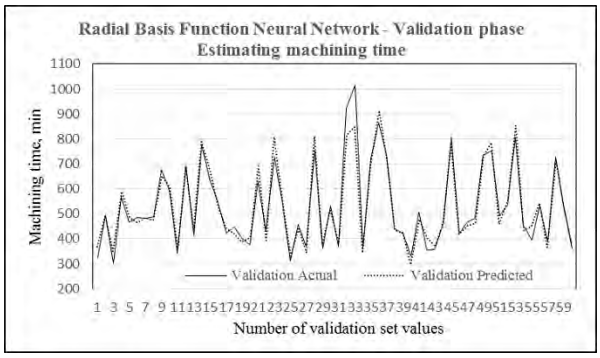

Figure 5: Presentation of realised RBFNN values in the validation phase.

In the output layer the outputs are calculated and the error is calculated with regard to the real outputs. In the output and hidden layer the training is performed according to the principle „with the trainer“. In performing experiments with RBFNN, after adjusting the network attributes results with the least root mean square error of 0.0214 (2.14 %) are achieved in the neural network training phase. The network thus designed achieved the result

of 0.0333 (3.33 %) in the validation process. Analysis of results in the processes of training and validation is given in Figs. 4 and 5.

General Regression Neural Network (GRNN) is generally used for the system modelling and prediction. Main advantages of GRNN are: quick learning, convergence to optimal surface regression in case of a great number of samples. It can be efficient even with a reduced number of data. GRNN uses a standard statistical formula for calculating the conditional mean Y of a scalar random variable y given a measurement X of a vector random variable x. The conditional mean is statistically the most likely value for the random variable Y given X. The vector random variable x corresponds to the ensemble of inputs of the network; the random variable y corresponds to the ensemble of outputs of the network. If there is more than one output node, the same formula is used on each output node. The formula for conditional mean requires knowledge of the joint probability density function of the random variables x and y. In GRNN, these joint probability density functions are approximated from the training vectors using Parzen estimation. Parzen estimation is a nonparametric estimation technique, which approximates a density function by constructing it out of many simple parametric probability density functions. Experimental work with GRNN, after adjusting the network attributes, resulted in the neural network least root mean square error of 0.0701 (7.01 %) in the learning (training) phase. In the process of validation the network designed in this way gave the result of 0.0749 (7.49 %). The results achieved in the training phase and in the validation phase are presented in Figs. 6. and 7.

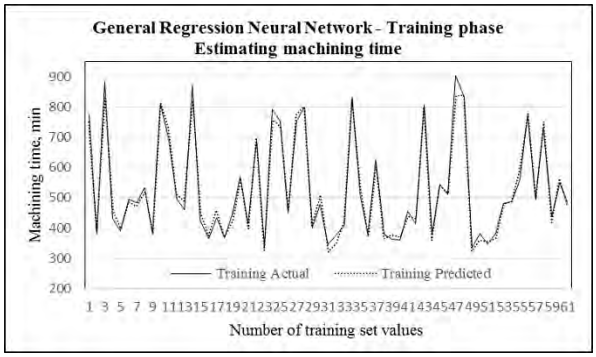

Figure 6: Presentation of realised GRNN values in the training phase.

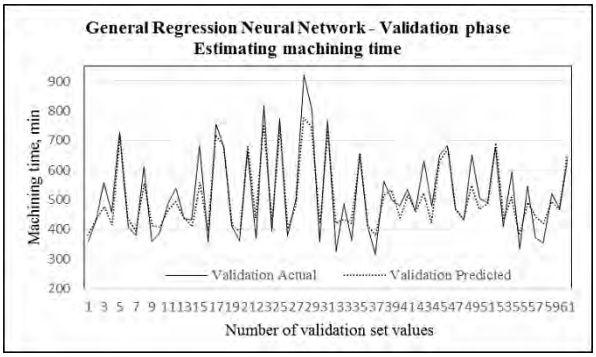

Figure 7: Presentation of realised GRNN values in the validation phase.

Self-Organizing Map Neural Network (SOMNN) is one of important architectures of neural networks and was developed in time between Adalin network and Hopfield network. Basic difference between SOMNN and other networks is in the fact that it learns without supervision. That is why the key word in its name is the word self-organizing. SOMNN is usually used in combination with other layers of neural networks particularly for the problems of estimation and classification.

The network starts learning (training) unsupervised; after that, supervision of learning (training) is required for the output layer. The network requires sufficient number of repetitions so as to stabilize. During this period of time, the learning rate of the weights going to the output layer is set to zero. Then, the learning rate of the weights in the output layer is set to a positive value and the learning rates for the Kohonen level become very small or zero. The output layer tends to learn very quickly when only one Kohonen PE has a positive output and this value is the constant 1.0. The experimental work with SOMNN, after adopting the best network architecture, resulted with the least root mean square error of 0.0813 (8.13 %) in the neural network training phase. In the validation phase the network gave the result of 0.1005 (10.05 %). The results achieved in the process of training and in the process of validation are given in Figs. 8 and 9.

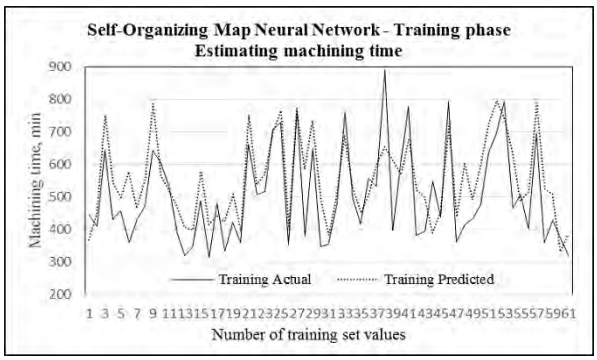

Figure 8: Presentation of realised SOMNN values in the training phase.

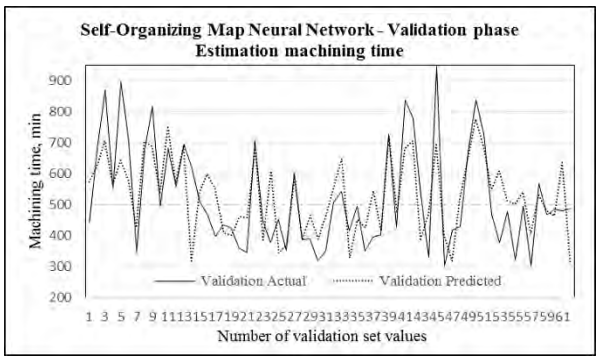

Figure 9: Presentation of realised SOMNN values in the validation phase.

4.4 Presentation of the best results generated in the process of designing ANN

Designing, modelling and experimental work with different architectures of neural networks within every algorithm generated more architectures in the function of different attributes. Combining different architectures, conducting the process of training and achieving the root mean square error results, the best neural networks were chosen in every algorithm. The realised RMS results in the training phase for the selected neural network are displayed in Table III. In the course of designing the neural networks different rules of training and transfer functions were used. The adopted training rules and transfer functions of other neural networks were not used for GRNN so the results are not displayed in Table III.

Table III: Review of RMS error for various neural networks.

No.	Learning rule	Transfer function	BPNN	MNN	RBFNN	SOMNN
1.	Delta-Bar-Delta	Linear	0.0445	0.0538	0.0719	0.2228
2.	Delta-Bar-Delta	Sigmoid	0.0121	0.0205	0.0633	0.0813
3.	Delta-Bar-Delta	Sinus	0.0368	0.0439	0.0665	0.2390
4.	Delta-Bar-Delta	Hyperbolic-Tangent	0.0290	0.0428	0.0640	0.2342
5.	Delta	Linear	0.0123	0.0237	0.0581	0.2167
6.	Delta	Sigmoid	0.0178	0.0174	0.0214	0.0849
7.	Delta	Sinus	0.0222	0.0139	0.0542	0.1899
8.	Delta	Hyperbolic-Tangent	0.0382	0.0142	0.0512	0.1821
9.	Ext. Delta-Bar-Delta	Linear	0.1018	0.0313	0.0681	0.1991
10.	Ext. Delta-Bar-Delta	Sigmoid	0.0123	0.0165	0.0240	0.1072
11.	Ext. Delta-Bar-Delta	Sinus	0.0554	0.0147	0.0583	0.2401
12.	Ext. Delta-Bar-Delta	Hyperbolic-Tangent	0.0254	0.0155	0.0544	0.2100
13.	Norm.-Cum. Delta	Linear	0.0125	0.0450	0.0547	0.2429
14.	Norm.-Cum. Delta	Sigmoid	0.0242	0.0175	0.0222	0.0882
15.	Norm.-Cum. Delta	Sinus	0.0185	0.0236	0.0529	0.02232
16.	Norm.-Cum. Delta	Hyperbolic-Tangent	0.0381	0.0262	0.0509	0.02116

Fig. 10 shows the best results of experimental work with different ANN architectures.

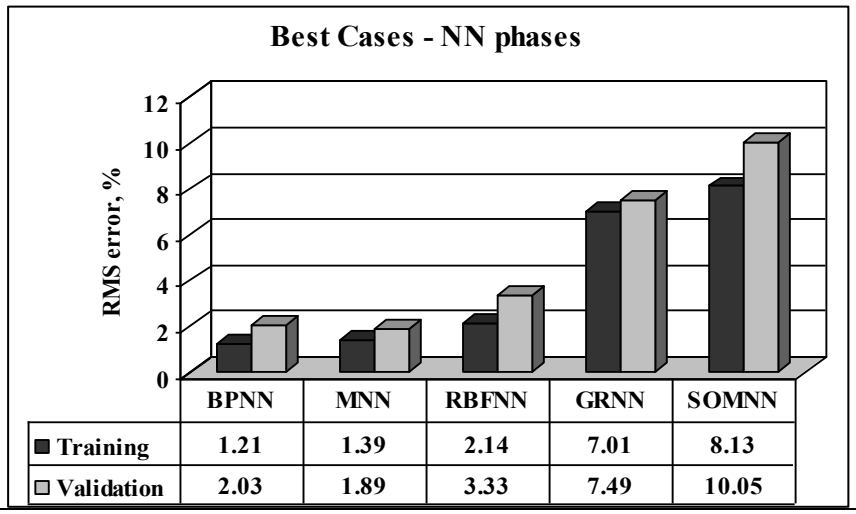

Figure 10: Results generated by different neural networks.

5. CONCLUSION

The paper describes the approach to solving machining time estimation in real manufacturing of complex production elements within the CNC machining systems. Through analysis of technologic-operative preparation, it was concluded that the process planning was conducted by the application of classical approach and that the planning and monitoring of production showed considerable discrepancies between the calculated and the realised machining times. To solve the problem, the vertical CNC machining centre was chosen and the production orders and data were collected and analysed. By setting up the model for experimental research important attributes were adopted that completely described the analysed technological and manufacturing process. Different algorithms of neural networks were selected and applied in estimating machining time. The designed prediction models based on five different neural networks gave the following results: BPNN RMS in training phase 1.21 %, and in validation phase 2.03 %; MNN in training phase 1.39 %, in validation phase 1.89 %; RBFNN in training phase 2.14 %, in validation phase 3.33 %; GRNN in training phase 7.01 %, in validation phase 7.49 %; SOMNN in training phase 8.13 %, in validation phase 10.05 %. For all five algorithms the generated errors in the training phase were up to 6.92 % and up to 8.02 % in the validation phase.The errors generated with BPNN, MNN and RBFNN were low while they were somewhat higher with GRNN and SOMNN. The levels of errors generated by BPNN, MNN and RBFNN provide full justification for the application of the selected model. The levels of errors obtained with GRNN and SOMNN can also provide justification for its application but the priority in case of possible exploitation should nevertheless be given to BPNN, MNN and RBFNN. The results generated with BPNN and MNN confirm the theoretical bases according to which better results are expected by using MNN. In the validation phase the results generated by MNN are better than those generated by BPNN.

Further investigations should also be aimed at other machining systems as this could be the way to create the conditions for designing and modelling the system that could give support to technologists in process planning.

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