Strojniški vestnik - Journal of Mechanical Engineering 54(2008)3, 179-188
UDC 681.5

Paper received: 10.5.2007
Paper accepted: 19.12.2007

Application of Neural Networks in Evaluation of Technological Time

Goran Šimunović* - Tomislav Šarić - Roberto Lujić
University of Osijek, Mechanical Engineering Faculty in Slavonski Brod, Croatia

The traditional approach to the process planning mostly based on experience of technologists, requires a lot of accumulated knowledge, is inflexible and time consuming. The application of artificial intelligence methods can support and greatly improve this approach. This paper describes the results obtained by investigating the application of neural networks in evaluating the manufacturing parameters and, indirectly, technological time of the seam tube polishing. Various structures of a back-propagation neural network have been analysed and the optimum one with the minimum RMS (Root Mean Square) error selected. The obtained model was integrated into the ERP system (Enterprise Resource Planning system) of a manufacturing company. The more precise evaluations of technological time obtained by the ERP system model complete the previously defined manufacturing operations and form the basis for production planning and times of delivery control. The work of technologists is thus made easier and the production preparation technological time made shorter.

Keywords: process planning, artificial intelligence, neural networks

0 INTRODUCTION

The fulfilment of the basic requirements modern enterprises are faced with, such as a product optimum quality, low production costs, holding to the agreed times of delivery and a more rational material and information management in a production system, cannot be imagined without new scientific approaches in production preparation. The level of knowledge and organisation in production preparation sectors has a considerable impact upon the final characteristics of a product and an indirect effect on production costs and the 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. 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) 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] to [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. 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, etc.) is described and implemented in the works of many authors [5] to [8]. The authors [5] and [6] 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

*Corr. Author's Address: University of Osijek, Mechanical Engineering Faculty in Slavonski Brod, Trg I. Brlić-Mažuranić 2, HR-35000 Slavonski Brod, Croatia, goran.simunovic@sfsb.hr

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 [7] to [9]. The authors [10] and [11] also deal with the optimization of machining parameters but by the application of the modified GA with the self-organizing adaptive penalty (SOAP) strategy i.e. by the application of parallel GA and simulated annealing (SA). Besides the GA the neural networks (NN) [12] to [15] 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) [13] is proposed. In this paper the NN represents the relationship between the cutting conditions and machining-related variables, and Genetic Algorithm (GA) obtains the optimum operational condition. The paper [14] 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 [15] and [16] is also proposed. Neural networks are also used for evaluation of the machined surface roughness [17] i.e. of the tool wear in the machining process [18]. The authors [17] and [18] compare the results obtained by the application of neural networks with the results obtained by analytical models. It is also possible to use neural networks for intelligent tool path generation for the milling of free surfaces [19] and [20]. In their work the authors take the required surface quality as a primary technological requirement for free surface milling programming. Therefore the application of artificial intelligence for the solution of specific manufacturing problems is in most cases justified in the conclusions of all the mentioned works. In multi-dimensional problems in which the mathematical dependence of input and output variables is difficult or almost impossible to set up, the application of neural networks is certainly significant. Nevertheless, no matter what the main objective of the application of neural networks, there are few authors only who speak about improvement in terms of the previously trained network integration into a corresponding data base within which the results the network gives might be repeatedly used. It is exactly the problem of predicting technological time by the application of neural networks and integration of a trained network into the ERP system that the present paper deals with.

1 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 minimum 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.

It is almost impossible to establish a mathematical model of the polishing rate due to a number of influential parameters, which will be described later. Therefore, one of the goals of this paper, which deals with the evaluation of technological parameters and indirectly of technological time of the seam tube polishing, is to develop a processing model based on the application of neural networks. The developed model will be integrated into the existing ERP system of the company Đuro Đaković Welded Vessels Ltd. The values of input variables in the model will be based on the ERP system real data and the results the model gives should form the basis for a more precise assessment of delivery times and production planning. The integration of the model into the ERP system should upgrade the activities in the technological preparation of production and the jobs connected with production planning and make the data the model gives generally accessible and useful for the company as a whole.

Neural networks are selected for establishing the model because 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. Real data for setting up the model have been collected over a longer period of time in the company Đuro Đaković Welded Vessels Ltd. in the production of stainless steel seam tubes.

2 EVALUATION OF THE MACHINING PARAMETERS BY THE APPLICATION OF THE BACK-PROPAGATION NETWORK

2.1 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. Figure 2 shows the structure of a back-propagation network with one hidden layer (there can be more hidden layers), while the structure of an artificial neuron is shown in Figure 3.

During the process of learning the aim is to enable fast convergence and reduce global error given by:

$$E = 0,5 \cdot \sum \left(d_k - x_k \right)^2 \quad (1).$$

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:

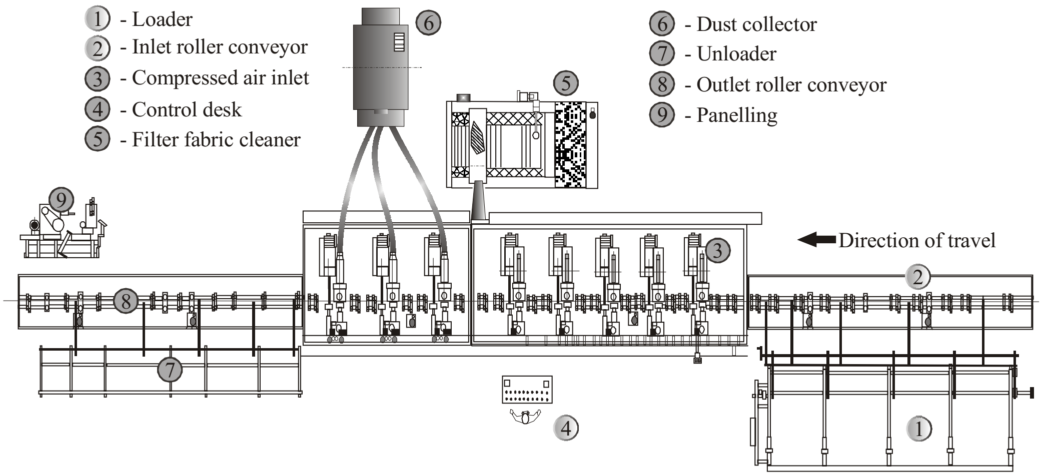

Fig.1. *Scheme of the polishing and grinding line*

$$\Delta w_{ji}^{[s]} = -\alpha \cdot \left(\frac{\partial E}{\partial w_{ji}^{[s]}} \right) \quad (2),$$

where α is the learning coefficient.

Derivations given above can be calculated as:

$$\frac{\partial E}{\partial w_{ji}^{[s]}} = \left(\frac{\partial E}{\partial I_j^{[s]}} \right) \cdot \left(\frac{\partial I_j^{[s]}}{\partial w_j^{[s]}} \right) = -e_j^{[s]} \cdot x_i^{[s-1]} \quad (3).$$

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

$$\Delta w_{ji}^{[s]} = \alpha \cdot e_j^{[s]} \cdot x_i^{[s-1]} \quad (4),$$

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:

$$e_j^{[s]} = \frac{-\partial E}{\partial I_j^{[s]}} \quad (5).$$

The learning coefficient should be kept law to avoid divergence although this could result in a very slow learning. This situation is solved by including a momentum term into expression (4):

$$\Delta w_{ji}^{[s]} = \alpha \cdot e_j^{[s]} \cdot x_i^{[s-1]} + momentum \cdot \Delta w_{ji}^{[s]} \quad (6) .$$

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:

$$X_i = \{x_{i1}, x_{i2}, x_{i3}, ..., x_{in}\} \Rightarrow$$
$$\Rightarrow Y_o = \{y_{o1}, y_{o2}, y_{o3}, ..., y_{on}\} \quad (7),$$

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

2.2 Application of the Back-Propagation Network in Evaluations of Machining Parameters

In the given problem the model vector has one output variable – the rate of polishing. The technological time is calculated from the rate of polishing. Input variables are: kind of material, tube external diameter, wall thickness, oval shaping of the tube after the first phase of production, gradation of the belts used for grinding or polishing adjusted on machine (conveyor), condition of belts (time of usage), pressure of belts, required and performed roughness of the surface, length of tubes and polishing phase (Table 1).

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

$$RMS = \sqrt{MS} = \sqrt{\frac{\sum_{n=1}^{N} (d_n - y_n)^2}{N}} \quad (8),$$

where:

MS Mean Square error,

N Number of pairs of the training set input-output

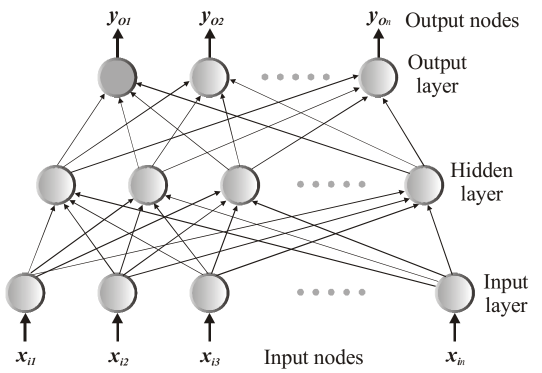

Fig. 2. *Structure of a back-propagation network*

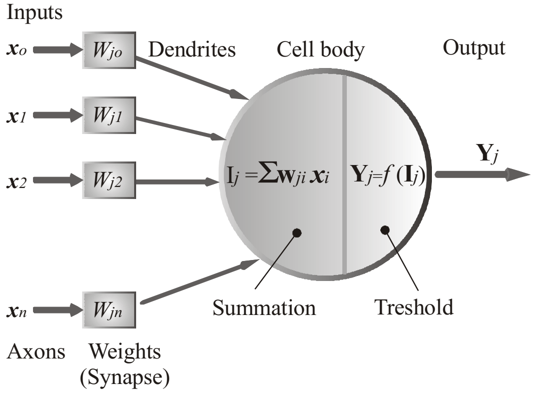

Fig. 3. *Model of a neuron structure [20]*

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.

In expression (9) the formula for the Delta rule is given:

$$\Delta w_{ji} = \alpha \cdot y_{cj} \cdot \varepsilon_i \qquad (9),$$

where 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:

$$\Delta w_{ji} = \Delta w_{ji}^{k} - \Delta w_{ji}^{k-1} \qquad (10),$$

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:

$$\varepsilon_i = y_{ci} - y_{di} \qquad (11),$$

where y_{dj} is the actual (desired) output. The error given by the expression (11) 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.

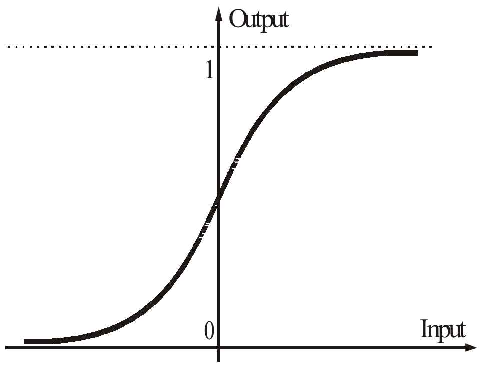

Fig. 4. *Graph of a Sigmoid transfer function*

The transfer function used in this paper is the Sigmoid function calculated according to expression:

$$Output_i = \frac{1}{1+e^{-G \cdot input_i}} \qquad (12),$$

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 graph of the function is continuously monotonous and is shown in Figure 4. As it can be seen the values of this transfer function are in the [0,1] interval range.

2.3 Obtained Results

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 attributes of the network that gives minimum RMS error are shown in Table 2. This network architecture generated the network output with

Table 1. *Variables with a value range for the proposed model*

No	Variable	Minimum value	Maximum value
1.	Kind of material	1	4
2.	Tube external diameter [mm]	10	50
3.	Wall thickness [mm]	0.5	2.5
4.	Tube oval shaping after first phase of production [μm]	0.04	0.1
5.	Gradation of belts for grinding or polishing	80	700
6.	Condition of belts (time of usage) [min]	0	1200
7.	Pressure of belts	0.8	2.5
8.	Required roughness [μm]	8	12
9.	Performed roughness [μm]	10	14
10.	Length of tube [mm]	1000	6000
11.	Phase of polishing	1	3

Table 2. *Attributes of neural network with minimum RMS error*

No.	Attributes	Accepted denotation
1.	Input number of neurons	11
2.	Output number of neurons	1
3.	Number of hidden neurons	6
4.	Learning rule	Delta
5.	Transfer function	Sigmoid
6.	Epoch Size	11
7.	Maximum number of training epochs	75000
8.	Number of training epochs between tests	215
9.	Attempts	45
10.	Learning Rate	0.21; 0.095; 0.1; 1.0
11.	Momentum	0.2; 0.05; 0.1; 0.8
12.	RMSE in learning phase	0. 0301
13.	RMSE in validation phase	0. 0482
14.	Correlation Coefficient	0.9870

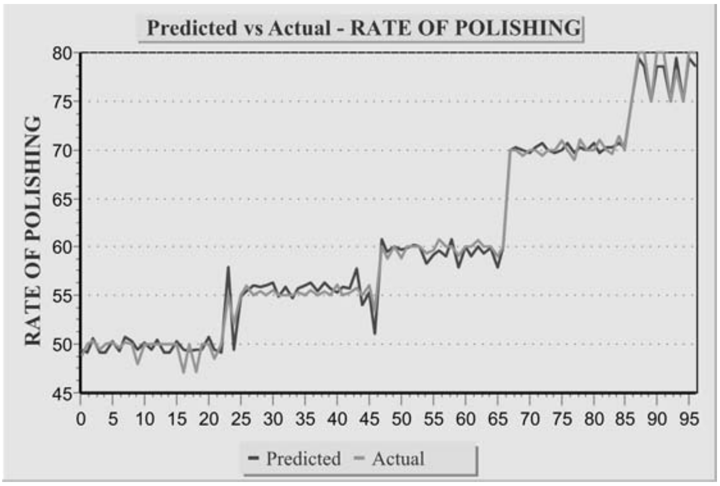

Fig. 5. *Presentation of actual and predicted values given by NN for the rate of polishing*

3.01% rate of RMS error in the training phase and 4.82 % in the validation phase.

Therefore the neural network whose attributes are given in Table 2 approximates best to experimental results. The graph in Figure 5 shows the results obtained by this network structure with regard to experimental results.

Subsequently an investigation into the importance of particular variables for a neural network model was also performed aimed at the possibility of reducing their number. As compared to the defined neural network structure with minimum rate of error (Table 2) a process was developed in which a reduced data model containing 10 input variables and 1 output one was observed. The network was trained with the reduced data model and the given results were analyzed subsequently. The results, shown in Table 3, point to a higher RMS error for each step (with the model reduced by one variable) compared with the initial model.

Therefore the conclusion is that leaving any of the variables out of the model would lead to an increase in error. In an extended model reduction process the dependence of polishing rate on two variables was also studied (Figs. 6 and 7).

3 INTEGRATION OF A PREDICTION MODEL BASED ON NEURAL NETWORKS INTO A TECHNOLOGICAL SUBSYSTEM

The company in which the study was carried out had an ERP (Enterprise Resource Planning) system integrated previously. The structure and

Table 3. *Importance of variables in the model*

No	Variables	RMS	Difference
0.	All model variables	0.0301	0.0000
1.	Kind of material	0.1216	-0.0915
2.	Tube external diameter [mm]	0.0819	-0.0518
3.	Wall thickness [mm]	0.0912	-0.0611
4.	Tube oval shaping after first phase of production [μm]	0.2230	-0.1929
5.	Gradation of belts for grinding or polishing	0.3377	-0.3076
6.	Condition of belts (time of usage) [min]	0.1484	-0.1183
7.	Pressure of belts	0.0867	-0.0566
8.	Required roughness [μm]	0.0473	-0.0172
9.	Performed roughness [μm]	0.0675	-0.0374
10.	Length of tubes [mm]	0.1241	-0.0940
11.	Phase of polishing	0.0672	-0.0372

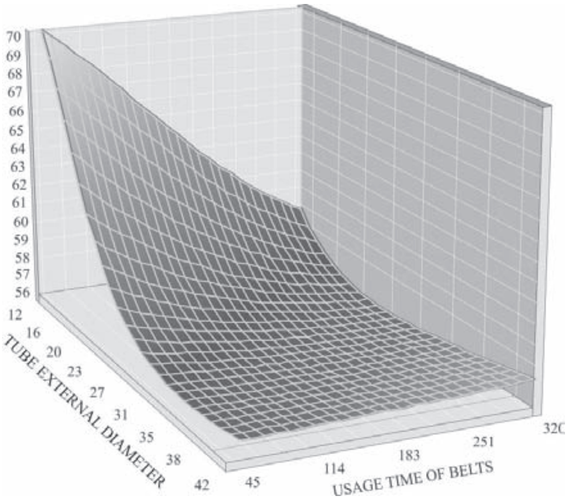

Fig. 6. *Rate of polishing dependence on tube external diameter and usage time of belts*

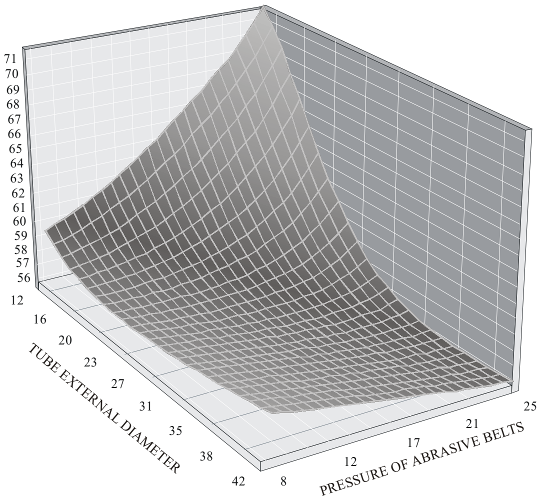

Fig. 7. *Rate of polishing dependence on tube external diameter and pressure of abrasive belts*

components of the ERP system are shown in Figure 8.

By implementing the ERP system the organization level of the preparation, manufacturing and service jobs has raised, quality of management has improved and control of the processes of preparation and production has become easier. Stocks of materials, production costs, costs of quality deviation (scrap, refinish), costs of customer complaints, costs of penalties due to delays in delivery have all been reduced. Production cycle time and production preparation time have been cut, number of required documents and amount of manual work needed for data entering and copying has become smaller. The time necessary to repair damages and machine breakdowns has been reduced. The ERP system technological subsystem DEPTO makes it possible to enter and define materials, raw materials, work-pieces, assembly blocks and products, product components with standards for raw materials, materials and finished parts. It also enables the definition of manufacturing processes, material ratings, technological times per operation resulting from experience, connection and inspection of drawings of parts, assembly blocks and products and print-out of technological documentation.

Determination of the feasible times of delivery based on offers and later also on orders in the Selling and Calculation subsystem – PROKA is mainly experientially based. The system users only rarely carry out multi-criteria analyses. A major factor in determining the times of delivery is the technological time. The overall time of a manufacturing process can be calculated from the ERP technological subsystem previously defined technological parameters, including the rate of polishing. However, this theoretical, empirical value of the polishing rate based on the condition of the tubes, machine and equipment, changes. That is why the obtained model based on the application of neural networks has been integrated into the existing ERP system of the company Đuro Đaković Welded Vessels Ltd. The model is directly integrated into the DEPTO subsystem.

Therefore, one of the goals of the prediction model integration into the ERP system is to more precisely predict the rate of polishing, thus the time of machining and feasible times of delivery, on the basis of the system obtained model actual data. Such precise predictions of the rate and time of polishing that the previously obtained model gives, are essential in the planning and scheduling of production and particularly of the production plan revision.

Based on the system data and application of the prediction model it is also possible to make a correction of the empirical (theoretical) rate of polishing at the moment of the preparation of technological documentation and perform launching with the real technological times.

A month long application of the integrated model has proven efficient as it gives the actually needed times of polishing (Fig. 9). The necessary data that represent the input into the obtained model are collected from the following subsystems and modules (Fig. 10): Commerce and Sales, Definition of Products and Technology, Supply and Inventory, Maintenance of Production Facilities, Common Data Base, Production Monitoring, and Production Planning and Scheduling.

4 CONCLUSION

This paper outlines the results of the application of neural networks in evaluating the technological parameters and technological time of seam tube polishing. The prediction model based on neural networks gives the results with a less than 10% error. Although high, this is a limit to the model acceptability. 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.

By integrating the model into the ERP system the process planning of the seam tube polishing has become easier and the time needed

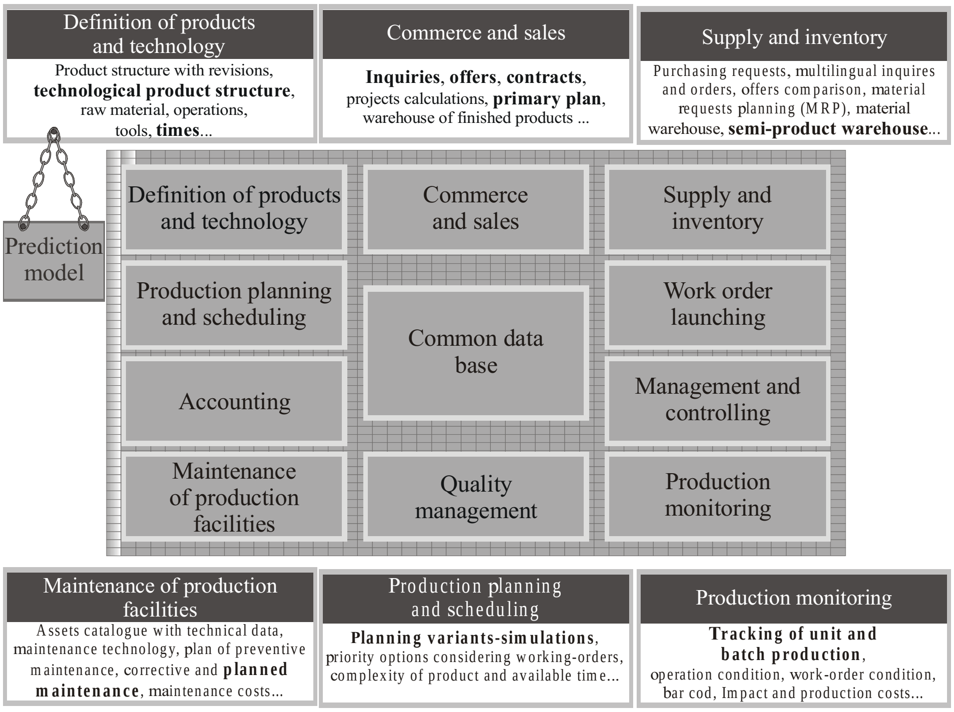

Fig. 8. *The ERP system structure*

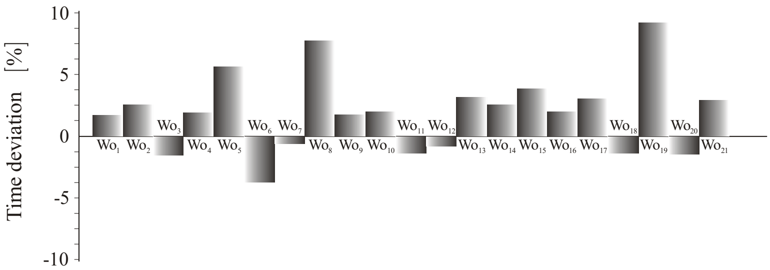

Fig. 9. *Deviation of the actual from scheduled time by a work order*

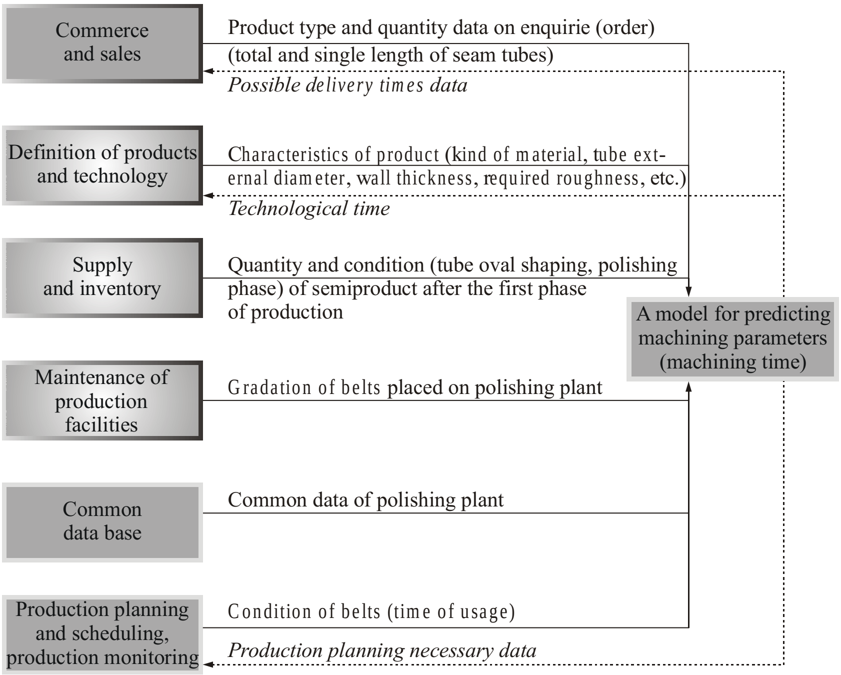

Fig. 10. *Neural network model integration into the ERP system*

for technological preparation of production has been reduced.

Monitoring of the application of the model within the ERP system showed that with the more precise predictions of the rate of polishing and of the values of technological times the model facilitates the activities of production planning and scheduling and of defining the times of delivery.

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 after learning and training the network will give better results i.e. smaller error and that 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 optimum machining parameters considering the ERP system data and condition of the semi products and equipment in the plant.

Acknowledgements

This research forms part of the project “Development of the ERP system for a digital enterprise“ financed by the Ministry of Science, Education and Sports of the Republic of Croatia. Our acknowledgment alo goes to Mr Zdenko Frid, manager of the plant for production of stainless steel seam tubes in the company Đuro Đaković Welded Vessels Ltd.

5 REFERENCES

[1] Grabowik, C., Knosala, R. The method of knowledge representation for a CAPP system. *Journal of Materials Processing Technology,* 133(1-2):90-98, 2003.

[2] Wang, K.S. An integrated intelligent process planning system (IIPPS) for machining. *Journal of Intelligent Manufacturing,* 9(6):503-514, 1998.

[3] Park, K.S., Kim, S.H. Artificial Intelligence Approaches To Determination of CNC Machining Parameters In Manufacturing - A Review. *Artificial Intelligence in Engineering,* 12(1-2):127-134, 1998.

[4] Kim, C., Park, C.W. Development of an expert system for cold forging of axisymmetric product - Horizontal split and optimal design of multi-former die set. *International Journal of Advanced Manufacturing Technology,* 29(5):459-474, 2006.

[5] Singh, G., Choudhary, A.K., Karunakaran, K.P., Tiwari, M.K.) An evolutionary approach for multi-pass turning operations. *Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture,* 220(2):145-162, 2006.

[6] Sardinas, R.Q., Santana, M.R., Brindis, E.A. Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes. *Engineering Applications of Artificial Intelligence,* 19(2):127-133, 2006.

[7] Cus, F., Balic, J. Optimization of cutting process by GA approach. *Robotics And Computer-Integrated Manufacturing,* 19(1-2):113-121, 2003.

[8] Cus, F., Milfelner, M., Balic, J. An intelligent system for monitoring and optimization of ball-end milling process. *Journal of Materials Processing Technology,* 175(1-3):90-97,2006.

[9] Balic, J. Intelligent CAD/CAM systems for CNC programming - an overview. *Advances in Production Engineering & Management (APEM) journal*, 1 (1):13-22, 2006.

[10] Ahmad, N., Tanaka, T., Saito, Y. Cutting parameters optimization and constraints investigation for turning process by GA with self-organizing adaptive penalty strategy. *JSME International Journal Series C-Mechanical Systems Machine Elements & Manufacturing*, 49(2):293-300, 2006.

[11] Wang, Z.G., Rahman, M., Wong, Y.S., Sun, J. Optimization of multi-pass milling using parallel genetic algorithm and parallel genetic simulated annealing. *International Journal of Machine Tools & Manufacture*, 45(15):1726-1734, 2005.

[12] Tansel, I.N., Ozcelik, B., Bao, W.Y., Chen, P., Rincon, D., Yang, S.Y., Yenilmez, A. Selection of optimal cutting conditions by using GONNS. *International Journal of Machine Tools & Manufacture*, 46(1):26-35, 2006.

[13] Jain, R.K., Jain, V.K. Optimum selection of machining conditions in abrasive flow machining using neural network. *Journal of Materials Processing Technology,* 108(1):62-67, 2000.

[14] Zuperl, U., Cus, F., Mursec, B., Ploj, T. A hybrid analytical-neural network approach to the determination of optimal cutting conditions. *Journal of Materials Processing Technology,* 157-58 (Special Issue SI):82-90, 2004.

[15] Zuperl, U., Cus, F. Optimization of cutting conditions during cutting by using neural networks. *Robotics And Computer-Integrated Manufacturing*, 19(1-2):189-199, 2003.

[16] Sanjay, C., Jyothi, C. A study of surface roughness in drilling using mathematical analysis and neural networks. *International Journal of Advanced Manufacturing Technology,* 29(9-10):846-852, 2006.

[17] Ozel, T., Karpat, Y. Predictive modelling of surface roughness and tool wear in hard turning using regression and neural networks. *International Journal of Machine Tools & Manufacture*, 45(4-5):467-479, 2005.

[18] Balic, J., Korosec, M. Intelligent tool path generation for milling of free surfaces using neural networks. *International Journal of Machine Tools & Manufacture,* 42(10):1171-1179, 2002.

[19] Balic J. *Intelligent manufacturing systems.* Univesity of Maribor, Faculty of Mechanical Engineering, Maribor, 2004. (In Slovenian).

[20] Novaković, B., Majetić, D., Široki, M. *Artificial neural networks*, University of Zagreb, Faculty of Mechanical Engineering and Naval Architecture, Zagreb, 2004. (in Croatian).