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ORIGINAL PAPER

ARTIFICIAL NEURAL PSEUDO-NETWORK FOR PRODUCTION CONTROL PURPOSES

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ABSTRACT. **Background:** Experience from the implementation of the industry 4.0 concept has proved that the key success factor is the use of techniques and methods of artificial intelligence. One of these techniques is artificial neural networks. The development of artificial neural networks has been taking placefor a long time and has led to a number of important applications of this technique in industrial practice. Along with the development of practical applications, a wide theoretical base has also been created regarding the concepts, tools and principles of using this technique.
Methods: This paper contains an attempt to use the theoretical basis of artificial neural networks to build a specialized tool. This tool is called a pseudo-network. It is based not on the whole of the theory of artificial neural networks but only on the targeted elements selected for it. The selection criterion is the use of an artificial neural pseudo-network to control production.
Results: The paper presents the assumptions of an artificial neural pseudo - network, the architecture of the developed solution and initial experience of using it.
Conclusions: These initial results proved the assumptions made by an author. The architecture of the pseudo-network has been developed. Work to build a system demonstrator representing the artificial neural pseudo - network have been initiated and is still in progress.

Key words: artificial intelligence, neural networks, production control, industry 4.0.

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INTRODUCTION

Experience from the implementation of the industry 4.0 concept has proved that the key success factor is the use of artificial intelligence tools [Lee et.al 2018]. When considering these artificial intelligence tools, the analogy method seems to be the most common approach. Solutions are developed on the basis of available knowledge and of understanding how a particular system functions. Observing the natural environment is another source of inspiration when searching for new solutions [Bouffanais 2016, Key 2016]. The third source of inspiration in thinking about artificial intelligence tools are abstract concepts in the field of mathematics, sociology or psychology, such as the concept of belonging to a set (group). These have inspired tools based on fuzzy set theory or grey set theory.

Artificial neural networks are one of the groups of artificial intelligence tools. These are information systems that imitate the operation of the human brain. The development of artificial neural networks has been going on for a long time. Networks consist of a number of typical elements, such as: processing elements (neuron analogs), inputs and outputs information, transfer functions,

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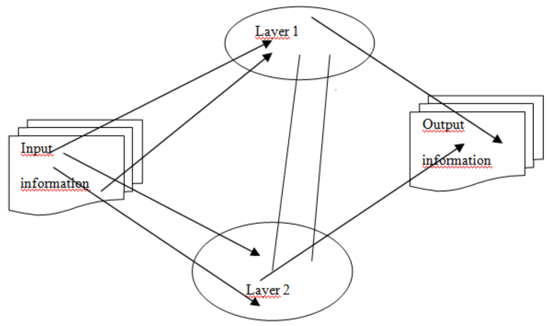
interconnections of processing elements, network learning principles.

It was quickly noted that artificial neural networks could be used to control processes [Willis et al. 1995]. This research trend still continues [Bouzenad K. and Ramdani M., 2017]. The usefulness of artificial neural networks in production scheduling as well as in tracking and adjusting the production process was also identified quickly [Guillot et al. 1994, Burduk 2017.]. This trend in research also continues and is present in many publications [Zhang et al. 2016]. The experience gained during attempts to use artificial neural networks for production control has modified the general approach to this problem. A mixed approach has appeared, based on combining artificial neural networks with other artificial intelligence techniques (hybrid approach), [Sittisathanchai, Dagli 1993, Lee, Dagli 1997, Massaro et al. 2019] or models of operational research [Foo, Takefuji, 1988]. Research based on this approach is also on-going [Singh et. al. 2019].

The paper presents the concept of an IT system developed for production control in an industrial enterprise that produces complex products under discrete production conditions. The system is part of the production planning and control system. It cooperates with the production planning system from which it periodically downloads the data on production tasks covering the assortment of manufactured products, production programs of individual assortment items, production start and end dates, as well as production updates. In turn, it reports to the production planning subsystem about the progress in implementing the current production tasks. The production planning and control system is a part of the cyber-physical system architecture for Industry 4.0 manufacturing system. It belongs to the cognition level, where it participates in collaborative diagnostics and decision-making functions [Lee et al. 1915, Wong et al. 2018, Rojek 2017].

An essential part of the proposed system is an artificial neural network. Its structure, however, does not correspond to any of the typical artificial neural network architectures presented in the literature. Elements of the system and relations between them have been selected to enable the system to perform production control. The author calls this solution a neural pseudo-network. The architecture of this neural pseudo-network is shown in Figure 1.



Source: own work

Fig. 1. Architecture of artificial neural pseudo–network

Processing elements in both layers of the neural pseudo-network are interconnected:

– via an infrafield connection in the same layer,
– via an interfield connection between processing element in both layers. Processing elements in the first layer are connected with processing elements in the second layer. This type of connection is unidirectional.

The proposed pseudo-network operates on the basis of the self-organizing map model. Cheung [Cheung 1994] suggested the possibility of using this model to solve production control problems. The self - organizing map includes an array of inputs with numerous connections to the processing layer. Every input element is connected to the processing layer through a localization function represented by the lateral connection weights.

The pseudo–network developed here consists of two layers of processing elements. The first one maps the production task, monitors the progress of its execution, and determines the order for performing all the technological operations comprising the production task. The second layer assigns technological operations to the work stations in the production system, and tracks and analyses the state of the production system.

The IT system based on the proposed architecture builds a schedule of produced elements that constitute a production task on an ongoing basis. It also has the feature of a smart system - the ability to create a virtual copy (digital twin) of physical reality and the ability to act autonomously until the situation requires no intervention from a higher level of management. Adding to this interoperability (the ability of machines, devices, products and services and people to communicate with each other) results in defining a system capable of operating in the architecture of cyber-physical systems for Industry 4.0 manufacturing systems.

This paper presents the architecture of the first network, its elements and operating principles. It also presents the results obtained when testing the network prototype.

INPUT INFORMATION TO THE FIRST LAYER

The first Layer 1 maps the production task, monitors the progress of its execution, and determines the order for performing all the technological operations comprising the production task.

The matrix describing technological processes

The matrix will contain descriptions of the technological processes of elements manufactured in the production system. The matrix is presented below in the form of a table.

Table 1. The matrix describing technological processes

Nr	Element ID	Operation number O	Σt_j	β
		Workstation ID		
		t_j operating time		

Source: own work

The elements in the table are ordered:
- by number of operations - from max to min
- if these are identical - by Σt_j value i.e. from max to min
- if the previous two criteria are identical - according to the value of the identifier - from max to min.

In the matrix of the description of technological processes there is also β - identifier of the possibility of starting a given operation, which takes either the value β = 1, when the operation is possible within the time limit or β = 0 in the opposite case.

The purpose of the matrix describing the technological processes of the elements produced in the production system is to provide data for calculations carried out by the processing layer, which calculates (dynamically modifies) the localization function and the lateral connection weights.

The matrix describing a production task to be carried out in the planning horizon

The matrix will present a description of the production task to be carried out in the given planning horizon. On the lines there are individual elements planned for execution in the given planning horizon, and in the columns, individual planning orders (parts of elements) are presented. Elements in the matrix will be ordered corresponding to the modified order in the matrix describing technological processes.

The elements in the table 2 are ordered:
- by number of operations - from max to min
- if these are identical - by Σt_j value i.e. from max to min
- if the previous two criteria are identical, according to the size of the production program, which is the sum of the size of individual orders, from max to min.

The matrix is presented below in Table 2.

Table 2. Matrix presenting a description of the production task planned to be carried out in the given planning horizon

Nr	Element ID	order number N		$P_{p.}$
			n_o	
			t_r	
			t_z	

Source: own work

The data in the matrix describing the production task in the columns concerning individual production orders are taken from the MRP module of the ERP system:

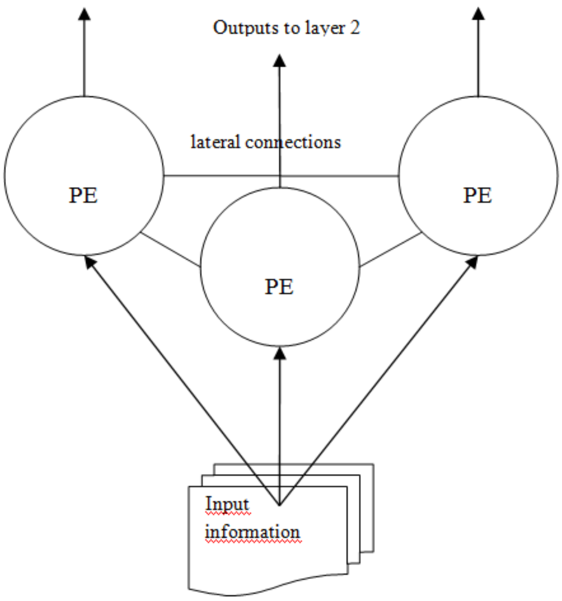
- n_o - size of the production order
- t_r - start date, the moment when task is launched
- t_z - end date., the moment when task is finished

The order numbers are assigned consecutively, according to the start date - from the earliest to the most recent.

The size of the production program given in the last column of the matrix for a given element is the sum of the individual sizes of the production tasks: $P_p = \Sigma n_o$.

OPERATION OF THE FIRST LAYER

Architecture of the first layer is shown in figure 2. The first layer consists of processing elements (analogs of biological neurons). The number of processing elements in this layer corresponds to the number of orders numbers.



Source: own work

Fig. 2. Architecture of the first layer of the neural pseudo–network

The processing element in layer 1 is shown in Figure 3.

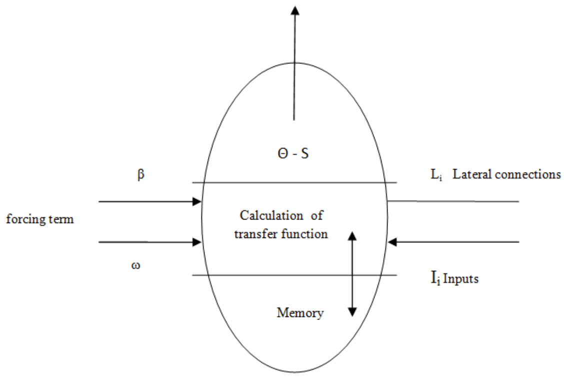


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Fig. 3. Processing element in layer 1

Each processing element in the first layer has two extra inputs (forcing term):

- β = 1 when the realization of the technological operation is possible at the given moment or β = 0 in the opposite case
- ω = 1 when the processing element has been selected or ω = 0 in the opposite case.

Inputs to processing elements in the first layer are:

- $I_{1-\tau}$ = te-ts for each order number,
- I_2 –operation number O,
- I_3 - lateral connection - infrafield connection in the same layer. These have a value of 1 or 0,
- I_4 - memory value of processing elements,
- $I_5 = \beta$.

The transfer function is the mechanism of translating inputs signals to an output signal. In a pseudo-network it is a linear function calculated according to the formula [1].

$$S = \sum Ii \qquad [1]$$

where i Є <1;5>.

The first layer of the pseudo-network works according to "the winner takes everything" principle, which means that at each step of the network's operation only one neuron with the highest value of transfer function is active.

The output value is calculated according to the following rules:

– in the case when $S > \theta$ and $\beta = 1$ and $\omega = 0$, then for the maximum value of $S - \Theta$ output the value is {N, O}- two-element set of information,
L - lateral connection value = 1, the value of memory for all remaining processing elements is increased by 0.5 (competitive learning).
– in the case when $S > \theta$ and $\beta = 0$ and $\omega = 0$, then the processing element is not active,
– in the case when $S < \theta$ and $\beta = 1$ and $\omega = 0$, then the processing element is not active,
– in the case when $S > \theta$ and $\beta = 0$ or 1 and $\omega = 1$, then for the maximum value of $S - \Theta$ output is {N, O}, lateral connection value = 1, the value of memory for all other processing elements is increased by 0.5 (competitive learning).
– threshold value θ is calculated from formula 2.

$$\Theta = \tau + N \qquad [2]$$

For each activity of a given neuron, this value is calculated according to formula 3.

$$\Theta = \Theta + 1 \qquad [3].$$

EXAMPLE OF THE FIRST LAYER OPERATION

The operation of the first layer of the network was tested on data from technological processes of eight randomly selected elements. The test results are presented in Table 3.

Table 3. Ranges of parameters used in computational experiments

N	1	2	3	4	5	6	7	8	F	KR	
O	4	4	4	3	3	3	2	1	-		
τ	5	6	5	4	6	6	7	3			
θ	6	8	8	8	11	12	14	11			
S	7	8	7	6	8	8	9	5			
S- θ	1	-	-	-	-	-	-	-	1	N 1	S- θ max
L/M	-/-	1/ 0	1/0	1/0	1/ 0	1/0	1/ 0	1/ 0			
θ	7	8	8	8	11	12	14	11			
S	8	9	8	7	9	9	10	6			
S- θ	1	1	-	-	-	-	-	-	2	N 2	ω = 1
L/M	1/-	-/ .5	1/.5	1/.5	1/ .5	1/.5	1/ .5	1/ .5			
θ	7	9	8	8	11	12	14	11			
S	9	9.5	8.5	7.5	9.5	9.5	10.5	6.5			
S- θ	2	.5	.5	-	-	-	-	-	3	N 1	S- θ max
L/M	-/ .5	1/ 1	1/ 1	1 / 1	1 / 1	1 / 1	1/ 1	1/ 1			
θ	8	9	8	8	11	12	14	11			
S	9.5	11	9	8	10	10	11	7			
S- θ	1.5	2	1	-	-	-	-	-	4	N 2	S- θ max
L/M	1/ .5	- / 1.5	1/ 1.5	1/ 1.5	1/ 1.5	1/ 1.5	1/ 1.5	1/ 1.5			

Source: own work

CONCLUSIONS

The preliminary results confirm the assumptions made by the author and presented in this paper. A concept for a production control IT system has been developed with a new approach by combining selected elements of the theory of artificial neural networks with other components. The fundamental component of the system developed is an artificial neural pseudo-network. The architecture of the pseudo-network has been developed. It consists of two cooperating layers of processing elements (artificial pseudo-neurons). The operating principles of the first layer of the pseudo-network have already been developed and tested. The results obtained confirmed the assumptions made. Work on building a system demonstrator representing the new concept has been initiated. This demonstrator is to be based on IT systems required by the concept of Industry 4.0 and to simulate the work of a production planner, and moreover, if necessary, support problem-solving in the production control area. The functional features of such an IT system combining elements of artificial intelligence tools with knowledge of the principles of production control are currently difficult to determine. This work is still in progress.

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SZTUCZNA PSEUDOSIEĆ NEURONOWA W STEROWANIU PRODUKCJĄ

STRESZCZENIE. **Wstęp:** Doświadczenia z wdrażania koncepcji Industrie 4.0 wskazują, że kluczowym czynniku sukcesu jest stosowanie metod i technik z zakresu sztucznej inteligencji. Jedną z tych technik są sztuczne sieci neuronowe. Rozwój sztucznych sieci neuronowych trwa od długiego czasu i doprowadził do wielu istotnych zastosowań tej techniki w praktyce przemysłowej. Równolegle z rozwojem zastosowań praktycznych stworzona została baza teoretyczna koncepcji, narzędzi i zasad stosowania tej techniki.
Metody: Artykuł ten zawiera próbę wykorzystania teoretycznej bazy sztucznych sieci neuronowych do stworzenia specjalnego narzędzia. Nosi ono nazwę sztucznej pseudo - sieci neuronowej. Opiera się ona nie na całości dorobku teorii sztucznych sieci neuronowych ale na celowo wybranych jego elementach. Kryterium doboru było zastosowanie sztucznej pseudo-sieci neuronowej do sterowania produkcji.
Wyniki: Artykuł przedstawia założenia do opracowania sztucznej pseudo-sieci neuronowej, architekturę opracowanego rozwiązania i wstępne doświadczenia z prób jego zastosowania.
Wnioski: Wstępne wyniki potwierdziły założenia przyjęte przez autora artykułu. Opracowana została architektura sztucznej pseudo - sieci neuronowej. Zapoczątkowane zostały pracy nad budową demonstratora sztucznej pseudo-sieci neuronowej. Prace trwają nadal.

Słowa kluczowe: sztuczna inteligencja, sieci neuronowe, kontrola produkcji, Industry 4.0

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