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Quantifying the thermal damping effect in underground vertical shafts using the nonlinear autoregressive with external input (NARX) algorithm

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ABSTRACT

As air descends the intake shaft, its infrastructure, lining and the strata will emit heat during the night when the intake air is cool and, on the contrary, will absorb heat during the day when the temperature of the air becomes greater than that of the strata. This cyclic phenomenon, also known as the "thermal damping effect" will continue throughout the year reducing the effect of surface air temperature variation. The objective of this paper is to quantify the thermal damping effect in vertical underground airways. A nonlinear autoregressive time series with external input (NARX) algorithm was used as a novel method to predict the dry-bulb temperature (T_d) at the bottom of intake shafts as a function of surface air temperature. Analyses demonstrated that the artificial neural network (ANN) model could accurately predict the temperature at the bottom of a shaft. Furthermore, an attempt was made to quantify typical "damping coefficient" for both production and ventilation shafts through simple linear regression models. Comparisons between the collected climatic data and the regression-based predictions show that a simple linear regression model provides an acceptable accuracy when predicting the T_d at the bottom of intake shafts.

1. Introduction

Climatic models are usually developed and used to predict the climatic conditions in future underground mines and determine whether a mine's ventilation system (primary/auxiliary) can provide adequate thermal conditions in the development and production workings. Climatic models can also be developed and used for existing underground mines to quantify the heat generated by various heat sources, and to assess what cooling method would be the most cost-effective strategy to control the thermal environment. For existing operations, ventilation and climatic data collection are essential to validate the ventilation and climatic models, which can then be used to understand transient heat transport processes along vertical and horizontal airways, determine the heat profile of the mine and to prepare short-term and long-term airflow delivery plans. To design and manage an underground ventilation system with respect to safety and cost, it is important to incorporate time-dependent heat exchange processes in the system, so that any unusual activities and rapid changes can be taken into account. For future underground operations, there are several key elements which need to be captured and incorporated into the climatic model to accurately predict temperature and humidity levels. These key elements include the thermal damping effect, the dynamic heat exchange processes between the ventilating air and the surrounding rock, and equipment activity profiles throughout localized production and development areas and mine-wide.

With the exception of one mine ventilation software that is under development and testing, no other ventilation or climatic modeling software packages have the ability take into account the "thermal damping effect" (also known as the thermal flywheel effect) when modeling the thermal environment in deep and hot mines. The major difficulty in incorporating the "thermal damping effect" (TDE) comes from a large number of variables interacting with each other plus the time-dependent heat and mass transport processes that control the flow of strata heat into/from the mine airways. Stroh introduced the TDE in the mine ventilation litera-

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ture as a phenomenon that was observed in several shaft surveys, and he defined the thermal damping "... as a value which varies from mine to mine." [1]. Danko et al. developed analytical solutions to take into account the effect of temperature damping based on the transient thermal mass transport processes, which are presently incorporated into a mine ventilations simulator [2]. Brake reported a descriptive explanation of the TDE (as low and high) for the intake airways in two underground mines in Australia [3]. Furthermore, Brake defined the TDE as a function of the travel time and contact distance for air traveling along the intake airways [4]. McPherson mentioned that because of significant surface temperature variations during daytime and nighttime, it is common for the walls and the surrounding rock to absorb heat during the day and to emit heat during the night [5]. Describing thermal damping, he noted that: "...the phenomenon continues along the intake airways and tends to dampen out the effects of the surface temperature variation as the air travels down vertical airways into an underground mine". Kocsis and Hardcastle observed the effects of the TDE experimentally during climatic data collection in deep underground mines in Canada [6]. Their study showed that during summer and winter there is a change in the phase angle of the periodic and harmonic air temperature variations. A recent study also verified this phase shift and its effect on the temperature of the mine air through climatic simulations performed on a ventilation-thermal-humidity (VTH) model [7].

The main objective of this paper is to introduce a novel method to quantify the thermal damping effect using "artificial neural networks" (ANNs) based on a "nonlinear autoregressive with external input" (NARX) algorithm. In this paper, the important ventilation, climatic, and geotechnical parameters that affect the damping of the mine air along vertical airways are also described. Input-output time series analyses were conducted using NARX on two production shafts and one ventilation shaft at two underground precious-metal mines in Nevada. Furthermore, time series analyses were also performed to develop simple correlation coefficients, which would help to predict the dry-bulb temperature (T_d) at the bottom of the production and ventilation shafts as a function of the surface temperature.

2. Thermal damping effect (TDE)

Heat is transferred to the mine air from a variety of sources including auto-compression, strata, mining equipment, explosives, etc. In many cases, the airflow itself is sufficient to remove the heat which has been transferred to the mine air along vertical and horizontal airways and during the mining processes. In deep metal mines, however, the heat removal, which is usually the dominant environmental problem, may necessitate the use of some method of cooling (e.g. mine-wide, localized). When cool air passes through a horizontal airway, its temperature usually increases. This is caused by the natural geothermal heat being conducted through the rock toward the airway. The geothermal heat will then pass into the mine air through the boundary layers that exist in the air close to the rock surface. The envelope of rock close to the newly driven airway will rapidly cool, and there will be a relatively high rate of initial heat release into the mine air. This will decline in time, and the rock surface will gradually cool and approach an equilibrium state when its temperature equals that of the mine air. Furthermore, if the airway is wet, then the increase in the dry-bulb temperature is less noticeable, or it may even fall. This is a result of the cooling effect of evaporation. Heat may still emanate from the strata. However, much of this heat is utilized to transfer the water molecules into the mine air in the form of water vapor [5].

When air descends an intake shaft, its lining and the surrounding strata will emit heat during the night when the incoming air is cool and, on the contrary, absorb heat during the day if the air temperature becomes greater than that of the strata temperature. The depth of the intake shaft where heat flow reverses varies by season (to some extent even daily), firstly due to the initial starting conditions of the air (T_d, T_w, BP), and secondly, due to the surface temperature of the rock and its geothermal step. The change of the phase angle of the periodic, harmonic and temperature variation is known to be the "thermal damping effect".

Figs. 1 and 2 illustrate the thermal damping effect in a production shaft. For example, Fig. 2 shows that during summertime, the temperature at the top of the shaft varies widely, from a high value

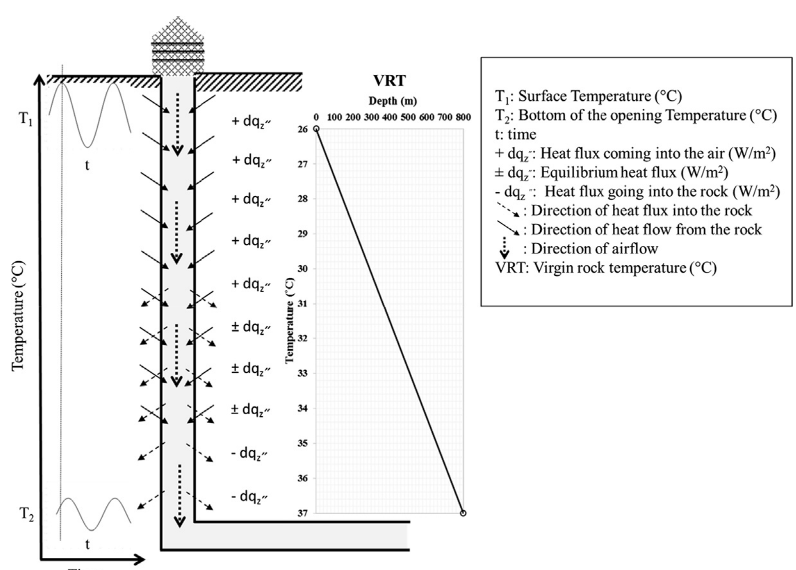

Fig. 1. Heat exchanges along a vertical opening during day and night as a function of surface air temperature and strata virgin rock temperature.

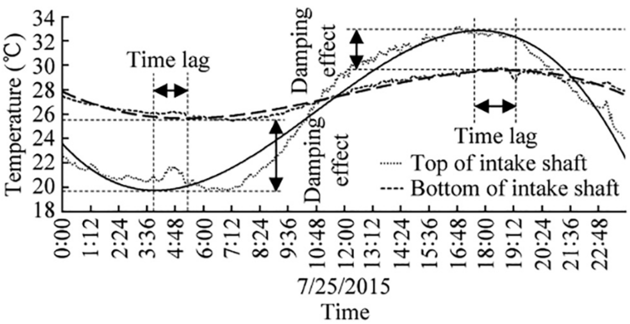

Fig. 2. Dry-bulb temperature damping at the bottom of an intake shaft during a 24 h time period.

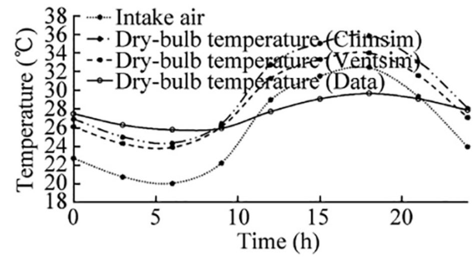

Fig. 3. Comparison between measured air temperatures (e.g. DATA) at the bottom of an intake shaft and simulated air temperatures by ventilation and climatic software packages.

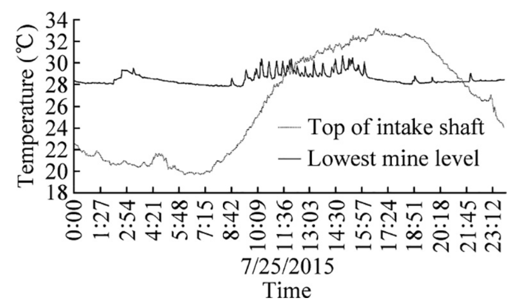

Fig. 4. Thermal damping effect depends on the travel time and the airflow-wall contact distance-For an airway located at a long distance from the collar of the intake shaft, daily temperature variations are negligible.

of 33 °C during a sunny midday to a low value of 19 °C in the middle of the night, which represents a temperature difference of $\Delta T_{d\text{-surface}} = 14$ °C. However, at the bottom of the shaft, the amplitude of the air temperature variation is much smaller and varies from 29.5 to 25.5 °C, which represents a temperature difference of $\Delta T_{d\text{-bottom}} = 4$ °C. Measured climatic parameters indicate that the lining of the shaft and the surrounding rock act as an energy reducing mechanism, which reduces the amplitude of the temperature wave. Furthermore, during the daytime, at some depth down the intake shaft, the air temperature in the intake shaft, which is also heated by auto-compression, develops higher values than that of the virgin rock temperature (VRT) of the surrounding rock. Consequently, sensible heat is transferred from the intake air into the rock, actually cooling the air. However, during the night, as the temperature of the air on surface cools, there is a greater potential for the heat to flow from the rock into the mine air.

There are many conventional mine ventilation and climatic simulation programs available to conduct heat studies and predict the climatic conditions in future underground mines. The most relevant transport processes for heat and humidity can be modeled with any of these software packages. However, short-time variations such as hourly or daily and more importantly seasonal temperature changes can induce significant modeling errors if the strata heat does not follow a true instantaneous heat flux model. As shown in Fig. 2, the daily temperature variation at the bottom of an intake shaft can be much less than at the top of the intake shaft, which is a function of many factors including the contact time between the mine air and the lining of the shaft, and travel distance. It is important to accurately predict the temperature and the humidity levels at the bottom of the intake airways for future underground mines because a well design ventilation system may be sufficient to provide adequate climatic conditions. However, climatic modeling errors that are induced by ignoring the TDE can indicate that a refrigeration system is needed to provide adequate work conditions. In some cases, the additional capital and operating costs related to the refrigeration system could indicate that an economically viable ore deposit would be unfeasible.

To evaluate the accuracy of the standard ventilation programs, the intake shaft at an underground mine was modeled using Climsim™ and Ventsim™. A comparison between the measured climatic values at the bottom of the intake shaft and parameters generated through the use of ventilation/climatic models is provided in Fig. 3. Fig. 3 indicates that current commercially available mine ventilation programs do not take into account the TDE along the vertical shaft. Therefore, the models predict the same diurnal temperature variations on surface and at the bottom of the shaft without taking into account thermal damping. One software package with its time-dependent solution engine may have the ability to simulate the TDE and the associated time lag [8]. However, this program is under development and testing, and it is not yet commercially available.

The thermal damping effect on the mine air depends on many ventilation, climatic and geotechnical parameters including the air temperature on the surface, air volume, contact distance, wall wetness, the virgin rock temperature (VRT), the thermal properties of the rock, etc. For instance, it has been observed that the thermal damping effect along an intake decline is much higher than the thermal damping effect of a similar amount of air that travels to the same production level through a vertical airway. The longer the intake route to the mining horizon, the greater the tempearture damping. This is why the air temperature underground at some point, which is located at some distance from the collar if the intake shaft is not affected by diurnal or even seasonal air temperature variation on the surface (See Fig. 4). At depth, Fig. 4 effectively shows activity related heat to be the dominant characteristic for temperature variation with background variations within 1 °C.

The most important environmental, physical and dynamic parameters that affect temperature damping in underground mines are summarized in Table 1.

Table 1
Critical parameters that influence temperature damping in underground vertical openings.

Environmental parameter	Physical parameter	Dynamic parameter
Surface temperature	Size of opening	Air quantity
Intake relative humidity	Shape of opening	Travel time
Barometric pressure	Wall roughness	Contact distance
Groundwater	Wall wetness	
Air density	Disturbance objects	

3. Quantifying the thermal damping effect using NARX

3.1. Climatic data collection at underground mines

Climatic and ventilation parameters were collected at two underground precious-metal mines in Nevada. The primary ventilation system in both mines is of the exhaust type, with the primary fans located at the top of the exhaust shaft. The selection criteria for the climatic monitoring units focused on data storage and their capability to continually measure and record climatic and ventilation parameters. Other requirements included: (1) the monitoring units should be lightweight, easy to instal, and should not interfere with the mining operations; (2) the monitoring units should include built-in batteries with no external power source requirements; (3) the monitoring units should require minimum maintenance, and the calibration procedure to be straight forward; (4) recording and downloading the climatic data must be straightforward and quick; (5) the units should be accurate for climatic and ventilation surveys.

The "ACR Smart-Reader Plus" multi-channel monitoring units (See Fig. 5) were selected to monitor and record the climatic parameters in the production stopes, dead-end development headings and throughout the mine. The units continually measured and recorded T_d, RH, and BP. From these parameters, the wet-bulb tempearture (T_w) was then calculated. The monitoring units were capable of recording these values at various time intervals specified by the user, and each unit had a storage capacity of 128 kB. The climatic parameters were downloaded on a mobile computer as shown in Fig. 5. The collected climatic and ventilation data was used to validate the climatic models.

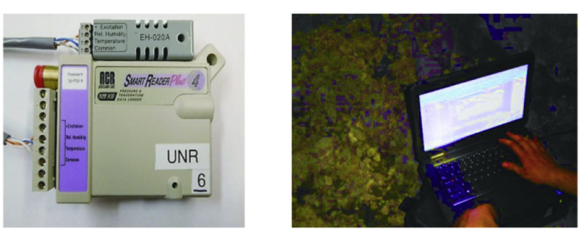

Fig. 5. Climatic data recorded by the monitoring units was downloaded on a laptop computer.

At two underground operations, two production shafts and one ventilation shaft (intake) were selected for climatic data collection. The climatic monitoring units were programmed to collect T_d, RH and BP readings at 2 min intervals for a 4-week time frame. Table 2 summarizes the geometrical elements of the production and ventilation shafts and their intake air volumes.

One monitoring unit was installed on the surface to measure and record the climatic conditions during daytime and nighttime. The following units were installed just below the collar of the production and ventilation shafts to capture any heat added to the mine air around the collar of the shaft and to eliminate the effect of radiation. Monitoring units were also installed at the bottom of the production and ventilation shafts. Table 3 presents the locations where the units were installed and the climatic monitoring plan. It should be mentioned that no cooling system was employed at these two underground mines.

3.2. Nonlinear autoregressive with external input (NARX) algorithm

An artificial neural network (ANN) is an interconnected group of nodes, where each node represents an artificial neuron, and an arrow represents a connection from the output of one neuron to the input of another. Artificial neural networks can be considered as a form of machine learning exercises, in which the system learns to recognize an output variable based on a series of input variables [9,10]. Data is processed through a number of interconnected neurons which form synaptic connections from the input nodes through a hidden layer before converging on the output neurons. Each input and hidden neuron consist of statistical weights which are capable of adapting the exact parameters that are modified by an algorithm over the course of network training procedures [11,12]. These weights essentially form the synaptic connections among neurons, which will activate during network construction. This form of computation is capable of operating in parallel units, much like the human nervous system. The ANNs are capable of nonlinear modeling and can, therefore, provide a useful alternative approach to a number of both theoretical and real-world problems (e.g. [13–16]).

Table 2
Geometrical elements of the production and ventilation shafts.

	Type of shaft	Shaft diameter (m)	Shaft area (m^2)	Shaft depth (m)	Quantity (m^3/s)
Shaft #1	Production shaft	7.3	41.85	580	205
Shaft #2	Production shaft	6.7	35.26	579	241
Shaft #3	Ventilation shaft	6.1	29.22	503	223

Table 3
Climatic monitoring plan at two underground precious-metal mines.

Intake shafts (production/ventilation)	
Locations	On surface, and at the top and bottom of the production/ventilation shafts
Purpose	To identify and quantify the thermal damping effect
	To understand the transient heat exchange processes between the mine air and the surrounding rock
Monitoring plan	The ACR units were installed at the top and at the bottom of the shafts to record climatic data at two-minute intervals for four weeks at a time. The unit on surface was set to record the surface climate and any unusual activities that can affect the temperature of the intake air

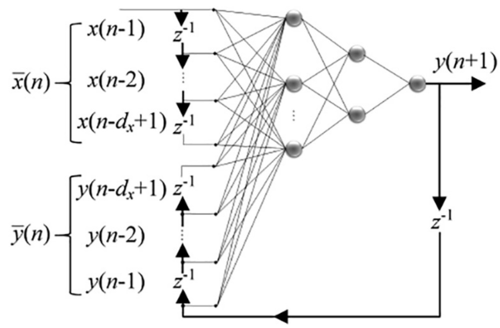

Fig. 6. Topology of the NARX model (Z^{-1} is the unit time delay).

In this study, artificial neural network modeling was used as a time series predicting tool to estimate the temperatures at the bottom of the production and ventilations shafts by taking into account the thermal damping effect as a function of the surface temperature. The NARX algorithm is a class of discrete-time and non-linear system that can be presented as Eq. (1). The topology of an NARX network is shown in Fig. 6.

$$y(n+1) = f[y(n), \ldots, (y(n-d_y+1); \\ x(n-k), x(u-k+1), \ldots, x(n-d_u-k+1)] \quad (1)$$

where x(n) and y(n), respectively, are the input and output of the model at discrete-time step "n"; $d_x \geq 1$, $d_y \geq 1$, and $d_y \geq d_x$ the input memory and output memory orders, respectively; k ($k \geq 0$) is a delay term, known as the process dead-time [16]. Considering k = 0, the NARX model can be simplified as:

$$y(n+1) = f[y(n), \ldots, y(n-d_y+1); x(n), x(u), \ldots, x(n-d_u+1)] \quad (2)$$

The most common learning rule for the NARX network is the Levenberg-Marquardt backpropagation procedure (LMBP) [9,17–19]. This training function is often the fastest backpropagation-type algorithm. The LMBP algorithm was designed to approximate the second-order derivative with no need to compute the Hessian matrix, therefore increasing the training speed. However, this training function is not powerful in forecasting values for small and "*noisy*" datasets such as the datasets of daily temperature fluctuations in underground mines. The Bayesian regularized artificial neural networks are more robust than standard back-propagation networks and can reduce or eliminate the need for lengthy cross-validation procedures. The Bayesian regularization is a mathematical process that converts a nonlinear regression into a well-posed statistical problem in the manner of a ridge regression. This algorithm typically takes more time to process, but can result in good generalization for noisy data sets. The Bayesian regularization adds another term to Eq. (3).

$$F = \beta E_D + \alpha E_w \quad (3)$$

where F is the objective function; E_D the sum of squared errors; E_w the sum of the square of the network weights; and α and β the objective function parameters [11]. In the Bayesian network, the weights are considered as random variables, and thus their density function is written according to the Baye's rules, as follows [20]:

$$P(w|D, \alpha, B, M) = \frac{P(D|w, \beta, M)P(w|\alpha, M)}{P(D|\alpha, \beta, M)} \quad (4)$$

where w is the vector of network weights, D represents the data vector, and M is the neural network model being used. Forsee and Hagan assumed that the noise in the data was Gaussian, and with this assumption, they were able to determine the probability density function for the weights [20]. Forsee and Hagan proposed a Gauss-Newton approximation to the Hessian matrix, which is possible if the Levenburg–Marquardt training algorithm is used to locate minimum values [20]. This technique reduces the potential for arriving at local minima, thus increasing the generalizability of the network.

The novelty of this technique is the probabilistic nature of the network weights in relation to the given dataset and model framework. As a neural network grows through additional hidden layer neurons, the potential for overfitting increases dramatically, and the need for a validation set to determine a stopping point becomes crucial. In the Bayesian regularized networks, overly complex models are penalized, as unnecessary linkage weights are effectively driven to zero. The network will calculate and train on the non-trivial weights, also known as the effective number of parameters, which will converge to a constant as the network grows [21]. The performance of the model was calculated using coefficient of determination (R^2) and the mean square error (MSE). The mean square error can be calculated as follow:

$$SSE = \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \quad (5)$$

$$MSE = \frac{SSE}{n} \quad (6)$$

where $\hat{y}_i$ is the predicted outcome; and y_i the measured data.

4. Performance of NARX model when quantifying the thermal damping effect in vertical shafts

Data selection was carried out by a preliminary pre-processing application, which considered all ventilation and climatic parameters which were collected during a 3-month period on the surface, along the production shafts (intake), as well as parameters collected during a 2-month period along the ventilation shaft (intake). There are several unknown sharp temperature fluctuations, which should be removed from the climatic data, as shown in Fig. 7. The

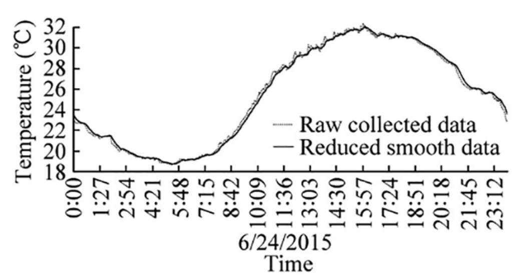

Fig. 7. Smoothed out data to eliminate unknown sharp temperature fluctuations within the database.

"smoothed out" graph was obtained using the exponential smoothing approach, which is provided in Eq. (7).

$$y(t) = \alpha x(t) + (1-\alpha)y(t-1) \tag{7}$$

where α is the smoothing factor ($0 < \alpha < 1$), and t is the time step ($t > 0$).

The climatic data that is influenced by natural occurrences such as rain/snow should also be detected and be treated so that the model performance is not influenced by unusual temperature changes. Furthermore, a subsequent step was also performed to separate data into a "training" dataset and a "test" dataset. For each intake shaft, an ANN model was developed and tested based on processed datasets. The data is not normalized because firstly, both input and output are in the same units and secondly, the actual values were needed to identify the damping ratio in the vertical production and ventilation shafts.

Fig. 8 illustrates the performance of the NARX model for Shaft #1. A set of data was selected, which consists of dry-bulb temperatures collated at the top and bottom of Shaft #1 during a 24 h time frame. The performance of the NARX model for the production and ventilation shafts is provided in Table 4. As shown in Table 4, the model can successfully predict the temperature at the bottom of the intake shaft, which was diminished by the effect of thermal damping. The same procedure was applied for shaft #2 (production) and shaft #3 (ventilation) to predict the dampened temperatures at their bottom.

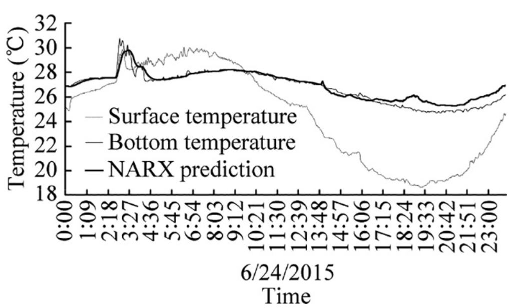

Fig. 8. NARX performance in Shaft #1 (R^2 = 0.99; MSE = 0.923).

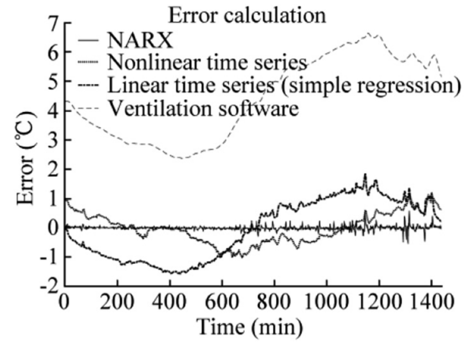

Fig. 9. Comparison of error estimations based on NARX, nonlinear time series & simple linear regression models.

Table 4
Performance of NARX model for the production and ventilation shafts.

Shaft number	Type of shaft	R^2	MSE
Shaft #1	Production shaft	0.99	0.129
Shaft #2	Production shaft	0.99	0.217
Shaft #3	Ventilation shaft	0.97	0.276

Table 5
Simple linear regression equations to predict the dry-bulb temperature at the bottom of intake shafts.

Shaft number	Equation	R^2	MSE
Shaft #1 (Production)	$T_B = 20.68 + 0.29xT_S$	0.78	1.12
Shaft #2 (Production)	$T_B = 25.47 + 0.31xT_S$	0.81	0.98
Shaft #3 (Ventilation)	$T_B = 21.59 + 0.40xT_S$	0.73	1.58

Note: T_B is the dry-bulb temperature at the bottom of the shaft, and T_S is the dry-bulb temperature on surface.

The ANN models based on NARX can be applied to any numerical method based ventilation and climatic modeling software to predict the thermal damping effect in vertical airways. The NARX network provides a high level of prediction accuracy, while the complexity of the system is reduced through exogenous data. Despite the fact that the ANN model based on the NARX algorithm is powerful and successful in forecasting diminished temperature values in vertical airways, it may not be practical to apply this method to predict the temperature at the bottom of the production and ventilation shafts due to the complexity of modeling work. Consequently, the time series model was simplified to a conventional time series model in an attempt to determine simple damping ratios for the intake shafts.

A nonlinear input-output time series equation can be written as:

$$y(n) = f[x(n), \ldots, x(n-d_u+1)] \tag{8}$$

where $f(.)$ can be approximated using a neural network.

These nonlinear input-output time series can be simplified to a "linear regression" model as shown in Eq. (9), and even further to a "simple linear regression" model, as shown in Eq. (10).

$$\begin{aligned} y(n) &= f[x(n) + \ldots + x(n-d_u+1)] \\ &= a_1x(n) + \ldots + a_nx(n-d_u+1) + b \end{aligned} \tag{9}$$

$$\boldsymbol{y(n)} = \boldsymbol{f}[\boldsymbol{x(n)}] = \boldsymbol{b} + \boldsymbol{a}$$

$$\begin{aligned} a &= f[Q, TDE, dimension, Frictional\,heat]; \\ b &= f[Autocompression, VRT, depth, strata\,heat] \end{aligned} \tag{10}$$

Table 6
Comparison of different time series prediction models performance.

Shaft number	Time series method	R^2	MSE	Error (°C)		
				Average	Maximum	Minimum
Shaft #1	NARX	0.99	0.123	−0.01	0.58	−0.54
	Nonlinear time series	0.97	0.712	0.04	1.34	−1.39
	Simple linear regression	0.81	0.986	0.08	1.93	−1.58

Table 5 shows these simple linear regression equations, which were developed for the production and ventilation shafts at two underground mines. The constant value "b" for each intake shaft is different due to the heat added to the system, which can vary as a function of depth and the virgin rock temperature profile of each mine (e.g. geothermal step). However, because the production shafts have comparable geometrical elements (e.g., diameter) and the intake air volume descending the production shafts is also comparable, the values of the damping coefficient "a" are very close (e.g. 0.29 versus 0.31).

The damping coefficient "a" for the ventilation shaft has a relatively different value (e.g. 0.40) as for the production shafts, because the ventilation shaft is not equipped with a hoisting system, and it is clear of steel frames that support the guiding rails of the cage and skips, as these mechanisms are also acting as a heat sink medium along the intake production shafts. Above all, the substantial benefit of these "simple linear regression" equations presented in Table 5 is that for similar airways such as production shafts or ventilation shafts, simple equations can be developed, which can be used to determine the temperature at the bottom of vertical airways at an acceptable level of accuracy. Furthermore, these damping coefficients could be used by ventilation and climatic modeling software, thus eliminating the need to code and incorporate complicated transient heat and mass transport algorithms in order to quantify the thermal damping effect along vertical airways.

Table 6 and Fig. 9 illustrate an example of error calculations when predicting the dampened temperatures at the bottom of production Shaft #1, based on various forecasting methods such as NARX, nonlinear time series, and simple linear regression models. As shown in Table 5, NARX has the most accurate prediction with $R^2 = 0.99$. By decreasing the complexity of the model to a simple linear regression, the model prediction accuracy decreases to $R^2 = 0.81$, with minimum and maximum dry-bulb temperature errors of -1.5 and 1.9 °C, respectively. While these errors are noticeable compared to the NARX model, these simple linear regression models have a much better performance in predicting the thermal damping effect than any of the current commercially available ventilation and climatic simulation programs, with the most advanced of them returning minimum and maximum errors of 2.5–6.6 °C, respectively. Furthermore, field observations in large and deep metal mines have shown that when the thermal damping effect is not taken into account, the difference between simulated and measured dry-bulb temperature values at the bottom of intake airways can vary from 6 to 10 °C [6].

These simple linear regression equations presented in Table 5, which were derived from the NARX algorithm can be used to estimate the damping effect along vertical intake airways, thus minimizing the errors when predicting the climatic conditions at the bottom of intake airways for future underground mines.

5. Conclusions

An artificial neural network (ANN) based on nonlinear autoregressive time series algorithm with external input (NARX) was used as a novel method to predict the dry-bulb temperature (T_d) at the bottom of the production and ventilation shafts. The performance of the ANN model based on the NARX algorithm was excellent in predicting the temperatures at the bottom of the intake shafts. However, due to the complexity of the modeling work, the "input-output time series" model was simplified to a linear regression model, which can be easily used to predict the temperature at the bottom of the production and ventilation shafts at an acceptable level of accuracy.

The substantial benefits of these simple linear regression equations presented in Table 5, can be used in conjunction with commercially available mine ventilation or climatic simulation programs to predict more realistic temperature values by taking into account the thermal damping effect in vertical airways. Furthermore, the damping coefficients (a and b) for the production and ventilation shafts could be easily implemented into ventilation and climatic modeling programs, thus eliminating the need to incorporate complicated time-dependent heat and mass transport algorithms in order to quantify the thermal damping effect in vertical airways.

A future related study should focus on the development of a general linear regression model, which would take into account the characteristics of the intake airways (e.g. shafts, raises) and the rock thermal properties at various underground operations such as shaft diameter, depth, lining material, virgin rock temperature and air volume. The same approach presented in this paper can also be used to predict the thermal damping effect on the wet-bulb temperature (T_w) at the bottom of production and ventilation shafts.

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