



INTEGRATED MODEL OF PRODUCT MANUFACTURING CYCLE TIME ESTIMATION

Received: 01 June 2023 / Accepted: 27 July 2023

Abstract: In modern business conditions, companies engaged in individual and small-batch production are faced with one of the key tasks of production management, which refers to weekly and, very often, daily production planning. Short delivery times, limited prices, and high requirements regarding the quality and method of product delivery all require timely planning of production capacities, tools, and devices, as well as the number of workers and their allocation to individual jobs. In such production conditions, which are determined by the market, it is of particular importance to determine the production time of the product quickly and qualitatively, including the production price, within the framework of making an offer according to the customer's demand. The paper presents a cycle time estimation model as a part of the overall product manufacturing time, using ANN and fuzzy neural networks.

Key words: Integrated model, Cycle time, Product, Estimation

Integrirani model procene ciklusnog vremena izrade proizvoda. *Preduzeća koja se bave pojedinačnom i maloserijskom proizvodnjom u savremenim uslovima poslovanja, suočavaju se sa jednim od ključnih zadataka upravljanja proizvodnjom, koji se odnosi na nedeljno, a vrlo često, i na dnevno planiranje proizvodnje. Kratki rokovi isporuke, limitirane cene i visoki zahtevi u pogledu kvaliteta i načina isporuke proizvoda, zahtevaju pravovremeno planiranje proizvodnih kapaciteta, potrebnih alata i uređaja, kao i broja radnika i njihovo raspoređivanje na pojedine poslove. U takvim proizvodnim uslovima, koje određuje tržište, od posebnog je značaja brzo i kvalitetno određivanje vremena izrade proizvoda, uključujući i određivanje proizvodne cene u okviru izrade ponude prema zahtevu kupca. U radu se prikazuje model procene ciklusnog vremena, kao dela ukupnog vremena izrade proizvoda, primenom ANN i fazi neuro mreža.*

Ključne reči: Integrirani model, Ciklusno vreme, Proizvod, Procena

1. INTRODUCTION

Cycle time, as a part of the operation time or the technological production process, represents one of the key data points necessary for solving numerous production management tasks, especially when it comes to individual and small-batch production.

The estimation of the effects of sequential, parallel, and combined methods of performing operations and processing, and the selection of the most favorable approach to the implementation of the technological process are based on data related to the cycle time. In the case of the sequential method of performing operations and processing steps, the overall manufacturing cycle time, also known as the technological cycle, is the longest, while in the parallel method of performing operations and processing steps, this time is the shortest. The combined way of performing operations and processing steps is a solution that provides a compromise between cycle time and the costs of waiting for the processing systems in individual operations.

The aforementioned highlights how the product manufacturing cycle time serves as the foundation for planning necessary production capacity, determining manufacturing and delivery deadlines, and devising the most advantageous strategy for initiating and organizing the technological manufacturing process.

Numerous methods for determining and estimating

the product manufacturing cycle time are presented in the available papers. For instance, paper [1] uses the MTM method to estimate the cycle time for human robotic work systems, while paper [2] uses delivery time—which has a big impact on manufacturing cycle time—to measure the competitiveness of industrial products in addition to quality and price.

Furthermore, it's crucial to delve into the synergies among these methods. The amalgamation of insights from various approaches holds the potential to significantly boost the accuracy and practicality of estimating cycle times. By synthesizing diverse methodologies, both researchers and practitioners can cultivate a more comprehensive comprehension of the intricate dynamics that influence product manufacturing cycle times across varied contexts. This collaborative approach fosters a more comprehensive and adaptable framework for optimizing manufacturing processes and ultimately improving overall efficiency.

A number of papers present the developed models of production cost estimation based on the application of ANN, for example, [3]. In the manufacturing and product cost estimation models, the discrete impact of the manufacturing cycle time isn't explicitly depicted. This is due to the inclusion of this cost component within the expenses of the completed products utilized for training artificial neural networks (ANN) and fuzzy neural networks.

2. PRESENTATION OF THE DEVELOPED MODEL

The basic structure of this model consists of two functional units, which relate to the preparation and application of the model, and the link between them is BP for product groups, KB for group technological processes, and KB for trained ANNs and fuzzy neural networks.

The key task that is solved by preparing the model is related to the development of a knowledge base for trained ANN and fuzzy neural networks for individual groups of parts in the observed company, while the application of the model solves the task of estimating the cycle time of making a new product in the production conditions of the observed company.

The basis for the preparation of the model is the analysis of the existing or realized production program of products or parts in the previous period under specific manufacturing conditions of the observed company and their grouping into groups based on the principles of group technology [4].

The formed groups, which are characterized by the similarity of individual technological processes for manufacturing parts within individual groups, are memorized in the corresponding database (Figure 1). Individual technological processes for manufacturing parts within individual groups are defined and checked under the specific production conditions of the observed company. The thus systematized individual technological processes of manufacturing parts, classified into individual groups, form group technological processes, which are memorized in the corresponding knowledge base.

Group technological processes, which are presented in matrix form, contain data on dimensions of blanks, operations, processing steps, and dimensions achieved in individual processing operations, as well as data on manufacturing cycle times for all parts classified into individual groups. The data thus displayed for group technological processes constitutes the input data for training ANN and fuzzy neural networks, as well as the possibility of developing a suitable knowledge base.

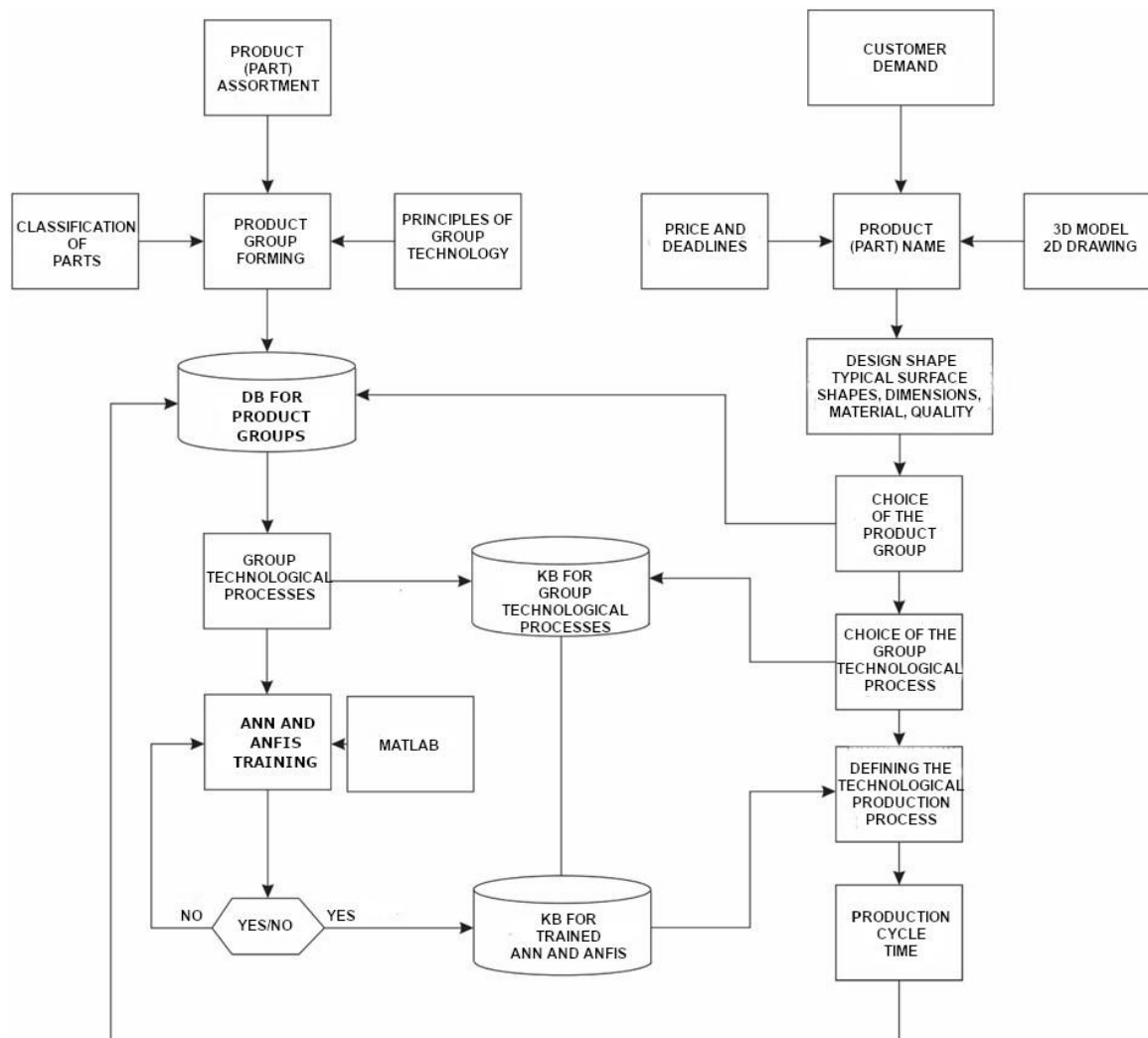


Fig. 1. Integrated model of product manufacturing cycle time estimation

The application of the model begins with the analysis of the design form of the observed new product, defined by the drawing, that is, the typical forms of the contour of the product, dimensions, materials, and quality of

workmanship according to the customer's demand. These data enable us to automatically, or most often visually, determine the product's belonging to the corresponding group (Figure 1). The choice of the group determines the

group's technological process of making the product based on the corresponding knowledge base, and thus the selection of an appropriately trained ANN and fuzzy neural network.

On the basis of the selected group technological process of production and drawings of the new product, the individual technological process of its production is defined interactively in terms of dimensions of the blank, required operations and steps, and dimensions achieved within individual operations and steps.

These data form the input data on the basis of which the cycle time of the creation of the observed new product is estimated by applying the corresponding ANN, or fuzzy neural network.

3. PREPARATION OF THE MODEL IN THE OBSERVED COMPANY

As part of the preparation of the model in the observed company, an analysis of the existing production program was performed, as well as the production program that was implemented in the previous period of

several years. This company is engaged in individual and small-batch production of prismatic and rotary parts made of steel and aluminum. Visual classification created two groups of rotary components and four groups of prismatic components.

Of the four groups of prismatic parts that are processed on vertical machining stations with CNC control, one has been singled out, which refers to prismatic steel parts with typical standard contour shapes.

This group includes 21 prismatic steel parts, for which individual technological processes of their production were developed and checked in production conditions, with data presented in matrix form (Table 1). Individual technological processes for manufacturing parts, which are classified in this group, actually represent a corresponding group technological manufacturing process.

The cycle times for the production of individual parts, which are classified in this group, were checked in stable production conditions at the company, which primarily relate to the reliability of vertical machining stations and hard metal cutting tools as well as rational processing modes.

Table 1. Group technological processes of manufacturing prismatic steel parts with standard type contour shapes

PRODUCT		OPERATIONS AND PROCESSING STEPS										
NO.	NUMBER OF DRAWING	BLANK DIMENSIONS (mm)			CUTTING-OFF		FACE MILLING OF FLAT SURFACES AND GROOVES					
		Width	Thickness	Length	Width	Thickness	Dimensions of the processing step (mm)					
							Width	Length	Length	Width	Length	Length
		B0	H0	L0	B0	H0	B1	H01	L1	B2	H02	L2
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
New part		40	20	180	40	20	40	1	180	40	1	180

The group technological process, i.e., group operations, contains data on blanks, types of operations and processing steps, dimensions achieved in operations and processing steps, as well as data on manufacturing cycle times of all parts of the observed group. The dimensions achieved during the processing of the typical contour shapes of individual parts are expressed in values

that are achieved by effective processing by cutting. Surfaces that are not processed, as well as typical forms that do not appear on individual parts, are marked with a value of zero (Table 2). The data contained in the group technological process of manufacturing the observed group constitute the input data for training ANN and fuzzy neural networks (Table 3).

Table 2. Group data of surfaces that are not processed as well as typical forms that do not appear on individual parts

OPERATIONS AND PROCESSING STEPS															
FACE MILLING OF FLAT SURFACES AND GROOVES			CONTOUR MILLING			MILLING OF ROUNDINGS				BORING THE OPENINGS					
						EXTERNAL ROUNDING		INTERNAL ROUNDING		SMOOTH OPENINGS		STEPPED OPENINGS			
Dimensions of processing steps (mm)															
Width	Depth	Length	Width	Length	Depth	Radius	Length	Radius	Length	Diameter	Length	Diameter	Length	Diameter	Depth
B3	H03	L3	B4	L4	H04	R1	L01	R2	L02	d	l	d1	l1	D	L5
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
34	8	72	18	440	2	3	636	3	144	0	0	0	0	0	0

Table 3. Group constitute the input data for training ANN and fuzzy neural networks

OPERATIONS AND PROCESSING STEPS												
THREAD CUTTING						INTERNAL THREAD ROLLING						CYCLE TIME (min/pc)
M5-M7		M8-M10		M11-M14		M12-M14		M15-M18		M19-M24		
Dimensions of processing steps (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
0	0	10	20	12	54	0	0	0	0	0	0	

3.1 Training of ANN

Supervised training of the Artificial Neural Network (ANN) was meticulously executed utilizing the sophisticated capabilities of the Matlab software. The comprehensive training, rigorous testing, and meticulous validation of the trained ANN have yielded remarkably high correlation factors in the regression analysis, as visually represented in Figure 2. These results underscore the effectiveness and robustness of the ANN model in capturing complex patterns and relationships within the data, showcasing its potential for accurate predictions and reliable performance in various applications.

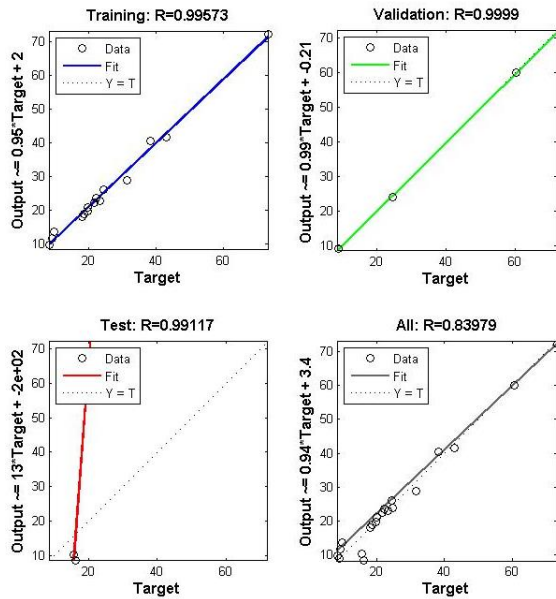


Fig. 2. Correlation factors of regression analysis

3.2 Training of fuzzy neural networks

The fuzzy neural network was trained by using the same input data, which are contained in the group technological process of creating the observed group (Table 1). When training this network, 21 production rules were used, and the training error was less than 0.5%. A graphical representation of the manufacturing cycle time, based on a suitably trained fuzzy neural network, as a function of some variables is given in Figure 3.

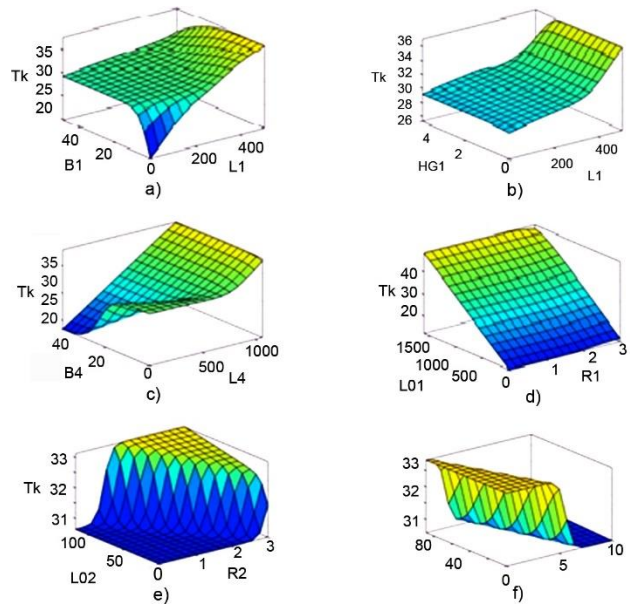


Fig. 3. Graphical presentation of manufacturing cycle time

4. APPLICATION OF THE MODEL IN THE OBSERVED COMPANY

The application of the developed model in the observed company, as a case study, was carried out on the example of estimating the manufacturing cycle time of a new product according to the customer's demand (Figure 4).

The beginning of the application of the model (Figure 1) foresees the analysis of design and technological requirements, defined by the drawing of the new product. Based on the analysis of the design shape of this product, typical contour shapes, dimensions, materials, and quality of workmanship, its belonging to the group of prismatic steel parts with standard typical contour shapes was visually determined. For this group, a group technological production process was defined (Table 1) for which appropriately trained ANN and fuzzy neural networks were memorized in the knowledge base.

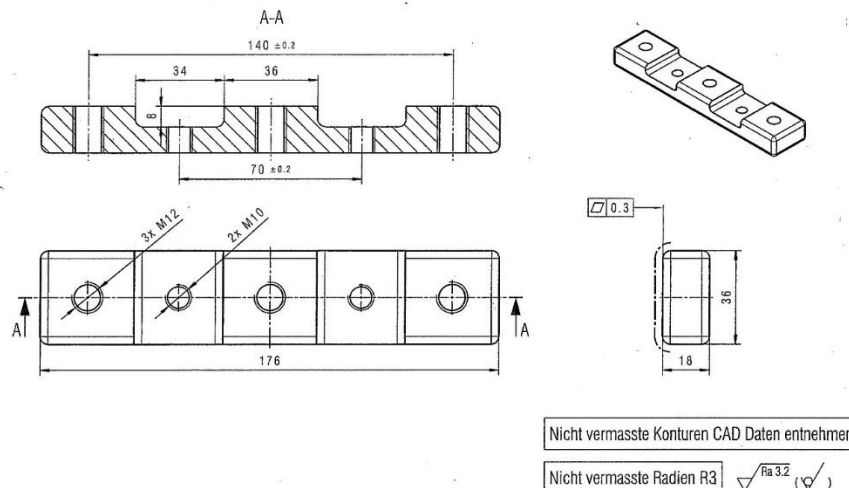


Fig. 4. The observed new product

On the basis of the chosen group technological process of manufacturing the mentioned group and of the design technological requirements, defined by the drawing of this product, the technological process of its manufacturing was specified by determining the dimensions of the blank, the necessary operations, and the processing steps, with the dimensions achieved by cutting.

Surfaces that are not processed and type shapes that do not appear on the observed product are marked with a value of zero.

The above data, which for the observed product are shown in the last row of Table 1, constitute the input data on the basis of which the overall cycle time of the observed product was estimated by applying the corresponding trained ANN I fuzzy neural networks in the following amounts:

- *Using the trained ANN, the cycle time is $T_k=17.76$ min/pc,*
- *Using the trained fuzzy neural network, the cycle time is $T_k= 24.73$ min/pc.*

For the observed example, the manufacturing cycle time was checked in actual manufacturing conditions, which is 23 min/pc.

5. CONCLUSIONS

The integrated model provides a reliable estimation of the product manufacturing cycle time, because the estimation is made in two ways, i.e. by applying ANN and fuzzy neural networks. This enables the user to adopt a compromise value of the cycle time within the two obtained values.

The same prepared input data are used in the observed company to estimate the product manufacturing cycle time using ANN and fuzzy neural networks, which confirms the rationality of the application of the integrated model.

The training of ANN is performed in several iterations, until acceptable values of the correlation factors of the regression analysis are obtained, while the

training of fuzzy neural networks is usually completed in the first iteration.

Development processes in modern business conditions require companies to develop a database for realized products and corresponding technological processes, databases, and knowledge bases for off-cycle times in the observed production conditions. Based on the estimated cycle time and the adopted values for off-cycle times, it is possible to determine the overall production time per unit of the observed product. This, along with the developed knowledge base for trained ANN and fuzzy neural networks, enables quick determination of the manufacturing price of products in individual and small-batch production, planning of production capacities, launch dynamics, and the management of manufacturing deadlines.

Previous research experiences, as well as the obtained results for the product manufacturing cycle time estimation, which were checked in actual manufacturing conditions, show that more reliable results are obtained by applying fuzzy neural networks.

6. REFERENCES

- [1] Komenda, T.; Brandstotter, M; Schlund, S.: *A comparison of and critical review on cycle time estimation methods for human-robot work systems*, Procedia CIRP, Vol. 104, pp 1119-1124,2021.
- [2] Deng, S.,Yeh, T.-H.: *Using least squares support vector machines for the airframe structures manufacturing cost estimation*, Int. J. Prod. Econ., vol. 131,701–708, 2011.
- [3] Duran, O., Maciel, J., Rodriguez, N.: *Comparisons between two types of neural networks for manufacturing cost estimation of piping elements*, Expert Syst. Appl., vol. 39, pp. 7788–7795, 2012.
- [4] Mitrofanov, S.P.: *Naučnaja organizacija mašinstroiteljnova proizvodstva*, Mašinstrojenije, Lenjingrad.,1976.

Author: Vladimir Todić PhD, University of Novi Sad, Faculty of Technical Sciences, Trg Dositeja Obradovica 6, 21000 Novi Sad, Serbia.

E-mail: vladimir.todic@uns.ac.rs