7th INTERNATIONAL MULTIDISCIPLINARY CONFERENCE
Baia Mare, Romania, May 17-18, 2007
ISSN-1224-3264

THE APPLICATION OF ARTIFICIAL INTELLIGENCE METHOD IN ORGANIZATION OF MACHINING PRODUCTION PROCESS

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Abstract: *The paper discusses the application of artificial intelligence concept in determining labour consumption of selected production operations. The purpose of the work was to examine the possibility of neuron network application in prediction of time of thermo-chemical treatment of manufactured machine elements. Numerical experiments were carried out which enabled to select the appropriate structure of neuron network allowing for prediction of processing time. The analysis has been applied to real environment conditions related to manufacturing of toothed transmission gear.*
Key-words*: artificial intelligence, neuron network structure, labour consumption, thermo-chemical treatment, toothed gear.*

1. Introduction – determination of manufacturing process data using neural networks

Neural networks became increasingly useful in many application related to organization of manufacturing process (Fig.1). Among others, neural networks have been already applied in production scheduling [1], image recognition in quality control [2], design of work-centres [3], modelling of manufacturing process [5], monitoring of technical conditions of machines [6]. They are also applicable in definition of machining parameters [4], forecasting of geometric accuracy of the product [7], cost estimate of machine parts [8], as well as form grouping of machine construction elements [9].

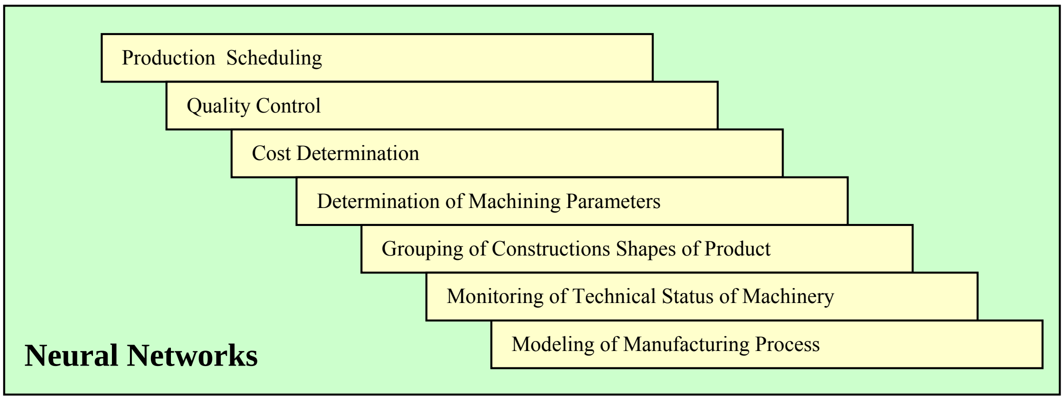

Fig.1. Selected areas of application of neural networks concept in process engineering

The data related to time of technological operations from preparation to breaking-down are critical for organization of production process. These data enable to determine the overall enterprise productivity and allow for general production scheduling and costing.

2. Application Area – use of Neural Networks for determination of time of technological operations

The artificial neural networks are modern analytical tools, allowing for data processing based on the principle of human brain. Neural networks may be considered as a model of unknown characteristic, thus a system of mutually connected elements processing the data (neurons). Weighing elements are assigned to element connections and they determine the strength of these connections defined in learning process. The phase of learning and the phase of reaction to specific stimulus can be distinguished in their performance. The model of solving the specific problem is being built during the learning process – absorbing the knowledge on the basis of presented examples. It is not necessary to determine the way of solving the problem, it is sufficient to collect large enough and representative sample population. Neural networks are a specific modelling technique, capable of representing complex relations. Considering neural networks from the point of view of algorithms applied the following alternatives can be distinguished:

- Supervised learning: the learning data contains the characteristics of input signals and system reactions. Network learning consists of selection of weighing elements such that network reaction to stimulus corresponds to reaction of a real system with highest precision;
- Unsupervised learning – consists of delivering input data to the network without information about the reaction to specific stimulus; the network itself analyses the relations among the input data.

The network architecture has to be determined before it is applied as a tool to data analysis. Neural networks can be:

- Unidirectional – where the signal is transferred to input layer, than across the hidden layers to output layer, without the recurrent reverse connections;
- Recurrent – in these networks the existing of cycles is acceptable; the output signal can be transferred to input;
- Cellular – where neurons are connected within the neighbourhood.

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Over 80% of all applications of neural networks are related to so called multi layer networks, learning by back-propagation algorithm [11].

3. Goal of research and Analytical Algorithm

The research goal of this work was to design the architecture of neural network and to construct the learning set. Determination of properties which would allow in the future to define the requirement for time per unit of thermo-chemical treatment of toothed gear was of particular interest. The data used in this analysis were taken from production practise of the enterprise having many years of experience in production of gear boxes.

The forecasting of time of thermo-chemical treatment has been performed using Multi-Layer Perception network, learning by back propagation method with logistic function of neuron activation [10].

The algorithm of experimental proceeding was the following:

1. Selection of input data - the analysis of production program of hardening plant, determination of real times per unit during thermo-chemical treatment of toothed elements.
2. Numerical experiments – comparison of RMS error for networks examined, choice of network with minimal RMS

$$MSE_P = \frac{1}{n}\sum_{i=0}^{n-1}(T_i - O_i)$$

$$MSE = \frac{1}{m}\sum_{i=0}^{m-1}MSE_P$$

$$RMS = \sqrt{MSE}$$

   where:

   n – network number of outputs

   m – number of iteration presented in one epoch

   Ti – expected value of i-th output of the network

   Oi – actual value of i-th output of the network

3. Sensitivity analysis of input variables
4. Generating of network response.

4. Method

The analysis was limited to technologically similar class of elements. The time periods required for thermo-chemical treatment of toothed gear were taken into consideration, i.e.

times for carbonizing, hardening, and tempering. The treatment was performed in a soaking furnace (Pegat 900), with maximum charge weight of 250 kg, and maximum batch dimensions of Φ500x760.

Production conditions of the company where the experiments were carried out are typical of unitary small series manufacturing. These conditions do not allow for full utilization of production capacity of the furnace, therefore the times per unit of thermo-chemical operations were not easy to establish. Typical representative of learning set is shown in Fig. 2.

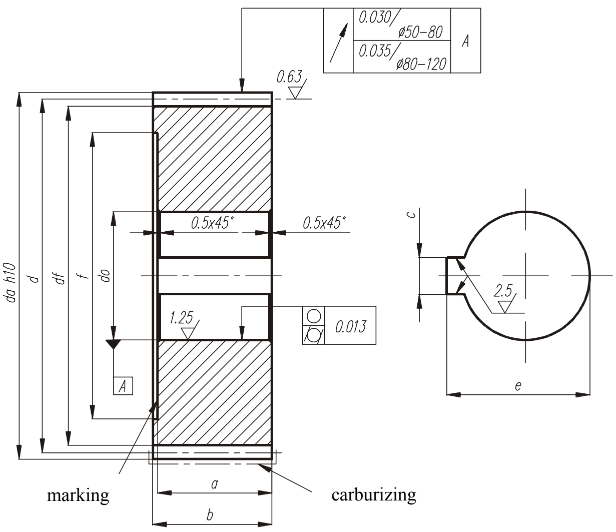

Fig.2. Representative element of learning set

The following vector of properties has been taken as input data for analysis:

- nominal modulus
- mass
- type of treatment

The network output has been set by times per unit of thermo-mechanical treatment.

The set of experimental data collected comprised 70 cases, which were divided randomly into three subsets:

- learning set: 35 cases,
- valuation set: 18 cases,
- testing set: 17 cases.

The experimental part consisted of numerical experiments which allowed to determine product properties with decisive effect on learning results of neural network and selection of network structure leading to satisfactory learning results. The sensitivity analysis of input data enabled to estimate the significance of features important for network learning process. The initial data for analysis are shown in Fig.3.

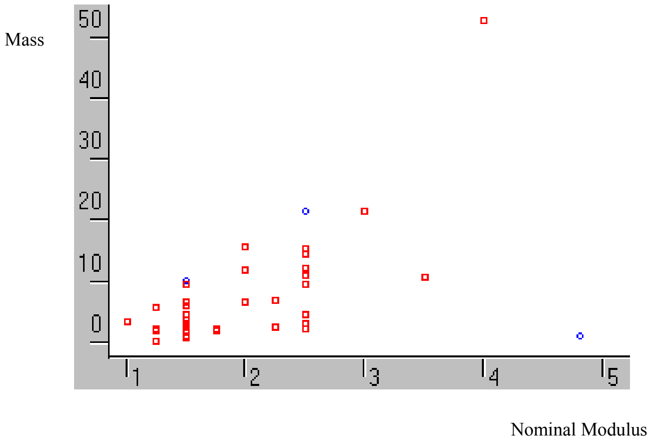

Fig.3. The range of analysed input data

5. Results and Discussion

The best network structure properly approximating the time per unit of thermo-chemical treatment was found to be the network with three neurons in the input layer, seven neurons in hidden layer and 1 output neuron. The structure of this network is shown in Fig. 4.

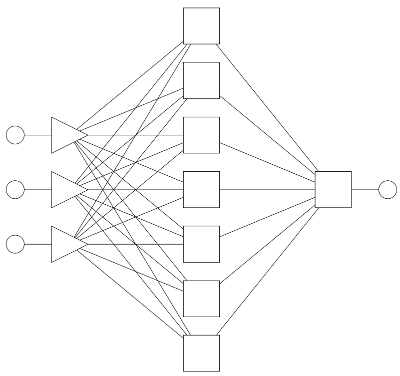

Fig.4. Selected structure of neural network

The Root Mean Squared (RMS) error has been taken as the basic indicator of network configuration. The RMS error for selected network was equal to 23.16144.

In order to assess the significance of input characteristics the analysis of sensitivity has been performed featuring the error indicator. The higher the indicator, the more significant given characteristic from the viewpoint of effectiveness of network learning. These indicators for both learning and valuation set were determined separately (Table 1).

Table 1. The analysis of sensitivity of input variables

Network inputs / Error indicator	Nominal Modulus	Mass	Treatment Type
Error – learning set	1.037458	1.401692	1.054896
Error – valuation set	0.9952839	1.298526	1.176918

The performed analysis proved that the number of teeth and the nominal modulus are of importance for proper network functioning. The results of regression analysis for network outputs are shown in Table 2 and they indicate the functioning quality of trained neural network.

Table 2. Regression analysis for time per unit of thermo-chemical treatment

Data set / Analyzed value	Learning set	Valuation set	Testing set
Mean	59.74457	49.15235	47.80722
Standard Deviation	72.84156	34.9514	49.63937
Error Mean	-11.23606	1.640281	0.002249
Error St.Deviation	50.14693	23.81432	41.02148
Absolute Error Mean	27.90545	16.77179	26.52252
Deviation Ratio	0.6884384	0.6813553	0.82639
Correlation	0.8073817	0.731994	0.5962453

The regression analysis enabled to estimate the following: mean for network outputs (thus average time per unit), standard deviation, mean error calculated as average of differences of set values and values obtained at network output, mean absolute error as well as standard deviation of error and of correlation.

The deviation ratio provides for valuable information indicating the degree of accuracy of prediction. Smaller values (much below 1) point at good quality of outputs generated by the network. Performed analysis shows that selected neural network properly reflects the process time. Graphical representation of the response of network predicting the time of thermo-chemical operation is given in Fig. 5.

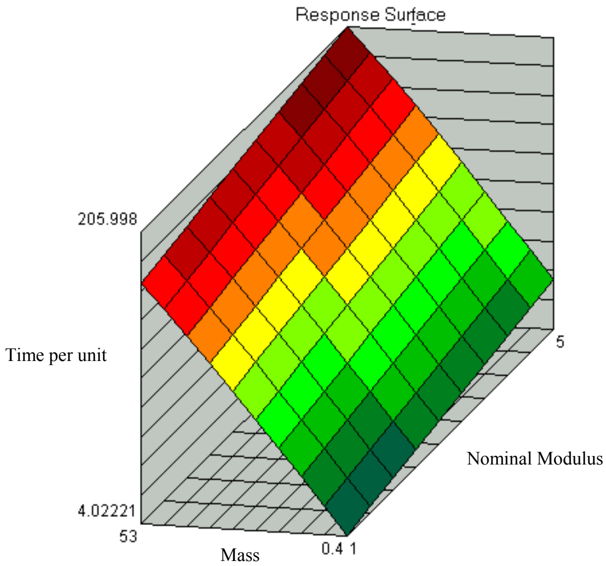

Fig.5. Predicted time of thermo-chemical operation

6. Conclusions

Proposed method may be applied for a group of technologically similar elements, which are being processed by the same manufacturing process.

Practical use of the method elaborated and described here will become effective when characteristics constituting the input vector of neural network will be easy to define for a new product and will be registered by the IT system of manufacturing company.

Seen that many factors may be considered in the modelling process in view of determination of labour consumption, neural networks are promising in regard to possibility of construction of the model reflecting manufacturing process. This requires the collection of process data and selection of the vector of input data, as well as configuration of neural network itself.

Practical application of elaborated method calls for selection of data of input vector which would be easy to acquire before realization of manufacturing process.

Acknowledgements

The authors wish to express their thanks to Mr. Jan Haniszewski, M.Sc., B.Eng., for helpful discussions.

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