ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20211231154627
Original scientific paper

Hybrid Product Cost Calculation Model as a Decision Support Tool

Stevan PEROVIC, Vladimir TODIC*, Jovan PERVAZ, Ilija COSIC, Slobodan RADISIC

Abstract Cost calculation is of huge importance both for determining a rational and competitive price of the product and preparation of offers according to customer's demand, where deadlines for sending offers are limited. In individual and small batch production, which is characterised by a wide product range, reduced quantities, and short delivery times, cost calculation in forming the price of the product according to customer requirements is of essential importance. Traditional methods of calculating the cost of products in these cases are inefficient, considering the number of offers that need to be made, timing, as well as their competitiveness in the market. For product cost calculation in individual and small batch production, it is necessary to apply modern, efficient methods and models based on the application of artificial intelligence. A wide range of products, which is characteristic of individual and small batch production in some companies, enables the development of modern costing models with the use of basic principles of group technology. The constructional and technological similarity of products enables the formation of groups of similar parts and appropriate group technological processes. Combining that with artificial intelligence, it is possible to develop appropriate cost calculation models. This paper presents a developed model for production cost calculation, based on the principles of group technology and adaptive neuralfuzzy networks (ANFIS).

Keywords: ANFIS; calculation; costs; group technology; product

1 INTRODUCTION

Above mentioned basic characteristics of the global market and customer requirements demonstrate that companies are forced to continuous development and improvement of their products and production processes by looking for the most favourable solutions determined by price, time, cost, quality, and flexibility.

Given that market demands in terms of flexibility are imposed by the need to produce a variety of high-quality products with modern design, low price, short delivery deadlines, it could be concluded that product costs are one of the most important instruments of business policies, which refers to target cost management (target profit), and product competitiveness on the market.

The cost of the products, which includes development and production costs, has significant importance in planning the target profit or the product's market price, which remarkably depends on the competition in the market.

Therefore, product costs, where target profit is provided for a particular market price, are used for strategic management in target cost or profit planning. Target costs or product costs management is performed in the product development phase and the production process, which requires continuous improvement and innovation.

Product cost calculation, both in the development phase and in the economic evaluation of production process variants, requires the application of efficient product costing methods and models.

In companies engaged in individual and small-scale production of a wide range of products, usually with short delivery deadlines and limited prices, cost calculation requires the application of modern methods and models, especially if we consider the need to make many offers for the production of products with specific customer's demands.

For cost predictions there have been developed numerous, mainly traditional methods, but also newer methods and models, some of which are presented based on the available literature.

2 LITERATURE REVIEW

The structure of product complexity and production complexity are the two main factors that affect the production time and the costs in the production process in the aviation industry [1]. Production cost planning in the development phase of these products can affect production costs by 95%, and the competitiveness of industrial products is measured by quality, prices, and delivery time. Production costs estimation of the mentioned products was performed by applying inverse Artificial Neural Networks (ANN) and regression analysis on two samples.

The results of comparing the application of two types of Artificial Neural Networks (ANN) are shown to estimate the cost of production of shells and tubular heat exchangers [2]. With the statement that the estimate of production costs in the development phase of these products affects 80% of product costs, the authors concluded that ANN provides greater accuracy in cost estimation than methods based on regression analysis. Input parameters for estimation of production costs in this paper were mass, type of welding, pipe diameter, complexity, number of cavities or heat exchangers, and their type.

A comparative analysis of the application of Process Based Costing (PBC) and Activity Based Costing (ABC) methods for estimating production costs has previously been presented [3], and research has shown that the application of parametric techniques achieves greater accuracy in cost estimation, while analogue methods are used when there is data about costs of a larger group of similar products that have been realized. The paper presents the application of the PBC method for estimating the cost of products consisting of several items or parts.

Using the ABS method, a model for estimating product cost of production in complex production systems that operate on the principles of Just In Time (JIT) systems has been created [4]. The ABS method is applied in mathematical simulation models for the product's production cost estimation in automated production systems.

An integrated model for estimating production costs in the product development phase, which is based on its characteristics, has been previously developed [5]. The framework of this model consists of CAD/CAM systems, the module for analysis, and the reference model. Since this model is based on product characteristics, its application requires model construction, adoption of tolerances, determination of data geometric characteristics, productivity assessment, and production time characteristics estimation for determining costs.

Artificial Neural Networks (ANN) have been used to develop a model for estimating the cost of producing cardboard boxes [6]. The model is established on an estimate of production costs based on the cost-related characteristics of similar products, whose cost data were used to train ANN. Among the most important cost-related characteristics which affect the production costs of these products are material, type of printing, type of colour, and quantities.

A study was presented to estimate the cost of products in the automotive industry, which is based on multiple techniques of gathering relevant knowledge such as interviews, process models and analysis of six British automotive manufacturers [7]. The study used the IdfF3 and eXpert Process Knowledge Analysis Tool (X-PAT) techniques as a tool for the process of expert knowledge analysis. The process model for cost estimation is based on a detailed BOTTOM-UP analysis which includes information gathering, information estimation, material and production process identification, machine selection, labour determination, cost per unit and tools estimation, machine selection, labour determination, general costs, logistics cost, etc.

Previous research indicates a hybrid and polynomial cost-tolerance model for estimating processing costs based on the application of fuzzy neural networks [8]. In the hybrid model, the cost function can be exponential, linear, reciprocal and combined, while in the polynomial model, this function is in the form of polynomials of the second, third, fourth and fifth degree. In both models mentioned, the processing cost function is defined depending on the size of the product tolerance field and weight coefficients of influencing factors such as tools, processing method, sequence of operations, processing time, measurement method, server training, etc. Based on that, the paper shows the possibility of determining the size of tolerance fields for processing at which the processing costs are the lowest for the observed production systems.

A system for estimating the cost of making a mould can also be based on a semi-analytical model [9]. This system, in addition to analytics, also relies on the principles of analogy between product shape and mould. For each elementary part of the product shape, the appropriate parameters are defined, the processing processes are generated, and therefore the appropriate processing time. In the next phase of application of this model, the quantity of material that is removed in the process of making the mould is determined, and processing costs are estimated based on that. The CAD product model, production technology, and material removal data are basic inputs for cost estimation. When estimating processing costs, they might be overestimated or underestimated, and on that basis, the wrong conclusion can be made about the actual processing costs.

A model for estimating casting costs can also be based on the product model and its attributes such as material type, geometric shape, quality and specific production requirements [10]. The estimation of these costs is done in the development phase, given that estimation of the costs of materials, energy and work are done analytically, while the costs of tools are estimated on the parametric principle, based on the parameters of product complexity. The costs of the casting process are estimated based on the parameters of the casting process. In the detailed model presented, the necessary input data for its application were shown.

Shape characteristics or the shape of the product have previously been used to estimate costs [11]. The information about individual parts of the contour is related to the appropriate processing phase, so it is possible to estimate the processing costs of the entire product accurately. This cost estimating model was applied to four groups or product classes, such as rotary, prismatic, plate and parts, which are grouped according to the characteristics of rotation.

Existing research establishes a model for estimating the cost of laser processing of low-volume products [12]. In this model, the costs include material costs, laser guidance speed, manufacturing accuracy, surface finishing and others.

Statistical analysis and Artificial Neural Networks (ANN) have previously been used to present a model for estimating costs of production, utilisation and recycling, or reuse [13]. In the input to the ANN, 21 attributes that affect the costs of the three mentioned phases of the product life cycle are entered, and the model is used in the product development phase when evaluating and selecting the most favourable solution.

There are existing cost analyses of plastic injection moulding products, which include research and development costs, mould manufacturing costs, and injection moulding process costs [14]. The mentioned phases of development, mould making, and injection moulding processes are presented through appropriate activities, and the integration of partial optimisation and feedback neural networks were used to estimate these costs.

To understand the context, we need to understand the history of the development and application of the Target costing method [15]. It was thought that in the 1960, Japanese companies introduced the Target costing method. However, in the works of the American economic consultant Joel Dean, it is stated that before Target costing, the method of "product tailoring" was developed and applied, which is considered to be the predecessor of the Japanese Target costing method. Also, some authors point out that it is the same method.

Previous research shows the calculation of the target costs of the product having been done in order to initially determine the selling price and the desired profit [16]. As a strategic management tool, target costs are focused on the product design development phase and cost estimation. These product costs provide production where the target selling price and target profit are achieved.

The method of target costs is a generally accepted method, and its application contributes to the high quality of products, cost reduction, as well as general customer satisfaction [17]. As cost reduction is performed in the product design development phase, the Target costing method has proven to be very effective in the product development phase.

Existing software development efforts and cost estimation models and techniques have shown that there is no single technique that is the best for all situations [18]. They proposed a hybrid approach for SDCE because that way, the limitations of one model and technique are complemented by the merits of the other model or technique.

Fuzzy logic can also be used to develop models that reduce uncertainty in the strategies of technical trading, which pertain to market timing and order size [19]. The models of technical trading usually rely on technical indicators that are comprised of previous pricing information and order size which generate discrete trading recommendations. The main goal of this research is the application of alternative indicators for technical trading, which tolerate the uncertainty present in the financial market.

ANFIS has previously been used to show the prediction of stock market return [20]. The goal of this research is to determine the possibility of accurate predictions in the stock exchange using Adaptive Neural Fuzzy Inference System (ANFIS) algorithms developed through MATLAB software. The authors conclude that the ANFIS system can be a useful tool that is used by economists and stock market return prediction practitioners.

An integration of Principal Component Analysis (PCA) and Adaptive Neural Fuzzy Inference System (ANFIS) is used through developing an appropriate model that enables the estimation of the impact of bad loans on the technical efficiency of banks [21]. Bad loans are considered to be a negative indicator of the technical efficiency of banks using PCA. Using the ANFIS system, the relationship between bad loans and the technical efficiency of banks is measured.

There are new capabilities of improving the risk-adjusted performance of stock market trading through using Artificial Neural Network (ANN), Adaptive Neural Fuzzy Inference System (ANFIS), Dynamic Evolving Neural Fuzzy Systems (DENFIS) models [22]. The ANN model, according to this research, has shown to be a sustainable model in specific cases of transactional costs through risk-adjusted objective functions, while the innovative ANFIS model has shown stable performance, which changes across time in multiple modes of trading.

Previous research shows the development of a weighted evolving fuzzy neural network for forecasting printed circuit board (PCB) sales, which is carried out through four steps: gathering 15 macroeconomic factors, choosing the combination of key factors that have the biggest impact on PCB sales, PCB sales, and determining seasonal effects as well as applying historical data for training the Weighted Evolving Fuzzy Neural Network (WEFuNN) for sales forecasting [23]. Using this network, precise PCB forecasting was carried out at a company in Taiwan, with the goal of easier capacity planning and material flow preparation.

Applying a Hybrid Neural Fuzzy controller (PATSOS), enables forecasting daily bitcoin price fluctuation [24]. The suggested methodology is better than the models, one of which was based on the neural fuzzy approach, and the other one based on Artificial Neural Network (ANN). PATSOS is applicable to other cryptocurrencies as well. Research shown in the paper is the first that applies to developing a neural fuzzy model for bitcoin price forecasting. The developed model shows that bitcoin pricing can be forecasted based on historical data.

The combination of the Artificial Neural Network (ANN) and Fuzzy Logic Controllers (FLC) can be applied to forecasting the currency exchange rate one day in advance [25]. The application of the ANN and FLC combination enables generating sets of trading strategies that yield a higher profitability rate. The research shows that the usage of fuzzy logic is useful because it expands the daily currency exchange forecasting capabilities through using ANN.

The demonstrated developed models of calculating production costs mostly refer to cost calculation models in mass production of certain products, or the cost calculation of producing certain products. In several papers [19-25], the application of specific artificial intelligence tools is shown in the financial marketplaces trade.

In this paper, a model of production cost calculation is set and developed, and it is based on the application of the principles of group technology and adaptive neural fuzzy networks.

This model is intended to be used, above all, to calculate production costs of product components in small and medium-sized businesses which are carried out on conventional and flexible technological systems with CNC functionality [26]. This production is characterized by a wide range of products with smaller batches, as well as limited pricing and turnaround times.

Due to these factors, a fast and effective product cost calculation is important in terms of creating offers based on customer specifications.

With the use of artificial neural networks, good results are achieved in solving tasks based on experimental data. Their main shortcoming is reflected in the small interpretation of the results and the impossibility of working with inaccurate data.

Fuzzy logic has the ability to solve tasks based on inaccurate data but cannot independently generate rules by which that data is processed. Therefore, new hybrid models have been developed that represent an extension of the possibilities of fuzzy logic and models of artificial neural networks [27].

Hybrid neural fuzzy systems form a modern class of these systems in which the neural network and the fuzzy system form a homogeneous structure. These systems can be conditionally understood as a neural network characterised by fuzzy parameters. This type of architecture is already widely used in adaptive neural fuzzy networks, i.e. ANFIS.

The basic idea of the neural adaptive learning technique is based on the methods of modelling and learning phases based on a given set of data. The calculation of the parameters of the membership functions takes place in such a way that the corresponding phase locking system (FIS) with the smallest error corresponds to the given pairs of input-output data.

Adaptive Neural Fuzzy Inference System (ANFIS) forms a Fuzzy locking system (FIS), in which the parameters of member functions are adjusted based on the back-propagation algorithm or in combination with the least squared error method. This approach allows the fuzzy system to learn based on the data it models.

Adaptive neural fuzzy systems represent a specific combination of artificial neural networks and fuzzy logic, which combines the ability to learn artificial neural networks and logical interpretation characteristic of fuzzy logic [28].

2.2 Research Methodology

The research process in the paper consists of several steps. The first step refers to the development and setting up of a product cost calculation model which consists of the preparation and application phase. Then, the developed model was applied, which is based on the principles of group technology and adaptive neural fuzzy systems to determine the time of production and price of the product.

To determine the time of production and price for the observed product according to the customer's request in the observed company, data on technological processes of production were collected for 21 observed products for which the production times are known.

The ANFIS system was trained, and it was used to determine the required time for making a new product according to the customer's request. The price of that new product was then determined using the value of the hourly rate and a target profit of 10 per cent.

3 DEVELOPED MODEL REVIEW

The developed model includes two main phases, the preparation, and the application phase. Both phases require certain procedures and appropriate activities; the preparation phase includes three and the implementation phase five activities, Fig. 1.

The first activity in the preparation phase includes analysis, classification, and grouping of products, i.e. parts, into groups whose production within the production program of a particular company was realised in the previous period, based on adopted technological processes, with verified and determined production times. Classification and grouping of these parts into technological groups is performed based on the principles of group technology [29], using construction-technological classifiers or visually, based on construction-technological similarity. Technological groups consist of parts that are characterised by mutual structural similarity and similarity of technological processes of their production. Technological groups of parts formed in that way, with data about total times and cyclic times that have been checked in real production conditions are stored in the appropriate database.

Within the second activity of this phase, technological processes of production of parts of formed technological groups are adopted, as well as processing operations with appropriate operations, dimensions, total times and cyclic times, and dimensions of preparations for all parts within individual technological groups. The data prepared and systematised in this way for individual parts of technological groups form the database for technological processes and are used as input data for training appropriate adaptive neural fuzzy networks within the third activity of the model preparation phase.

Technological processes for the production of parts within the formed technological groups enable the development of appropriate group technological processes that are stored in the knowledge base for group technological processes.

The first activity in the phase of model application includes the analysis of bid request requirements and technical-technological data, contained in the 3D model and 2D drawing of the observed product according to customer requirements, while the second activity refers to the analysis of construction shape, surface shapes, quality, dimensions and materials of the observed product or part, as key parameters for the selection of the appropriate technological group, which is done within the third activity of this phase, Fig. 1.

Selection of the appropriate technological group from the database to which the observed new product belongs is made within the third activity, based on the classification code of the observed new product, or visually, especially in cases when the technological group does not include many similar parts. For the selected technological group, an appropriate group technological process is defined in the knowledge base for group technological processes, which enables a technological process for production for an observed new product to be established.

The fourth activity of this phase includes estimating the cyclic time (T_k) of a new observed product, using appropriately trained adaptive neural fuzzy network and input data, which are contained in the technological process of making the observed new product, and relate to the size of the base material and the adopted processing phases with appropriate operations, as well as the dimensions that are achieved in the processing of typical surface shapes of this product, in accordance with the requirements of the drawings.

Cycling time in the developed model is the main data for the calculation of costs in the formation of new product prices according to customer requirements, as the fifth activity of the model, Fig. 1.

3.1 Product Cost Calculation Method

In service production businesses that produce a wide range of products or product parts, with smaller batches and shorter turnaround times, creating offers in a fast and efficient way is especially important.

Product costs can be determined based on the time cycle of producing the products and machine and equipment time needed which is used in specific operations [30]. These costs include elements of fixed and variable costs.

In the developed model, costs per product unit (T), which are determined as a part of the offer, are determined based on the total production time and the average production costs of the machines and equipment in the observed company expressed per hour (N_h). The (N_h) value, which includes fixed and variable costs, is usually known in small and medium enterprises as the value norm time, which is managed by the management of the company.

The total production time per the product unit is determined based on the total cycle (T_k) and out-of-cycle (T_{vc}) time. The total cycle time, which is estimated through this model, is composed of cycle times of specific operations, while the out of cycle time, which is composed of out of cycle production operations time, is accepted based on the experience in the observed company within the determined percentage of the time (T_k).

If the costs of raw part (C_p) for the production of the observed product, as part of variable costs, are shown separately, then the total costs per product unit (T) are defined with the following expression:

$$T = C_p + (T_k + T_{vc}) \times N_h \quad (1)$$

Costs of raw part (C_p) by piece, are determined by its market price.

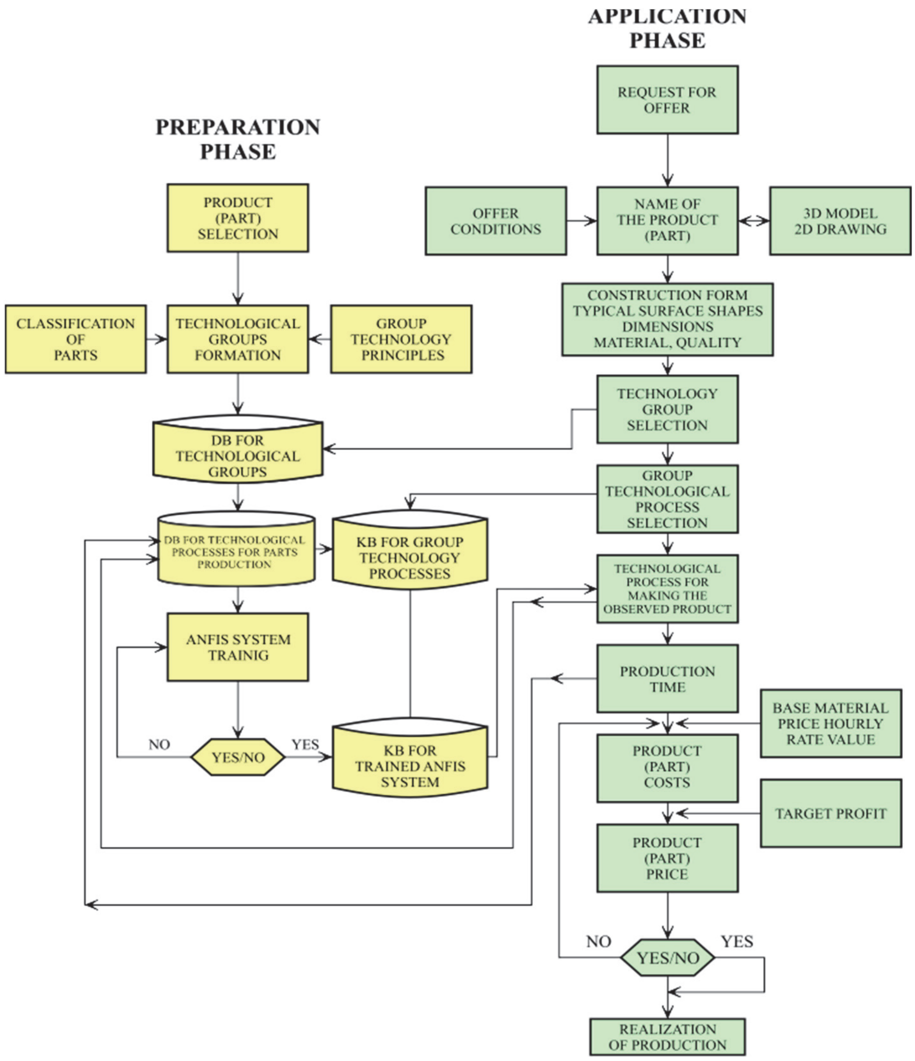

Figure 1 Product cost calculation model

4 APPLICATION OF THE DEVELOPED MODEL

The case study refers to an example of a cost calculation for a new product according to the customer's request using a developed model, in a company engaged in the production of metal parts in the form of service activities.

To calculate the costs of a new observed product or part, by applying the developed model, the appropriate phase of preparation and the phase of application of the model in the observed company will be shown, in Fig. 1.

As part of the preparation of the model, an analysis of the realized production program of this company in the previous seven-year period was performed. Using visual classification six technological groups of manufactured products or parts in that period were formed, such as:

- Prismatic steel parts with flat surfaces,
- prismatic parts made of aluminium with flat surfaces,
- prismatic parts made of steel with complex surfaces,
- prismatic parts made of aluminium with complex surfaces,
- rotating steel parts and
- rotating aluminium parts.

Technological processes of making prismatic parts are realized on vertical machining centres with CNC control and rotary on lathes with CNC control.

In the previous seven-year period, the production of many of the mentioned parts was realized and significant production experience was gained in terms of the development of standard technological processes, as well as their optimization, with the use of modern hard metal cutting tools and rational processing modes.

In accordance with the model, Fig. 1, in the preparation phase, technological processes for the making of the parts mentioned technological groups were adopted and training of appropriate adaptive neural fuzzy networks was performed. Thereby, in the preparation phase, the knowledge base for group technological processes of making parts of technological groups and knowledge base for trained adaptive neural fuzzy networks were formed, which form the basic support for the model application phase.

Adopted technological production processes of making parts for the mentioned technological groups contain data about the dimensions of preparations, processing operations and appropriate operations with dimensions that are achieved during processing, as well as data on cyclic times of all parts within the formed technological groups.

For the technological group of prismatic steel parts with flat surfaces, which includes 21 different parts, whose drawings are protected in the observed company, technological processes of production are shown in Tab. 1. Cyclic times of individual parts within this technological group were checked in stable production conditions of the observed company, and they included all elements of cyclic time.

Table 1 The technological process of making prismatic steel parts with flat surfaces

Product					Operations and processing phases							
Number	Drawing number	Material size / mm			Cutting		Front milling of flat surfaces and grooves					
					Processing dimensions / mm							
		Width	Thickness	Length	Width	Thickness	Width	Depth	Length	Width	Depth	Length
		*B*0	*H*0	*L*0	*B*0	*H*0	*B*1	*H*01	*L*1	*B*2	*H*02	*L*2
1.	AL 2330568	70	15	65	70	15	0	0	0	0	0	0
2.	AL 2344353	50	30	365	50	30	50	4	365	50	4	365
3.	SP 000018252	30	25	1025	30	25	0	0	0	40	20	60
4.	SP 000018563	50	30	325	50	30	0	0	0	0	0	0
5.	BZ 2222879	60	15	80	60	15	60	15	80	60	1,5	80
6.	BZ 2235095	90	20	190	90	20	0	0	0	0	0	0
7.	BZ 2235091	130	40	170	130	40	0	0	0	0	0	0
8.	SP 000018243	60	15	85	60	15	0	0	0	0	0	0
9.	AL 2344296	50	15	255	50	15	0	0	0	0	0	0
10.	AL 2344535	50	15	195	50	15	50	1	195	50	1	195
11.	AL 2178476	50	15	95	50	15	50	1	95	50	1	95
12.	BZ 2220725	30	10	165	30	10	30	1	165	30	1	165
13.	SP 000018293	50	30	605	50	30	0	0	0	0	0	0
14.	SP 000018561	50	30	125	50	30	0	0	0	0	0	0
15.	SP 000018562	50	30	255	50	30	0	0	0	0	0	0
16..	BU 3302694	35	20	105	35	20	0	0	0	0	0	0
17.	BU 3064392	25	25	255	25	25	25	1,5	510	25	2,5	510
18.	SP 000018087	35	20	135	35	20	35	1,5	135	35	1,5	135
19.	BZ2222862	60	30	185	60	30	0	0	0	0	0	0
20.	BU 3252655	40	20	85	40	20	40	0,5	85	40	0,5	85
21.	BU 2687015	25	20	165	25	20	25	1,5	330	25	3,5	330

Table 2 Technological process of making prismatic steel parts with flat surfaces - Continued

Operations and processing phases															
Front milling			Contour milling			Round milling				Drilling holes					
						External rounding		Internal rounding		Smooth holes		Step holes			
Processing dimensions / mm															
Width	Depth	Length	Width	Length	Depth	Radius	Length	Radius	Length	Diameter	Length	Diameter	Length	Diameter	Depth
*B*3	*H*03	*L*3	*B*4	*L*4	*H*04	*R*1	*L*01	*R*2	*L*02	*d*	*l*	*d*1	*l*1	*D*	*L*5
0	0	0	15	130	1	3	532	0	0	0	0	0	0	0	0
0	0	0	22	830	2,5	2	1620	0	0	0	0	0	0	0	0
80	20	60	25	60	2,5	2	4080	0	0	0	0	0	0	0	0
0	0	0	30	750	2,5	2	1580	0	0	0	0	0	0	0	0
0	0	0	12	280	2	3	812	0	0	0	0	0	0	0	0
0	0	0	20	180	2	0	0	0	0	12	40	9	20	15	22
0	0	0	40	637	2,5	0	0	0	0	27	40	0	0	0	0
0	0	0	15	290	2,5	2	552	0	0	0	0	0	0	0	0
0	0	0	15	610	2,5	3	1240	0	0	0	0	0	0	0	0
0	0	0	13	480	2,5	3	992	0	0	0	0	0	0	0	0
0	0	0	13	290	2,5	2	540	0	0	0	0	0	0	0	0
0	0	0	8	60	2	3	760	0	0	0	0	0	0	0	0
0	0	0	30	100	2,5	3	1010	3	100	0	0	0	0	0	0
0	0	0	30	350	2,5	2	330	0	0	0	0	0	0	0	0
0	0	0	30	610	2,5	2	1180	0	0	0	0	0	0	0	0
0	0	0	20	70	2,5	3	540	0	0	0	0	0	0	0	0
0	0	0	20	1070	2,5	3	1000	0	0	0	0	0	0	0	0
0	0	0	17	340	4	2	560	0	0	0	0	6	17	8	5
60	20	60	30	120	2,5	3	840	3	120	0	0	0	0	0	0
0	0	0	19	125	5	0	0	0	0	17	38	0	0	0	0
30	13	44	0	0	0	3	400	3	88	0	0	0	0	0	0

Table 3 Technological process of making prismatic steel parts with flat surfaces - Continued

Operations and processing phases												
Thread cutting						Internal thread rolling						Cyclic time / min/pc
M5-M7		M8-M10		M11-M14		M12-M14	M15-M18			M19-M24		
Processing dimensions / mm												
Diameter	Length	Diameter	Length	Diameter	Length	Diameter	Length	Diameter	Length	Diameter	Length	T_k
$d2$	$l2$	$d3$	$l3$	$d4$	$l4$	$d5$	$l5$	$d6$	$l6$	$D1$	$l7$	
6	30	0	0	12	45	0	0	0	0	0	0	15,7
0	0	10	44	0	0	0	0	16	88	0	0	20
0	0	10	75	0	0	0	0	16	250	0	0	73,1
0	0	10	60	12	120	0	0	0	0	0	0	21,6
6	24	8	48	0	0	0	0	0	0	0	0	31,5
0	0	0	0	0	0	0	0	0	0	0	0	23,45
0	0	0	0	0	0	0	0	0	0	0	0	60,5
6	30	10	60	0	0	0	0	0	0	0	0	9,1
0	0	10	30	12	45	0	0	0	0	0	0	18,2
0	0	10	52	0	0	0	0	0	0	0	0	18,6
0	0	10	39	0	0	0	0	0	0	0	0	9,7
6	32	0	0	0	0	0	0	0	0	0	0	8,3
0	0	10	60	0	0	12	60	0	0	24	120	43
0	0	10	90	0	0	12	120	0	0	0	0	9,4
0	0	10	60	0	0	0	0	16	120	0	0	16,2
0	0	0	0	0	0	0	0	0	0	20	20	19,9
6	40	0	0	12	80	0	0	0	0	0	0	38,3
6	24	10	34	0	0	0	0	0	0	0	0	19,8
0	0	8	20	0	0	0	0	0	0	20	60	24,7
0	0	0	0	0	0	0	0	0	0	0	0	22,2
6	36	0	0	12	36	0	0	0	0	0	0	24,5

In the technological processes of making this and other technological groups, the dimensions of the elementary type shapes of the surfaces of individual parts, which are achieved in the appropriate cutting processes, are expressed in values related to effective processing.

Based on the data in Tab. 2, which refer to the technological group of prismatic steel parts with flat surfaces, training of the appropriate adaptive neural fuzzy network was performed, for which the results of the training test are shown in Fig. 2, and it can be seen that the training test error of the ANFIS model is less than 0.5%.

The entry data used in the neural fuzzy model refers to the dimensional data of 21 products and applicable raw parts, as well as data of dimensions achieved in specific operations and processing of these products, Tab. 2.

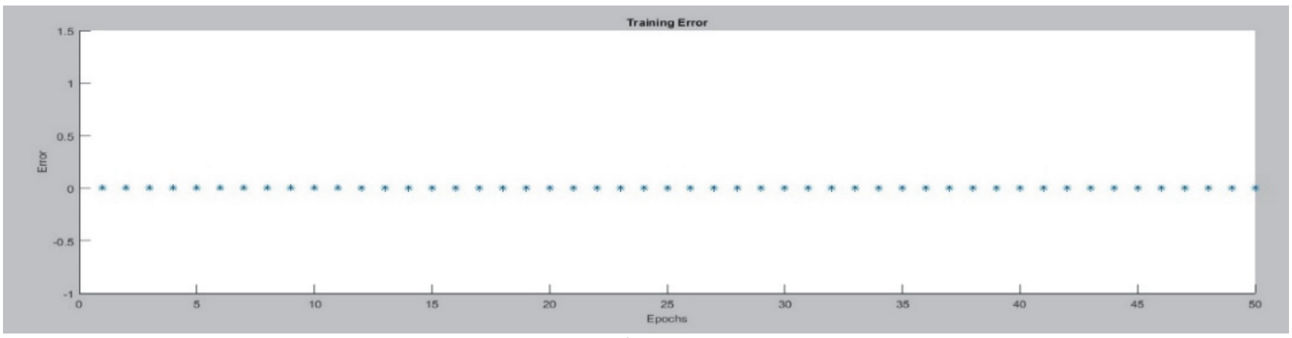

Figure 2 ANFIS model training test

For training the model, twenty-one production rules based on IF-THEN rules were used, based on expert knowledge covered by 21 products, Tab. 3.

A graphical representation of cyclic time (T_k), depending on some variables, based on the developed appropriate adaptive neural fuzzy network is given in Fig. 3.

a) $T_k = f(L1, B1)$
b) $T_k = f(L1, H01)$
c) $T_k = f(L4, B4)$
d) $T_k = f(R1, L01)$
e) $T_k = f(R2, L02)$
f) $T_k = f(d3, l3)$

The first and second activities of the model application phase include analysis of the request bid requirements and technical - technological data contained in 3D model and 2D drawing, i.e. analysis of construction shape, typical surface shapes, quality, dimensions and materials of a new observed product, according to customer requirements, Fig. 4.

For the observed new product, the buyer, along with the request for offer, which he submitted to this company, attached a drawing and 3D model, Fig. 4, and set a deadline of seven days to submit a bid for the production of 150 of these parts, as well as a delivery deadline of 30 days after offer acceptance, with the condition that the material is provided by the buyer.

The basic shape of this product is prismatic, with typical surface shapes such as flat surfaces, grooves, internal radius transitions, rounded edges, and threaded openings.

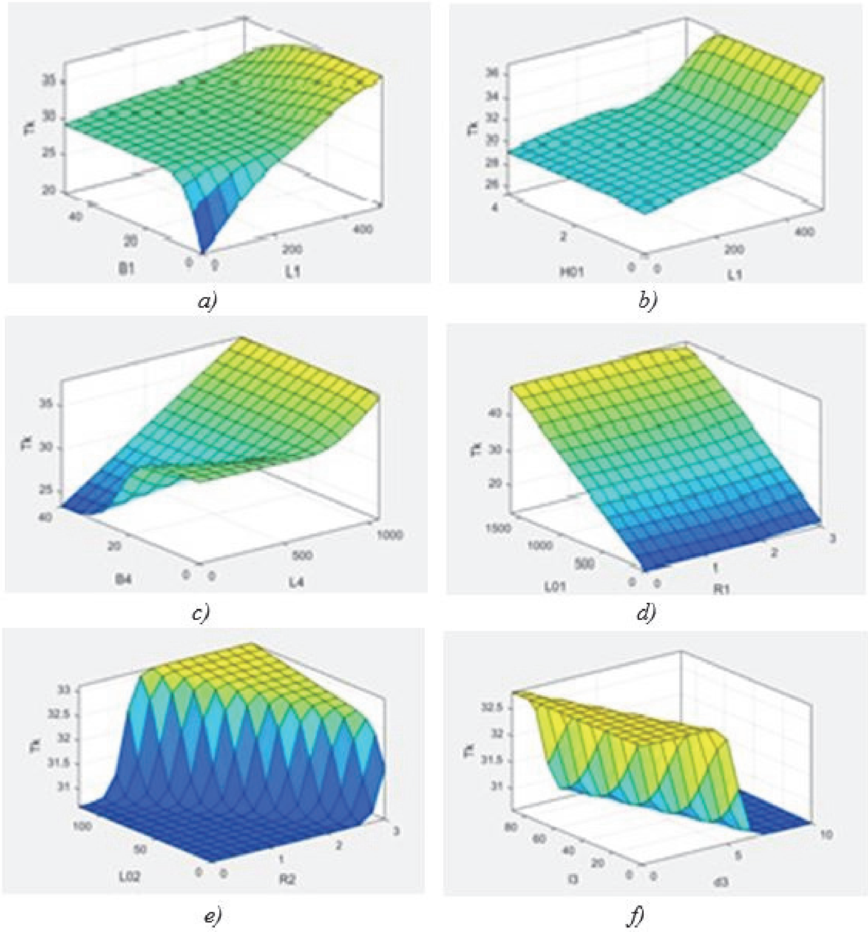

Figure 3 Graphical representation of cyclic time T_k

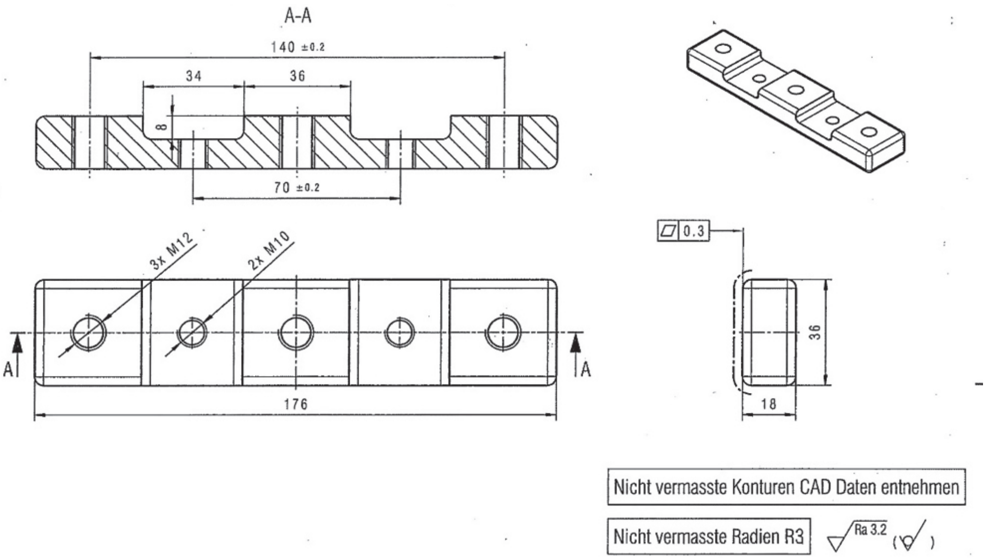

Figure 4 The product, according to the customer's request

Within the third activity of model application, it was visually determined that the observed new product belongs to the technological group of prismatic steel parts with basic flat surfaces, for which the appropriate technological processes of production for all the parts are stored in the database for technological processes, Tab. 4, as well as corresponding group technological processes of production, which are stored in the knowledge base for group technological processes. Appropriate trained adaptive neural fuzzy networks are stored in the knowledge base for the trained adaptive neural fuzzy networks.

Starting from group technological processes of the mentioned technological group, where the observed new product belongs, the technological process of making this product is defined, with data used as input data for determining the cyclic time of making (T_k), using an appropriately trained adaptive neural fuzzy network.

Based on the input data for the observed product according to the customer's request, which refers to the dimensions of preparations, adopted necessary processing operations and interventions with dimensions, Tab. 5, and appropriately trained adaptive neural fuzzy network, the total cyclic time for all operations of production of this product was estimated T_k = 24,73 min/pc, as the fourth activity of the model application.

Table 4 Technological process of making the observed new product

Product					Operations and processing phases							
Number	Drawing number	Material size / mm			Cutting		Front milling of flat surfaces					
					Processing dimensions / mm							
		Width	Thickness	Length	Width	Thickness	Width	Depth	Length	Width	Depth	Length
		*B*0	*H*0	*L*0	*B*0	*H*0	*B*1	*H*01	*L*1	*B*2	*H*02	*L*2
New product		40	20	180	40	20	40	1	180	40	1	180

Table 5 Technological process of making the observed new product - Continued

Operations and processing phases															
Front milling			Contour milling			Round milling				Drilling holes					
						External rounding		Internal rounding		Smooth holes		Step holes			
Processing dimensions / mm															
Width	Depth	Length	Width	Length	Depth	Radius	Length	Radius	Length	Radius	Length	Radius	Length	Radius	Depth
*B*3	*H*03	*L*3	*B*4	*L*4	*H*04	*R*1	*L*01	*R*2	*L*02	*d*	*l*	*d*1	*l*1	*D*	*L*5
34	8	72	18	440	2	3	636	3	144	0	0	0	0	0	0

Table 6 Technological process of making the observed new product - Continued

operations and processing phases												
Thread cutting						Internal thread rolling						Cyclic time / min/pc
M5-M7		M8-M10		M11-M14		M12-M14		M15-M18		M19-M24		
Processing dimensions / mm												
Radius	Length	Radius	Length	Radius	Length	Radius	Length	Radius	Length	Radius	Length	T_k
*d*2	*l*2	*d*3	*l*3	*d*4	*l*4	*d*5	*l*5	*d*6	*l*6	*D*1	*l*7	
0	0	10	20	12	54	0	0	0	0	0	0	

Since the buyer provides the material for the production of this part, the price that is submitted in the offer (C) is based on the value of the hourly rate in the amount of N_h = 15 €/h, adopted total off-cycle time T_{vc} = 30% T_k, and the target profit which is calculated in the observed company in the amount of 10% according to Eq. (1) is:

$C = (T_k + T_{vc}) \times N_h \times 1{,}1$

$C = 1{,}3 \times T_k \times N_h \times 1{,}1$

$C = 1{,}3 \times 24{,}73 \times 15/60 \times 1{,}1$

C = 8,84 €/pc

In the observed example, the buyer accepted the offer, and the company accepted the requested delivery date.

5 CONCLUSION

The developed model, which is based on the basic principles of group technology and the application of adaptive neural fuzzy networks, enables calculation or cost calculation when forming the price of product production according to customer requirements, with a satisfactory level of accuracy.

Accuracy of product cost calculation using this model mainly depends on the reliability of systematised data in the database for realised products and knowledge base for appropriate group technological processes in the production conditions of the observed company, as well as on the expertise of technologists, who are users of this model.

The database for realised products, with data for total and cyclic times, grouped products into technological groups and development of appropriate group of technical processes, as well as developed adaptive neural fuzzy networks, have special significance in the development of knowledge base in observed production conditions of a company.

The database for realised products in the integrated production management system has particular importance for the application of artificial intelligence in the development processes of modern companies.

6 REFERENCES

[1] Deng, S. & Yeh, T. H. (2011). Using least squares support vector machines for the airframe structures manufacturing cost estimation,. *Int. J. Prod. Econ.*, *131*, 701-708. https://doi.org/10.1016/j.ijpe.2011.02.019

[2] Duran, O., Maciel, J., & Rodriguez, N. (2012). Comparisons between two types of neural networks for manufacturing cost estimation of piping elements. *Expert Syst. Appl.*, *39*, 7788-7795. https://doi.org/10.1016/j.eswa.2012.01.095

[3] Tang, S., Wang, D., & Ding, F. Y. (2012). A new process-based cost estimation and pricing model considering the influences of indirect consumption relationships and quality factors. *Comput. Ind. Eng.*, *63*, 985-993. https://doi.org/10.1016/j.cie.2012.06.010

[4] Özbayra, M., Akgűn, M., & Tűrker, A. K. (2004). Activity-based cost estimation in a push/pull advanced manufacturing system. *Int. J. Prod. Econ.*, *87*, 49-65. https://doi.org/10.1016/S0925-5273(03)00067-7

[5] Ou-Yang, C. & Lin, T. S. (1997). Developing an Integrated Framework for Feature-Based Early Manufacturing Cost Estimation. *Int. J. Adv. Manuf. Technol.*, *13*, 618-629. https://doi.org/10.1007/BF01350820

[6] Zhang, Y. F. & Fuh, J. Y. H. (1998). A neural network approach for early cost estimation of packaging products. *Comput. ind. Engng.*, *34*(2), 433-450. https://doi.org/10.1016/S0360-8352(97)00141-1

[7] Roy, R., Souchoroukov, P., & Shehab, E. (2011). Detailed cost estimating in the automotive industry: Data and information requirements. *Int. J. Prod. Econ.*, *133*, 649-707. https://doi.org/10.1016/j.ijpe.2011.05.018

[8] De Cos, J., Sanchez, F., Ortega, F., & Montequin, V. (2008). Rapid cost estimation of metallic components for the aerospace industry. *Int. J. Prod. Econ.*, *112*, 470-482. https://doi.org/10.1016/j.ijpe.2007.05.016

[9] Bouaziz, Z., Ben Younes, J., & Zghal, A. (2006). Cost estimation system of dies manufacturing based on the complex machining features. *Int. J. Adv. Manuf. Technol., 28*, 262-271. https://doi.org/10.1007/s00170-004-2179-3

[10] Chougule R. G. & Ravi, B. (2006). Casting cost estimation in an integrated product and process design environment. *Int. J. Comput. Integr. Manuf.*, *19*(7), 676-688. https://doi.org/10.1080/09511920500324605

[11] Jung, J. Y. (2002). Manufacturing cost estimation for machined parts based on manufacturing features. *J. Intell. Manuf.*, *13*, 227-238. https://doi.org/10.1023/A:1016092808320

[12] Ruffo, M., Tuck, C., & Hague, R. (2006). Cost estimation for rapid manufacturing-laser sintering production for low to medium volumes. *J. Eng. Manuf.*, *220*(9), 1417-1427. https://doi.org/10.1243/09544054JEM517

[13] Seo, K. K., Park, J. H., Jang, D. S., & Wallace, D. (2002). Prediction of the life cycle cost using statistical and artificial neural network methods in conceptual product design, Int. J. Comput. *Integr. Manuf.*, *15*(6), 541-554. https://doi.org/10.1080/09511920210143417

[14] Wang, H. S., Wang, Y. N., & Wang, Y. C. (2013). Cost estimation of plastic injection molding parts through integration of PSO and BP neural network. *Expert Syst. Appl.*, *40*(2), 418-428. https://doi.org/10.1016/j.eswa.2012.01.166

[15] Zhou, X. & Da, X. (2010). Feasibility Analysis of The Comprehensive Profit Target. *World Rev. Polit. Econ.*, *1*(4), 652-674.

[16] Pazarceviren, S. Y. & Celayir, D. (2013). Target Costing Based on The Activity-Based Costing Method and a Model Proposal. *Eur. Sci. J.*, *4*, 1-21.

[17] Wu, H. H. & Yu, F. J. (2007). A practical implementation of target costing technique in improving product quality from cost consideration. *J. Stat. Manag. Syst.*, *10*(5), 743-755. https://doi.org/10.1080/09720510.2007.10701282

[18] Rashid, J., Nisar, M. W., Mahmood, T., Rehman, A., & Arafat, S. Y. (2020). A Study of Software Development Cost Estimation Techniques and Models. *Journal of Engineering and Technology*, *39*(2), 413-431. https://doi.org/10.22581/muet1982.2002.18

[19] Gradojevic N. & Gencay R. (2013). Fuzzy Logic, Trading Uncertainty and Technical Trading. *Journal of Banking & Finance*, *37*(2), 578-586. https://doi.org/10.1016/j.jbankfin.2012.09.012

[20] Boyacioglu, M. A. & Avci, D. (2010). An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul Stock Exchange. *Expert Systems with Applications*, *37*(12), 7908-7912. https://doi.org/10.1016/j.eswa.2010.04.045

[21] Firoozaeh, H., Mohamad, H. G., Jinus, R., & Loghman, H. S. (2013). Assessment of the effect on technical efficiency of bad loans in banking industry: a principal component analysis and neuro-fuzzy system. *Neural Computing and Applications*, *23*(1), 315-322. https://doi.org/10.1007/s00521-013-1413-z

[22] Vince, V. & Wing, L. N. (2014). Enhancing risk-adjusted performance of stock market intraday trading with neuro-fuzzy systems. *Neurocomputing*, *141*(1), 170-187. https://doi.org/10.1016/j.neucom.2014.03.026

[23] Chang, C., Wang, Y-W., & Liu, C-H. (2007). The development of a weighted evolving fuzzy neural network for PCB sales forecasting. *Expert Systems with Applications*, *32*(1), 86-96. https://doi.org/10.1016/j.eswa.2005.11.021

[24] Atsalakis, G. S., Atsalaki, I. G., Pasiouras, F., & Zopounidis, C. (2019). Bitcoin price forecasting with neuro-fuzzy techniques. *European Journal of Operational Research*, *276*(2), 770-780. https://doi.org/10.1016/j.ejor.2019.01.040

[25] Gradojevic N. (2007). Non-linear, Hybrid Exchange Rate Modelling and Trading Profitability in the Foreign Exchange Market. *Journal of Economic Dynamics & Control*, *31*(*2*), 557-574. https://doi.org/10.1016/j.jedc.2005.12.002

[26] Lukić, Lj. (2008). *Fleksibilni tehnološki sistemi, struktura, konstrukcija, upravljanje I tehnologija*. Mašinski fakultet, Kraljevo.

[27] Mamdani, H. E. & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, *7*(1), 1-13. https://doi.org/10.1016/S0020-7373(75)80002-2

[28] Sugeno, M. & Kang, G. T. (1988). Structure identification of fuzzy model. *Fuzzy sets and Systems*, *28*, 15-33. https://doi.org/10.1016/0165-0114(88)90113-3

[29] Mitrofanov, S. P. (1976). *Naučnaja organizacija mašino stroitelj nova proizvodstva*. Mašinostrojenije, Lenjingrad.

[30] Gowthorpe, C. (2008). *Upravljačko računovodstvo*. Data status, Beograd.

Contact information:

Stevan PEROVIC, M.Sc.
Gooten Inc, Head of People Operations,
228 Park Ave S, Suite 21651, New York, New York 10003-1502 US
E-mail: perovic.di13.2015@uns.ac.rs

Vladimir TODIC, PhD, Science Associate
(Corresponding author)
Faculty of Technical Sciences,
University of Novi Sad,
Dositeja Obradovica Square 6, 21000 Novi Sad, Serbia
E-mail: vladimir.todic@uns.ac.rs

Jovan PERVAZ, M.Sc.
Offset print d.o.o., Sales and Purchasing Director,
Primorska 84, 21000, Novi Sad, Serbia
E-mail: jovan@offsetprint.eu

Ilija COSIC, PhD, Professor Emeritus
Faculty of Technical Sciences,
University of Novi Sad,
Dositeja Obradovica Square 6, 21000 Novi Sad, Serbia
E-mail: ilijac@uns.ac.rs

Slobodan RADISIC, PhD
Faculty of Technical Sciences,
University of Novi Sad,
Dositeja Obradovica Square 6, 21000 Novi Sad, Serbia
E-mail: sradisic@uns.ac.rs