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DEVELOPMENT OF INTELLIGENT MODEL FOR ESTIMATING MANUFACTURING COST IN SHEET METALWORKING

Rimašauskas, M.; Bargelis, A.

Abstract: *In modern manufacturing, high product quality, manufacturing flexibility and low production cost are main keys to competitiveness. For this reason, manufacturing cost is always the point of primary concern.*
Basically, the manufacturing cost of a sheet metal part is determined by its shape complexity, perimeter, size, a number of design features, material properties and thickness. If these data can be obtained and considered in a design stage, estimation of manufacturing cost during the early design stage will be a feasible task.
This research submits a framework for estimating the manufacturing cost in sheet metalworking. The manufacturing cost estimation method is based on Artificial Neural Networks (ANN). ANN is helpful in the situations when conventional linear regression does not work.
The obtained results have been considered, discussed and appropriate conclusions have been drawn.
Key words: neural network, cost forecasting, laser cutting.

1. INTRODUCTION

In recent years, the importance of manufacturing cost estimation has greatly increased. It is determined not only by the growth of production but by the rise of energy resources and material costs as well. It is interconnected with the competition which has up surged in all fields, in a production sector especially. Moreover, variety of products has immensely increased, thus aggravating the manufacturing cost forecasting at an early production stage of a product.

1.1 Survey of manufacturing cost estimation methods

Nowadays, in many cases researchers publish their methods developed for forecasting the manufacturing cost at an early production stage of a product. In 2002, J.Jung published his work on manufacturing cost forecasting based on splitting a machine part into design features [1]. Furthermore, he emphasizes that manufacturing cost forecasting is the main task of an enterprise and it is to be accomplished at an early product design stage by applying virtual manufacturing methods. The author, however, presents the model of manufacturing cost estimation of the products being turned and milled only. A.Smith et al. analyze the advantages and shortcomings of neural networks and regression in estimating manufacturing costs. Their conclusions say that neural networks can suitably replace regression used for estimating the manufacturing cost [2]. Their other article, analyzing laser cutting and CNC cutting technologies, proposes a parametric model for forecasting the manufacturing cost in sheet metalworking industry [3]. Literature on this subject presents various attempts to classify the manufacturing cost forecasting models according to the applied methods, the main of them being [4]:

- Parametric cost forecasting;
- Forecasting by applying artificial intelligence;

- Forecasting based on experts' experience;
- Forecasting by means of knowledge-bases;
- Forecasting by means of classifiers.

1.2 Survey of application of an artificial intelligence method

The origin of artificial intelligence is related to the work of Samuel and Neweek in 1960, when self-contained game playing and solution seeking programs were being developed [5]. Whereas, A. Gunasekaran in his paper on productivity and quality improvement issues states that the latter are toughly related to production automation and up-dating, i.e. they are necessarily connected to the application of expert systems (ES) and artificial intelligence [6]. In 1998, Manfred Geiger with his colleagues published an article on application of neural networks to a large scale production of sheet metal parts [7]. Actually, they analyzed manufacturing cost of products produced by conventional sheet-metal stamping. In their conclusions the authors say that application of neural networks makes it possible to estimate the cost at an early production stage. Neural networks enable the forecasting precision to be from 5 to 15%. In 2001, Q.Wang and D. Stockton presented their manufacturing cost model based on artificial neural networks making it possible to forecast the turning operation cost [8]. The authors highlight the advantages of their models emphasizing that the effect of the model depends on accuracy and amount of primary data. Their following article presents the model with DSS containing neural network for production quality assurance [9]. In 1998, Y. Zhang and his co-authors had introduced a neural network approach to cost forecasting and practically they applied it to an early cost estimation of packaging products [10]. M. Barletta and co-authors applied the neural network model to simulation of thin sheets formation. In that case neural networks help forecast permanent sets and the force to be used in the formation process [11]. According to the authors, neural networks can be applied to the solution of such non-linear problems. F. Meziane and his co-authors have comprehensively described the possibilities of neural network application to industrial engineering. They state that neural networks are appropriate to classification and optimization and accentuate their advantages in image identification and quality control [12]. That article emphasizes the benefit gained from applying various artificial intelligence tools such as fuzzy logic, expert systems, genetic algorithms, knowledge base systems to mechanical engineering. B. Al-Najjar and I.Alsyouf recommend using an artificial intelligence method in quality assurance. They say that artificial neural networks, fuzzy logic and expert systems have really helped the systems become adaptive, learning and knowledge based [13].

2. DEVELOPMENT OF MANUFACTURING COST ESTIMATION MODEL

An important point of production efficiency estimation is estimating manufacturing costs with respect to product characteristics and a performed technological process. The former cost forecasting parametric model estimated the manufacturing costs with sufficient accuracy [3]. Nevertheless, its basic drawback was extracting of product parameters and their submission to the model. That process was done by an engineer. In the above given survey it is evident that a neural network model may be used in costs prediction. A newly developed model based on neural networks contains an integrated module extracting the geometric parameters of sheet metal products, thus enabling specialists to quicken the cost estimation process. Extraction of the product geometric parameters is based on determination of sheet parts contour parameter, internal holes parameter and the quantity of design features from the graphic data file. 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.

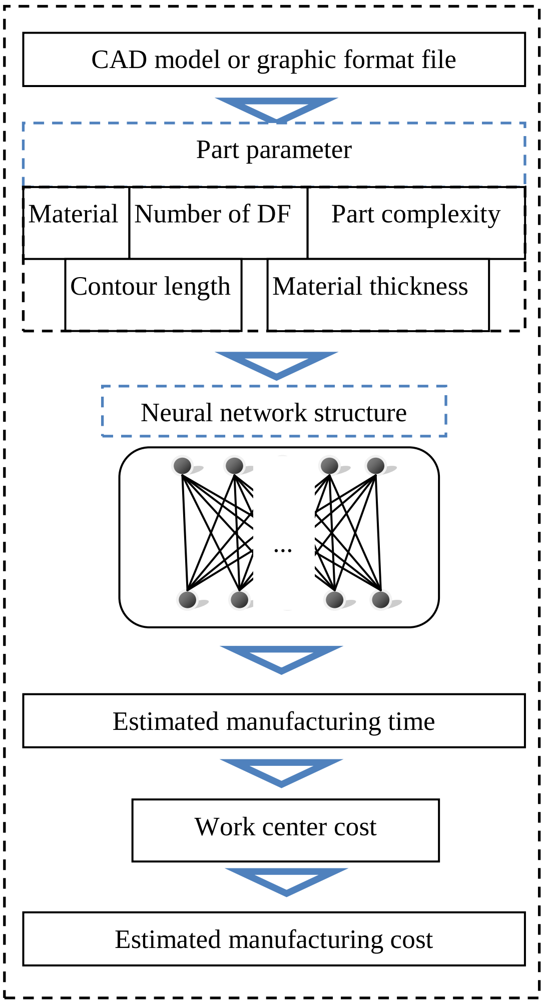

Fig. 1. Structure of cost forecasting model

A network input layer is formed of the following part parameters: thickness, number of design features, material, and perimeter of a contour being cut. The input parameters may be obtained either from 3D CAD systems or the special software; in this case a developed extraction module of parts graphic parameters will be used. The following significant step is selection of a neural network structure. 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. Neurons of a hidden layer are selected experimentally.

To solve the task a two layer neural network is sufficient. The structure of a neural network consists of a one hidden layer of neurons, an input layer and an output layer. In a hidden layer a hyperbolic tangent transfer function is used:

$$y = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{1}$$

and in an output layer a linear transfer function is used. The one neuron transfer function may be expressed as follows:

$$y = f\left[\sum_{i=1}^{n} w_i x_i + b\right] \tag{2}$$

here $x_1 - x_n$ – neuron input values, $w_1 - w_n$ – weight values, b – displacement. A neural network is formed of several layers with interconnected neurons. Mathematical model of a two layer neural network may be expressed as follows:

$$Y = f_2[W_2 f_1(W_1 X)] \tag{3}$$

$$Y = f_2\left[\sum_{i=1}^{h} w_i f_1\left(\sum_{j=1}^{g} w_j x_j\right)\right] \tag{4}$$

here X – matrix of input values, W_1 – matrix of the first layer weight values, W_2 – matrix of the second layer weight values, Y - matrix of output values, w_i – weights of the second layer neurons, w_j – weights of the first layer neurons, x_j – input values, f_1 – hyperbolic tangent function, f_2 – linear transfer function.

Learning of neural networks is based on the error minimization methods. Here sum square error (SSE) minimization methods are used. SSE is obtained by summing the errors in all network derivatives for the whole data sample set.

$$SSE = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{p}(y_j^i - d_j^i)^2 \qquad (5)$$

Selecting a neural network, the following parameters have been used: tested network with one hidden layer, a number of neurons in a hidden layer varied from 2 to 10 neurons.

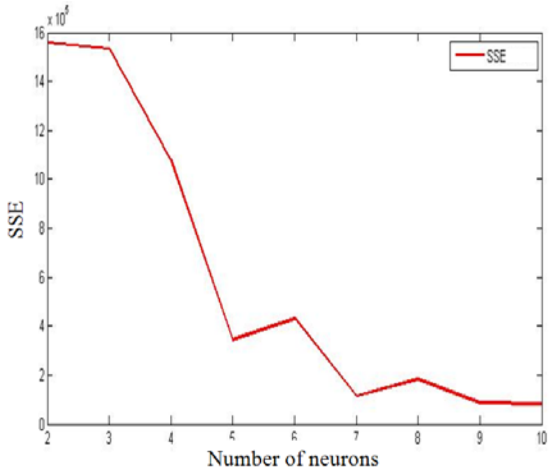

Fig. 2. Identification of hidden neural quantity for AMADA equipment

Figure 2 indicates that the best neuron network structure for AMADA equipment is 7 neurons in a hidden layer. In this case neural network of a moderate structure and the lowest mean of SSE are obtained. The neural network of a smaller structure is chosen because it preferably generalizes the data. If you want to estimate the difference between the usage of seven and nine neurons network, you have to calculate Student's t-test criterion.

In calculation, the taken significance level p will be equal to 0.05. The obtained Fisher's criterion t = 0.000122 is lower than 2p, and it is possible to state that the difference between dispersions is statistically significant. The obtained Student's t-test criterion t = 0.264 is lower than critical Student's t-test criterion value 2.042 and it may be stated that a zero hypothesis is confirmed and the difference between the means with confidence of 95% probability is statistically insignificant. In this way, the selected neural network structure with seven neurons in a latent layer is the best.

In order to find the best threshold values, 50 neural networks of the same structure are to be generated changing their threshold values. Fig. 3 shows that the best selected threshold values are in the 25th network.

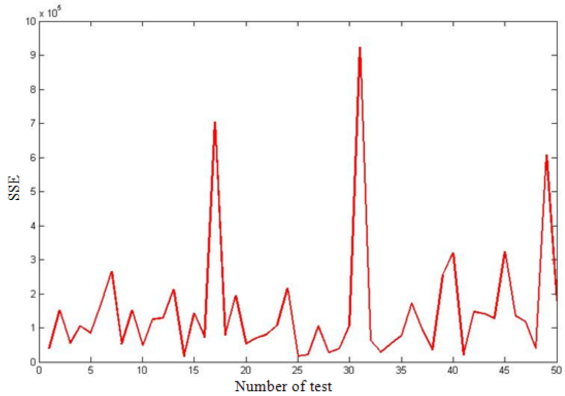

Fig. 3. Selection of the best neural network structure for AMADA equipment

Figure 4 illustrates that the best neural network for Bystronic equipment is with 7 neurons in a hidden layer.

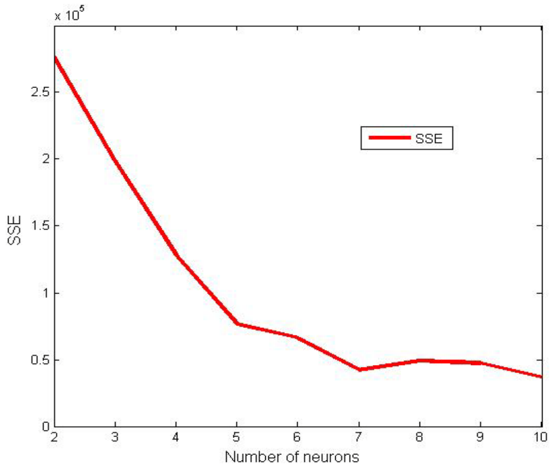

Fig. 4. Identification of hidden neurons quantity for Bystronic equipment

Figure 5 shows that the best threshold values have been selected with a second try. A neural network of that structure is stored and further experiments have been made with it.

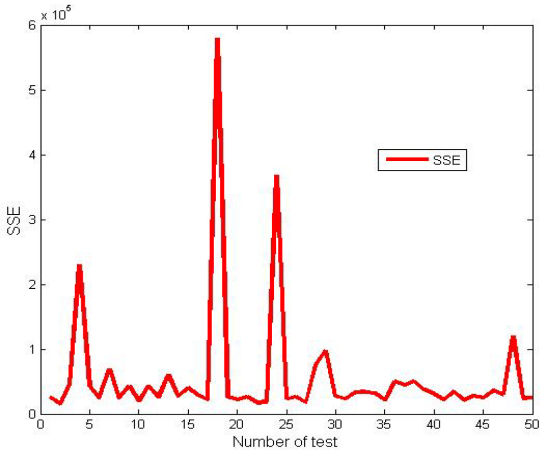

Fig. 5. Selection of the best neural network structure for Bystronic equipment

3. CASE STUDY

In this section the operation of a developed intelligent model is examined. In an above mentioned article a parametric manufacturing cost estimation model and its reliability have been positively evaluated [3]. The results of that model have been compared to those of the formerly presented parametric model. As seen from Fig. 6, the model based on neural networks estimates the manufacturing costs fairly accurately compared to a parametric model.

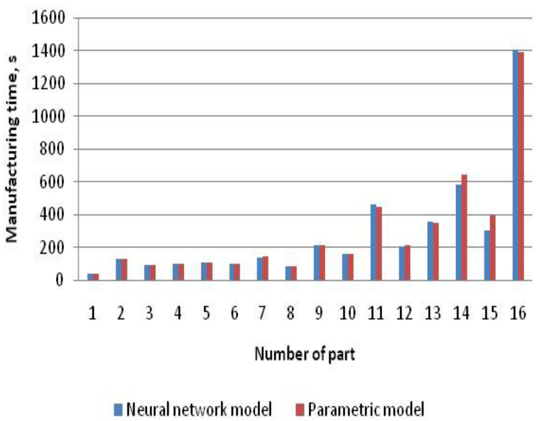

Fig. 6. Comparison of manufacturing costs forecasting models by using AMADA laser cutting lathe

Analogically, a manufacturing cost forecasting model has been developed and tested using 3 kW Bystronic equipment.

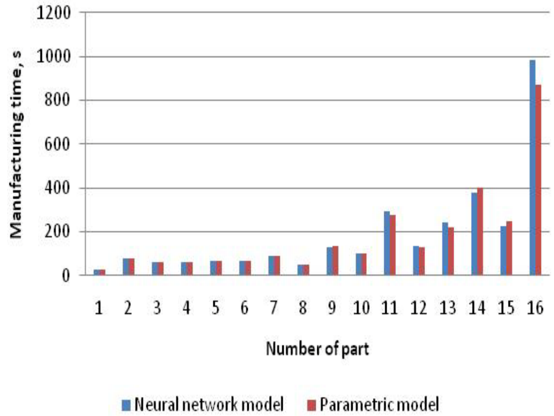

Fig. 7. Comparison of manufacturing cost forecasting models by using Bystronic equipment

Figure 7 illustrates the results of different manufacturing cost forecasting models intended for a three kilowatt cutting equipment. It is evident that production time differs slightly except modelling of the 16th part. It can be explained that the 16th part perimeter is the largest, over 10,000 mm. When developing this model based on neural networks, the parts with perimeters over 6,000 mm have not been suitably tested. As seen from graphs given in Figs 6 and 7, an error of the results of forecasting models based on neural networks compared to those of parametric models is up to 10%.

4. CONCLUSIONS

A developed model of forecasting manufacturing cost of metal sheets based on neural networks evaluates their manufacturing costs at an early production stage with sufficient accuracy. In many cases a forecasting error does not exceed 5%, whereas it does not apply to products of greater overall sizes. In order to estimate their manufacturing costs, their neural model of manufacturing cost forecasting is to be specified with new data. A forecasting error for products whose perimeter is over 6,000 mm may be from 9 to 13 %. Application of a product geometric parameters extracting model makes it possible to estimate manufacturing cost of a product quickly and effectively with smaller resources.

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6. ADDITIONAL DATA ABOUT AUTHORS

Rimašauskas Marius, PhD stud.
Kaunas University of Technology
Kęstučio 27, LT -44312 Kaunas, Lithuania
Phone: +370 614 99258
E-mail: marius.rimasauskas@ktu.lt

Bargelis Algirdas, Professor, Habil. Dr.
Kaunas University of Technology
Kęstučio 27, LT -44312 Kaunas, Lithuania
Phone: +370 685 44381
E-mail: algirdas.bargelis@ktu.lt