CONSTRUCTION OF CONTROL SYSTEMS OF FLOW PARAMETERS OF THE MARINE SMART CONVEYOR USING A NEURAL NETWORK

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I. INTRODUCTION

Nowadays automated systems are increasingly advancing. Thanks to modern technologies, all production processes and technological operations significantly accelerate not only the work of enterprises but also bring profit. One of the most popular types of automated systems is a belt conveyor which is an endless continuously moving belt transporting bulk cargo. It is widely used in many industries - metallurgy, coal, chemical, in the production of building materials, processing and disposal of waste and others. The belt conveyor is preferably better than other modes of transport designed to transport large volumes of cargo. Also one of its advantages is simple in design, reliable in operation has high productivity taking into account its small operating costs.

Actuality of theme. This work is devoted to the topical problem of modeling the marine conveyor transport system at different productions. There are problems to increase the reliability of marine conveyor transport at various types of enterprises, increase production efficiency, forecast and control all work processes and equipment to avoid dangerous situations, prevention of dangerous modes of equipment, automatic alarms, regulation, control, etc.

The purpose of the study – an information system for predicting the flow parameters of a marine smart conveyor using a neural network.

The object of study – a marine smart conveyor transport system.

The subject of research – a model for predicting the flow parameters of the marine smart conveyor using a neural network.

II. WORK OF MARINE SMART CONVEYOR AND INSPECTION OF CONVEYOR TYPE TRANSPORT SYSTEMS

The leading trend of the "Fourth Industrial Revolution" which is happening before our eyes - Industry 4.0. Now we live in the era of the end of the third digital revolution where the characteristic features are the development of information and communication technologies, automation and robotization of production processes. Characteristic features of Industry 4.0 are fully automated productions where all processes are controlled in real time taking into account changing external conditions.

The conveyor belt is one of the areas that need to be prepared for the implementation of Industry 4.0 (smart conveyor). Because of the introduction of basic technologies of Industry 4.0 on the conveyor, there are many advantages, some of them: preventive maintenance, information exchange is used between not only people but also devices, sensors, data exchange and information processing without human intervention, machine tracking algorithms, etc. The use by factories of transport systems that can make smart decisions that track, sort, combine and accumulate products is very justified and logical. Thus, they can provide all the necessary information to monitor the overall efficiency of equipment, sensors and key performance indicators.

Cyberphysical System (CPS) is the operational basis of Industry 4.0. It combines two key components of the Internet of Things (IoT) and the Internet of Services (IoS). In particular, CPS in combination with IoT and IoS creates the basis for Industry 4.0. This combination can be understood as a network in which different information is constantly processed by various powerful software tools and specializes in user interfaces.

A smart conveyor is a CPS consisting of a conveyor of any type that performs two-way data transmission. Then the data is transmitted in a compatible form and depending on the operation of the smart-conveyor, the data is processed and evaluated in a suitable system. This process aims to obtain a wide range of different indicators that provide information about the belts of the conveyor process. Based on the obtained and evaluated data, control sequences can be generated using an expert control system. Then they are sent back according to the communication interface with the conveyor control unit. Intelligent conveyors with IoT functionality have tools that allow you to replace preventive maintenance with preventive. Maintenance personnel will not need to turn off the conveyor surfaces to inspect them. Instead, arrays of sensors monitor online equipment. With enough information, smart pipelines can begin to predict when and where equipment may fail allowing businesses to anticipate problems before they shut down systems. Smart conveyors in these automated settings minimize quality control problems to obtain the most homogeneous product as well as increase productivity through smart conveyors [1].

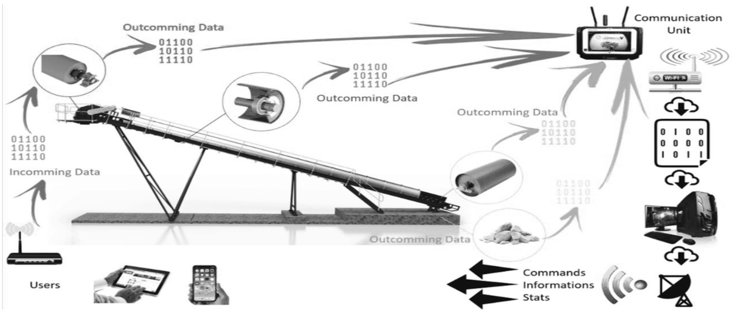

Fig. 1 – Smart conveyor [1]

A belt conveyor is a fast and convenient way to transport material from one place to another. In addition to transportation, conveyors perform unloading and loading functions and important structural units in warehousing operations [2]. An example of the use of conveyor systems is the international company BEUMER GROUP, which specializes in the development and production of systems for transportation, loading, stacking, packaging, sorting and distribution. Examples of installations using conveyor systems you can see in figure 2.

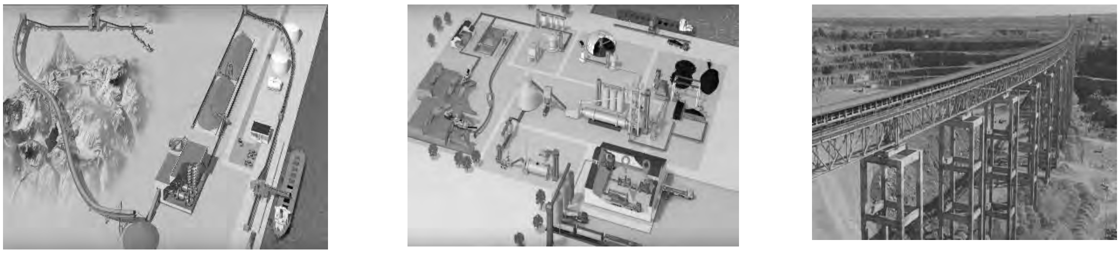

Fig. 2 – An example of a company's conveyor systems BEUMER GROUP [3]

Many examples using the conveyor can be given abroad, the length of transport routes can exceed 100 km and continues to increase. To increase the reliability of transport routes are divided into sections, the technology of transportation of material which provides a length of up to 20 km. Common world practice shows that the conveyor is an efficient and environmentally friendly way to supply raw materials.

2.1 Model using a neural network in modeling a marine smart conveyor

Models using neural networks are a very promising class of models for designing highly efficient control systems for a distributed dynamic conveyor-type transport system. The main models used to design optimal control systems for the parameters of the flow of the transport conveyor are numerical methods. Based on the review of conveyor-type transport systems it can seen that most systems are very large, multi-section, causing significant difficulties and requiring significant computing resources. In such cases, it is appropriate to use a neural network model as it significantly speeds up the entire calculation process. Neural network learning is a major factor in determining the quality of a model. Qualitative training of a neural network capable of modeling a specific transport system requires the collection of relevant data in large quantities. Artificial neural networks are the simplest definition of the human brain and the building blocks are neurons. In multilayer artificial neural networks, there are also neurons located similarly to the human brain. Each neuron is associated with other neurons with certain coefficients. During training information is distributed to these connection points, so that the network learns [4].

The most important advantage of control systems based on neural network models is that the response time of the control system is much less than for numerical models. A model using a neural network can be successfully used to describe multi-section pipeline systems if data are available for neural network training [5]. Similarly, the advantage of using an artificial neural network is that the information is stored throughout the network, rather than in a database. The disappearance of several pieces of information in one place does not interfere with the network. The neural network is able to work with incomplete knowledge: after learning an artificial neural network, the data can give results even with incomplete information. If one or more cells are damaged, the neural network does not interfere with the generation of the output signal. This feature makes networks fault-tolerant. If we talk about the memory of the neural network, it is distributed: in order for the network to learn, it is necessary to identify examples and train the network in accordance with the desired result, showing these examples in the network. Another advantage is the possibility of parallel processing: artificial neural networks have a numerical force that can perform more than one job at a time [4].

However, there is a downside to using neural networks. One of the main disadvantages is the hardware dependency. Artificial neural networks require processors with parallel computing power according to their structure. An important problem of an artificial neural network is the incomprehensible behavior of the network. When a network develops a solution for research, it does not give clues as to why and how, and this reduces trust in the network. There is no specific rule for determining the structure of artificial neural networks. The appropriate structure is achieved through trial and error. Another disadvantage is that the duration of the network is unknown: the network is reduced to a certain value, an error in the sample means that the training is completed. This value will not give us optimal results [5].

All the above advantages and disadvantages of neural networks and the problems that arise during their use are very relevant today. All the disadvantages of artificial neural networks are developing in the field of science that will be eliminated in the future, and their advantages are growing every day that means that artificial neural networks will become an integral part of our lives, which is becoming increasingly important. Despite the shortcomings of the artificial neural network this paper develops a neural network model for a multi-section pipeline to predict flow parameters.

IV. RESULTS

To analyze the learning process of the neural network, the order of data for learning is recorded. This allowed for multiple repetitions of training with different network parameters and to compare the effect of changing parameters. The weights were initialized by random values in the range $[0.0;1.0]$ c uniform distribution density. The learning process for some variants of the parameters reached 279,000 epochs (so-called one iteration in the learning process). Characteristics are used as input nodes of the neural network for modeling the transport system $\gamma_m(\tau)$, $g_m(\tau)$ input sections 1, 2, 4, 5 at intervals $0 \le \tau \le T_k = 100$.

In the course of the experiments, calculations were performed for 1, 2, 4 and 5 sections. A study was also conducted when the input sections were: a) 1 and 2, the output – 3; b) 1, 2, 4 and 5, initial – 6; c) 1, 2, 4, 5, output – 7 and 8. Number of hidden layers – 20. Type of functions of flow parameters $\gamma_m(\tau)$ i $g_m(\tau)$ for the input sections for the time interval $0 \le \tau \le 2$ shown in figure 3 and figure 4.

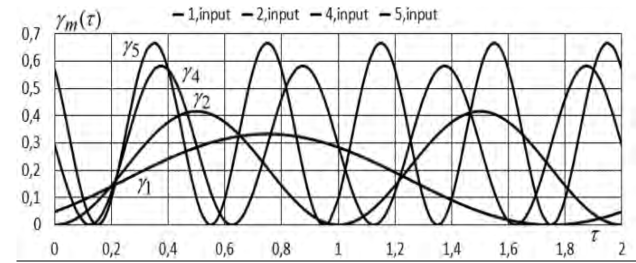

Fig. 3 – Type of material flow function $\gamma_m(\tau)$ at the entrance of sections

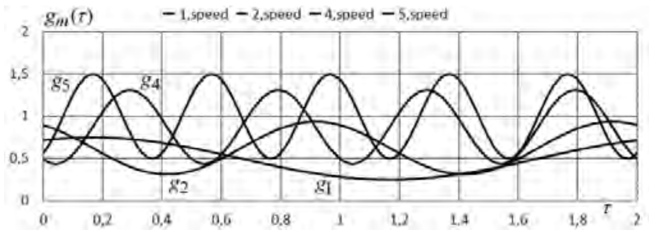

Fig. 4 – View of the belt speed function $g_m(\tau)$ of sections

4.1 The results of predicting the flow parameters of the marine smart conveyor using a neural network

According to formula 3.3, the minimum errors were found for each study:

$MSE_1 = 0{,}0026$; $MSE_2 = 0{,}0026$; $MSE_3 = 0{,}0068$;
$MSE_4 = 0{,}0096$; $MSE_{1,2\_3} = 0{,}0023$; $MSE_{1,2,4,5\_6} =$
$MSE_{1,2,4,5\_7,8} =$ $0{,}2338$;
$0{,}2240$.

You can see the difference, for example, between MSE1 and MSE4. MSE4 is larger, indicating the presence of peak values of the output stream. Characteristics are used as input nodes of the neural network for modeling the transport system $g_m(\tau)$ input sections 1, 2, 4 and 5 on the interval $0 \le \tau \le T_k = 100$. Predicting the values of the output flow parameters for sections 1, 2, 4, 5 is presented in figure 5.

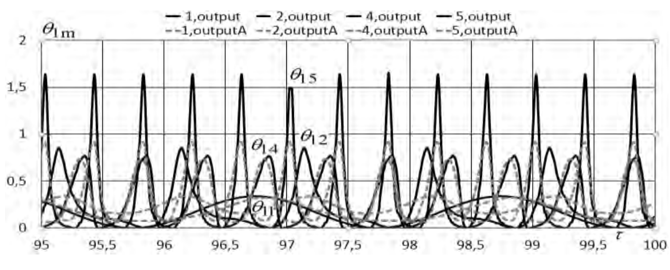

Fig. 5 – Calculation of the initial material flow $\theta_{1m}(\tau,\xi_m)$ m - th using a neural network

In figure 6 shows the calculation of the material flow of the 1st and 2nd sections, the source – the 3rd. In figure 7 calculated the material flow of sections 1, 2, 4 and 5, at the output 6 and 7.

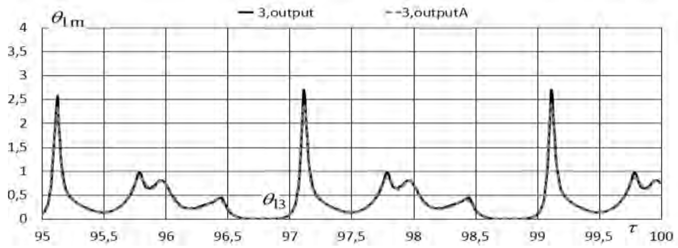

Fig. 6 – Calculation of the initial material flow $\theta_{1m}(\tau, \xi_m)$ 3rd using a neural network

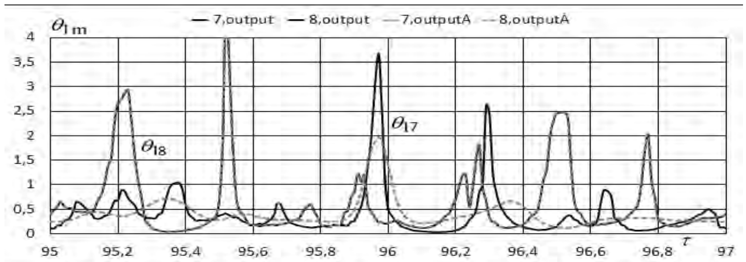

Fig. 7 – Calculation of the initial material flow $\theta_{1m}(\tau, \xi_m)$ 7th and 8th using a neural network

The value of MSE for each subsequent section increases. The exception is the last 2 experiments. For these sections, the prediction error remains approximately on the same level as the prediction error of the previous section. Probably, this is because the flows after the sixth section diverge, and the total forecasting error decreases accordingly.

V. CONCLUSIONS

Industry 4.0 has ceased to be just a concept addressed to a narrow range of industrial areas. Such areas include the transportation of materials by different types of conveyors. The priority is to find ways to implement and use Industry 4.0 for smart pipeline issues, and the main goal is to make work easier and more efficient. Large conveyor transport systems were inspected. The need for modeling of these systems is considered. The use of neural networks and their architecture, the main advantages and disadvantages for predicting a smart conveyor to ensure the functioning of cement, asphalt plants, etc. are considered. Neural network models were considered to create the smart pipeline of the future.

An information model for predicting the flow parameters of a smart conveyor is proposed. The analysis of the model using the neural network and the corresponding calculations are carried out. The results of the analysis of the neural network model show that the neural network is a good tool for predicting control systems for the output flow parameters of the smart pipeline. Especially effective when the conveyor consists of a large number of individual sections. The forecast model allows to determine the peak values of the transport system parameters. In addition to the main purpose of the work, the method of estimating the value of the duration of the transition period, forecasting parameters for multi-section transport systems is additionally given. Analysis of the experiments shows that the reduction of prediction error can be achieved by including additional sensors which are the speed of the conveyor belt.

An important result of the research is the conclusion that this information model using a neural network is appropriate and successful in the use of conveyor-type transport systems because it successfully copes with the task – forecasting flow parameters. The assumptions obtained during the experiments can be considered a prospect for further research to improve the forecast of the smart pipeline.

VI. REFERENCES

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