http://doi.org/10.29227/IM-2021-02-32 Received: 15 Jun 2021, Accepted: 15 Sep 2021, Published: 10 Nov 2021

Method of Air Temperature Forecast in Mechanized Longwall Workings in the Conditions of Vietnamese Mines

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Abstract. In the most recent years, the Vietnam National Coal - Mineral Industries Holding Corporation Limited (VINACOMIN) has been dynamically developing mechanization technologies in underground coal mines. The climatic conditions of Vietnam, as well as increasing the depth of the coal seams and the production capacity, contribute to an air temperature increasing in mining excavations. The article presents statistical equations enabling air temperature forecasting at the outlet of mechanized longwall workings. The results of numerical calculations, obtained from the solutions of the adopted mathematical descriptions, were compared with the measurement results and the statistical significance of the obtained deviations was determined. The performed analysis allowed to assess the practical usefulness of the adopted model for the air temperature forecasting in the workings of mechanized underground mines in Vietnam. The presented method can be used as a tool for mining services in the fight against the climate threat in underground excavations.

Keywords: Climatic conditions, Temperature forecasting, Statistical data analysis

1. Introduction

Air temperature is one of the most important variables for environmental conditions in an underground mine. Environmental conditions in underground mine workings are critical to the health, safety and efficiency of miners, as well as to the operation of machinery and equipment. These factors must be taken into account when planning mining.

According to the regulations in force in Poland, the permissible air temperature in the workplace should not exceed 28°C [1] , and in Vietnam - the maximum air temperature is 30°C [2]. In order to achieve the climatic conditions in the mine workings required by the regulations, it is necessary to ensure proper airflow or use cooling devices. However, it is not possible to provide the required and time invariant microclimate conditions in an underground mine. Very often the mine ventilation system is ineffective and insufficient due to limitations related to the maximum air velocity specified by mining regulations and the topology of the ventilation network. In addition, an increase in the power of energomechanical equipment in high performance longwall systems contributes to an increase in temperature and causes changes in the microclimate at workplaces [3, 4, 5, 6]. Underground mines in Vietnam, Poland as well as around the world are exploiting deposits at increasing depths and using more advanced mechanised systems as global demand for minerals continues to drive rising production rates.

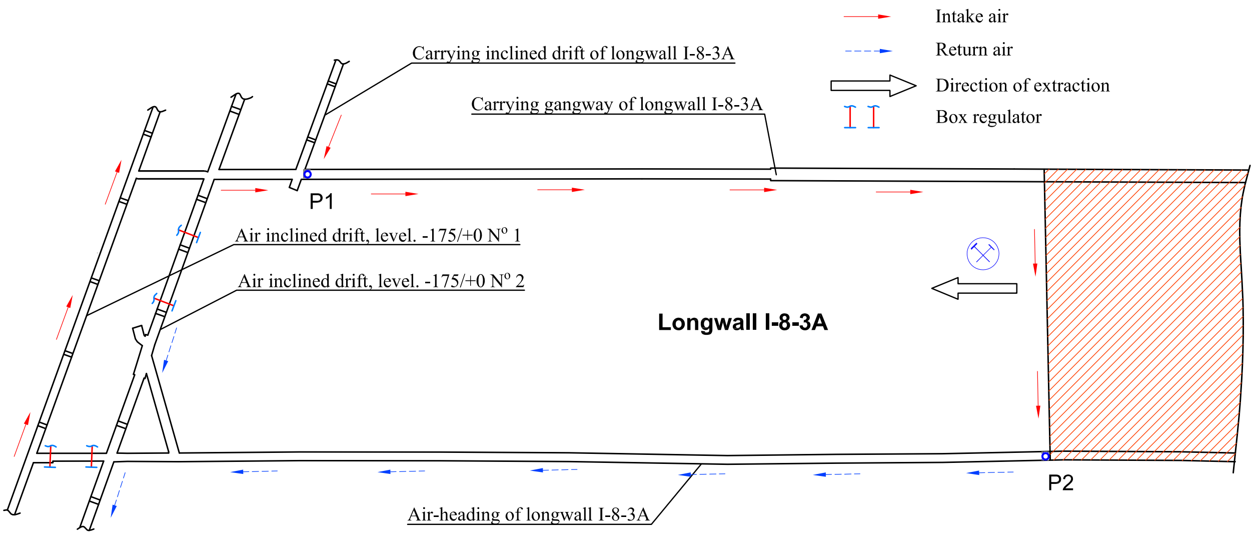
Only a deep analysis of air parameters, heat sources, operating conditions and energomechanical equipment used in longwall areas can be used to predict air temperature. Based on the forecast air temperature, technical and organisational measures can be taken to achieve the required air parameters. Besides, the improvement and adjustment of the ventilation system and the use of cooling equipment will contribute to ensuring microclimate parameters at workplaces.

Currently, the prediction of air temperature in underground mine workings is performed using various models, taking into account the characteristic parameters of the workings and the prevailing climatic conditions. Shiyue Wu et al. [4] proposed mathematical models to predict temperatures in groups of workings in an underground mine, such as: vertical workings (e.g. shaft), horizontal and inclined workings (e.g. crosscut, drift, gallery, ramp, slope mine, etc.), corridor faces and longwalls. Air parameters in the corridor workings were also predicted using CLIMSIM software developed at the University of Nottingham [7]. The CLIMSIM model was developed to simulate climate conditions in workings with streamlined air currents. In 2004, the authors modified the mathematical model to predict climatic conditions in blind workings with separate ventilation [8]. A model of environmental and climatic parameters in mine workings was developed and written in C++ [9]. Artificial Neural Network (ANN) based on nonlinear autoregressive time series algorithm with external input (NARX - Nonlinear Autoregressive Exogenous) was applied as a novel method to predict temperature in mining and ventilation shafts. In [10], an ANN model based on the NARX algorithm is presented for predicting air temperature at the shaft station and for assessing air quality [11]. The models for predicting the temperature in the workings use the principles of energy conservation and it is necessary to consider the heat sources such as autocompression of air, mining machinery and equipment, heat input from the rock mass to the air, etc. The prediction of temperature in the streamlined air current is determined from a linear regression model in which the dependent variable includes inlet temperature, volume air flow rate, and working length [12]. Compared with measured results, these models achieve sufficient accuracy for mining to predict air temperature in pits. However, in order to improve the accuracy of air temperature prediction modeling, more local heat sources in mine workings should be considered.

This paper presents an integrated approach for predicting air temperature at the outlet of mechanised longwalls in Vietnam using statistical models. The main goal is to create accurate linear and nonlinear equations between the dependent variable and the independent variables. In these equations, the dependent (explained) variable is the outlet air temperature (t_p). On the other hand, the independent (explanatory) variables are: air temperature at the longwall inlet (to), relative humidity (φ), volume air flow rate (V), heat source power (Q) and working depth (z). The thermodynamic parameters of working air, volume air flow rate, and working depth are mostly well known or easily measured by ventilation and power services at the mine. Therefore, the criteria given in this paper for predicting the air temperature at the outlet of mechanised longwalls can be useful for temperature prediction by ventilation services. The models presented can serve as a tool for mine services to deal with climate hazards in underground workings in Vietnamese underground mines.

2. Research results of selected mechanised longwalls in Vietnam

By the end of 2021, most underground coal mines in Vietnam will use mechanised mining [13]. Mechanised longwalls use machines and equipment that have high electrical power, such as in Ha Lam mine (the total power of the electrical equipment working in the I-11-16 mechanised longwall was 1503 kW) [14], Duong Huy coal company (in the TT-11-6 mechanised longwall, the total power of electrical equipment was 1389.5 kW) [15], the total power of electrical equipment used in the working was 1689 kW in the I-8-3A mechanised longwall in Vang Danh mine [16], etc. Mechanised longwalls were also ventilated with the system at U. The volume air flow rate was high and varied from 1045 to 1609 m^3/min. The average working depth of the studied longwalls (calculated from the ground surface) varies from 163.2 to 293.2 m. The primary temperature of the rock mass in the excavated workings ranged from 30.9 to 32.9°C. On the other hand, daily coal extraction from these longwalls averaged approx. 1150 to 1975 Mg. Figure 1 shows the ventilation scheme of the I-8-3A mechanised longwall area in Vang Danh mine. The figure shows the layout of the excavations with the direction of air flow marked on it. Besides, points P1 and P2 mark the places where air parameters are measured.



http://doi.org/10.29227/IM-2021-02-32 Received: 15 Jun 2021, Accepted: 15 Sep 2021, Published: 10 Nov 2021

Fig. 1. Diagram of ventilation in the area of the I-8-3A longwall of deposit No. 8 in the Vang Danh mine, P_1 - inlet to the longwall region; P_2 - outlet from the longwall [16].

To create a mathematical model using statistical tools to predict the air temperature at the outlet of longwalls, the data of measurement points P1 and P2 from mining workings in Vang Danh, Ha Lam, Duong Huy mines were used. Ventilation measurements were taken at the designated measuring stands, including measurements of the air velocity and the area of working cross-sections to calculate the volume air flow rate (V), measurements of the air temperature (t_o) at the inlet (at point P1) and the air temperature (t_p) at the outlet (at point P2), measurements of the relative humidity of the air (φ). Heat source power (Q) was determined based on the calculation of heat from equipment, dredged material transport process and coal oxidation. The depth of the workings was determined by the average depth values of the longwall working sections to the surface. The data used is from May 2018 to September 2020. The results of air temperature measurements at the longwall outlet and air parameters at the inlet, heat source power, and working depth for all 198 alternatives are shown in Figure 2.

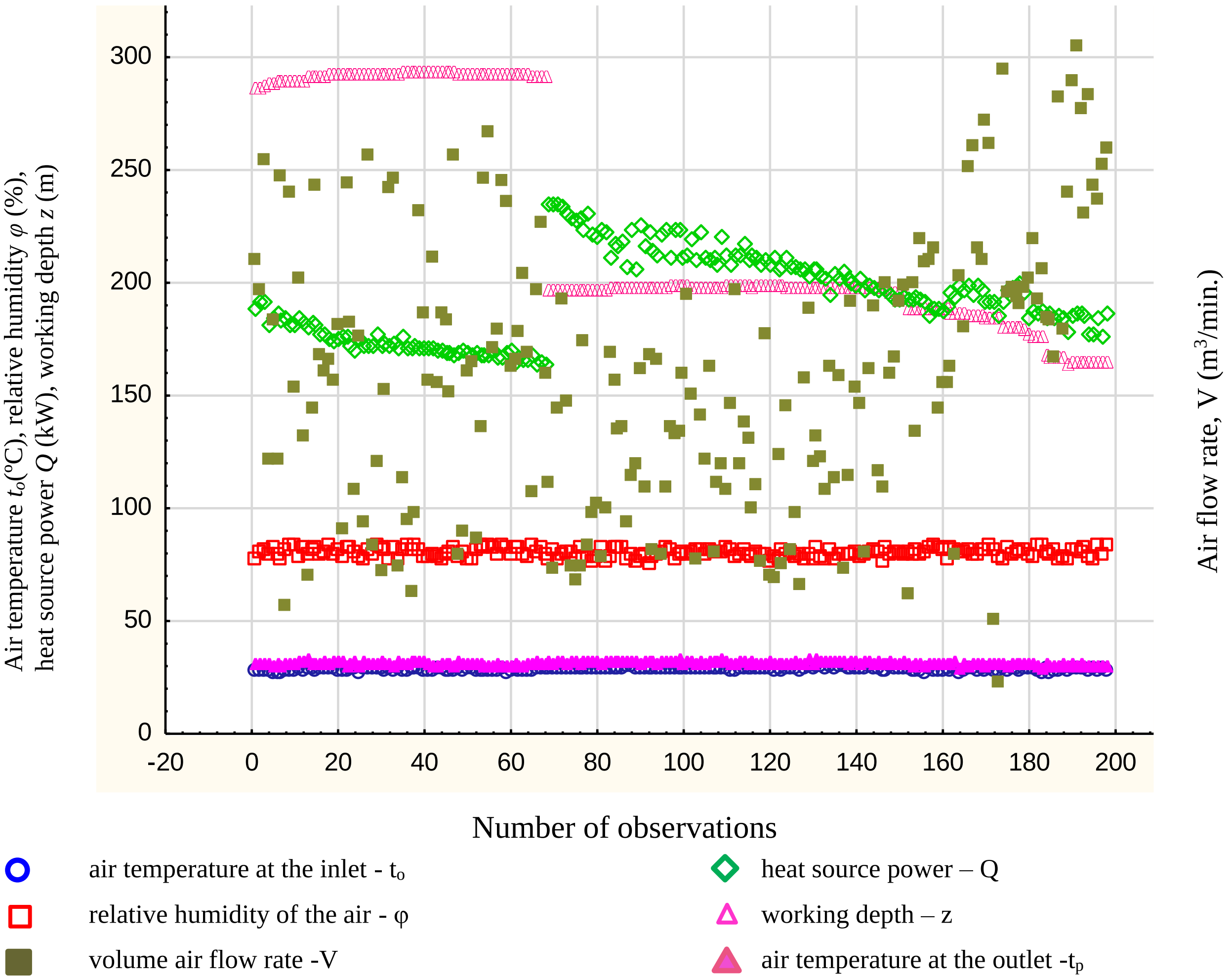


Fig. 2. Results of measurements of air temperature at the longwall outlet and air parameters at the inlet, heat source power and working depth used.

3. Analyses of basic statistical parameters

This paper analyses and evaluates the influence of technical and thermodynamic factors on the variation of air temperature at the outlet of mechanised longwalls. All independent variables and the dependent variable were verified for the type of statistical distribution by comparing them with a standardised normal distribution. Descriptive statistics characterise parameters such as arithmetic mean, geometric mean, median, mode, mode count, minimum, maximum, standard deviation, coefficient of variation, skewness, kurtosis.

When data are not normally distributed and measurements are at best expressed on an ordinal scale, then the calculation of standard descriptive statistics (e.g. mean, standard deviation) is not the best way to represent data collectively. Nonparametric statistics and distributions allow us to define a number of different measures of position (mean, median, mode, etc.) and dispersion (variance, mean deviation, fractional interval data, etc.), thus providing a complete picture of the variability of the data. Nonparametric statistics and distributions allow the calculation of a wide range of different measures of location, thus giving a complete picture of the data [17, 18]. Table 1 shows the basic descriptive statistics determined for the variables analysed for the mechanised longwalls.

Tab. 1. Descriptive statistics of predictors and dependent variable for mechanised longwalls in a 198 element study sample.

Parameter	Air temperature at the inlet, t_o [°C]	Relative air humidity, φ [%]	Volume air flow rate, V [m^3/min]	Power heat source, Q [kW]	Working depth, z [m]	Air temperature at the outlet, t_p [°C]
Arithmetic mean	28.552	80.114	1317.343	193.365	225.320	31.141
Geometric mean	28.546	80.090	1311.994	192.456	220.328	31.132
Median	28.7	80.1	1319.0	192.3	198.0	31.2
Mode	29.1	79.4	Multiple	172.2	Multiple	31.2
Mode count	22	8	3	4	10	14
Minimum	26.8	75.5	1045.0	163.6	164.2	28.9
Maximum	29.7	83.9	1609.0	234.7	293.2	33.1
Standard deviation	0.5986	1.9720	119.3295	18.8999	49.0107	0.7796
Coefficient of variation	2.0966	2.4615	9.0583	9.7742	21.7516	2.5033
Skewness	-0.7223	-0.0315	0.2091	0.2845	0.5522	-0.3652
Kurtosis	0.1296	-0.8484	-0.6425	-0.9355	-1.5285	-0.0245

It is clear from this table that there is not much difference between the arithmetic mean and the geometric mean. Except for the z variable, the differences between the arithmetic mean and the median are very small. For the working depth variable (z), this difference is 27.32 m, which is approx. 12%. For the individual variables, the largest difference in standard deviation was determined for the working depth and is approximately 22%. When evaluating measures of clustering and dispersion and inferring the normality of the data distribution, kurtosis and skewness deserve attention. The analysis of skewness (asymmetry of distribution) and kurtosis (flattening of distribution) measures allows us to conclude that in all cases we are dealing with normal distributions or distributions close to normal ($|\text{skewness}|<1.5$, $|\text{kurtosis}|<3$) [19]. For all variables, the skewness value ranges from -1.0 to 1.0 Analysis of the flattening measures showed that the distributions of all variables are close to the normal distribution in this respect. The modal value, or dominant, is the value that occurs most often, with the highest probability. For volume air flow rate and working depth, the distribution shows features of multiple mode. Multiple mode is common; in fact, many physical phenomena have multiple mode distributions. This regularity of a characteristic often occurs in situations where the human factor and the repeatability of a phenomenon play a role in the measurement procedure [20, 21].

According to the [22, 23] important element of variable description is the shape of its distribution, which informs about the number of values of this variable in different areas of its variability. The normal distribution (with its characteristic "bell curve" shape, symmetrical with respect to the mean) is a theoretical probability distribution commonly used in statistical inference as an approximation to the sample

http://doi.org/10.29227/IM-2021-02-32 Received: 15 Jun 2021, Accepted: 15 Sep 2021, Published: 10 Nov 2021

distribution. The nature of the distributions of the measurement data was apparently examined on the basis of the prepared histograms and using the statistical Kolmogorov-Smirnov test modified by Lilliefors and the Shapiro-Wilk test at the 0.05 significance level. Figs. 2-7 present graphs in the form of histograms of the variation of the values of all the variables used in the statistical analysis for the mechanised longwalls. The figures also show the results of the performed tests of normality of distributions, the symbols used mean respectively: K-S - Kolmogorov-Smirnov test, d - value of K-S test statistic, S-W - Shapiro-Wilk test, W - value of S-W test statistic, p - significance level.

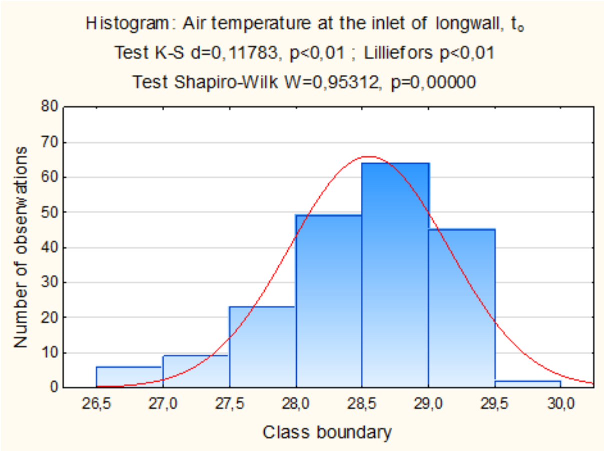


Fig. 3. Air temperature distribution at the outlet for mechanised longwalls.

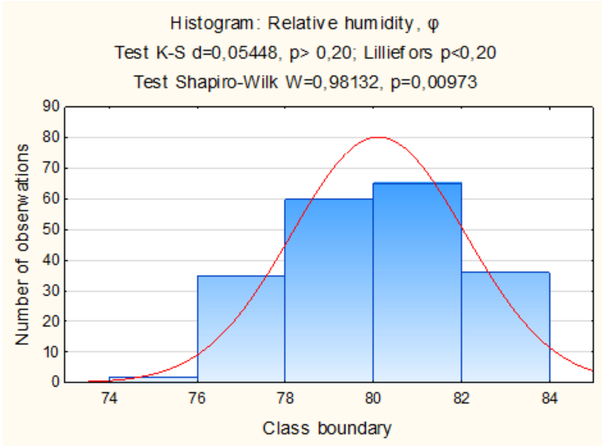


Fig. 4. Air humidity distribution for mechanised longwalls.

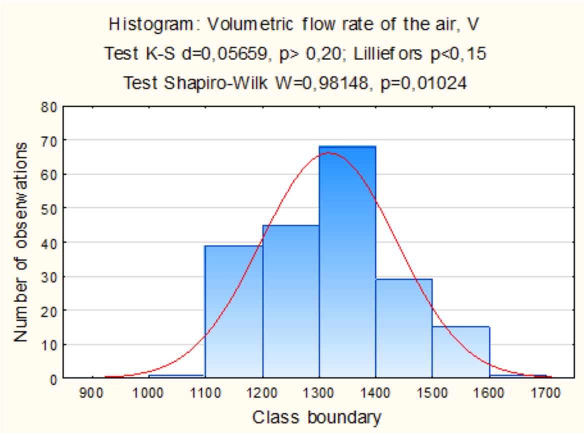


Fig. 5. Volume air flow rate distribution for mechanised longwalls.

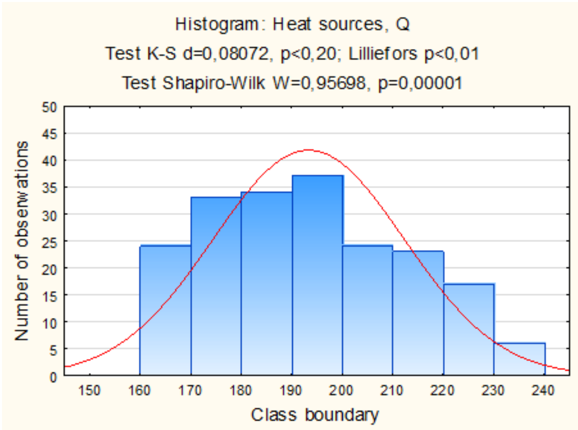


Fig. 6. Power distribution of heat power sources for mechanised longwalls.

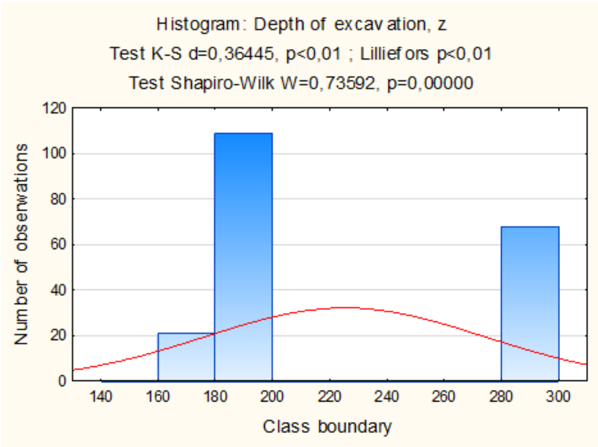


Fig. 7. Working depth distribution of for mechanised longwalls.

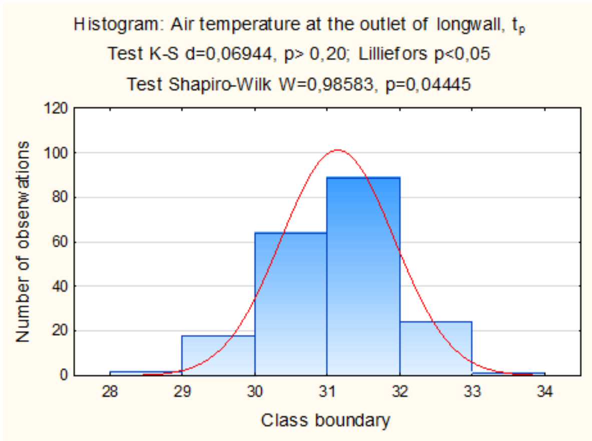


Fig. 8. Air temperature distribution for mechanised longwalls.

Based on the graphs and Shapiro-Wilk test results for all variables, the significance level values were found to be less than 0.05. Therefore, the H_o hypothesis was rejected in favor of the alternative hypothesis that the variables t_o, φ, V, Q, z, t_p are not normally distributed. For the Kolmogorov-Smirnov test, the value of p-significance is also less than 0.05. Therefore, like the Shapiro -Wilk test, the H_o hypothesis is rejected and the variables t_o, φ, V, Q, z, t_p do not have a normal distribution. However, by visually evaluating the test values obtained for these variables and the shape of the graph, it can be concluded that the distributions of these variables are close to a normal distribution. For variable (z), it can be observed that values between 180-200 m and 280-300 m are dominant, as there is not much variation in the level of coal seams and their exploitation in the longwall region. The difference in depth is due to the change in depth of the inlet and outlet of the mining longwall.

After an initial multiple regression analysis of the first model, several residuals were found that did not fit the standardised straight line. Which shows that there are outliers in the model. These values reduce the estimation efficiency of the linear regression model. On this basis, 30 variants were eliminated from the model. Table 2 collects the basic descriptive statistics determined for the 168 element sample.

Tab. 2. Descriptive statistics of predictors and dependent variable for mechanised longwalls in a 168 element study sample.

Parameter	Air temperature at the inlet, t_o [°C]	Relative air humidity, φ [%]	Volume air flow rate, V [m^3/min]	Heat power sources, Q [kW]	Working depth, z [m]	Air temperature at the outlet, t_p [°C]
Arithmetic mean	28.548	79.945	1,320.506	192.982	223.818	31.133
Geometric mean	28.541	79.921	1,315.056	192.105	218.815	31.125
Median	28.700	79.800	1,321.000	192.050	197.900	31.200
Mode	29.1	79.4	1158.0	172.2	197.3	Multiple
Mode count	20	8	3	3	9	12
Minimum	27.0	75.5	1,045.0	163.6	164.2	28.9
Maximum	29.7	83.9	1,609.0	234.6	293.2	32.4
Standard deviation	0.6002	1.9943	120.5605	18.5504	49.0535	0.7060
Coefficient of variation	2.1024	2.4945	9.1299	9.6125	21.9167	2.2676

Parameter	Air temperature at the inlet, t_o [ºC]	Relative air humidity, φ [%]	Volume air flow rate, V [m^3/min]	Heat power sources, Q [kW]	Working depth, z [m]	Air temperature at the outlet, t_p [ºC]
Skewness	-0.6905	0.0789	0.1890	0.2786	0.5931	-0.5111
Kurtosis	-0.0146	-0.8121	-0.6192	-0.8937	-1.4726	-0.0544

Table 2 shows that, as in the first model, there is no significant difference between the arithmetic mean and the geometric mean. Except for the z variable, the differences between the arithmetic mean and the median are very small. For the working depth variable, the difference is 25.92 m, which is approx. 12%. For the individual variables, the greatest difference in standard deviation was found for the working depth and this value is approximately 22%. When evaluating measures of clustering and dispersion and inferring the normality of the data distribution, kurtosis and skewness deserve attention. Analysis of skewness and kurtosis indices allows us to conclude that in all cases we are dealing with normal or near-normal distributions (|skewness|<1.5, kurtosis<3). For all variables, the skewness values range from -1.0 to 1.0. The kurtosis values of all variables are less than 0. Thus, the variables have a platocurtic (more flattened) distribution. Analysis of the flattening measures showed that the distributions of all variables are close to the normal distribution in this respect. In the case of the air temperature at the outlet, the distribution shows the characteristics of a multiple mode.

In the absence of statistically significant differences in the histograms and their effect on the multiple regression process with reduced sample size, the histograms for the 168 element sample are not presented in this paper.

4. Linear and nonlinear regression analyses

Linear and nonlinear statistical equations were determined for a set of measurements consisting of 168 observations to predict the air temperature at the outlet of the mechanised longwalls. All statistical calculations were performed using Statistica version 13, IBM SPSS Statistics version 25 and EViews version 8.

The general equation of air temperature at the outlet of the longwall t_L for the multiple linear regression model determined by the least squares method presents the relationship (1):

$$t_L = \beta_1 \cdot t_o + \beta_2 \cdot \varphi + \beta_3 \cdot V + \beta_4 \cdot Q + \beta_5 \cdot z + \beta_o \tag{1}$$

where: $\beta_1 - \beta_5$ – regression coefficients expressing the direct effect of variables t_o, φ, V, Q, z.

βo – absolute term, is the coefficient of freedom (coefficient of intersection), which is the starting point of the theoretical regression line, showing the influence of other factors on the value of the explained variable than the independent variables used in the model.

The best fit of the results of a model built using linear regression is obtained when the following assumptions are met: the residuals of the model must have a normal distribution, there are no outliers, the residuals of the model are homoskedastic, there is no collinearity between the independent variables, and there is no autocorrelation of the model residuals [18, 20, 23, 24].

After meeting the above requirements, the dependent variable t_L is described by the independent variables t_o, φ, V, Q, with a linear regression equation in the form (2):

$$t_L = 0,7340 \cdot t_o - 0,0334 \cdot \varphi - 0,0021 \cdot V + 0,0089 \cdot Q + 0,0045 \cdot z + 12,8567 \tag{2}$$

The value of the coefficient of determination R^2 = 0.793 of the model indicates a strong correlation relationship of the t_L variable with the independent variables. The results of VIF test (collinearity test), Jarque-Bera test (normal distribution test of residual component), White test and Breusch - Pagan test (heteroskedasticity test of residuals), Durbin-Watson test and Breusch - Godfrey tesst (autocorrelation test of residuals) meet the criteria of linear regression. The model presented in equation 2 is a good fit to the measured data analysed, explaining the variation in air temperature at the t_L longwall outlet.

In order to simplify the model and obtain a more convenient form of the equation for practical use, a modification was made to the values of the coefficients of function (2). The modification was done to get the best possible functional representation. Thus, equation (2) after modifying the values of the function coefficients has the form (3).

$$t_{L-z} = 0,73 \cdot t_o - 0,03 \cdot \varphi - 0,002 \cdot V + 0,009 \cdot Q + 0,005 \cdot z + 12,5 \tag{3}$$

where by t_{L-z} the air temperature at the outlet of the mechanised longwalls after modifying the function coefficients.

Figure 9 shows the relationship between the measured values of air temperature at the outlet of the mechanised longwalls and the values of this temperature determined from the statistical equations created, before and after modification of the function coefficients (Eqs. 2 and 3).

Analysing the results obtained, it can be observed that the largest deviation for which the difference between the air temperature at the longwall outlet resulting from the measurements and the value obtained from the linear equation is 0.6ºC (2%). In contrast, the deviation calculated from the linear equation with corrected function coefficients for this variant is 0.7ºC (2.2%). Comparison of t_L and t_{L-z} values from the two models shows that there are not very large differences between the models, the largest being 0.1ºC (0.27%).

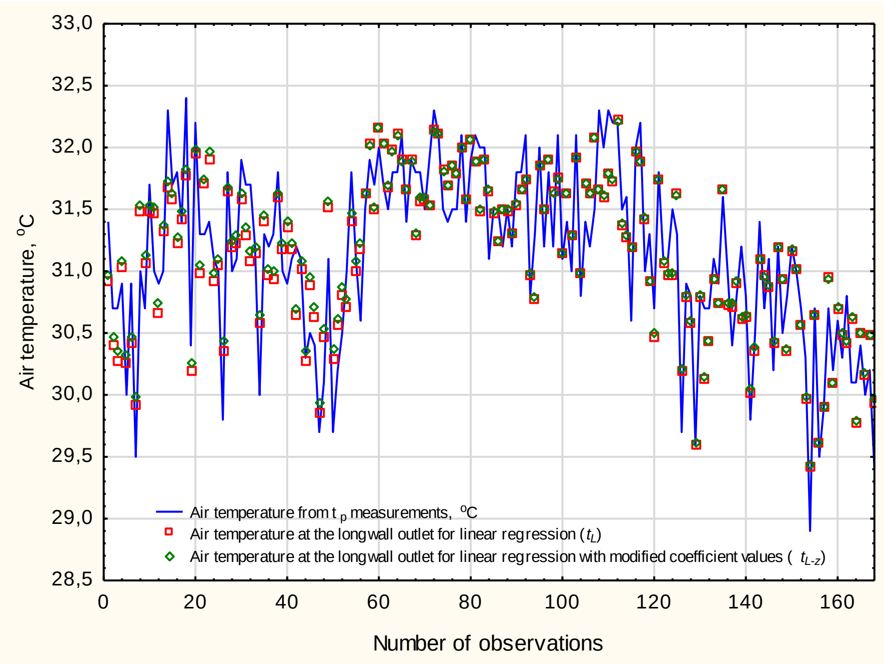


Fig. 9. Correlation of observed and predicted values of air temperature at the longwall outlet for linear regression before and after modification of function coefficients.

To determine better model fit than the linear regression model, correlation analysis between the dependent variable and each independent variable was conducted for the linear, logarithmic, quadratic, power, and exponential models. In most cases, the correlation between the factors analysed and air temperature at the longwall outlet is significant or high. Only the correlation relationship of air humidity (φ) and working depth (z) is small. Except for variable (z), the values of p-significance of tests for the other variables are less than 0.05, which indicates the statistical significance of these variables in the regression model. Considering the results of the partial correlation analysis, the fit of the linear function was found to be as good as that of the power or exponential function, so this paper presents the analysis of the linear function.

Based on the Levenberg-Marquardt nonlinear estimation of the system displacement for the above variables, a nonlinear model of the change in air temperature at the longwall outlet (t_K) was determined in the form (4):

$$t_K = -0,0342 \cdot t_o^2 - 2,21 \cdot 10^{-4} \cdot \varphi^2 + 6,619 \cdot 10^{-7} \cdot V^2 - 9,838 \cdot 10^{-5} \cdot Q^2 - 5,788 \cdot 10^{-5} \cdot z^2$$
$$+8,864 \cdot 10^{-7} \cdot t_o \cdot Q \cdot V + 2,449 \cdot t_o - 84,43 \cdot 10^{-4} \cdot V + 0,0135 \cdot Q + 0,0321 \cdot z - 8,9727 \tag{4}$$

The value of the coefficient of determination is R^2= 0.804 and indicates a very strong correlation relationship between air temperature at the outlet t_K and the independent variables used.

Received: 15 Jun 2021, Accepted: 15 Sep 2021, Published: 10 Nov 2021

As in the case of linear regression, in equation 4, the values of the coefficients standing by the independent variables were modified, resulting in a new form of the function, equation (5):

$$t_{K-z} = -34,2 \cdot 10^{-3} \cdot t_o^2 - 22,1 \cdot 10^{-5} \cdot \varphi^2 + 66,2 \cdot 10^{-8} \cdot V^2 - 98,4 \cdot 10^{-6} \cdot Q^2 - 57,9 \cdot 10^{-6} \cdot z^2$$
$$+88,6 \cdot 10^{-8} \cdot t_o \cdot Q \cdot V + 2,5 \cdot t_o - 84,4 \cdot 10^{-4} \cdot V + 0,014 \cdot Q + 0,032 \cdot z - 10,5 \quad (5)$$

where by t_{K-z} is the air temperature at the outlet of the mechanised longwalls after modifying the function coefficients.

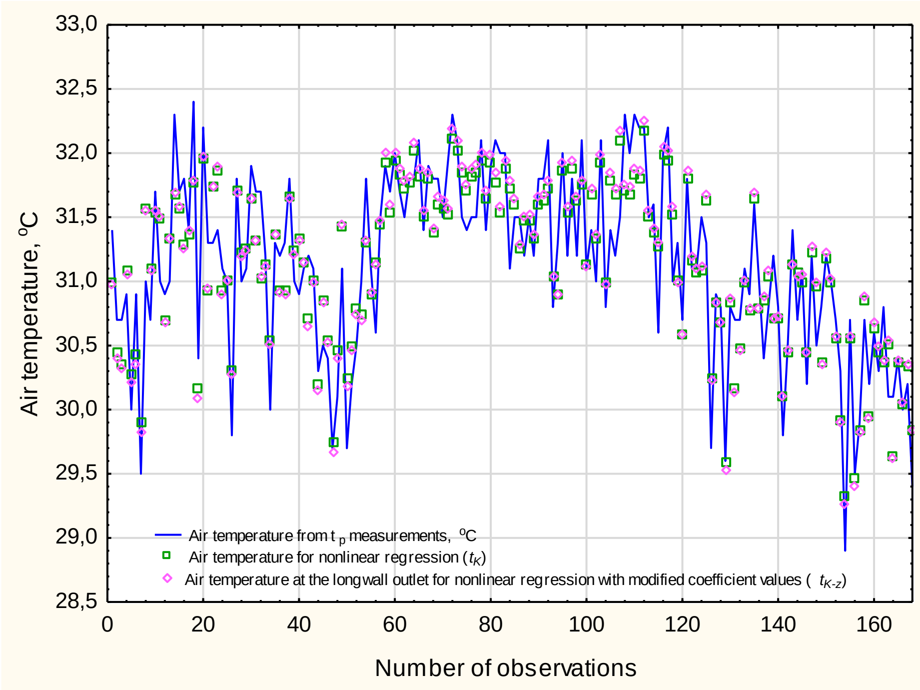


Fig. 10. Correlation of observed and forecasted air temperatures at longwall outlet for nonlinear regression before and after modification of function coefficient.

After analysing the air temperature values at the longwall outlet obtained from the statistical equations created (Eqs. 4 and 5), it can be concluded that the largest deviation of the air temperature value obtained from the measurements and the model value calculated from the nonlinear equation is 0.7°C (2.2%). In contrast, the deviation calculated from the linear equation with corrected function coefficients for this variant is 0.7°C (2.3%). The comparison of the values of t_K and t_{K-z} from the two equations shows that there is no significant difference in value between the two models. The largest difference between t_K and t_{K-z} is 0.1°C (0.25%). The distribution of air temperature values at the outlets of the t_p, t_K, t_{K-z} longwalls is shown in Figure 10.

5. Air temperature prediction under Khe Cham III mine conditions

In the 14-5-5 longwall in Khe Cham III mine, the air flow rate at the inlet of the longwall varied from 1165 to 1475 m^3/min. This longwall was ventilated by a U-system, and the primary temperature of the rock mass was 31.1°C. Figure 11 shows the ventilation scheme for the area of the 14-5-5 longwall in Khe Cham III mine. A longwall shearer MG150/375-W of 375kW power and two longwall conveyors SGZ630/264 with drives of total power of 528kW (upstream and downstream of the powered roof support) operated in the longwall. The transport gallery was equipped with a scraper conveyor type SZZ630/110, a belt conveyor type DSJ100/80/110, a crusher type PLM 800 and some other equipment. The total power of the electrical equipment operating in the workings was 1358 kW. The longwall output ranged from 600 to 2610 Mg/day.

In the analysed example of mechanised longwall 14-5-5 in Khe Cham III mine, the determined criterion equations (3) and (5) with modified values of function coefficients were used to predict the temperature at the longwall outlet. Table 3 shows the values of the characteristic parameters-required for air temperature modeling, the measured air temperature values at the outlet of the 14-5-5 longwall (shown in gray), and the predicted air temperature values t_{L-z} and t_{K-z}.

http://doi.org/10.29227/IM-2021-02-32 Received: 15 Jun 2021, Accepted: 15 Sep 2021, Published: 10 Nov 2021

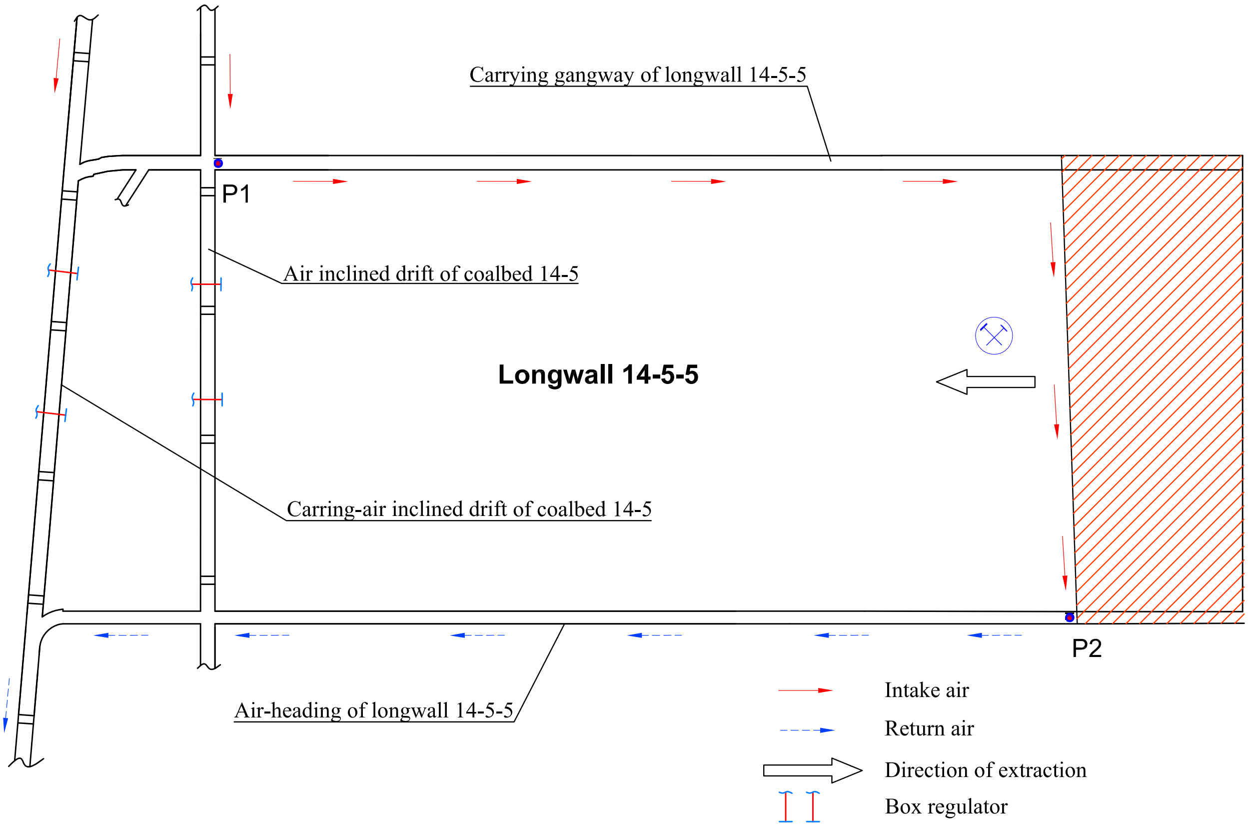


Fig. 11. Ventilation scheme for longwall area 14-5-5 in Khe Cham III mine [25].

Tab. 3. Results of measuring and predicting air temperature at the outlet of the 14-5-5 mechanised longwall in Khe Cham III mine.

Ordinal	Air temperature at the inlet	Relative air humidity	Volume air flow rate	Heat source power	Working depth	Air temperature at the outlet		
	t_o	φ	V	Q	z	t_p	$t_{L\text{-}z}$	$t_{K\text{-}z}$
	ºC	%	m^3/min.	kW	m	ºC		
1	27.8	82.0	1165	204.4	277.5	31.8	31.2	31.2
2	28.2	80.3	1206	203.1	276.5	31.5	31.5	31.5
3	28.7	81.1	1327	200.3	276.5	31.7	31.5	31.6
4	28.7	81.8	1416	200.2	276.5	31.2	31.3	31.4
5	28.4	81.5	1261	212.4	276.5	30.9	31.6	31.5
6	28.1	81.2	1370	202.1	276.4	30.7	31.0	31.1
7	27.3	81.3	1347	201.8	275.1	31.3	30.5	30.4
8	27.3	81.5	1463	195.6	275.0	29.9	30.2	30.2
9	26.9	79.3	1254	193.1	275.0	30.7	30.4	30.3
10	27.0	77.5	1475	195.7	274.9	30.1	30.1	30.0

Based on the analysis of the obtained results, it can be concluded that the average error between the measured values and the forecast values is 0.3 ºC (1.1%) (linear equation) and 0.4 ºC (1.2%) (nonlinear equation). The largest temperature deviation for the linear equation is 0.81ºC (2.60%) and for the nonlinear equation is equal to 0.85ºC (2.73%). Such small deviations of the predicted air temperature for the 14-5-5 longwall in Khe Cham III mine, allow to use the created statistical models with modified function coefficients (Eqs. 3 and 5). The models obtained by statistical analysis can be used as a tool for mine services to predict the air temperature at the outlet of the exploited longwall.

6. Summary

This paper discusses methods for predicting air temperature at the outlet of mechanised longwalls in Vietnamese underground mines. The equations obtained by the method of multiple regression and nonlinear estimation determine the dependence of the air temperature at the longwall outlet on the air temperature at the longwall inlet, relative humidity of the air, volume air flow rate, heat source power and working depth. Modifying the values of the function coefficients to a simpler form yielded new equations that are less complex and more convenient for practical use. Using the criterion equations formed by statistical methods, a prediction of the air temperature at the outlet of the 14-5-5 mechanised longwall at the Khe Cham III mine was made. By analysing the obtained results, it can be concluded that there is a high fit between equation (3) and equation (5), and the measured longwall outlet temperature, where the differences of the obtained temperatures do not exceed 1.2%. The criterion equations presented with modified function coefficients allow for simple modeling and prediction of air temperature at the longwall outlet. The function models presented can serve as a tool for mine services to predict the air temperature at the outlet of mechanised longwalls under Vietnamese mine conditions.

Acknowledgements

We are grateful to the Faculty of Civil Engineering and Resource Management, AGH University of Science and Technology for providing essential equipments for this study. Data used for this study were provided from the Mining Safety Center – Institute of Mining Science and Technology (IMSAT), Vinacomin – Khe Cham Coal Company, Vinacomin – Vang Danh Coal Joint Stock Company, Vinacomin – Duong Huy Coal Company and Vinacomin – Ha Lam Coal Joint Stock Company.

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