Modeling of Industrial Limestone Grinding Process Using Regression Models and Neural Networks

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https://doi.org/10.29227/IM-2025-02-04-018

Submission date: 28-11-2025 | Review date: 14-12-2025

Abstract

The article discusses the problem of mathematical identification of the limestone grinding process in an industrial roller-bowl mill, with particular emphasis on assessing its energy consumption. This is a key stage in the optimization of the grinding process because the development of effective indicators models to assess the technological process guarantees its effective optimization. Therefore, technological and energy indicators were proposed that assess the limestone grinding and classification process, based on which regression models and neural networks were built. These models show the relationships between the process evaluation indicators and the energy and technological data obtained during a factorial experiment at the milling facility. The industrial experiment aimed to examine the nature and dynamics of changes in process parameters. During the experiments, the controllable technological parameters of the tested process were changed within a wide and technologically acceptable range. Process identification was based on data from control and measurement devices and the process control system, which enabled full mathematical modeling of the process and explanation of the interdependence of process parameters. Regression and neural network models were determined, allowing an effective identification of the operation of the entire limestone grinding and classification process. The models were subjected to statistical diagnostics which aimed to verify their construction's correctness and compare the operation's effectiveness. Regression models were more practical in assessing the grinding process, while neural networks were more useful in control, thanks to the possibility of automatic learning and updating in dynamically changing process conditions.

Keywords: *limestone grinding process modeling, evaluation indicators, regression models, neural network models, process control*

1. Introduction

Modern companies, including processing plants, operate on the basis of economic criterion, which is the most important factor determining their activities. It forces actions aimed at minimizing costs and improving the quality and efficiency of production through full automation of processes. This is particularly difficult in mineral processing plants, where the processes are diverse, multistage, and complex [10,11].

Effective control of these processes requires identification of individual technological operations. Mathematical modeling is one of the methods used to identify and describe processes. These models are then used for prediction and analysis of processes and as algorithms in control systems, allowing optimization of the entire process. The choice of mathematical modeling methods depends on the complexity of technological processes and the purpose of using the models [9]. Among the most commonly used methods is regression modeling, which can be linear or non-linear [2]. Linear models are popular because of their simple construction and interpretation, but they do not always adequately describe complex relationships. In such cases, non-linear models are used. Nowadays, for control purposes, artificial intelligence-based modeling is most often used; these are 'black box' models such as neural networks or genetic algorithms [12].

Special focus in the economic criterion should be given to the energy consumption of processes, because the cost of electricity is the main component of the cost of mineral processing [7]. The grinding and classification system is the node of the most energy intensive process also in the limestone processing, which is why it was selected for the model studies [3,4]. The cost analysis, presented in the article, also showed a very high energy intensity of this system in terms of station for KW Czatkowice Ltd. Information from the control system of this node, combined with energy-technical data, was used to develop mathematical models that describe the dependencies in the limestone grinding and classification process.

The study compared regression models and neural networks developed for energy indicators that evaluate the operation of the limestone grinding and classification node. Identification of this process consisted of determining effective mathematical models that would explain the interdependence of process parameters as fully as possible. The effectiveness of the models was evaluated using statistical indices that indicate the accuracy of the fit and prediction errors. The models were calculated using data from industrial experiments carried out in the factory.

2. Material and Methods

The article presents and compares mathematical models that identify the industrial limestone grinding and grading process necessary to control and optimize the process. The main objective of these activities was to minimize the cost of limestone processing. Therefore, regression models and neural networks were built based on indicators of process evaluation of a technological and economic nature. As practice and literature show, indicators evaluating this type of technological facility should take into account the amount of raw material processed and the parameters that generate the main processing costs. It was indicated that the main costs in the limestone milling unit are electricity and gas consumption. Therefore, two effective evaluation indicators S and W were developed and calculated based on the process data provided

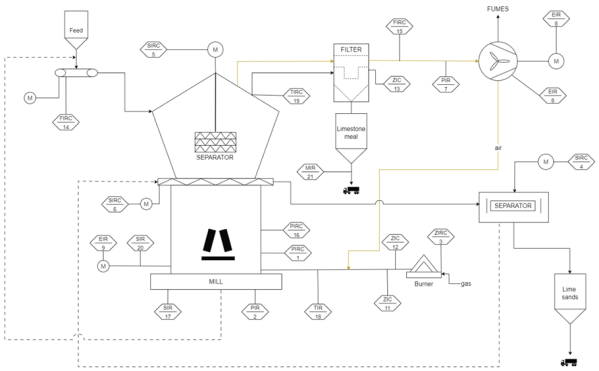

Fig. 2.1 Simplified diagram of the technology of control of the grinding system and classification of limestone at KW Czatkowice
Rys. 2.1 Uproszczony schemat technologii kontroli układu mieleni i klasyfikacji kamienia wapiennego w KW Czatkowice

Tab. 2.1 List of selected measured process parameters
Tab. 2.1 Lista wybranych mierzonych parametrów procesowych

L.P.	Tag name	Description	Unit
1	AI_5.01M1_PIRCSAHHL.PV	Pressure before the mill	mbar
2	AI_5.03E1_PIRSAHHHHL.PV	Pressure in the hydraulic system (lift)	bar
3	AI_3.01E1_ZIRC.PV	Burner load	%
4	AI_8.14M1_SIRC.PV	RPM of the external separator	obr./min
5	AI_2.05M1_SIRC.PV	RPM of the internal separator motor	obr./min
6	AI_8.24M1_SIRCAH.PV	Rotation of the mill screw conveyor motor	obr./min
7	AI_2.02M1_P1.PV	Pressure before the main fan	mbar
8	AI_2.03M1_JIRSAHH.PV	Main fan motor power	kW
9	AI_5.01M1_JIRSAHH.PV	Mill motor power	kW
10	AI_2.03M1_SIR.PV	Vibration of main fan, right side	mm/s
11	AI_2.07M1_ZIC.PV	Gas throttle position 1	%
12	AI_2.08M1_ZIC.PV	Position of gas damper 2	%
13	AI_2.02M1_ZIC.PV	Position of the shutter on the filter	%
14	AI_6.06E1_6.13E1_FI.PV	Mass flow of stone into the mill	Mg/h
15	AI_2.02M1_FIRCAL.PV	Air flow upstream of the main fan	m^3/h
16	AI_5.01M1_PDIRCSAHL.PV	Pressure differential at the mill	mbar
17	AI_5.03E1_CYL_AVG.PV	Average position of cylinders	mm
18	AI_5.01M1_TIRSAHH9.PV	Temp. before the mill	°C
19	AI_5.01M1_TIRCSAHHL.PV	Temp. after the mill	°C
20	AI_5.01M1_SIR.PV	Vibration of the mill shaft	mm/s
21	AI_9.05_Rh.PV	Moisture content of the meal	%

by the control system during the factorial experiments carried out at the KW Czatkowice milling plant.

2.1 Description of the research object

Kopalnia Wapienia 'Czatkowice' Ltd. is an open-pit mining facility exploiting high quality deposits of Carboniferous limestone, located in the municipality of Krzeszowice, about 30 kilometers from Krakow. The mined $CaCO_3$ limestone is used for the raw material-demanding production of, among other things, flue gas treatment sorbents, which are used in power plants to remove sulfur compounds.

The entire technological process related to mining and processing takes place at:

- Mining Plant (mining and grit production)
- Mineral Processing Department (mechanical processing plant, limestone milling plant, storage and loading node, packaging of ground products).

Exploitation of the Carboniferous limestone deposit is carried out by the open-pit method, using the longwall and boarding system with multi-wing progression of the work front. Exploitation is carried out on six mining levels: 330, 350, 370, 390, 410 and 420 meters.

The milling plant facility is equipped with two twin milling lines, the main equipment of which are MPS drying and grinding mills from Gebr. Pfeiffer AG and a sand screening system. Limestone milling is carried out in the grinding system of the mill's bowls and rotary roles along with simultaneous drying with hot gases from a burner using natural gas, which flow through the mill and its integrated separator.

The dust-air mixture is transported to the process filter. The fine fraction - lime meal with a granulation of 0,0÷0,045 mm is extracted pneumatically through the mill separator and precipitated in the process filter, and then collected from the hoppers by a set of screw and bucket conveyors and further transported to storage tanks. The coarse fraction with a granularity of 0,045÷2 mm is discharged directly from the mill by a screw conveyor and then transported through a conveyor system to a double-deck sifter. The product separated in the screening process with a granulation of 0,1÷0.4 mm and 0,1÷1,2 mm is fed to storage tanks, and the remaining coarse fraction with a granulation of more than 1,2 mm is returned by the conveyor system to the mill or fed on the transport line to storage tanks.

The cleaned air from the filter is transported to the mill fan, pumping it further to the chimney and back to the mill inlet (closed circuit).

A simplified diagram of the operation of the milling line is shown in Figure 2.1 together with the most relevant measuring points of the process variables, is shown in Figure 2.1. The designations of the control and measuring points are explained in Table 2.1.

All process lines have been brought under the control of Wonderware's SCADA system, which allows the collection and statistical processing of data describing the operation of both the entire line and individual machines.

More than 3,500 variables are analyzed in the system. In the face of such a large number of variables, it becomes crucial to

Tab. 2.2 Conditions for the implementation of the factorial experiment in the milling plant facility

Tab. 2.2 Warunki realizacji eksperymentu czynnikowego na obiekcie przemiałowni

Adjustable parameters	Experiment no.	Rotation of the mill screw conveyor motor [rpm/min]	Temperature after the mill [°C]	Air flow before the fan [m³/h]	Pressure difference at the mill [mbar]
Rotation of the mill screw conveyor motor	1	**51**	75	170000	30
	2	**33**	75	170000	30
Temperature after the mill [°C]	3	42	**71**	170000	30
	4	42	**82**	170000	30
Air flow before the fan	5	42	75	**166000**	30
	6	42	75	**173000**	30
Pressure difference at the mill	7	42	75	170000	30
	8	42	75	170000	**35**
	9	42	75	170000	**25**

Tab. 3.1 Descriptive statistics of process data and evaluation indicators extracted from factorial experiments in the milling plant facility

Tab. 3.1 Statystyki opisowe danych procesowych oraz wskaźników oceny pozyskanych z eksperymentów czynnikowych na obiekcie Przemiałowni

Variable	n	Average	Min.	Max.	coefficient of variation
Pressure before the mill [mbar].	2194	-9,8	-10,9	-8,9	2,8
Pressure in the hydraulic system [bar].	2194	99,8	96,2	106,3	1,2
Burner load [%].	2194	21,4	12,2	36,9	28,9
RPM of the external separator. [rpm]	2194	133,8	132,9	134,6	0,2
Internal separator motor rotation [rpm].	2194	120,0	119,2	120,2	0,2
Rotation of the mill's helical conveyor motor [rpm]	2194	37,2	29,9	51,2	18,1
Pressure before the main fan [mbar].	2194	-65,0	-75,4	-55,8	5,0
Motor power of the main fan [kW]	2194	637,7	599,0	681,4	2,0
Mill motor power [kW]	2194	595,8	441,4	796,4	8,2
Vibration of main fan right side [mm/s].	2194	1,3	0,8	2,1	17,2
Gas throttle position 1 [%]	2194	99,6	99,5	99,7	0,1
Gas throttle position 2 [%]	2194	0,7	0,7	0,8	5,4
Position of louvers on filter [%].	2194	64,1	58,3	72,8	3,9
Scale mass flow [Mg/h].	2194	58,8	37,6	77,6	11,5
Air flow before fan [m3/h]	2194	168009	161805	173726	1,2
Pressure differential at the mill [mbar]	2194	29,4	22,7	39,3	7,7
Average cylinder position [mm]	2194	65,6	46,3	94,9	11,4
Temp. before the mill [°C]	2194	160,2	119,3	228,9	15,0
Temp. after the mill [°C]	2194	73,3	67,4	80,9	3,2
Mill shaft vibration [mm/s].	2194	1,0	0,7	2,2	17,4
Moisture content of flour [%]	2194	0,2	0,0	0,4	40,6
S [kWh/Mg]	2194	21,3	15,4	31,6	11,7
W [kWh/Mg]	2194	4,5	2,3	8,0	26,6

identify valuable and significant information and to skillfully separate important data from those that are not of major importance [5]. The collected data form the basis for further processing at higher levels in terms of maintenance, semi-finished product inventory and instantaneous product flow volumes.

To select the process that generates the highest unit cost of the product, an analysis of the costs of all extraction and processing operations carried out at the mine was performed. The costs incurred by this type of enterprise in its operations are varied and can be considered from different points of view, but they should provide information that is primarily necessary for effective production management and, consequently, for making the right business decisions.

An important area that forms the basis for carrying out optimization of the technological process due to the possibility of its control is the cost of utility consumption, especially electricity and gas.

Analyzing the distribution of costs from this angle, conclusions were drawn that the milling process is the most energy-intensive. In addition, it is the only process that consumes gas, which is used to dry the products. Also taking into account the amount of machinery and equipment working in the system, which are the most common in this process, it was selected as a facility that qualifies for a factorial experiment, and so it seems to be the most suitable for carrying out optimization of its operation.

2.2 Evaluation indicators and process parameters

Following the economic criterion, two indices were formulated to evaluate the limestone grinding and classification process. The unit power consumption index S considered the power consumed by the main drives operating in the facility (mill and main fan) about the mass flow rate of the feed (limestone).

$$S = \frac{\text{Mill power} + \text{Main fan power}}{\text{Mass flow of stone (feed)}} \qquad [kWh/Mg]$$

In addition to the unit energy consumption index S used to evaluate the operation of the grinding node and the classification, a new index W was developed and calculated that additionally takes into account the gas consumption of the mill, expressed as a percentage of the gas burner load.

$$W = \frac{\text{Mill power} + \text{Main fan power}}{\text{Mass flow of stone (feed)}} \cdot \%\ \text{burner load} \qquad [kWh/Mg]$$

In assessing the energy intensity of the limestone grinding and classification process, the value of the above indicators should be as low as possible.

The most relevant process parameters recorded in the SCADA control and command system were used for the indicator modeling process (Table 2.1). These parameters were selected based on technological knowledge of the process and statistical correlation analysis of process data with evaluation indicators. Variables strongly correlated with S and W indicators but weakly correlated with each other were selected to avoid collinearity.

2.3 Experimental conditions

The process data for modeling came from a factorial experiment carried out at the milling plant facility at KW Cza-

Tab. 3.2 Parameters of the linear regression model of the evaluation index S

Tab. 3.2 Parametry liniowego modelu regresyjnego wskaźnika oceny S

n = 2194	S [kWh/Mg] R= 0,7405, R^2= 0,5484; F(6,2187)=442,64 p<0,0000; Standard error of estimation: 1,6767					
	b*	St. error b*	b	St. error b	t(2187)	p
Free expression			-7,7186	2,3450	-3,2915	0,0010
Rotation of the screw conveyor motor	-0,3012	0,0170	-0,1112	0,0063	-17,6738	0,0000
Gas throttle position 2	0,5299	0,0185	32,8938	1,1464	28,6938	0,0000
Burner load	-0,3315	0,0178	-0,1335	0,0072	-18,6072	0,0000
Mill shaft vibration	0,1935	0,0170	2,7481	0,2418	11,3642	0,0000
Temp. after the mill	0,2421	0,0180	0,2534	0,0189	13,4253	0,0000
Pressure in front of the fan	0,1961	0,0172	0,1509	0,0132	11,4080	0,0000

S = - 7,719 - 0,111 · (Rotation of screw conveyor motor)+ 32,894· (Position of gas damper 2) - 0,133 · (Burner load) + 2,748 · (Mill shaft vibration) + 0,253 · (Temperature after mill) + 0,151 · (Pressure before fan)
± 1,677 kWh/Mg

Tab. 3.3 Parameters of the linear regression model of the evaluation index W

Tab. 3.3 Parametry liniowego modelu regresyjnego wskaźnika oceny W

n = 2194	*W* [kWh/Mg] R= 0,8908, R^2= 0,7935; F(4,2189)=2103,1 p<0,0000; Standard error of estimation: 0,5422					
	b*	St. error b*	b	St. error b	t(2187)	p
Free expression			2,6427	0,4187	6,3121	0,0000
Pressure difference at the mill	-0,1041	0,0101	-0,0544	0,0053	-10,2766	0,0000
Temp. before the mill	0,8530	0,0103	0,0424	0,0005	82,9522	0,0000
Temp. after the mill	-0,1209	0,0100	-0,0606	0,0050	-12,1275	0,0000
Vibration of the main fan, right side	0,1584	0,0099	0,8168	0,0510	16,0307	0,0000

W = 2,643 - 0,054 · (Pressure differential at mill) + 0,042 · (Temperature before mill) – 0,061 · (Temperature after mill) + 0,817 · (Vibration of main fan)
± 0,542 kWh/Mg

tkowice during five working shifts in November and December 2023. Four relevant and controllable process parameters were selected: screw conveyor motor speed, temperature after the mill, air flow before the fan, and differential pressure at the mill. The values of these parameters were changed into three ranges. The conditions of the industrial experiments are shown in Table 2.2.

Each of the nine experiments lasted 3 hours, and an hour's time was assumed between experiments to reach steady-state conditions. Control loops in the SCADA system were turned off during the experiment.

2.4 Modeling methods

Multivariate regression, linear and non-linear, and neural network models were used to model evaluation indicators. Calculations and model verification were performed using Statistica integrated statistical data analysis system and Statistica Neural Networks developed by StatSoft.

Regression modelling

Regression is a method of studying the effect of one or more explanatory variables on the explained variable whose course we are looking for. When we analyze the effect of multiple variables on the explained variable, we speak of multivariate or multidimensional regression. Regression analysis involves estimating the parameters of the theoretical regression equation that most accurately represent the relationship that occurs. If we have n observations of the variables x1,x2,… ,xk,, which can affect the variable y, the linear multivariate regression model can be described by the equation [2]:

$$y = \beta_0 + \beta_1 x_1 + \beta_1 x_1 + \beta_2 x_2 + \beta_k x_k + \varepsilon$$

where:

β_i – model parameters (regression coefficients) describing the impact of the i-th variable,

ε – random component

Neural network modelling

Today, neural networks are widely used to model and control various industrial processes, including mineral processing. Neural networks are structures inspired by biological nervous systems in which neurones, acting as elementary processors, are connected in a manner similar to that of axons and dendrites in biological systems. These connections can be excitatory or inhibitory.

Each neurone executes a simple programme that involves calculating a weighted sum of inputs and sometimes adding a fixed component. The efficiency of the modeling depends on the adopted values of modifiable weights, which are numerical coefficients that can take positive values for excitatory connections and negative values for inhibitory connections.

The value of the output signal from the neurone is calculated in two stages. In the first stage, the input signals are multiplied by their corresponding weights and summed. In the second stage, the result of the internal processing function is transformed by a specific input-output function, called the activation function, which most often takes the form of linear, unit jump, sigmoidal or hyperbolic tangent. Finally, the output signal of a single neuron is calculated from the following relation [13, 8]:

$$y = \mathrm{f}\left(\sum_{i=1}^{n} w_i x_i\right)$$

where:

x_i – vector of input data,

Tab. 3.4 Parameters of the nonlinear regression model of the evaluation index S

Tab. 3.4 Parametry nieliniowego modelu regresyjnego wskaźnika oceny S

n = 2194	*S* [kWh/Mg], R= 0,74520, R^2=0,5553; F(6,2187)=455,20, p<0,0000; Standard error of estimation: 1,6638					
	b*	St. error b*	b	St. error b	t(2187)	p
Free expression			- 15,5981	2,3252	-6,7084	0,0000
Pressure before fan	0,1747	0,0170	0,1345	0,0130	10,3065	0,0000
Gas throttle position 2	0,5217	0,0183	32,3852	1,1382	28,4522	0,0000
Mill shaft vibration	0,1737	0,0171	2,4661	0,2431	10,1438	0,0000
Temp. after the mill	0,2344	0,0180	0,2455	0,0188	13,0501	0,0000
(1/Burner load)	0,3702	0,0180	57,3840	2,7836	20,6147	0,0000
(Rotation of screw conveyor motor.)²	-0,2828	0,0168	-0,0013	0,0001	-16,7840	0,0000

S = - 15,598 + 0,134 · (Pressure in front of the fan) + 32,385 · (Gas damper position 2) + 2,466 · (Mill shaft vibration) + 0,245 · (Temperature after the mill) + 57,384 · (1/burner load) – 0,0013 · (Screw conveyor motor speed)2 ± 1,664 kWh/Mg

Tab. 3.5 Parameters of the nonlinear regression model of the evaluation index W

Tab. 3.5 Parametry nieliniowego modelu regresyjnego wskaźnika oceny W

n = 2194	*W* [kWh/Mg] R= 0,8917, R^2= 0,7952; F(4,2189)=2124,9 p<0,0000; Standard error of estimation: 0,5400					
	b*	St. error b*	b	St. error b	t(2187)	p
Free expression			-6,5820	0,3923	-16,7777	0,0000
Temp. before the mill [°C]	0,8524	0,0102	0,0423	0,0005	83,2851	0,0000
Pressure differential at the mill [mbar]	-0,1032	0,0101	-0,0540	0,0053	-10,2300	0,0000
Vibration of the main fan, right side	0,1574	0,0098	0,8114	0,0507	15,9911	0,0000
(1/Temp after the mill)	0,1280	0,0099	350,2002	27,1555	12,8961	0,0000

W = - 6,582 + 0,042 · (Temperature before the mill) - 0,054 · (Pressure differential at the mill) + 0,811 · (Vibration of the main fan) + 350,20 · (1/Temperature after the mill) ± 0,540 kWh/Mg

w_i – vector of weights,
f – activation function,
y – output signal,
n – the number of input signals.

3. Results and discussion

3.1 Characteristics of process data and evaluation indicators

In the course of the experiments, the adjustable technological parameters of the process under study were changed within a wide, technologically permissible range. The values of the process parameters were measured and recorded by control and measuring devices installed at the grinding and classification facility, cooperating with the process control system. Data were recorded with a sampling period of 10 seconds. In order to stabilize instantaneous spikes in values and discard erroneous readings, the data were averaged over a period of 1 minute and filtered, thus obtaining 2194 instances of process data from the experiments. The statistics of the collected data and the evaluation indices S and W calculated from them are shown in Table 3.1. The index S showed more than twice the variability compared to the index W. Among the process parameters, the lowest coefficient of variation characterized the position of the gas damper 1 and the rotation of the motors of the outer and inner separators. The highest variability was recorded for the meal moisture parameter (40,6%) and the gas burner load (28,9%).

3.2 Modeling results

After verifying and filtering the data from the experiments and selecting the most favorable process variables, mathematical models of the evaluation indicators of the limestone grinding and classification process S and W were calculated using regression equations and neural networks. The parameters of the models and the statistical indices of their significance and fit are presented in Tables 3.2÷3.7. In addition, regression models are presented in the form of mathematical equations with estimated coefficients and estimation errors.

Regression models

The results of regression modeling, including the estimated parameters of the regression equations and statistics evaluating the degree of fit of the models to the empirical data, are presented in the tables below. They include the values of the estimated coefficients of the models b and their standardized b* values, the average estimation errors of the regression coefficients, their significance levels p, as well as the parameters for assessing the accuracy of model fit and statistical significance of the models:

- correlation coefficient R,
- coefficient of determination R^2,
- Fisher-Snedecor test value F,
- standard error of estimation (prediction error).

Analysis of the calculated regression models indicates very high statistical significance of most coefficients in independent variables (p = 0,0000(...) < passumed= 0,05), which confirms the significance of the technological parameters that affect the estimated indicators. The value of the Fisher-Snedecor test, which is used, among other things, to verify the hypothesis of significance of the entire model, while assessing the significance of the directional coefficient, the coefficient of determination R^2 and the linear relationship between the analyzed variables, confirms the statistical significance of all models with very high probability (rejection of the inverse hypothesis at a very low level of significance p < 0,0000..0).

Tab. 3.6 Summary of S-index neural network models with parameters for evaluating network performance

Tab. 3.6 Zestawienie modeli sieci neuronowych wskaźnika S wraz z parametrami oceny efektywności sieci

Summary of active S-index networks									
Network name	Quality of teaching	Quality of testing	Quality of validation	Error of teaching	Error of testing	Error of validation	Learning algorithm	Activation (hidden)	Activation (output)
MLP 6-3-1	0,8015	0,8146	0,7971	1,1535	1,0350	0,9922	BFGS 60	Logistic	Logistic
MLP 6-9-1	0,8388	0,8219	0,8012	0,9563	0,9955	0,9656	BFGS 137	Tgh	Exponential
MLP 6-10-1	0,8587	0,8379	0,8123	0,8475	0,9286	0,9274	BFGS 271	Logistic	Logistic
MLP 6-10-1	0,8128	0,8007	0,7986	1,0949	1,0983	0,9734	BFGS 74	Exponential	Tgh
MLP 6-11-1	0,8538	0,8433	0,7999	0,8742	0,8853	0,9859	BFGS 281	Tgh	Linear

Tab. 3.7 Summary of neural network models of the W index, along with parameters for evaluating the effectiveness of the network

Tab. 3.7 Zestawienie modeli sieci neuronowych wskaźnika W wraz z parametrami oceny efektywności sieci

Summary of active W-index networks									
Network name	Quality of teaching	Quality of testing	Quality of validation	Error of teaching	Error of testing	Error of validation	Learning algorithm	Activation (hidden)	Activation (output)
MLP 4-7-1	0,9144	0,9244	0,9246	0,1170	0,1025	0,1044	BFGS 189	Tgh	Tgh
MLP 4-8-1	0,9122	0,9230	0,9231	0,1200	0,1041	0,1058	BFGS 117	Logistic	Linear
MLP 4-9-1	0,9174	0,9269	0,9255	0,1131	0,1000	0,1028	BFGS 229	Logistic	Linear
MLP 4-4-1	0,9073	0,9195	0,9240	0,1263	0,1086	0,1049	BFGS 77	Tgh	Exponential
MLP 4-3-1	0,9067	0,9201	0,9250	0,1271	0,1078	0,1032	BFGS 232	Tgh	Linear

Tab. 3.8 Summary parameters of the S and W evaluation index models of the limestone grinding and classification process

Tab. 3.8 Parametry podsumowujące modele wskaźników oceny S i W procesu mielenia i klasyfikacji kamienia wapiennego

Model parameters	Regression models				Neural network models	
	Linear		Nonlinear			
	S	*W*	*S*	*W*	*S*	*W*
R [%], (network quality)	74,05	89,08	74,52	89,17	83,63	92,33
R^2 [%]	54,84	79,35	55,53	79,52	69,94	85,25
Standard error of estimation [kWh/Mg]	1,677	0,542	1,664	0,540	0,901	0,105
Relative error of estimation [%]	7,87	12,04	7,81	12,00	4,23	2,33
Number of inputs/neurons	6	4	6	4	6	4
Number of hidden neurons	-	-	-	-	10	9

The degree to which individual models explain the overall variation in indicators, as expressed by the coefficient of determination R^2, varies. The highest value, exceeding 79%, is achieved by the W indicator model, which is high for models based on technological data from a real industrial process. In contrast, the R^2 value for S-index models of about 55% is relatively low.

Standard errors of estimation, which report the average magnitude of the deviations of the empirical values of the dependent variables from the values calculated from the models, that is, the degree of 'fit' of the models to the empirical data, are approximately 1.67 kWh/Mg and 0.54 kWh/Mg of ground limestone, respectively, for the indicator models S and W.

The developed linear regression model of the S-index uses six independent variables, including two control variables (the speed of the screw conveyor motor in the mill and the temperature behind the mill). All independent variables show a high level of statistical significance (p = 0,0000(..) < passumed= 0,05). The strongest influence on the modeled indicator is the position of gas throttle 2, as evidenced by the highest absolute value of the standardized coefficient b* at this variable. The strength of the effect of the parameter on the value of the estimated indicator is positive, which means that opening the throttle by one unit [%] would increase the value of the S-index by 32,8938 kWh/Mg. The burner load and the rotation of the screw conveyor motor in the mill have an equally significant effect on the variability of this indicator. Both variables have negative strength, which means that increasing their values by one unit would favorably reduce the value of the S-index by 0,1335 kWh/Mg and 0,1112 kWh/Mg, respectively. The standard error of the model estimation is 1,6767 kWh/Mg (relative error of 7,87%) and is interpreted as the average deviation of the S-index calculated from actual process data from the theoretical index determined from the model. The value of the coefficient of determination R^2 = 0,5484 means that almost 55% of the variation in the estimated S-index is explained by the model. As a general rule, it is estimated that the degree of explanation of the indicator should not be lower than 70% for industrial conditions. Therefore, the above model has a rather low coefficient of determination R^2, making it unreliable in predicting the indicator for new cases of process data. Despite such a serious shortcoming, the model achieves a low estimation error, indicating a good fit of the model to real data.

An analogous analysis of model construction can be presented for the W linear indicator model W. Its structure is simpler compared to that of the S indicator model, which increases the possibility of its use in control tasks because of its more stable performance. The model depends on four variables, including two control variables (differential pressure at the mill and temperature behind the mill). As in the S-index model, all independent variables have high statistical significance. By far the strongest influence on the modeled W index is the temperature in front of the mill. A decrease of one °C in temperature results in a decrease of 0,0424 kWh/Mg in the W index. The standard error of the model estimation is 0,5422 kWh/Mg (relative error of 12,05%), which is larger relative to model S, but acceptable. On the other hand, the value of the coefficient of determination R^2= 0,7935 is much higher than that of the S indicator model, making it stable for new data cases.

In reality, the relationships between variables are often not strictly linear. For this reason, an attempt has been made to describe the S and W indicators using non-linear regression. Nonlinear models are not only more efficient in many cases, but also more versatile in process optimization. This is be-

cause a non-linear objective function makes it possible to find optimal solutions for the entire range of technological parameters, and not just for boundary points, as is the case with a linear function. The same variables as in linear models were used to build nonlinear models. Nonlinear relationships were analyzed using scatter plots of the dependent variables S and W against the independent variables.

Non-linear models of the S and W evaluation indicators were obtained, taking into account quadratic and hyperbolic relationships between variables (Tables 3.4 and 3.5). These models proved to be slightly more effective than linear models and were similarly characterized by high statistical significance. The most important evaluation indicators for these models are shown in Table 3.8.

Neural network models

Based on the same process variables that described the regression models, neural network models of the evaluation indicators S and W were designed. Network design, after selection of input variables, consisted of the following steps [1]:

- Selecting the initial network structure, usually with a single hidden layer (MLP, RBF, linear networks).
- Iteratively conducting experiments with different network configurations and retaining the best configuration based on validation error.
- If the network is underlearned (when it does not reach the set error level), new neurons had to be added to the hidden layer or the entire layer had to be added.
- In the case of overlearning the network (when the validation error increases before reaching a satisfactory level), a number of hidden neurons or entire layers had to be removed.
- Once the optimal network configuration was found, sampling was done to obtain new networks with the same configuration.

Many of these procedures are done semi-automatically using Statistica Neural Networks computer software, which allows testing different types of networks with different architectures. Coupled gradients and Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm were used to teach neural networks with the following learning parameters: learning coefficient 0,1, inertia 0,3, number of epochs 200. The activation functions of the hidden and output neurons were linear, logistic, hyperbolic tangent and exponential. After testing different types of network, the programme selected the five most effective neural networks. Tables 3.6 and 3.7 summarize the structure and evaluation parameters of these networks. The type and number of neurons in the input, hidden and output layers, the quality of learning, testing and validation, the errors of running the network on a subset of learning, validation and test data, as well as the network learning algorithm used and the activation function of hidden and output neurons are given.

An increase in the validation error relative to the testing error at a certain stage of network learning indicates network overfitting. The value of this error should primarily be taken into account when deciding which network is stable in performance. The qualities of learning, validation, and testing depend mainly on the nature of the network, and in regression issues are expressed by Person's correlation coefficients calculated between the actual and model-calculated values of the explanatory variable [6]. A higher value of the correlation coefficient, especially in the validation set, indicates a better quality (efficiency) of the model. For very good models, the coefficient should not be less than 0,9 (90%).

The most effective neural network modeling the S-index turned out to be a three-layer No. 3 multilayer perceptron (MLP 6-10-1) network. It was built with six neurons in the input layer, ten neurons in the hidden layer and one neuron in the output layer. It had the highest quality parameters and the lowest learning, testing, and validation errors. It used the BFGS learning algorithm and logistic activation functions of hidden and output neurons.

For the W evaluation index, network No. 3 (MLP 4-9-1) proved to be the most effective network model. It consisted of four neurons in the input layer, eight nine neurons in the hidden layer and one neuron in the output layer, making it simpler than the network model of the S indicator. This network achieved even higher learning, testing and validation quality parameters of 0,9174, 0,9269 and 0,9255, respectively. Furthermore, it had lower learning, testing and validation errors of 0,1131, 0,1000 and 0,1028 kWh/Mg, respectively. The BFGS algorithm and activation functions were used to learn the network: logistic in the hidden layer and linear in the output layer.

Comparative analysis

A comparison of the effectiveness of the calculated models is presented in Table 3.8, which summarizes key statistical indicators: correlation and determination coefficients, model fitting errors, the number of input variables, and for neural networks, the number of neurons in the hidden layer, characterizing the complexity of the network structure.

When comparing regression models, it is necessary to take into account in particular the number of process variables, their technological nature, process control possibilities, and the coefficient of determination R^2. Taking into account these parameters, it can be stated that the most effective regression model is clearly the nonlinear model of the W index. It is characterized by a very high degree of explanation of the model by independent variables, ranging from almost 80%, which is a very good result under industrial conditions. Furthermore, this model uses a small number of input variables (four variables, including three technological variables and two control variables) and achieves an acceptable error in predicting the value of the W index at the level of 12%.

Among the neural network models, the W indicator model has the simplest structure. It consists of four input neurons and nine hidden neurons. It is characterized by the highest average quality parameters (R) and the lowest average estimation errors in the training, test and validation sets.

Analyzing the key evaluation parameters included in Table 3.8, the W indicator neural network model can be indicated as the most effective. It is characterized by the highest values of correlation and determination indices, the lowest estimation error and a relatively simple three-layer architecture.

Conclusions

An effective process model developed using the regression method should be characterized by a high degree of fit

to the process data, while limiting the number of independent variables. These variables should not be strongly correlated with each other.

An effective neural network model used for regression problems should have a simple architecture. The number of hidden neurons is a measure of the complexity of the network, therefore models with a smaller number of hidden neurons and inputs are more beneficial, provided that this does not significantly reduce their efficiency. Such models should be characterized by low validation errors and high correlation coefficients.

When comparing two different methods of regression modeling and neural networks, it is difficult to clearly indicate the superiority of one model over the other. The models obtained using neural networks show higher correlation coefficient values and lower prediction errors compared to regression models, suggesting their greater efficiency. Regression models provide a mathematical function of the regression curve, while in neural networks, this function is implicit. In the case of neural networks, the model is the structure of the network. For the above reasons, regression models are more practical and universal for assessing the process and analyzing its functioning. In turn, neural networks can be more useful in controlling and optimizing the process. The question of using the developed models to automate the limestone grinding and classification system will be the subject of further research, and the results of these studies will be published.

The developed technological and energy index W, taking into account the power of the mill and fan drives, the gas consumption in the mill, and the amount of ground limestone, is the most effectively modeled indicator for assessing the limestone grinding and classification system, both in the form of regression equations and neural networks.

The research was carried out as part of the 'Implementation Doctorate' – 4th edition programme.

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Modelowanie przemysłowego procesu mielenia kamienia wapiennego z wykorzystaniem modeli regresyjnych i sieci neuronowych

Artykuł omawia problem identyfikacji matematycznej procesu mielenia kamienia wapiennego w przemysłowym młynie rolowo-misowym, ze szczególnym uwzględnieniem oceny jego energochłonność. Jest to kluczowy etap w optymalizacji procesu mielenia, bowiem opracowanie efektywnych modeli wskaźników oceny procesu technologicznego gwarantuje skuteczną jego optymalizację. Zaproponowano więc wskaźniki technologiczno-energetyczne oceniające proces mielenia i klasyfikacji wapienia, na podstawie których zbudowano modele regresyjne i sieci neuronowe. Modele te pokazują zależności pomiędzy wskaźnikami oceny procesu a danymi energetyczno-technologicznymi pozyskanymi w trakcie eksperymentu czynnikowego na obiekcie przemiałowni. Realizacja eksperymentu przemysłowego miała na celu zbadanie charakteru oraz dynamiki zmian parametrów procesowych. W trakcie doświadczeń zmieniano w szerokim, dopuszczalnym technologicznie zakresie, możliwe do sterowania parametry technologiczne badanego procesu. Identyfikacja procesów opierała się na danych z urządzeń kontrolno-pomiarowych i systemu sterowania procesem, co umożliwiło pełne modelowanie matematyczne procesu i wyjaśnienie współzależności parametrów procesowych. Określono zarówno modele regresyjne oraz modele sieci neuronowych, które pozwoliły na skuteczną identyfikację pracy całego procesu mielenia i klasyfikacji kamienia wapiennego. Modele zostały poddane diagnostyce statystycznej, która miała na celu weryfikację poprawności ich budowy oraz porównanie efektywności działania. Modele regresyjne okazały się bardziej praktyczne w ocenie procesu mielenia, natomiast sieci neuronowe były bardziej przydatne w sterowaniu, dzięki możliwości automatycznego uczenia i aktualizacji w dynamicznie zmieniających się warunkach procesowych.

Słowa kluczowe: *modelowanie procesu mielenia wapienia, wskaźniki oceny, modele regresyjne, modele sieci neuronowych, kontrola procesu*