The use of ANN in improving efficiency and ensuring the stability of the copper ore mining process

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The aim of the article is to propose a concept for controlling the loading and haulage process and copper ore in a mine with a pillar-chamber system. An appropriate method of control should ensure the production level assumed in the production plan at the lowest costs of the process. It is important to properly select the cost account showing the impact of cost factors (variable parameters) on the total costs of the process. In the presented concept, it is proposed to build an SSN model which will allow for such control of the rigs and haulage process, so that the process remains stable in the assumed period and the economic result is as large as possible. The process will remain stable if the extraction volume is consistent with the volume planned in the production plan. In addition, process control will be aimed at ensuring the lowest total costs of rigs and hauling off the output. The decision model proposed in the article will enable quick decisions to be made, allowing for the implementation of production plans while ensuring the criterion of production efficiency. Optimization of processes often leads to problems where there is a need to resolve the issues of process evaluation based on more than one objective function. The proposed solutions have been adapted to mining systems operating under the conditions of a given enterprise.

Key words: *ANN, process costs, process efficiency, controlling the loading and haulage process of the output*

Introduction

Currently, the costs of copper production in Poland in comparison to the competition are high and are constantly growing. In order to join the group of large global copper producers, one of the strategic pillars is the improvement of efficiency aimed at reversing the trend of rising costs by investing in new technologies, modernizing infrastructure, optimizing processes and organizing production (Gwiazda et al., 2017; Azadegan et al., 2011; Wirth et al., 2016). The high unit production costs of copper ore to a large extent result from organizational and process inefficiencies (Tworek et al., 2018). Cost savings can be found, in the proper management of mining processes, among others. The concept of controlling the loading process and copper ore presented in the article ensures, on the one hand, the stability of the process, and the lowest mining costs on the other.

The concept of stability is derived from the systems theory. Most definitions found in the literature refer to the concept of the state of balance and define the stability of a system as its ability to return to the state of balance after the disturbances that caused the instability has ceased. The stability of a control system is its most important feature that characterizes the ability to accomplish the tasks, for which it has been built (Bubnicki, 2005, Janson and Jurenoks, 2012).

If the value of the parameter $P(t_i)$, which characterizes the production system at the time t_i is within the predetermined interval $P1 \leq P(t_i) \leq P2$, this will indicate a correct course of the process. Otherwise, corrective measures should be taken. Corrective measures usually consist in changing the values of control variables (inputs to the system) in such a way, so that the values of the parameters characterizing the controlled variables (outputs from the system) return to the process course standards established at the planning stage (Bubnicki, 2005). Production plans and parameters characterizing them usually constitute the standards. A correct decision will cause the system to return to the steady state (Krenczyk et al., 2017).

It can be said that a production system is in the steady state if values of the parameters defining it are within the ranges specified in the planning function and recorded in a standard, that is, a production plan, as schematically shown in Fig. 1.

On the one hand, it is necessary to ensure the stability of production processes and, on the other hand, low production costs in order to ensure the company's competitiveness (Fusko et al., 2017). This statement seems particularly important in relation to mining processes characterized by high volatility and uncertainty due to variable and unpredictable environmental conditions (Dohn et al., 2014; Litwin et al., 2017; Tahir et al., 2015). These processes are unstable and cost-intensive, and controlling them is very difficult.

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The aim of this study is to comprehensively present the concept of controlling the loading and haulage process in the copper ore mining process ensuring the stability of this process while maintaining the appropriate level of costs, and as a result, striving to improve its efficiency.

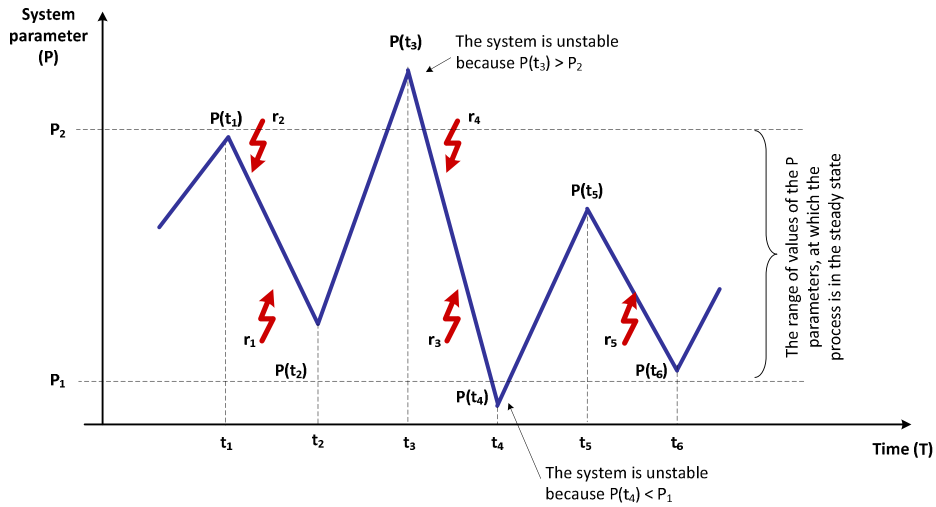

Fig. 1. The variability of the system parameter $P(t_i)$ is caused by the impact of disturbing factors (r_i) (Burduk, 2015).

The solution to this problem requires:

- determination of operating costs for the exploitation process, taking into account the cost-generating factors of the so-called variable input parameters that will comprehensively manage these costs,
- building an SSN model that enables controlling the loading and haulage process, while maintaining stability in the assumed period,
- proposing a model for the optimization of this process according to extraction criteria as a function of many variables and the total cost of the process also as a function of the same variables with constraints on the stability and limit (acceptable) cost of this process,
- determining the optimal process efficiency, which will enable obtaining knowledge of the value of cost factors (input parameters) depending on the size of the output as a function of many variables set by the artificial neural network.

Application of artificial neural networks (ANN) in control of a production system

Neural networks are modern computational systems that process information based on phenomena occurring in the human brain. The neural network is a mathematical model, consisting of a network of computational nodes called neurons and their connections. In addition, it has the ability to learn. Artificial neurons, like their natural counterparts, are connected by means of connections whose parameters (weights) are modified in the so-called learning process. Input signals, being data from the production process, are processed by the network and outputted as a solution to the task. Most networks have a multi-layer structure, with the input and output layers and the so-called hidden layers stand out. This means that SN can be treated as so-called black boxes, capable of solving the problem under investigation with greater accuracy than classical methods, without the need to understand all relations between elements of the system. In the mathematical sense, the neural network is a universal approximator of the functions of several variables and performs non-linear functions on the form (Barron, 1994):

$$y = f(x), \tag{1}$$

where x is the input vector, and y is the performed vector function of many variables.
They can be used to map complex relationships between input signals and selected output signals with a high probability of success, without the need to build complex mathematical models.

The primary objective of modeling the dynamics of a production process is to identify the temporal variability of its physical quantities or states (Azadegan et al., 2011; Bozejko et al., 2012). To this end, a time series, that is, an ordered sequence of values of a certain variable over time should be determined. A time series may have a form of the vector $y(t_1), y(t_2), \dots, y(t_N)$. Due to the fact that process parameters may differ in individual phases of the process, the time series vector can take the form of a vector defined in N-dimensional space. Individual components of this vector will be the states of the production process stages in the past, which in turn can be regarded as points in multi-dimensional output space. Thus the task of analyzing the temporal variability of the production process can be reduced to searching N-dimensional space for a certain trajectory, on which the analyzed output variable of the process "moves". Thus, a given quantity in the form of a time series is determined in order to predict its value in future moments.

A unidirectional neural network can describe the regularities occurring in a time series and allows predicting its future values. Future value of the time series $t(t+1)$ is usually predicted on the basis of the current value and "k" past values y of the series, as well as the current value and "l" past values of input variables x according to the formula:

$$y(t+1) = f(y(t), y(t-1), \dots, y(t-k), x(t), x(t-1), \dots, x(t-l), w). \qquad (2)$$

Unidirectional multilayer networks (without feedback) are used in over 80 % of all applications of neural networks (Barron, 1994). Fig. 2 shows a list of input and output data used in ANN models.

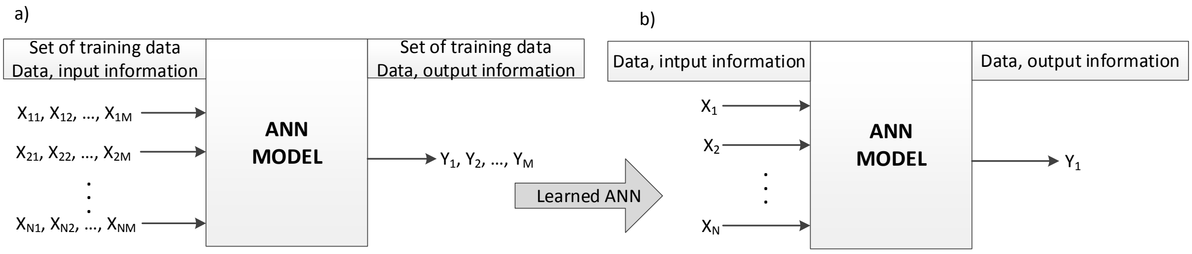

Fig. 2. List of input and output data in models of artificial neural networks a) network learning, b) conducting experiments.

Artificial neural networks are usually used to solve problems associated with the approximation, interpolation, prediction, classification, recognition, and control (Burduk, 2015; Rojek et al., 2012). Image recognition, which also includes classification, grouping, and processing, accounts for approx. 70 % of all industrial applications. In the management and operation of production systems, artificial neural networks are more and more often used for control of production processes, robots, analysis of manufacturing problems, diagnostics of electronic systems of machines, selection of personnel and input materials, optimization of the business activity, waste disposal, robot movements, planning overhauls of machines, forecasting of costs (Burduk and Jagodziński, 2015; Rojek et al., 2012).

Artificial neural network models can be used to control the production system, and thus to ensure its stability. The ease and speed of their construction make them a very useful tool. A large amount of data needed in the network learning process remains to be the only problem, which, however, in the era of the universality of information systems, parameterization and standardization of production processes cease to be a problem (Gola and Kłosowski, 2018; Furmann et al., 2017).

Application of the ANN model to ensure the stability of the copper ore mining process

The purpose of building the ANN model is to ensure such control of the copper ore (that is, an output) rigs and haulage process so that the process remains stable in the assumed period. The control will consist of an adequate selection of parameter values for process inputs in order to obtain an output value (that is, the production volume) consistent with the predetermined production plan. The process will remain stable if the production volume is consistent with the volume set in the production plan.

General characteristics of the production system

The study was conducted in one of the mining companies located in Lower Silesia, Poland. The mine, for which the neural network was built, covers an area of 158 km^2 underground, while mining operations take place at a depth from 610 to 850 m. One of the mining divisions of the mine (G-1 division) was selected for the analyses. The G-1 branch extracts copper ore from two mining fields XXIII/1 and XXIII/2. Machines operating in this branch are serviced by a heavy machinery chamber (KMC) C-2B. Fig. 3 shows a fragment of the mine map with the G-1 branch area marked out, roads followed by machinery from the heavy machinery chamber to mining fields and roads where copper ore is transported.

The operation process is the main process in the entire mining system, in the mine in question, it takes place in a pillar-chamber system, which means that the preparation of the field for operation consists in making pavements and excavation corridors. This is dictated by ventilation and transport considerations. The excavation corridor enables bringing large amounts of air into the operating fields, which is necessary due to the high primary temperature of the rocks and the combustion machines used in the operation process. The pavements enable organizing the movement for mining machines and the separation of the output route for haulage removal with conveyor belts.

The operation process consists of the following stages: encasing, drilling, blasting, rigs, and haulage, horizontal and vertical transport. The operation process consists of the stages described below, which run cyclically. The process itself takes place in many places simultaneously, in many fields of extraction in various parts (faces).

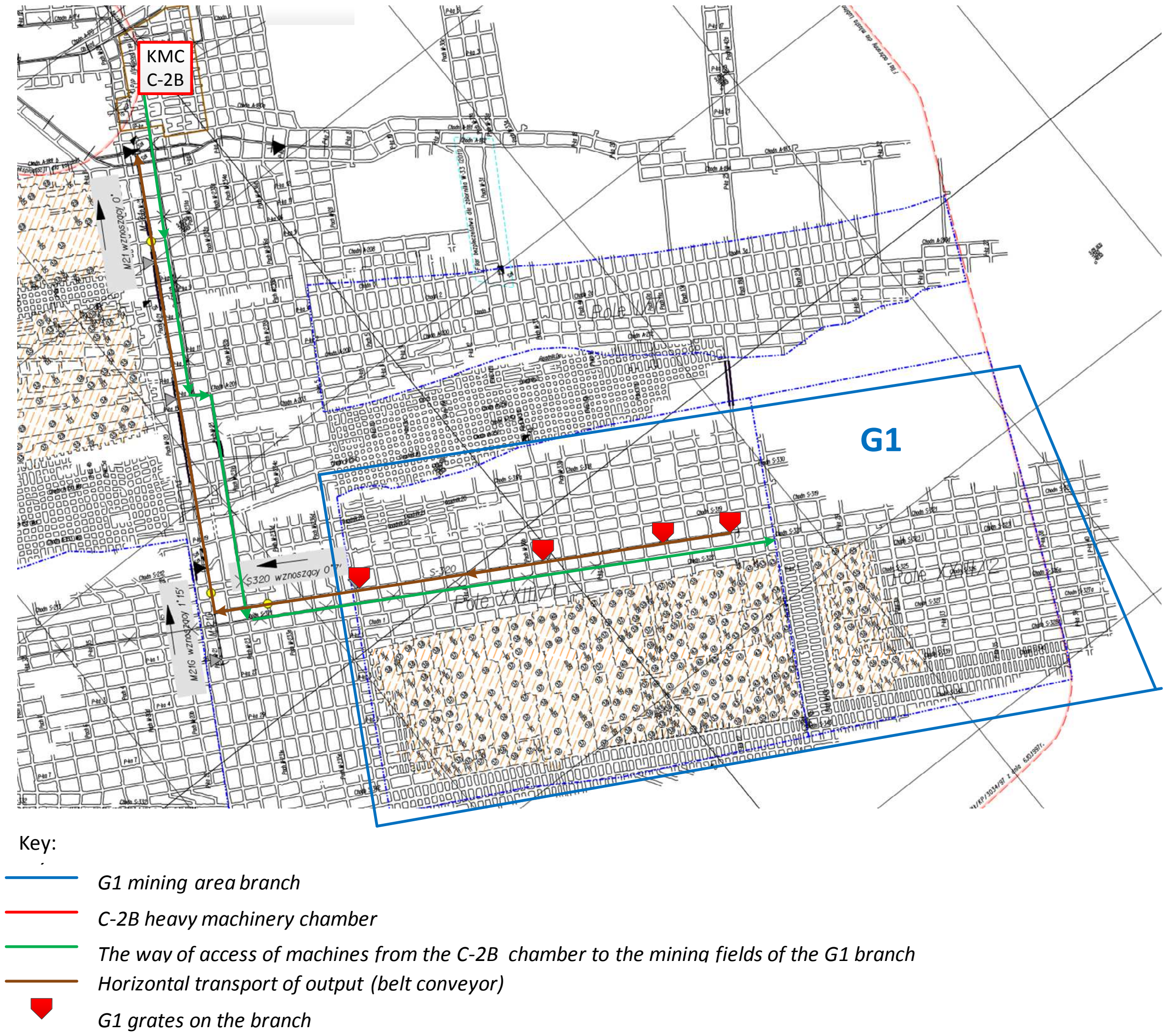

Fig. 3. Diagram of the G1 mining branch.

Enclosing consists in securing the selected space with the ceiling securing the roof with anchors. The purpose of this process is to protect the selected space for further stages of the operation process involving people and machines. If the copper content in the deposit is too small, then further exploitation becomes unprofitable, and the selected space is liquidated.

The aim of the drilling process is to make blast holes, to which an explosive will be fired in the mining sub-process. Drilling is performed using the so-called self-propelled drilling rigs (SWW) and consists in making blast holes in the deposit to a depth of about 3 m. The number of holes varies and depends on the type of rock. Then in the blasted holes, with the help of self-propelled rigs (SWS), an explosive is fitted. Blasting is performed twice a day, that is firing the fitted explosives.

The purpose of the rigs and haulage process is to transport the blasted copper ore to the transfer point (so-called grid). A set of three machines is usually involved in the loading and haulage process: excavator/loader (ŁK) and two haulage rigs (WO). Due to the necessity of maneuvering, the rigs of the WO takes place in the chambers closest to the blasted face. Due to the conditions of work, machines are subject to frequent breakdowns and failure. Availability is the basic parameter that measures the use of machines in the process. Accessibility is calculated as the ratio of time in which the machine worked in the process to the time which it was in repair, service, or failure. The average availability for the WO in the analyzed period was 60 %, and for ŁK-2 it was 70%.

The next stages of the mining process consist in transporting the output, first with the help of belt conveyors, and then with the rail transport to the so-called skip, or mining shaft, in which the output is transported to the surface from where it will go to the ore processing plant. Between the consecutive stages in the transport process, there are so-called pouring points, output weights, and retention tanks. Storage reservoirs are buffers protecting the process of supplying ore to ZWR against disturbances and are equivalents of warehouses in typical production processes.

In the operation process, the added value is generated, and a product is created (properly fragmented copper ore) for the external customer, which is an ore processing plant. The process of loading and haulage the output was selected in order to present the concept of control of the mining process, allowing to ensure the stability and economics of extraction.

Characteristics and cost analysis of the loading and haulage process

The rigs and haulage process is one of the most important processes in the mining process. Its purpose is to move the ore from the mine face to the grate, where the ore is crushed and discharged onto a belt conveyor. Main stages of this process are shown in Fig. 4.

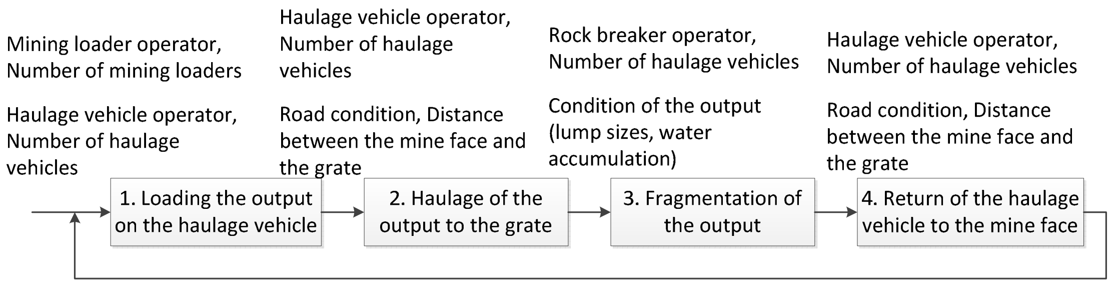

Fig. 4. Main stages of the rigs and haulage process.

1. Rigs the output onto a haulage vehicle. This operation is performed with the use of a mining loader in the mine face and consists in rigs a haulage vehicle with copper ore. Fig. 5 shows the model of rigs the output onto a haulage vehicle saved in BPMN notation.

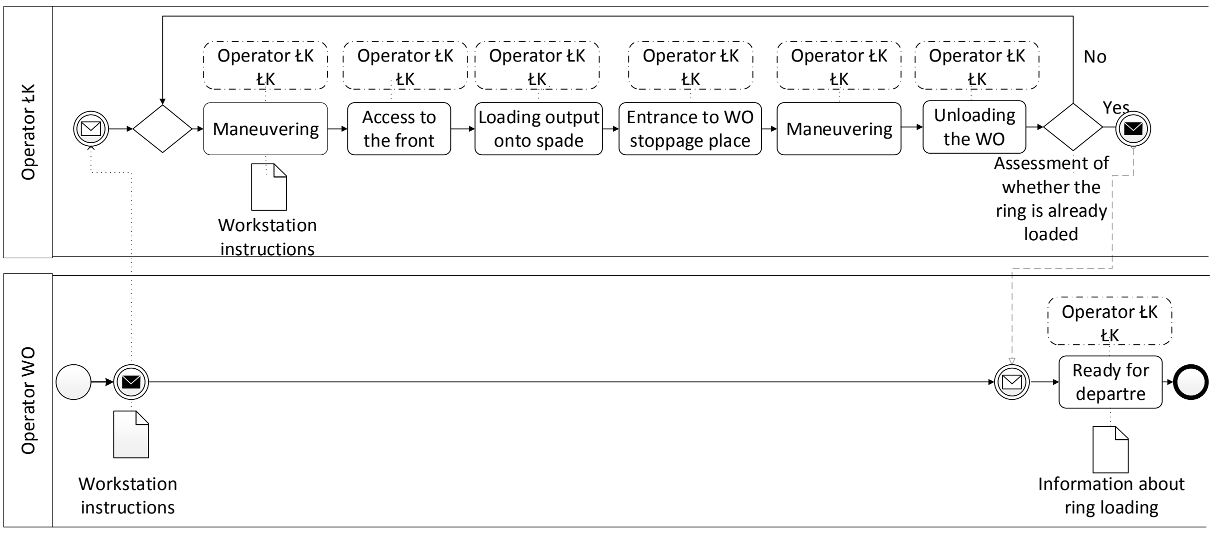

Fig. 5. Model of rigs the output onto a haulage vehicle saved in BPMN notation.

2. Haulage of ore to the grate. The haulage vehicle, after having been loaded, goes to the discharge point (grate). Haulage roads may have a different inclination angle, while their condition may vary depending on the type of rocks forming the road. If the rocks are fairly soft, the road becomes muddy over time and ruts are formed in it. As time goes on, the transport on such a road becomes more and more difficult and therefore longer.
3. Unrigs the output on the grate. The grate is located over the belt conveyor and is a discharge point, where the transport of the copper ore to the ore enrichment plant is started. Its role consists in adequate fragmentation of the output and retaining all impurities, such as metal anchors, props and other elements

that could damage the belt conveyor. There are four grates on the analyzed G-1 branch (Fig. 3). The method of unloading the WO on the grating, recorded in the BPMN notation, is shown in Fig. **6**.

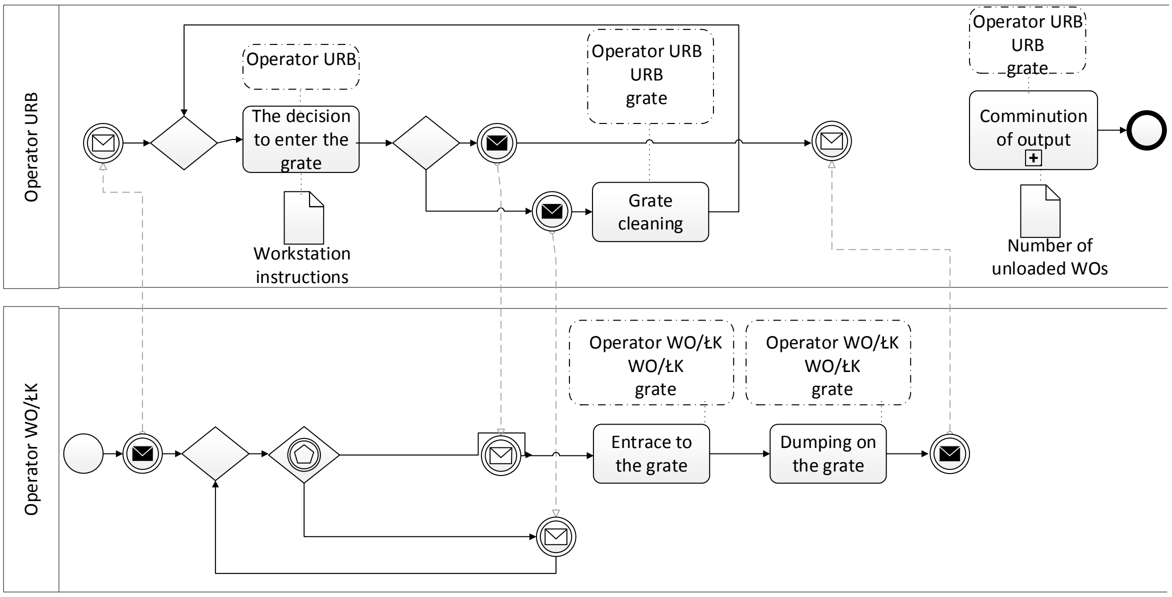

Fig. 6. Model of the process of unloading the WO on the grate recorded in the BPMN notation.

4. The haulage vehicle goes back to the mine face to be loaded again after having been unloaded on the grate.

In order to consider the mining process to be stable, it should deliver the established amount of copper ore to ore enrichment plants. Since the haulage vehicle has a constant and limited capacity (20 t), the amount of the ore getting to the processing plants depends on the number of haulage rigs unloaded on the grate. The shorter the time of the rigs and haulage process, the more haulage rigs can be unloaded on the grate during a work shift. The time of the rigs and haulage process depends on many factors and directly affects the total costs of this process.

The production cost model is based on the activity-based costing method for the operation process. The application of the calculation of costs of operations, including cost factors, that is, such process parameters that unambiguously determine the value of variables of separated cost components, enables a significant reduction of costs at the operational stage, which actively influences the cost planning in the future. The first stage in determining production costs is to determine the value of cost components, that is, the costs of direct operations comprising the cost of the operating process. On the basis of information available in financial and accounting systems about costs incurred in previous periods, information on the existence of separate activities in the mining system example specified the costs of direct operations. Having calculated the costs of direct actions and specific measures of the volume of processing of these operations, the rate of costs of individual actions that is, the so-called unit cost of operation can be calculated (Więcek and Więcek, 2018). The activities, their structure of operating costs of the loading and haulages process, and the calculated cost rate are presented in Tab. 1. In this table, the individual operational cost items were scaled in relation to the actual values due to the protection of information, which were given in unit costs (uc).

Tab. 1. Costs of the loading process and output disposal.

Operation	Cost structure	The unit cost of operation
Loading	- operating costs of the loader operator - amortization of the charger - consumption of materials (fuel) - costs of planned maintenance - indirect costs (including supervision, consumption of auxiliary materials, insurance costs, costs of failure)	10 [uc/loading]
Output haulage	- operating costs of haulage operators - amortization of haulage rigs - consumption of materials (fuel) - costs of planned maintenance - indirect costs (including supervision, maintenance costs, consumption of auxiliary materials, insurance costs, costs of failure, maintenance and maintaining the corridor)	30 [uc/haulage]

During the observation of the charging operation, it was noticed that its cost depends partly on the road of the loader. This road can be from 3 to 30 meters, and it is a variable cost component (kzj). Regardless of the route being traveled, in each case, the loader operator performs maneuvering in the place of the face and maneuvering in the parking place of the haulage rig, and this part of the cost is of a permanent nature (Ks).On the basis of measurements of loading time, change of unit cost depending on the route x_1 can be recorded using the linear function (3).

$$K_l = k_{zj} \cdot x_1 + K_s = 0{,}012x_1 + 0{,}64. \quad (3)$$

The same applies to the cost of delivering the output to the grate, which takes place on the designated roads. The distance of x_2 haulage can vary and depend on the place of loading and the place of the grating, for which permission to enter was obtained. The cost depending on the distance has the character of a variable cost (kzj). The coefficient of this cost reflects the time of the transport of the output and the time of returning the rig from the grate to the face. A fixed part of this cost (Ks) is the time of loading the output onto the rig, as well as the time of entering and pouring the output on the grate. On the basis of observation and measurements of the time of this operation, the change of its unit cost from the transport path is presented by the function (4).

$$K_h = k_{zj} \cdot x_2 + K_s = 0{,}005x_1 + 0{,}55. \quad (4)$$

The cost of output disposal also depends on the condition of the road, which may have a different angle of inclination and a different condition depending on the rocks forming it. The state of the d path is a discrete variable that takes values from the set $\{1,2,3,4\}$. It affects the function of the cost of the haulage through the parameter k_d accepting values:

- 1 for $d = 1$ - the advantage of an even and dry road,
- 1,4 for $d = 2$ - the advantage of an even and wet road,
- 1,2 for $d = 3$ - the advantage of an uneven and dry road,
- 1,6 for $d = 4$ - the advantage of an uneven and wet road.

When analyzing process stability depending on the route of the loader x_1, the route of the rig x_2, condition of the road d and crate number k different variants were generated W and a change of input attributes. The charger has a medium lifting capacity of 4 tonnes, and 20 tons for two two-way haulers. The total cost of loading and hauling for a given variant, depending on variables x_1 and x_2, taking into account the expected extraction n, which is a function of $x_{1,}x_2$ set by the artificial neural network, can be determined according to the formula (5).

$$K_{lh} = \frac{n}{4}(0{,}012x_1 + 0{,}64) \cdot 10 + \frac{n}{20}(0{,}005x_2 + 0{,}55) \cdot k_d \cdot 30. \quad (5)$$

Method of building the neural network

The elements that interfere with the loading and hauling process, apart from mining machinery failures, are variable ambient conditions. They cause that the transport time of the output and the time of the return of WO from the grate to the face is very different. The loading and unloading time depends mainly on:

1. The condition and length of the transport route from the face to the grating. The condition of the road is affected by the type of rocks on the floor, slope angle, and condition of wailing. Heavy road transport causes that after some time ruts are formed, and the mud layer reaches up to 80 cm.
2. Time of WO loading by ŁK. This parameter depends to a large extent on the way the loader must go from the place where the ore is located to the standstill point of the hauler. The rigs are loaded in Figure 2 chambers, that is, places where the corridors cross between the pillars. This route can be from 3 to 30 m.

These parameters, as well as the grate number, were selected as independent variables when building the ANN model, as presented in Fig. 7.

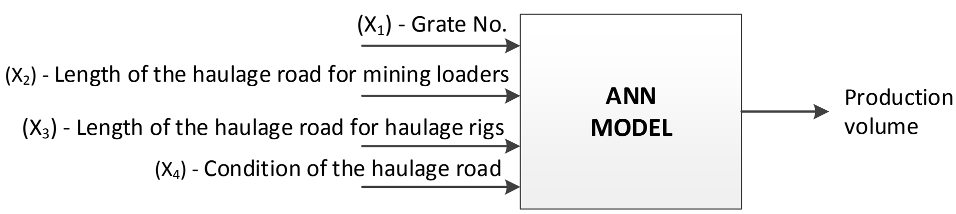

Fig. 7. Independent variables and the dependent variable used to build the ANN model.

In order to predict the amount of the excavated ore under the rigs and haulage process in the G1 division, at the assumed input values, a unidirectional neural network (perceptron) was built. The results of observations and measurements of times in the rigs and haulage process were used as the learning data set. In total, 211 measurements were made for 20 days, in 3 work shifts. The measurements were made by shift foremen with the use of forms prepared especially for this purpose. Four values have been introduced to describe the road condition:

1 - mostly even and dry road,
2 - mostly even and wet road,
3 - mostly rough and dry road,
4 - mostly rough and wet road.

The experiment was performed in the SAS Enterprise Miner 6.2 environment. The first step was to investigate the correlation between independent variables and the dependent variable. The results containing the correlation value are shown in Tab. 2.

Tab. 2. Values of the correlation between variables.

Independent attribute (variable)	**Correlation value**
Grate No.	-0.06787
Length of the haulage road for mining loaders	0.01009
Length of the haulage road for haulage rigs	-0.32767
Road condition	-0.07535

The obtained results indicate that it is pointless to use a linear regression method (absolute values of the correlation are below 0.5) for the analyzed problem. Therefore it is justified to use neural networks which form non-linear regression models.

As a part of further experiments, a model of a multilayer perceptron network was built, for which the number of neurons in the hidden layer was changed. In order to confirm the results of the correlation analysis, a neural network based on the generalized linear model was also built. Fig. 8 shows a screenshot of the SAS Enterprise Miner program 6.2 with models built in it.

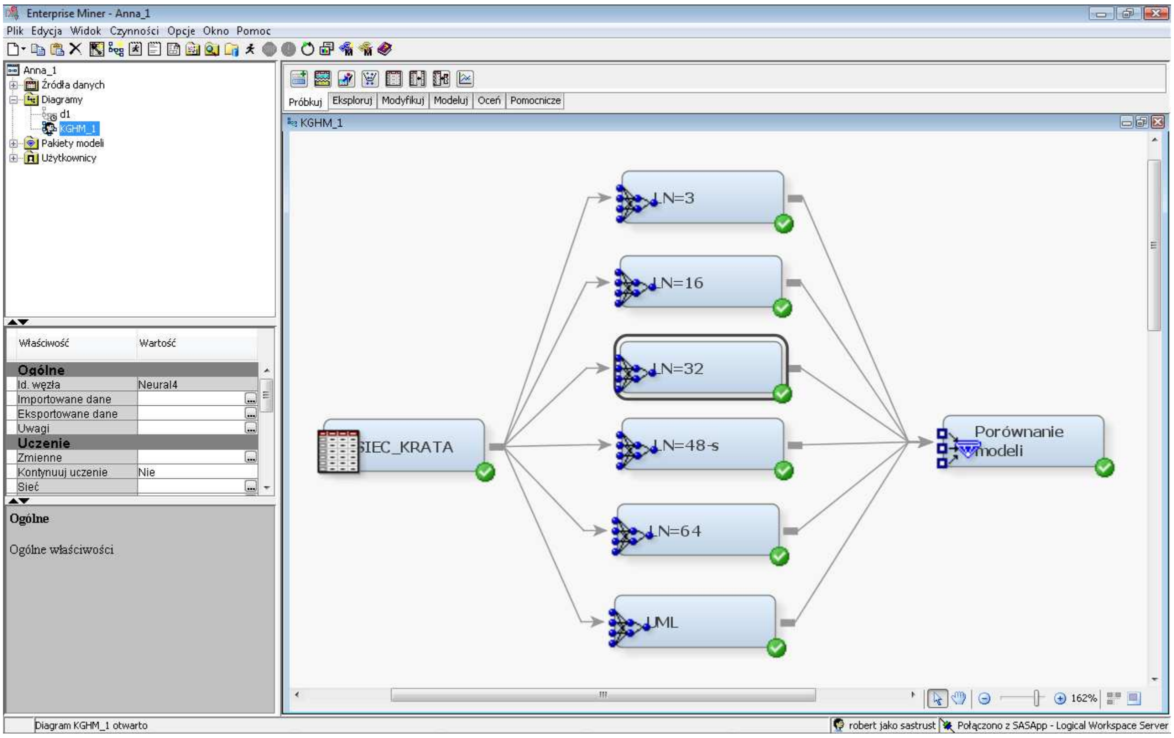

Fig. 8. The SAS Enterprise Miner 6.2 environment with models of neural networks covered by the analysis and their comparison.

For the neural network models built, a series of experiments for a different number of independent variables was conducted. The purpose of these experiments was to establish for which combination of independent variables the neural network will determine the value of the output in the best way. When building the models, different numbers of independent variables were considered. Their selection was dictated by previous experiments, that is, it depended on the absolute value of the correlation (Tab. 3). In experiment No. 1, all input attributes are used, while in experiment No. 2 the attribute "Length of the haulage road for mining loaders" (the lowest absolute value of the correlation) was discarded. In experiment No. 3 the attribute "Grate number" (the next lowest absolute value of the correlation) was discarded in addition. The results are presented in Tab. 3, where the values obtained represent the network selection criterion, that is, the mean square error. These results concern the analysis of the input data set, which was also used for the network training process.

Tab. 3. Results of the experiments conducted with the use of a neural network

Neural network model	**Mean squared error**		
	Experiment No. 1	**Experiment No. 2**	**Experiment No. 3**
MPN – NN=3	1228.59	1643.71	2375.39
MPN – NN=16	1072.43	1369.98	1851.50
MPN – NN=32	427.08	866.69	1033.93
MPN – NN=48	327.15	764.22	1019.25
MPN – NN=64	348.80	772.59	999.05
GLM	2440.74	2450.18	2537.86

Where:
MPN - a multilayer perceptron network,
NN - number of neurons in the hidden layer,
GLM - generalized linear model.

The analysis of the results confirms that linear models are not suitable for resolving this problem. In the case of each experiment, the worst results (with the highest mean square error) were obtained for a neural network built according to the generalized linear model. The best results were obtained for a multilayer perceptron network with 48 neurons under experiment No. 1. This neural network model was used for further experiments.

Determination of the stability of the rigs and haulage process with the use of a neural network with 48 neurons in the hidden layer

The selected neural network model was used to determine the stability of the process of ore mining in the G1 division. For this purpose, test data were prepared, and the "score" node of the SAS Enterprise Miner 6.2 environment was used.

The test data contain various variants of changes in input attributes (independent variables). For such data, the selected neural network model predicts the values of the output, which are interpreted in the context of the stability of the mining process. Sample test data, along with the predicted production volume, are presented in Tab. 3, Tab. 3, and Tab. 3. The planned output volume was set at 330 t. For the needs of the study, an assumption was made that the ore production is stable if the absolute value of the variation in the production does not exceed 20 tonnes. This corresponds to unrigs two haulage rigs per shift. Tab. 4 shows the production volume predicted by the ANN model depending on the length of the haulage road.

Tab. 4. Predicted production volume for the grate No. 1, the road for mining loaders 70m and road condition 2 at variable lengths of the haulage roads.

Network inputs				**Network outputs**
Gate No.	**Road for mining loaders** [m]	**Road for haulage rigs** [m]	**Road condition** [m]	**Anticipated output** [t]
1	70	900	2	350
1	70	1000	2	335
1	70	1100	2	315
1	70	1200	2	268
1	70	1300	2	240

The data included in Tab. 3 presented in the context of the process stability, are shown additionally in Fig. 9.

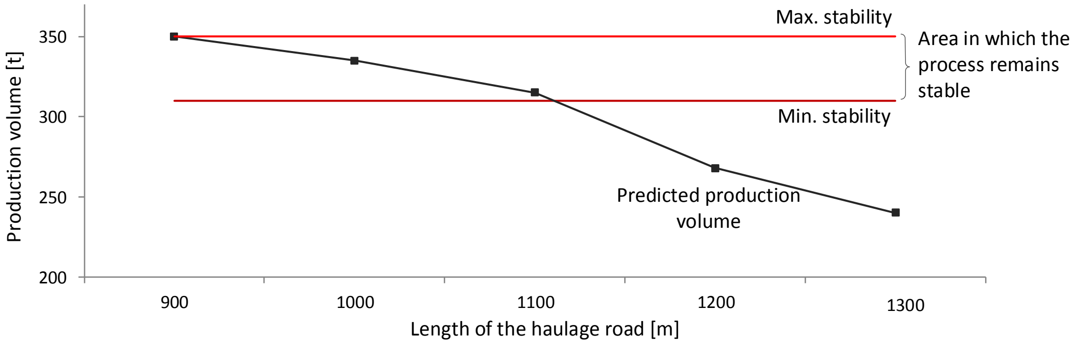

Fig. 9. Predicted production volume for the grate No. 4 at variable lengths of the haulage roads.

As it results from Table 4 and Fig. 9, the process becomes out of unstable, if the haulage road is extended to 1200 m. At this length, it is not possible to execute the assumed production plan. This is an indication for the decision-maker that the values of input variables should be changed, for example, by improving the condition of the roads.

Tab. 5 presents the production volume predicted by the ANN model depending on the condition of the haulage roads.

Tab. 5. Anticipated output for the grate No. 3 at variable road conditions.

Grate No.	**Road for mining loaders** [m]	**Road for haulage rigs** [m]	**Road condition**	**Anticipated output** [t]
2	50	1200	1	325
2	50	1200	2	299
2	50	1200	3	259
2	50	1200	4	185

The data presented in table 5 are illustrated also in Figure 10 in the context of the stability of the production process.

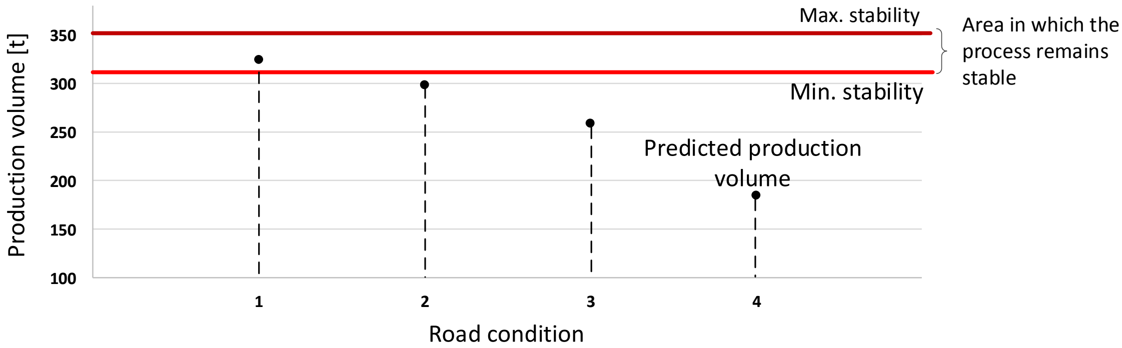

Fig. 10. Predicted production volume for the grate No. 3 at a variable condition of haulage roads.

As it results from table 5 and figure 10, for the the assumed lengths of the haulage road and the distance traveled by a mining loader when rigs a haulage vehicle, the process will remain stable only if the haulage road is even and dry. In other cases, it is not possible to execute the assumed production plan without changing the values of other input parameters.

Table 5 shows the production volume predicted by the ANN model, depending on the length of the haulage road travelled by a mining loader when rigs a haulage vehicle.

Tab. 6. Predicted production volume for the grate No. 4 for a variable length of the haulage road for the backhoe loader used to load haulage rigs.

Grate No.	**The road for mining loaders** [m]	**The road for haulage rigs** [m]	**Road condition**	**Anticipated output** [t]
1	30	1000	4	300
1	40	1000	4	264
1	50	1000	4	225
1	60	1000	4	194

Fig. 11 illustrates the data from Tab. 6 in the context of the stability of the rigs and haulage process, that is, the planned production volume of 330 t ± 20 t, depending on the length of the road traveled by a mining loader.

As can be seen from Tab. 6 and Fig. 11, there is no possibility that with the given parameters, it is possible to implement the production plan. In this case, it would be necessary to check whether the implementation of the plan will be possible if the weaning will take place on a different grate or the condition of the haulage will be improved.

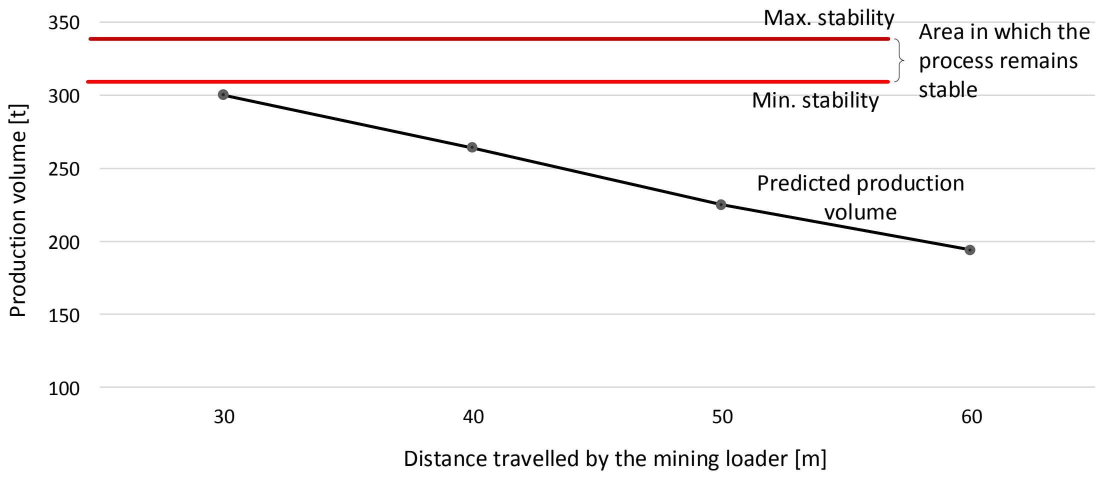

Fig. 11. Predicted production volume for the grate No. 1 at the variable length of the haulage road for the mining loader.

Optimization model of the loading and haulage process

Managers wanting to influence the total costs of the process should check, using the appropriate tools, previous process input parameters, and their implementation, and become familiar with the reasons for exceeding the assumed cost level and should predict the consequences of decisions and their impact on improving operational efficiency from a cost perspective. By analyzing the impact of alternative decisions at the production process control stage, one can estimate the level of total costs before decisions are taken and the resources needed to implement them are used. Process optimization often leads to problems where there is a need to solve the issues of process quality assessment based on more than one objective function. The Pareto method can be used to solve the above issues (Plonka and Oginski, 2014). Let us denote the considered set of variants of the studied process as W, where:

$$W = \{W_1, \dots, W_R\}. \tag{6}$$

A given variant has a specific set of value of cost-generating factors x_1, x_2, d, k, set by an artificial neural network, that is, such process parameters that unambiguously determine the value of variables regarding separated cost components and the way they are determined. The solutions received at this stage differ in the length of the loader's route, the frequency of the loader's haulage, the length of the haulage's road, the frequency of the haulage rig, the condition of the road, the availability of the grate, sometimes the haulage. Taking into account the above differences, it is necessary to select the variants according to the basic criteria: cost, obtained output and, indirectly, the processing time.

The optimization criteria for the selection of parameters are:

- mining in tonnes n, which is a function of variables x_1, x_2, d, k set by an artificial neural network, where $d \in \{1,2,3,4\}$ is a variable depending on the condition of the road, and k is the number of the grate,
- the total cost of loading and haulage, which is a function of variables x_1, x_2 and d. Crate number k is related to the variable x_2. The analysis of the generated variants aimed at comparing them with respect to the optimization criteria and determining the area of possible solutions is presented in Fig. 12. Limitations on optimization are:
- extraction, for which the process is stable (s_{min}, s_{max}) the size of the planned production ranges from 310 t to 350 tons,
- eligible cost k_{dop} – the value of this cost of 5,600 uc results from the adopted budget, in which the average cost from previous periods was reduced by 7 %.

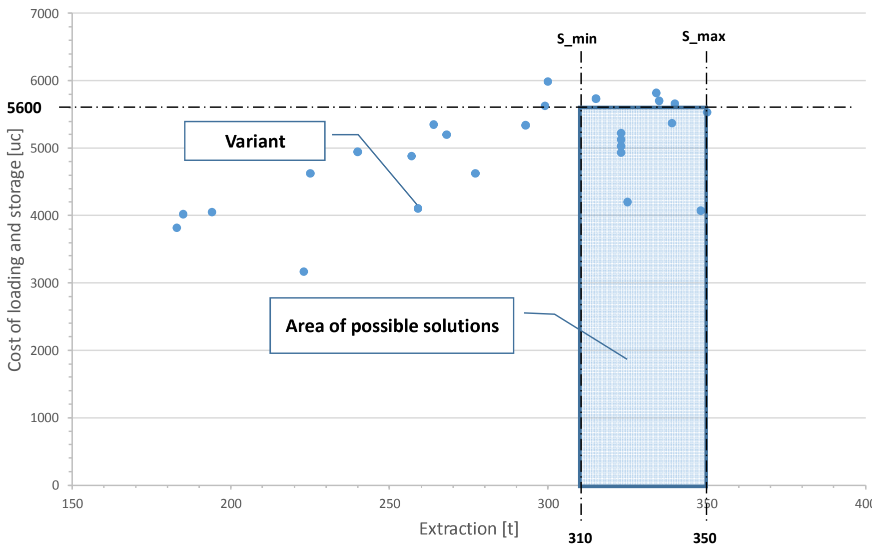

Fig. 12. Optimization of the loading process and spacing in the Pareto sense.

By introducing an additional restriction related to the permissible cost, for which $K_{lh} \leq K_{dop}$ the number of acceptable variants obtained in the previous step was reduced in determining process stability. If the variant $W(x1, x2, d, k)$ it is located in a set of possible solutions, the process will remain stable while maintaining the appropriate level of costs.

The generated variants can also be analyzed in terms of the economic efficiency of the loading and haulage process in order to compare them with each other and choose the final solution from Pareto solutions, for which profitability is the highest.

Economic efficiency of loading and haulage process

The measure of the economic result in the created model is the profitability calculated as the difference of revenues obtained at this stage of the process and the actual costs of loading and haulage. The starting point was determining the size of resources possible to extract for the adopted variant, from a set of possible solutions. Contractual income was determined as the product of the number of products/output to be obtained at this stage and the contractual unit internal price in the amount of 4uc. The use of internal prices allows establishing the responsibility for the size of the generated profit for separate units. If there is no internal price, the contractual revenue can be determined on the basis of the allowable cost. In this situation, the unit is only responsible for the level and cost control. The actual loading and hauling costs are in turn determined as the product of the quantity of extracted ore and the actual unit operational costs.

Finally, the function determining the profitability of extraction depending on the size of the output n and ways of loading accordingly x_1 and haulage x_2 is given in the model (7). It is important to remember that n is a function of variables x_1, x_2, d, k, set by an artificial neural network.

$$D(x_1, x_2, n) = 4 \cdot n - \left(\frac{n}{4}(0{,}012x_1 + 0{,}64) \cdot 10 + \frac{n}{20}(0{,}005x_2 + 0{,}55) \cdot k_d \cdot 30\right), \qquad (7)$$

where kd is a coefficient depending on the variable value d, that is, the condition of the route.

Finding optimal ways of loading and hauling boils down to determining the vector (x_1, x_2) from the area of possible solutions, maximizing the function D in this area. Knowing the parameters of the artificial neural network, that is, the weight between individual neurons of the network and the form of the neuron activation function, this problem can be solved using the so-called gradient method. For this purpose, however, it is necessary to set the values of discrete variables d and k in advance (k_d), to ensure the differentiability of the function D.

In the gradient method, the first data vector is randomly determined $\left(x_1^{(1)}, x_2^{(2)}\right)$ from the area of possible solutions and the function gradient is calculated D in point (x_1, x_2) according to model (8) – in the record, as variables of the function, the variables d and k are omitted, whose value is fixed.

$$\nabla D(x_1,x_2) = \Big[(1{,}575 - 0{,}03x_1 - 0{,}0075x_2)\cdot \frac{\partial n}{\partial x_1}(x_1,x_2) - 0{,}03\cdot n(x_1,x_2),\ (1{,}575 - 0{,}03x_1 - 0{,}0075x_2)\cdot \frac{\partial n}{\partial x_2}(x_1,x_2) - 0{,}0075\cdot n(x_1,x_2)\Big] \quad (8)$$

where:

$\frac{\partial n}{\partial x_i} = \frac{\partial f}{\partial net}(x_1,x_2)\sum_{j=1}^{m} w_j^2 w_{ji}^1 \frac{\partial f}{\partial net_j}(x_1,x_2)$, $\quad i = 1{,}2,$

$net_j = \sum_{i=1}^{2} w_{ji}^1 x_i$, $\quad j = 1,\dots,n$ – input j- this neuron of the hidden layer,

$net = \sum_{j=1}^{m} w_j^2 f(net_j)$ – the input of the output neuron,

$f(t)$ – neuron activation function,

w_{ji}^1 – connection weight *j*- this neuron in the hidden layer of *i*- this network input,

w_j^2 – connection weight - this neuron in the hidden layer with the output neuron.

Having set a gradient ∇D in point $\left(x_1^{(1)}, x_2^{(1)}\right)$ a new point is defined $\left(x_1^{(2)}, x_2^{(2)}\right)$ according to model (9).

$$\left(x_1^{(2)}, x_2^{(2)}\right) = \left(x_1^{(1)}, x_2^{(1)}\right) + \eta\nabla D\left(x_1^{(1)}, x_2^{(1)}\right), \quad (9)$$

where η is a predetermined positive constant, as small as possible.

For point $\left(x_1^{(2)}, x_2^{(2)}\right)$, the function D gradient is again determined, and the next point is determined analogously. The algorithm is repeated until the gradient $\nabla D\left(x_1^{(n)}, x_2^{(n)}\right)$ is close to zero (absolutely smaller than the given positive constant ε) or when the number of algorithm steps exceeds the set threshold N or the designated point does not belong to the area of possible solutions (in this case, the last point belonging to the area of possible solutions is considered the optimal point).

The discovered point $\left(x_1^{(n)}, x_2^{(n)}\right)$ approximates the vector maximizing the function determining profitability.

Conclusion

When managing the production process, attention should be paid to maintaining an adequate level of costs and time of production orders. However, modern enterprises are very complex and are characterized by high dynamics of manufacturing processes. In such conditions, making decisions becomes difficult and involves high risk. The solution to this problem may be the construction of models of manufacturing processes based on which decisions will be made. On the one hand, the models allow to limit the level of complexity and interaction with other elements of the real system, on the other hand, they contain all the important elements and features from the point of view of the research objective. Models of artificial neural networks can be used to control the production system, and so to ensure its stability. The ease and speed of their construction make them a very useful tool. The only problem remains a large amount of data needed in the network learning process, which, however, in the era of the universality of information systems, parameterization and standardization of production processes cease to be a problem.

Incorrect decisions made due to the lack of appropriate tools for comprehensive process control lead to high costs, and failure to comply with the production plan will result in a loss for the entire undertaking in a given period. The use of the method of determining the costs of the copper ore exploitation process presented in the article allows identification of the costs of activities and related cost factors, and at the same time ensures the reliability of services and managers in controlling the loading and haulage process. Thanks to the proposed solutions, it is possible to inform decision-makers for existing work conditions about the ability to implement a given mining plan, the cost of this process and the possibility of reducing them by paying attention to the parameters of options from the possible solutions and parameters of the optimal variant for the given output. The use of the above solutions enables a significant reduction of costs at the stage of controlling the operation process which has an impact on the total costs and economic efficiency of the enterprise and actively influences the cost planning in the future when making important decisions for this process.

The proposed methods require the implementation of the operation cost calculation, the registration of input parameters, internal price setting for units, and for the charging process and discontinuation of the output from the proposed artificial neural network, determination of the cost limit and application of the proposed optimization model in the Pareto sense. The proposed solutions have been adapted to mining systems operating under the conditions of a given enterprise.

References

Azadegan, A., Porobic, L., Ghazinoory, S., Samouei, P. and Saman Kheirkhah, A. (2011). Fuzzy logic in manufacturing: A review of literature and a specialized application. *International Journal of Production Economics, 132(2), pp.258-270.*

Barron, A. (1994). Approximation and estimation bounds for artificial neural networks. *Machine Learning, 14(1), pp.115-133.*

Bozejko, W., Hejducki, Z. and Wodecki, M. (2012). Applying Metaheuristic Strategies in Construction Projects Management. *Journal of Civil Engineering and Management, 18(5), pp.621-630*.

Bubnicki, Z. (2010). Modern control theory. *Berlin: Springer*.

Burduk A. (2015). The Role of Artificial Neural Network Models in Ensuring the Stability of Systems. 10th International Conference on Soft Computing Models in Industrial and Environmental Applications, Advances in Intelligent Systems and Computing, *vol 368, Springer, Cham, pp.427-437*.

Burduk A. and Jagodziński M. (2015) Assessment of Production System Stability with the Use of the FMEA Analysis and Simulation Models. IDEAL 2015, Lecture Notes in Computer Science, *vol 9375, Springer, Cham, pp.216-223.*

Dohn K., Gumiński A., Matusek M. and Zoleński W. (2014). The model of knowledge management system supporting sustainable growth in machine-building industry enterprises. IFKAD 2014: 9th International Forum on Knowledge Asset Dynamics, *Matera, Italy, pp.1856-1886*.

Fusko M., Rakyta M., Dulina Ľ., Sulírová I. and EDL M. (2018). Digitization in the technical service management system. *MM Science Journal, vol. 2018/March, pp.2260-2266*.

Furmann, R., Furmannová, B. and Więcek, D. (2017). Interactive Design of Reconfigurable Logistics Systems. *Procedia Engineering, 192, pp.207-212*.

Gola A. and Kłosowski G. (2018). Application of Fuzzy Logic and Genetic Algorithms in Automated Works Transport Organization. 14th International Conference, DCAI 2017, Advances in Intelligent Systems and Computing, *vol 620, Springer, Cham, pp.29-36*.

Gwiazda, A., Sękala, A., Banaś, W., Topolska, S., Foit, K. and Monica, Z. (2017). Design of strength characteristics on the example of a mining support. IOP Conference Series: *Materials Science and Engineering, 227, p.012054.*

Janson V. and Jurenoks V. (2012). Modelling the Behaviour of Stability of Production Systems of Economics. *Economics and Business, 22, pp.95-100*.

Krenczyk, D., Skolud, B. and Olender, M. (2017). The production route selection algorithm in virtual manufacturing networks. IOP Conference Series*: Materials Science and Engineering, 227, p.012074*.

Litvin, O., Tyulenev, M., Zhironkin, S., Prokopenko, S. (2017). Methodology of coal losses calculation at open pit mining for complex geological conditions – review. *Acta Montanistica Slovaca, 22/2, pp. 146-152*.

Plonka S. and Oginski L. (2014). Multicriterial Optimisation of the Manufacturing Process of a Spindle Working in a Ring Spinning Frame. *Fibres & Textiles in Eastern Europe, Vol. 22/6. Pp. 51-58*.

Rojek I., Kowal M. and Stoic A. (2012). Predictive Compensation Of Thermal Deformations Of Ball Screws In Cnc Machines Using Neural Networks. *Tehnicki Vjesnik-Technical Gazette, 24(6), pp. 1697-1703*.

Tahir M., Cagatay P. and Halil K. (2015). Determination of Optimum Production Capacity and Mine Life Considering Net Present Value in Open Pit Mining at Different Overall Slope Angles. *Acta Montanistica Slovaca, 20/1, pp. 62-70.*

Tworek, P., Tchórzewski, S., Valouch, P. (2018) Risk Management in Coal-Mines – Methodical Proposal for Polish and Czech Hard Coal Mining Industry. *Acta Montanistica Slovaca, 23/1, pp. 72-80*.

Więcek D. and Więcek D. (2018) The Influence of the Methods of Determining Cost Drivers Values on the Accuracy of Costs Estimation of the Designed Machine Elements. Proceedings of 38th International Conference on Information Systems Architecture and Technology ISAT 2017. *Advances in Intelligent Systems and Computing, vol 657. Springer, Cham, pp 78-88.*

Wirth, H., Kulczycka, J., Hausner, J. and Koński, M. (2016). Corporate Social Responsibility: Communication about social and environmental disclosure by large and small copper mining companies. *Resources Policy, 49, pp.53-60.*