ISSN 1392 - 1207. MECHANIKA. 2012 Volume 18(3): 354-359

The development of the intelligent forecasting model for productivity index in manufacturing

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crossref http://dx.doi.org/10.5755/j01.mech.18.3.1879

1. Introduction

Fast and competitive manufacturing of high quality products remains the greatest task in contemporary global production background. However, in order to produce competitive and nonexpensive products, knowing manufacturing technology, know-how applications and manufacturing strategy are the main milestones of productivity. The use of manufacturing productivity evaluating technique is one way of checking efficiency of technologies used by a company and evaluating general corporate efficiency. However the problem of rapid evaluation of manufacturing productivity of mechanical products, especially in early development stage, persists. For this purpose, it is necessary to have a technique which allows evaluating manufacturing costs, value, and manufacturing productivity taking into account parameters of a product already in early stage of its development. Thus, the application of artificial intelligence and, in particular, neural network and mathematical formalization must reduce manufacturing time, allow checking several alternatives, and design the best technology taking into account manufacturing costs. Neural network has been considered as a powerful tool for function approximation. One advantage of neural networks is that they are capable of learning by examples. This implies that they can be trained to perform tasks by presenting them with examples rather than specifying the procedure [1, 2]. Ideally, an effective data analysis technique, such as artificial neural networks, must assist in enabling the constraints to the development of cost models to be overcome and in addition be capable of meeting the user needs in terms of the required characteristics of the cost model [3]. Many researches are focused on finding the best combination of different types of artificial neural network (ANN) architecture and traditional process control methods to meet different manufacturing objectives like process improvement or process optimization to ensure quality assurance [4-6]. A.Smith et al. analyze the advantages and shortcomings of neural networks. Their conclusions say that neural networks can suitably replace regression used for estimating the manufacturing cost [7]. In the field of sheet metal working small and medium sized enterprises (SME) are normally supplier companies. They have to submit valid offers for manufacturing jobs within a short time. Within the investigated range of work pieces manufacturing cost calculation accuracies between 5% and 15% can be achieved [8]. The maximum deviation of cost estimate from the actual cost is about 13% which is still considered acceptable by the company, considering this is achieved in the early product design stage [1]. The effectiveness of any artificial intelligence (AI)-based tool depends on the task purpose. Factors such as model quality, model development, data characteristics should be used in their selection process. In general neural networks have high accuracy but need comprehensive training data [9]. In this paper the ANN tool has been developed and applied for productivity forecasting in order handled manufacturing companies that are suppliers of original components and parts for the end product producers. It is based on forecasting created value and incurred cost for this value. The product design and its process as a main factor have been used for the developed ANN tool.

2. Development of neural network-based manufacturing productivity forecasting model

Manufacturing productivity may be defined as the ratio of value created *vs* costs consumed in order to create it [10-12]. Mathematically, productivity may be defined as a function of various parameters. Manufacturing productivity is a very important indicator in mechanical engineering. In most cases, it depends on technology, product, and some other factors; and may be defined as follows

$$P_l = f(z_1, z_2, z_3, z_4, z_5, z_6, z_7) \quad (1)$$

where P_l is manufacturing productivity, z_1 is type of manufacturing technology chosen, z_2 is type of equipment, z_3 is manufacturing costs, z_4 is labor costs, z_5 is construction of a product, z_6 is production volume, and z_7 is other factors. The main components of manufacturing productivity may be classified even more detailed taking into account production volume, product type, and technologies used. In order to create manufacturing productivity forecasting model for mechanical products it is necessary to know what factors influence manufacturing productivity and in how. However, the evaluation of manufacturing productivity is not limited only by the estimation of it. One-time estimation of productivity shows nothing unless we do not have data for comparison. Therefore, in order to evaluate manufacturing productivity, it is necessary choosing the initial point from which the manufacturing productivity should be calculated; in addition, it is necessary knowing which production division shall be evaluated [11, 12].

Aiming to evaluate the change of manufacturing productivity, the indicator must be calculated in time periods t and t+1; aiming to design the best technology manufacturing productivity may be calculated for the same time period but for different manufacturing technologies. Manufacturing productivity in time period t may be defined as follows

$$P_t = \frac{O_t}{I_t} \tag{2}$$

Manufacturing productivity in time period t+1 should be defined analogically

$$P_{t+1} = \frac{O_{t+1}}{I_{t+1}} \tag{3}$$

where P_t is manufacturing productivity in time period t, P_{t+1} is manufacturing productivity in time period t+1, O_t is product value created in time period t, O_{t+1} is product value created in time period t+1, and, seemingly, I_t and I_{t+1} are manufacturing costs in time periods t and t+1 used to create values O_t and O_{t+1}.

Thus, aiming to get manufacturing productivity ratio, i.e. the value that enables setting conclusion on increase or decrease of manufacturing productivity, it is necessary to calculate efficiency ratio.

$$P = \frac{P_{t+1}}{P_t} = \frac{O_{t+1} I_t}{I_{t+1} O_t} \tag{4}$$

As mentioned before, absolute manufacturing productivity consists of the sum of various efficiency indicators [12]. Thus, manufacturing productivity index is expressed as follows

$$P^l = \frac{O}{I^l} = \frac{O_{t+1} I_t^l}{I_{t+1}^l O_t} 100\% \tag{5}$$

Product value is one of the main and the most important factors of manufacturing productivity. Thus, aiming to evaluate manufacturing productivity, it is necessary to know the value of the product developed. Product value depends on various factors, thus it can be defined as an abstract function.

$$O = f\left(M_n, F_u, Q, I, S_p, D_p\right) \tag{6}$$

where O is product value, M_n is market demand, F_u is functional parameters, Q is quality parameters, I is manufacturing costs, S_p is strength parameters, and D_p is product design. However, product value does not depend on technology or other factors related to production. The paper analyses the influence of functional factors of a product on manufacturing productivity considering that other factors are set to 1. The created technique of defining product value assumes that necessary quality parameters are always met. In order to forecast the value created as accurate as possible, taking into account specifics and manufacturing processes of sheet metal products is necessary. It is obvious that functional parameters of sheet metal products mostly depend on the construction of a product, the complexity of its shape, and the number of design features.

$$F_u = f\left(F_c, p_l, DF_t, DF_s\right) \tag{7}$$

where F_c is the complexity of product shape, p_l is product perimeter, DF_t is the type of construction elements, DF_s is the amount of construction elements. Since sheet metal product components may have various shapes, we classify them into three groups according to the complexity of contour: complex, medium, and noncomplex. Thus, the product value will be defined as follows

$$O = \sum_{i=1}^{n}\left(O_F^i + O_p^i + O_{Dfs}^i + M_E^i\right) \tag{8}$$

where O is the value created, O_F is the value which depends on the shape of a product, O_p is the value which depends on perimeter, O_{Dfs} is the value which depends on the amount of design features, M_E is the value of materials, n is the amount of components in a product.

An important point of manufacturing productivity estimation is estimating manufacturing costs with respect to product characteristics and performed technological process. To estimate the manufacturing costs an intelligent model based on neural networks has been developed. In enterprises the time-span and parameters of standard parts produced by separate equipment are stored in the data base. This information is used when making the structure of a neural network. The advantage of an intelligent model based on neural networks lies in the fact that a network of a properly selected structure can approximate any continuous function. The basic tasks involved in developing cost estimation models are data identification, data collection and data analysis. A network input layer is formed of the following part parameters: thickness, the number of design features, material type, and perimeter of a contour being cut. Table 1 depicts the parameters and their value ranges for all simulations. The input parameters may be obtained either from 3D CAD systems or the special software; in this case a 3D CAD system was used.

Table 1

Design parameters for the input layer of the ANN tested

Design parameter	Parameter range
Contour perimeter, mm	100-5000
Part thickness, mm	1-20
Material type	Steel, stainless steel, aluminum
Laser power, kW	2-3
Number of design features	0-70

The following significant step is selection of a neural network structure. In general the network size affects network complexity, learning time, but most importantly it affects quality of the network results. Many researchers agree that the quality of a solution found by a neural network depends strongly on the network size used [13, 14]. Currently, there is no analytical way of defining the network structure as a function of the complexity of the problem. The structure must be manually selected using a trial-and-error process [15]. In a lot of research papers there are emphasized that neural network structure must be as less as possible and related with data quantity and input – output neurons number. Theoretically, a neural network with one hidden layer containing sufficient neurons of that layer can approximate any continuous function. In practice, neural networks with one or two hidden layers are most frequently used. To solve the task a two layer neural network is sufficient. The structure of the neural network consists of one hidden layer of neurons, an input layer and an

output layer. In the hidden layer a hyperbolic tangent transfer function and in the output layer a linear transfer function was used. Learning of neural networks is based on the error minimization methods. Here the sum square error (SSE) minimization method was used. SSE is obtained by summing the errors in all network derivatives for the whole data sample set. Selecting a neural network, the following parameters have been used: tested network with one hidden layer, the number of neurons in the hidden layer varied from 3 to 12 neurons.

Fig. 1 indicates that the best neural network structure for laser cutting equipment is 10 neurons in the hidden layer. In this case neural network of a moderate structure and the lowest mean of SSE is obtained. The neural network of a smaller structure is chosen because it preferably generalizes the data.

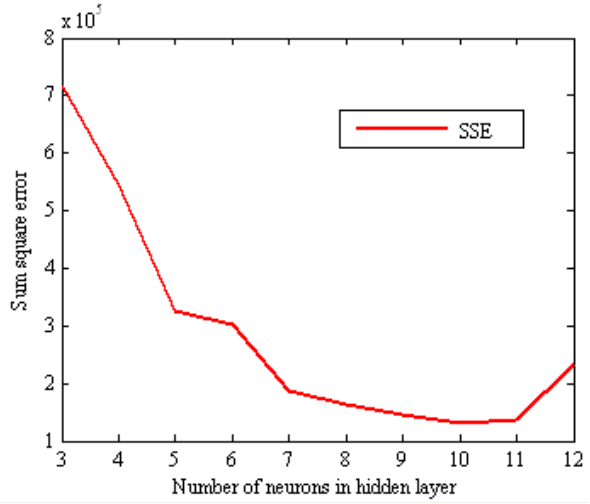

Fig. 1 Identification of neurons quantity in hidden layer

In order to find the best threshold values, 10 neural networks of the same structure are to be generated changing their threshold values. Fig. 2 shows that the best selected threshold values are in the 66th network.

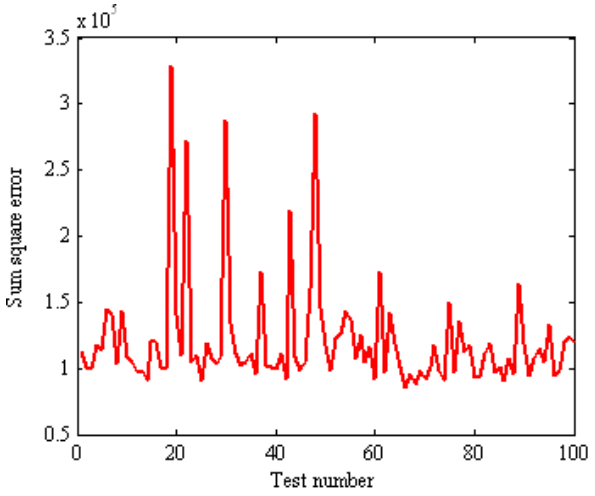

Fig. 2 Selection of the best neural network structure for laser cutting equipment

Some comparison between real and simulated data was performed. Fig. 3 plots the comparison between simulated and real values of the testing set. The correlation coefficient *R* is equal to 0.99.

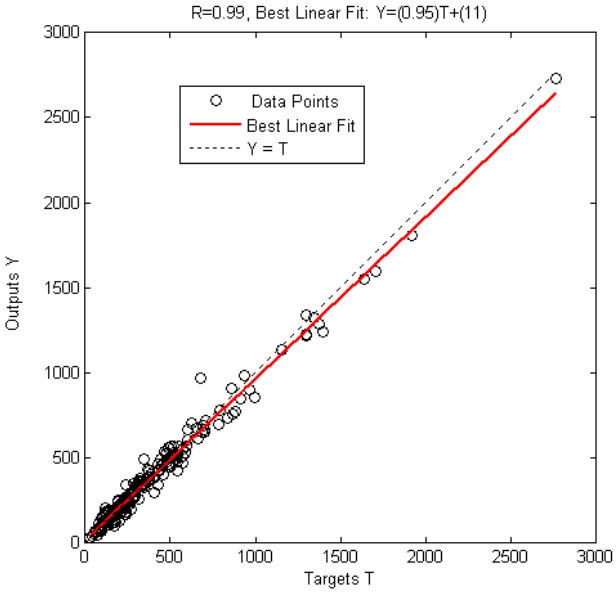

Fig. 3 Comparison between test data and output data

When CNC punching machine is used then part manufacturing time depends on another parameters, as perimeter, thickness, material, design features number and geometrical form (Table 2). For simplicity of definition the mentioned parameters to manufacturing time, the design features number and geometrical form have been approximated by part contour perimeter.

Table 2
Design parameters for the input layer of the ANN tested

Design parameter	Parameter range
Contour perimeter, mm	100-5000
Part thickness, mm	1-4
Material type	Steel, stainless steel, aluminum

On the net output the forecasted part manufacturing time is defined. The two layers NN has been applied in this case. Fig. 4 illustrates that the best neural network for AMADA CNC punching equipment is with 5 neurons in the hidden layer.

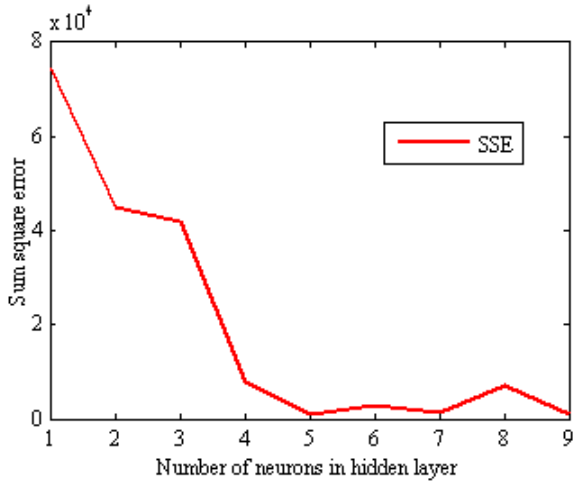

Fig 4 Identification of neurons quantity in hidden layer

3. Experimental investigations of neural network-based manufacturing costs forecasting model

Next stage of the investigations represented testing of neural network-based manufacturing costs forecasting module. The module was tested in a few industrial companies of Lithuania using laser cutting and CNC punching technologies. In contrary to previously described testing of the parameter-based module [16], experimental components were taken from outside the company. This was decided aiming to broaden the variety of components tested and disassociating the research from traditional components processed by the companies. Thus, fifteen components of different geometric shapes, perimeters, and purposes were chosen. Fig. 5 illustrates the distribution of manufacturing costs using the forecasting module and the actual ones. It is important to mention, that this was the case of testing manufacturing costs forecasting module oriented to laser cutting operations.

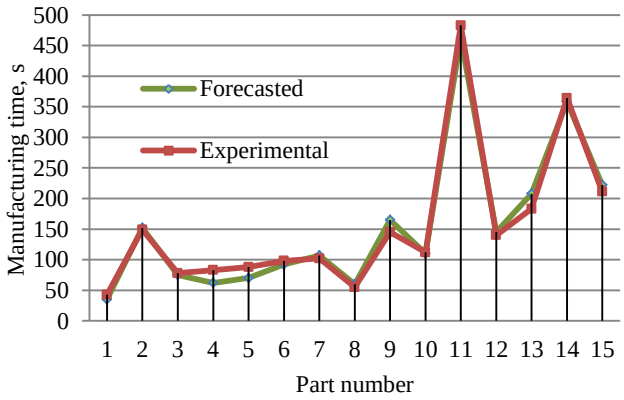

Fig. 5 Testing of neural network-based manufacturing cost forecasting module

Components sketched on Fig. 5 were drawn in ascending order by perimeter. Thus, it is obvious that perimeter is not always the critical factor of the manufacturing time. The deviation between total forecasted manufacturing time of the components tested and the actual ones does not exceed 10%. However a few components cross the limit of 10%. The analysis shows that the size of the deviation is affected neither by perimeter nor by the amount of design features, nor by the weight of the component. Component No. 11 encompasses 70 design features the deviation of 3% only. Component No. 6 encompasses 36 design features the deviation of 5%. Thus, it is possible to conclude that the manufacturing costs forecasting module rapidly adapts to changing environment in case of changing amount of design features. In addition, the analysis showed that the main factor for the deviation of the forecasted manufacturing time is complexity of a component.

In parallel, manufacturing costs forecasting module oriented to 3 kW *Bystronic* laser cutting device was tested. In this case, we have chosen completely different production company, but used the same 15 components. The results obtained are delivered in Fig. 6.

As we can see from Fig. 6, the accuracy of the module changes when perimeters of the components are larger. This may be explained by the fact that the data grip used when the structure of neural network was being

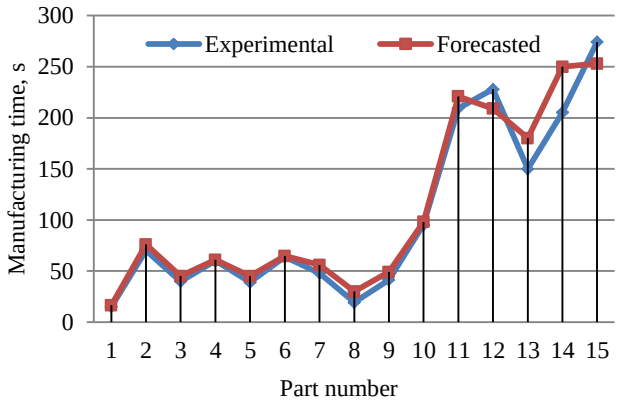

Fig. 6 Testing neural network-based manufacturing costs forecasting module

formed and trained did not involve a lot of data with larger perimeter than 4000 mm. Thus in order to use the grid of the structure created for forecasting manufacturing costs of the components with larger perimeters it will be necessary to retrain it using new data grip. In addition, it is important to mention, that this module does not take into account the complexity of geometric shape of a component. General deviation between the forecasted manufacturing time of the components tested the actual one, using this model, is 13.7%, but, as Fig. 6 shows, the forecasted manufacturing time of component No. 11 is slightly greater that the actual one. It is obvious that the module lacks of testing results with the perimeters above 4000 mm. Thus, in order to improve forecasting of the components manufacturing time with the perimeters smaller than 3000 mm, we can apply the correction coefficient. In order to reduce the deviation in components with the perimeters that exceed 4000 mm, new testing results shall be added. The next step of the experimental research was checking the accuracy of the neural network-based manufacturing costs forecasting module oriented to punching operations. The experiment involves 13 components since maximum punching thickness in the company where the research took place is 3 mm. Fig. 7 delivers the distribution of the forecasted and the actual manufacturing times.

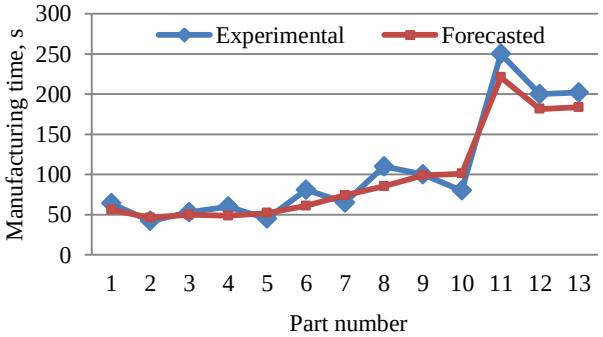

Fig. 7 Testing neural network-based manufacturing costs forecasting module on punching device

In this case, the deviation between the forecasted and the actual manufacturing times is 14%. This may be explained by the facts that the experiment was made using completely different components than those involved in creating manufacturing costs forecasting module. The main problem is such that punching technologies may employ a

lot of tools. The right choice of tools may significantly decrease manufacturing costs, and the wrong choice, on the contrary, may significantly increase manufacturing time. Special attention shall be paid to three experimental components, namely to their geometric shapes. The manufacturing of components No. 5, 9, and 10 was not possible to finish due to the complexity of their construction elements. Thus actual manufacturing time of such components should be a bit larger than indicated on Fig. 7, and conditions less deviation.

4. Evaluating manufacturing productivity of experimental products

The objective of the paper was to create the intelligent manufacturing productivity forecasting model for sheet metal products. This section presents the results obtained by the created model of manufacturing productivity forecasting. The results were obtained using manufacturing productivity evaluating technique for sheet metal products by Eq. (2), where the value is estimated by Eq. (8). Fig. 8 shows the forecasted productivity. In this case, 3 kW *Bystron* laser cutting machine was chosen as the initial point.

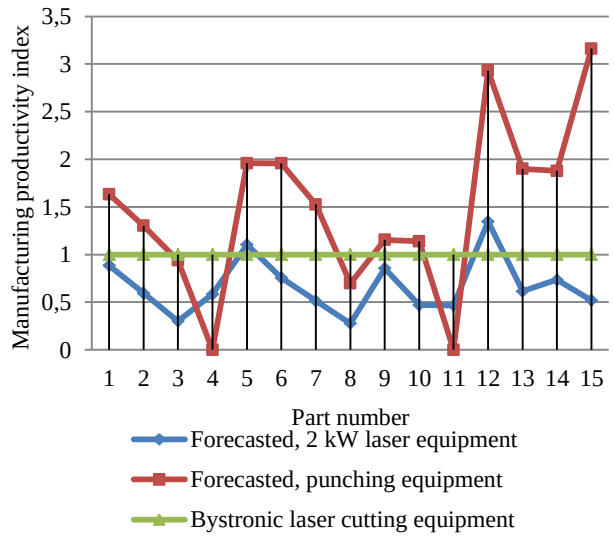

Fig. 8 The efficiency of various manufacturing technologies

Fig. 8 shows, that the manufacturing productivity of 2 kW laser device is lower than that of 3 kW laser device for most of the components. It would not be forgotten that power is not the only characteristic of the device, thickness of the material used and linear and curve driving speeds count too. In most cases, things like that may be known by experienced experts only, thus the model created will allow evaluating the potential of manufacturing technologies more rapidly. The biggest manufacturing productivity is gained in punching technology with a few exceptions in some components with more complex geometric shapes (in these cases it was smaller or equal to one). Manufacturing productivity of components No. 4 and 11 is shown as zero as it was not possible to manufacture these components with the punching equipment used for the experiment.

4. Discussion and conclusions

The research in this paper presents an intelligent productivity forecasting model in manufacturing industry. The main factors of manufacturing productivity have been identified applying experimental investigations, as a created value, functionality, quality, and the reliability of the product and manufacturing costs accumulated in manufacturing processes of the product. The manufacturing cost has been forecasted at the early stage of product development taking into account the main properties, e.g. its value and quality. The created technique of forecasting value and manufacturing costs of mechanical components allows evaluation of manufacturing productivity and making corrections by changing functionality, characteristics, and technology of a product in early stage of its development. Briefly it is concluded.

1. The artificial neural network-based manufacturing costs forecasting module enables definition of manufacturing costs up to 2 times faster that the parameter-based module. Results are delivered with the deviation of 2-10% in case of laser cutting using 2 kW device, 3-13% in case of 3 kW laser cutting device, and 5-14 percent in case of punching device.

2. The proposed technique for created value definition of product components and parts allows to estimate conditional value by their number and form of design features.

3. The developed intelligent productivity forecasting model defined productivity index can help make corrections of new product and process design at the early stage.

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INTELEKTINIO GAMYBOS NAŠUMO PROGNOZAVIMO MODELIO SUKŪRIMAS

R e z i u m ė

Šiame straipsnyje tiriamas sukurtas intelektinis gamybos našumo prognozavimo modelis. Šis modelis sukurtas naudojant dirbtinio intelekto neuroninius tinklus (ANN). Gamybos našumas skaičiuojamas kaip sukurtos vertės ir patirtų gamybos sąnaudų jai gauti tarpusavio santykis. Straipsnyje sukurta metodika vertei nustatyti gaminant detales ir komponentus gamybos organizacijose, dirbančiose pagal užsakymus. ANN metodas taikomas anksčiau minėtų gaminių gamybos sąnaudoms prognozuoti. Sukurtas gamybos našumo prognozavimo modelis patikrintas gamybos sąlygomis naudojant programinio valdymo, lazerinio pjovimo ir štampavimo procesus.

M. Rimašauskas, A. Bargelis

THE DEVELOPMENT OF THE INTELLIGENT FORECASTING MODEL FOR PRODUCTIVITY INDEX IN MANUFACTURING

S u m m a r y

This research deals with the development of the intelligent manufacturing productivity forecasting model. The development is based on artificial neural network (ANN). Manufacturing productivity as the ratio of value created vs cost incurred to create it has been applied in this paper. The methodology of value definition for order-handled producers of components and parts is created. ANN is used for forecasting of manufacturing cost for the above mentioned parts. The developed productivity forecasting model is tested by industrial case study applying CNC laser cutting and CNC punching machines processes.

Keywords: artificial intelligence, manufacturing cost forecasting, laser cutting.

Received April 29, 2011
Accepted June 13, 2012