Artificial neural networks to determine ventilation emissions and optimum degasification strategies for longwall mines

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ABSTRACT: In longwall mining, premining prediction of methane emission rate depends on a number of geological factors, geographical factors, and operational factors. These same factors also can impact the selection of a specific degasification system. This study proposes a principle component analysis (PCA) and artificial neural network (ANN) approach to predict the ventilation methane emission rates of U.S. longwall mines and the optimum combination of degasification boreholes based on the given characteristics of the mine. Artificial neural networks, more than conventional computer models, are adaptable systems that can solve problems such as non-polynomial or very complex relationships that are difficult to describe mathematically. Data on ventilation emissions and degasification system design were obtained from 63 longwall mines in 10 states and were combined with corresponding geological, geographical, and operational parameters for the period 1985-2005. PCA was used to determine the variables that most influence ventilation emissions and degasification system design. Different combinations of variables in the data set and network structures were used for network training, cross-validation, and testing. The resultant ANN models predicted ventilation methane emissions with a 90-95% accuracy and were superior to multi-linear and second order non-linear models. The ANN-based expert classification system was able to classify the design of the degasification system (no degasification, gob vent borehole, horizontal and gob vent borehole, and horizontal, vertical and gob vent borehole) with more than 80% accuracy. The models can be used as prediction and decision tools for the ventilation emissions and degasification system selection for specific site and mine-design conditions.

1 Introduction

Methane emissions can adversely affect the safety of underground coal miners. During longwall mining, methane emissions can originate from three major sources: 1) gas emissions from the ribs surrounding the bleeder ventilation system, 2) gas emissions from the active longwall face and mined coal on the conveyor belts, and 3) gas emissions from subsided strata (Mucho et al., 2000).

The first gas source originates from the unmined coalbed adjacent to the development entries of the bleeder system and from the solid coal ribs. Although this emission tends to decrease over time, its total may also become a significant contributor of gas to the bleeder ventilation system over time (Mucho et al., 2000). The second source is the combination of the gas content from the mined coal itself, the methane being emitted from the fresh face on the longwall, and the methane emitted from the coal transported out of the mine by the conveyer belts. Methane emissions from the face, ribs, and conveyor belt are directly discharged into the mine ventilation air; therefore, the ventilation system must have sufficient capacity to maintain methane levels within statutory limits. The third source is the fractured and caved rock in the subsided strata (gob) overlying the extracted panel as the longwall face advances. The thickness of the fractured zone can vary up to 100 times the height of the mined coalbed, depending on the size of the panel, the geology, and the geomechanical properties of the layers (Palchik, 2003). Generally, it is economically feasible to handle specific emissions (total gas emission per unit amount of coal mined) up to 1000 ft^3/ton (28.3 m^3/ton) with a well-designed ventilation system. At higher specific emission rates, however, it is difficult to stay within statutory methane limits using ventilation alone (Thakur, 2006). Thus, supplementary methane control measures, such as degasification of the coalbed, are needed prior to or during mining.

Gob vent boreholes are commonly used to control the methane emissions from the fractured zone and are drilled from the surface to a depth that places them above the caved zone. These ventholes generally become productive after the mining-induced fractures propagate under the well (Diamond, 1994; Karacan et al., 2007a). They are equipped with exhausters to capture gas from long distances and reduce methane migration from the fractured zone into the mine.

Degasification of the coalbed prior to mining is also effective in reducing face emissions. The most commonly applied methane control technique, especially in high in-place gas content coalbeds, is drilling drainage boreholes into the panel area prior to longwall mining to reduce the methane content of the coalbed. These boreholes can be vertical boreholes drilled from the surface or in-seam horizontal boreholes drilled from the gateroad entries or from the surface. Horizontal drilling and its applications to degasify coal seams are well-documented in the literature.

Vertical wells drilled from the surface to drain methane have the distinct advantage of not being conducted in the restrictive underground environment. They are mostly suited for highly gassy, deep, low-permeability coal seams where it takes a long time prior to mining to adequately degasify the coalbed. The drainage area of vertical wells is limited compared to that of horizontal boreholes. Thus, in most circumstances vertical wells need to be stimulated by hydraulic fracturing.

Accurate prediction of longwall methane emissions is important so that adequate ventilation air is supplied to dilute and render harmless high gas levels that threaten mine safety. This task is complex due to the large number of variables involved with these potential emission sources. The design of an effective degasification system to augment ventilation is also complex due to the number of factors involved. Modifications to an existing methane drainage system, especially after the methane problem has already become severe, may result in higher costs and may create safety problems. Thus, it may be advantageous to determine the emission rates and the need for and the most effective type of degasification before mining starts by considering the various geological, coalbed, and mining parameters. This type of assessment prior to mine development generally requires both empirical and theoretical approaches.

The complexity of the longwall mining process and its associated methane sources have been modeled by several researchers (Schatzel et al., 2006; Krog et al., 2006; Lunarzewski, 1998) who empirically determined the increase in emissions for wider longwall faces as a result of increased coal production. Although simple to use, these approaches are site-specific and require a long period of data collection before a correlation can be established for predictions. Also, they lump the variables into two empirical constants which limit their applicability for other mines with similar coal production levels but different mining or geological conditions. Some of the limitations of empirical models can be addressed by calibrating the models and realistically representing additional variables. Numerical techniques can also be used to predict the emissions for different mining settings and conditions (Lunarzewski, 1998; Karacan et al., 2005, 2007b).

These models require user expertise and, in most cases, specialized and expensive software packages. A comprehensive mine simulator combining mining operation, coalbed reservoir, and methane production parameters does not exist, and creating a model representing every process contributing to mine emissions and integrated degasification would be very difficult. Instead, artificial neural networks can be used to predict mine ventilation system emissions and select potential degasification systems for more detailed modeling. The key advantages of neural networks are their abilities to learn, to recognize patterns between input and output space, and to generalize solutions.

The aim of this paper is to develop ANN-based methodologies to predict ventilation emissions from longwall mines and to develop an expert classification system to identify the need and the type of degasification system for a longwall operation. Ventilation emission data and the type of degasification system utilized were combined with corresponding coalbed properties, geographical information, longwall operation parameters, and productivities. The database was analyzed using PCA to reduce complexity and to determine the variables to be considered for ANN modeling. The ANN model was built using a multilayer perceptron (MLP) approach and was trained and tested using the database to achieve minimum mean square error and high correlations between measurements and predictions. Outputs of this model were ventilation system methane emissions and identification of the optimal degasification option (N: None, G: Gob vent borehole, HG: Horizontal boreholes and gob vent boreholes, VHG: Vertical, horizontal boreholes and gob vent boreholes). This model can be used as a prediction tool for emissions and also as a decision-making tool for screening the available systems before designing degasification methods using more detailed numerical modeling approaches.

2 Description of Input Data and Database Construction for Predictive Modeling

In developing the database for modeling ventilation emissions, 63 longwall mines in 10 states operating between 1985 and 2005 were analyzed. Available data sources were searched and evaluated carefully for these mines to extract important parameters relevant to ventilation emissions and degasification system utilization. These sources provided gas contents of the mined coalbeds, annual coal productions and emissions, longwall operational parameters, and mine characteristics.

Gas contents of the mined coalbeds, based on their geographical location at the mining depths, were compiled from a report published by Diamond et al. (1986). The publication contains approximately 1500 coal samples taken during various drilling operations from more than 250 coalbeds in 17 states. The components of total gas content (lost, desorbed, and residual gas contents) were reported along with sample location (state and county), sample depth, coalbed name, coal rank, and ash content. The lost gas was determined by a graphical method which estimated how much gas was lost during core recovery. Desorbed gas was determined using the direct method determination of gas content (Diamond and Schatzel, 1998) and residual gas was determined after crushing the coal samples using a ball mill. The total gas content was reported as the sum of all three components.

Annual coal production and ventilation emission data of longwall mines included in this study were taken from the U.S. Environmental Protection Agency (EPA) reports (1994, 1997, 2005) published to identify coal mine methane production opportunities in U.S. coal mines. Coal production data reported in EPA reports were primarily based on the U.S. Energy Information Administration (EIA) database, which is supplemented with data from coal producing states and from the U.S. Mine Safety and Health Administration (MSHA). The data for 2004 and 2005 were taken directly from MSHA's data retrieval system (MSHA, 2007).

Mining parameters and mine characteristics affect how much and how fast methane will be generated as a result of coal production. These factors also affect how much strata gas will be released and how much of it will enter the ventilation system as a result of caving and fracturing of the overlying strata. The annual data representing mine characteristics and mining parameters were compiled from 1985-2005 issues of Coal Age (Mining Media, Inc.), which publishes longwall census data annually. The tabulated data for each operation in the corresponding year includes seam height, cutting height, cutting depth, overburden thickness, longwall panel width, longwall panel length, number of development entries, face conveyer speed, and stage loader speed.

Table 1 shows the number of longwall operations in each state. Table 2 lists variables and their units. After evaluation of all data, the database used for ANN modeling consisted of 538 data entries with 24 variables spanning a 20-year period. Of these 538 data entries, 93 (17%) had the G-type degasification method, 136 (25%) had the HG-type system, 153 (28%) had the VHG-type system, and 156 (30%) did not have any degasification system installed (N type).

A general discussion on database parameters for their potential effects on ventilation emissions and selection on degasification system can be found in Karacan (2007c). Those discussions indicate that complex relations exist between different factors and the resultant emission rates from longwall operations and the use and type of degasification system. In fact, these relations are too complex to be explained by simple polynomial relations or statistical methods, suggesting that an ANN approach may be a good candidate for modeling ventilation emissions.

3 Model Complexity Reduction for ANN Development: Principle Component Analysis (PCA)

As with any other prediction models, the number and selection of appropriate input parameters are very important in ANN modeling. The key issue is to determine and select the appropriate input parameters based on knowledge of the causal variables and a familiarity with the modeled system.

Table 1. The number of mines and the mine names in each state included in the methane emission database.

State	No. of Mines	Mine Names
Alabama	8	Blue Creek No.3, Blue Creek No.4, Blue Creek No.5, Blue Creek No.7, North River, Mary Lee, Oak Grove, Shoal Creek
Colorado	4	Deserado, Dutch Creek, Golden Eagle, West Elk
Illinois	7	Galatia, Old Ben 24, Old Ben 25, Old Ben 26, Orient No.6, Monterey No.1, Rend Lake
Kentucky	4	Wolf Creek No. 4, Wheatcroft No. 9, Camp No:11, Baker
Maryland	1	Mettiki
Ohio	4	Meigs No. 2, Meigs No. 31, Powhatan No.4, Powhatan No.6
Pennsylvania.	10	Bailey, Eigthy Four, Enlow Fork, Maple Creek, Cambria, Cumberland, Warwick, Homer City, Dilworth, Emerald
Utah	4	Aberdeen, Sunnyside No. 1, Dugout Canyon, West Ridge
Virginia	7	Buchanan, V. P. No.8, V. P. No.1, V. P. No.6, V. P. No.5, V. P. No.3, McClure No. 1
West Virginia	14	Blacksville No.2, Federal No.2, Loveridge No. 22, McElroy, Pinnacle No. 50, Robinson Run No. 95, Ireland, Osage No. 3, Shoemaker, Windsor, Shawnee, Arkwright, Blacksville No.1, Humphrey No.7

In this study, PCA was used for selecting the most appropriate input variables from all those presented in Table 1. Identifying principle components (PCs) reduces the dimensionality of a data set, while retaining as much of the variance in the data set as possible. This reduction is achieved by transforming the original variables into PCs, which are orthogonal and highly uncorrelated to each other. Most of the variance in the data set is retained in the first components that contribute to variance. Elimination of PCs that do not contribute to the variance of the data decreases the dimension of the data set, while revealing information on correlations between variables and their weights in corresponding PCs (Davis, 1986; Grima, 2000; Grima et al., 2000).

Before performing PCA for emission and degasification system selection, all the variables in Table 2 were evaluated. The variables of city, county, mined coalbed, calorific value (Btu) of the produced coals, ash contents, and sulfur contents were eliminated. This was done because these variables were more related to combustion efficiency rather than their methane emission potentials, or they were represented by other parameters in the data set. The variable "year" was categorical information and could not be used for future projects or for new operation conditions to predict emissions. Elimination of these factors reduced the number of variables for PCA.

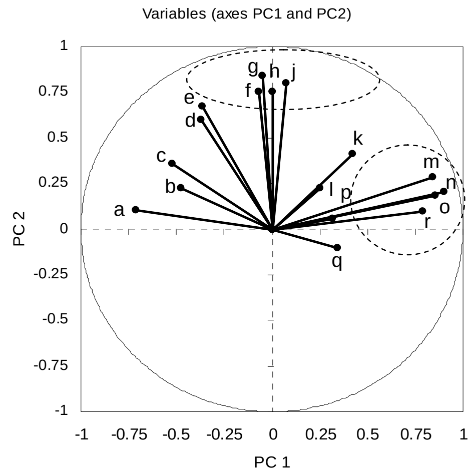
Initial principle component analysis showed that approximately 80% of the total variance in the data could be represented by the first five PCs for emission and degasification system selection models. Thus, the first five PCs were selected for the principle component matrix.

Table 2. The variables and their units in the database for each mine compiled from different sources. (Variables in bold were excluded from further analysis.)

Variable	Unit	Variable	Unit
State		**Ash**	%
Basin		Coal prod.	10^6 tons/y.
County		Seam height	inch
City		Cut height	inch
Degas.	Yes/No	Panel width	ft
Mined coalbed		Panel length	ft
Sulphur	%	Overburden	ft
Coal cal. value	BTU/lb	Number of dev. entries	
Lost+des. gas	scf/ton	Cut depth	inch
Residual gas	scf/ton	Face conv. speed	ft/min
Total gas	scf/ton	Stage load. speed	ft/min
Rank		**Year**	
Vent. emiss.	scf/day	Type of degas. system	

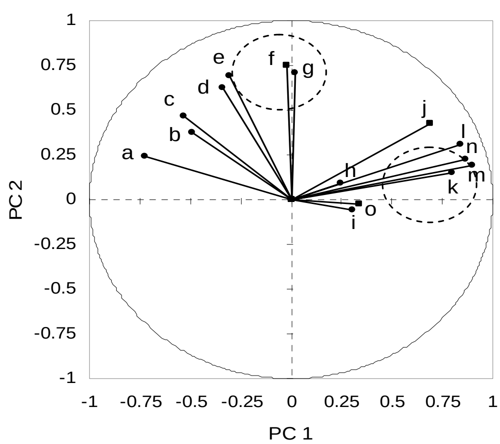
Figures 1 and 2 show the correlation circles for the factor loadings of the first two components of the PCA performed on the variables of emission and degasification system selections, respectively.

In these plots, if any two variables are both far from the center and close to each other, this indicates that they are significantly and positively correlated. If any two variables are orthogonal, then there is no correlation between them. On the other hand, if they are on the opposite sides of the center, then they are negatively correlated. When the variables are close to the center, it means that some information may be carried over to other axes, which is not seen on the graphs. Figure 1 shows that gas content and rank of the coal are correlated with overburden thickness and that they are significant for the first PC. Likewise, mine operation parameters and panel width are correlated and they are significant for the second PC. On the other hand, seam height and cut height are close to the center, suggesting that their information can be better represented by other axes. Figure 2 shows that total gas content, rank of the coal, and ventilation emissions are correlated with overburden thickness and that they are significant for the first PC. Likewise, panel length is correlated with coal production and these same variables are significant for the second PC. On the other hand, seam height, cut height, and number of gateroad entries are close to the center, suggesting that their information can be better represented by other PC axes.



a: Basin, b: State, c: Residual Gas, d: Panel Length, e: Coal Production, f: Panel Width, g: Face Conveyor Speed, h:Cut Depth, j: Stage Loader Speed, k: Degasification, l: Seam Height, m: Overburden, n: Total Gas, o: Lost + Desorbed Gas, p: Mining (Cut) Height, q: Number of Entries, r: Coal Rank

Figure 1. A correlation circle showing the magnitude and directions of the variable loadings in the first two principle components (emission modeling).



a: Basin, b: State, c: Residual Gas, d: Panel Length, e: Coal Production, f: Panel Width, g: Cut Depth, h: Seam Height, i: Mining (Cut) Height, j: Methane emission from ventilation system, k: Rank, l: Lost + Desorbed Gas, m: Total Gas, n: Overburden, o: Number of Entries

Figure 2. Correlation circle showing the magnitude and directions of the variable loadings in PC1-PC2 after PCA in degasification system selection parameters.

Table 3. Factor loadings of the variables after rotating the principle component (PC_R) matrix using Kaiser's varimax rotation. Bold entries show the most influential variables in each PC_R for ventilation emission modeling.

Variables	PC_R1	PC_R 2	PC_R 3	PC_R 4	PC_R 5
Degas.	0.472	0.221	0.163	0.245	**0.538**
Basin	-0.287	-0.007	**0.917**	-0.136	-0.145
State	0.002	0.049	**0.951**	-0.196	0.002
Seam height	0.064	0.113	-0.093	**0.925**	-0.063
Cut height	0.048	-0.027	-0.225	**0.911**	-0.043
Panel width	0.036	**0.798**	-0.006	0.004	-0.029
Panel length	-0.248	**0.701**	0.093	-0.202	0.052
Overburden	**0.808**	-0.075	-0.129	0.108	0.121
Number of ent.	0.271	-0.178	-0.045	-0.224	**0.805**
Cut depth	0.125	**0.745**	0.056	0.142	-0.076
Face conv. speed	0.145	**0.834**	0.116	0.056	-0.167
Stage load. speed	0.147	**0.811**	-0.048	0.070	0.105
Lost+des gas	**0.954**	0.024	-0.187	0.065	-0.011
Residual gas	-0.244	0.237	0.748	0.032	0.372
Total gas	**0.960**	0.077	-0.036	0.076	0.068
Rank	**0.907**	0.031	-0.174	-0.091	0.186
Coal prod.	-0.221	**0.688**	0.251	0.114	0.036

Figures 3 and 4 show a two-dimensional map of the factor scores of each mine on the first and second PC axes for emission and degasification system selections, respectively.

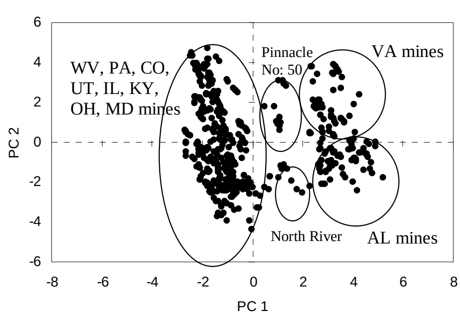


Figure 3. A two-dimensional distribution of factor scores of each mine on the first two principle components determined by PCA for 1985-2005. The plot shows the groupings of mines of with similar characteristics in terms of parameters affecting ventilation emissions.

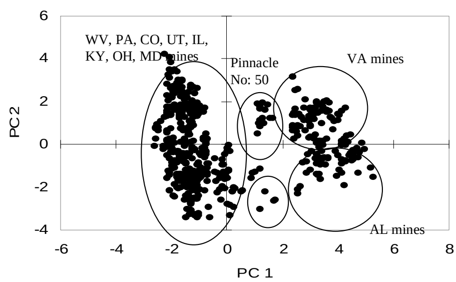


Figure 4. A two-dimensional distribution of factor scores of each mine on PC1-PC2 determined by PCA for the parameters influencing degasification system selection. The plot shows the groupings of mines based on different characteristics.

These plots enable analyses of the trends and groupings between observations. In both Figures, there are two major clusters: one formed by Virginia and Alabama mines and the other one formed by the mines in the remaining eight states in varying locations. Virginia and Alabama mines are separated from the others because of their mining depths, gassiness, emissions, and operational parameters. There are also some scattered data points between these two main clusters. These are due to operations having characteristics similar to those in either cluster. For instance, the data points between the clusters located on the positive side of the PC2 axis in Figure 3 belong to Pinnacle No. 50 mine. Although this mine is geographically located in West Virginia, it operates in the Pocahontas No. 3 coalbed, making it similar to the Virginia mines. Similarly, some of the data on the negative side of the second PC axis in Figure 3 belong to the North River mine in Alabama. However, its operating depth is shallower [150-180ft (500-600m)] and the gas content of this coalbed is less compared to the other Alabama mines. Thus, it is separated from the group and approaches those operations with which it shares similar characteristics.

In order to improve interpretability, PCA was continued with a new component matrix that was created by using Kaiser's varimax rotation method, in which PC axes are rotated to a position in which the sum of the variances of the loadings is a maximum (Grima, 2000; Grima et al., 2000). Tables 3 and 4 show the rotated matrix for the five components for each model discussed in this paper (Table 3 for emission, Table 4 for degasification system selection). It can be seen that the rotated table not only shows the loadings of each variable in new components (PCR), but also shows how the variables are separated between columns according to their characteristics or to the properties that they represent. Table 3 shows that the first PCR is mostly related to gas content of the mined coalbed, with both overburden and rank positively correlated with total and lost plus desorbed gas contents. The second PCR represents longwall panel dimensions, coal productivity, and underground coal transportation. The third PCR in Table 3 is related to geographical location of the mine determined by state and coal basin. The fourth PCR represents the coalbed and mining height in the longwall environment. The fifth PCR represents the ventilation system components. The only parameters that represent ventilation system components in the database are the number of gateroad entries and the presence or absence of any degasification system. Table 4 can be interpreted similarly.

Table 4. Factor loadings of the variables after rotating the principle component matrix using Kaiser's varimax rotation. Bold entries show the most influential variables in each rotated principle component (PCR) for degasification system selection model.

Variables	PC_R1	$PC_R 2$	$PC_R 3$	$PC_R 4$	$PC_R 5$
Basin	-0.296	0.010	-0.137	**0.907**	-0.133
State	-0.004	0.037	-0.198	**0.952**	-0.020
Seam height	0.070	0.076	**0.939**	-0.078	-0.070
Cut height	0.054	-0.036	**0.917**	-0.211	-0.067
Panel width	0.100	**0.820**	0.035	0.011	-0.059
Panel length	-0.187	**0.751**	-0.192	0.105	-0.035
Overburden	**0.817**	-0.083	0.112	-0.124	0.131
Number of ent.	0.276	-0.158	-0.168	0.022	**0.853**
Cut depth	0.186	**0.721**	0.118	0.064	-0.272
Lost+des. gas	**0.949**	-0.054	0.067	-0.173	-0.031
Residual gas	-0.212	0.279	0.042	**0.777**	0.285
Total gas	**0.962**	0.002	0.080	-0.016	0.029
Rank	**0.917**	-0.011	-0.082	-0.163	0.193
Coal prod.	-0.173	**0.755**	0.121	0.213	0.061
Vent. emiss.	**0.646**	0.339	0.104	-0.251	0.369

It should be noted that since the relationships between most of the parameters and the ventilation emissions are nonlinear, the results of PCA need to be evaluated with care. However, it seems reasonable to include input variables from each of the five PCs into the ANN model development in order to capture roughly 80% of the variance in the data and to represent those aspects impacting ventilation emissions.

4 Development of ANN for Predicting Ventilation Emissions and Degasification System Types

4.1 Basics

A neural network simulates a highly interconnected, parallel computational structure of the brain with many relatively simple individual processing elements, called neurons (Eberhart and Dobbins, 1990). The operation of a single neuron is dependent on the weighted sum of the incoming signals and a bias term, fed through an activation function, resulting in an output. This process can be shown as (Grima, 2000):

$$y_i = f\left(\sum_{r=1}^{n} w_{ir}\, f\left(\sum_{j=1}^{m} v_{rj} u_j + b_r\right) + c_i\right) \quad i = 1,\ldots,l \qquad (1)$$

where u is the m × 1 input vector, y the l × 1 output vector, n the number of neurons in the hidden layer, v and w the weight factors, f (.) the activation function, and br and ci the bias values of the neurons in the hidden and output layers. Neurons are represented by networking (topology) in a number of ways depending on the problem type and complexity. One of the most widely used topologies is the multilayer perceptron (MLP) because it can be applied in almost every kind of modeling, general classification, and regression. One of the critical issues in using MLPs is the choice of the number of neurons, and thus weights, in the hidden layers and their activation properties (Maier and Dandy, 2000).

The process of finding a suitable set of weights is called "training." Training is one of the most important steps in the development of the neural network, since the weights and the network characteristics will be used later in testing data sets and making subsequent predictions. The most common way of training the networks is via the supervised training algorithms, which require repeated showings (epochs) of both input vectors and the expected outputs of the training set to the network to allow it to learn the relations. During error minimization, it is preferable to find the global optimum rather than local optima. This situation is helped by applying a momentum factor between 0 and 1.

4.2 ANN Modeling of Ventilation Emissions from U.S. Longwall Mines

This section presents the results of initial modeling attempts to find the appropriate input parameters for ANN modeling. This attempt was undertaken using a heuristic approach. The strategy began with an ANN structure common to all models, where the input parameters were subsequently changed to find the model yielding the best results and with the model parameters given in Table 5.

For the initial models, a two-hidden layer ANN was constructed with 50 and 30 processing elements for the first and second layers, respectively. A hyperbolic tangent was selected as the transfer function for all layers and a momentum factor of 0.7 was applied for 1500 training epochs. The step size was 1 between the input and first hidden layer and 0.01 between the second hidden and output layer. In testing of these models, "model 8" was most efficient with an MSE (mean square error) of 1.82, an NMSE (nominal mean square error) of 0.10, and a regression coefficient of 0.95. Also, the maximum absolute error was 3.4 MMscf/day (95.8 × 103 m3/day). This model used total gas content, panel width; face conveyor speed, coal production, state, seam height, cut height, stage loader speed, and number of entries as input variables for the ventilation emission model.

Table 5. Different models tested in ANN for their efficiency in predicting ventilation emissions and the variables included.

Model number	Input variables*
1	OB, L+D Gas, Panel W, Face C.S., Coal P., State, Seam H.
2	OB, L+D Gas, Panel W, Face C.S., Coal P., State, Seam H., Panel L.
3	OB, L+D Gas, Panel W, Stage L.S., Coal P., State, Seam H.
4	OB, Total Gas, Panel W, Face C.S., Coal P., State, Seam H.
5	Total Gas, Panel W, Face C.S., Coal P., State, Seam H., Cut H.
6	Total Gas, Panel W, Face C.S., Coal P., State, Seam H., Cut H., Stage L.S.
7	Total Gas, Panel W, Face C.S., Coal P., State, Seam H., Cut H., Stage L.S., Rank
8	Total Gas, Panel W, Face C.S., Coal P., State, Seam H., Cut H., Stage L.S., Entries
9	Total Gas, Panel W, Face C.S., Coal P., State, Seam H., Cut H., Stage L.S., Cut D.
10	Total Gas, Face C.S., Coal P., State, Seam H., Entries

* OB: Overburden; L+D Gas: Lost + desorbed gas; Panel W: Panel width; Face C.S.: Face conveyor speed; Stage L.S.: Stage loader speed; Panel L.: Panel length; Seam H.: Seam height; Cut H.: Cut height; Cut D.: Cut depth; Coal P.: Coal production

After selecting the "model 8" input parameters, the optimum network parameters were determined to improve the predictive performance of the ventilation emission model. Various combinations of network parameters were tested to optimize prediction capabilities of the model. The final model used 56 and 38 processing elements between the first and second layers, respectively, hyperbolic tangent as the transfer function, and a momentum of 0.6. The step size was 1 between the input and first hidden layer and 0.1 between the second hidden and output layer. After 1500 training epochs, the optimized model produced a MSE of 1.61, a NMSE of 0.09, and an R-value of 0.96. The maximum and minimum errors were 3.1 and 0.003 MMscf, respectively.

Figure 5 compares the target emission rates in the test data set with the predicted values using the network. The comparison of the target data with the predicted values shows that the performance of the network in predicting emissions is reasonably good despite the large variations in the data. The predictive capability of the ANN model is also compared with multilinear and second-order non-linear statistical models in the form of:

$$\text{Emission} = a_0 + a_1V_1 + a_2V_2 + \ldots + a_9V_9 \quad (2)$$

$$\text{Emission} = a_0 + a_1V_1 + a_2V_2 + \ldots + a_9V_9 + b_1V_1^2 + b_2V_2^2 \ldots + b_9V_9^2 \quad (3)$$

In these equations, V_n are the variables (n=1 to 9), a_n values are the coefficients of first degree variables, and b_n values are the coefficients of second degree variables.

Figures 5-7 show the plots of measured emissions versus predicted values using the ANN, linear, and non-linear models, respectively. These Figures show that the ANN model is capable of predicting the data better than linear and 2nd order non-linear models. These data show that the ANN model is superior when compared to the statistical models in predicting ventilation emissions from longwall mines. A detailed discussion on this approach and the development details can be found in Karacan (2007c).

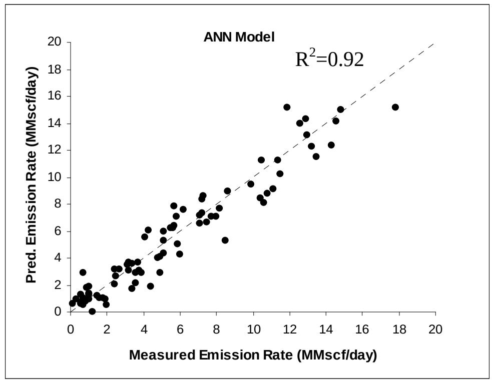


Figure 5. A scatter plot of measured methane emissions and ANN predictions of the "testing" data set.

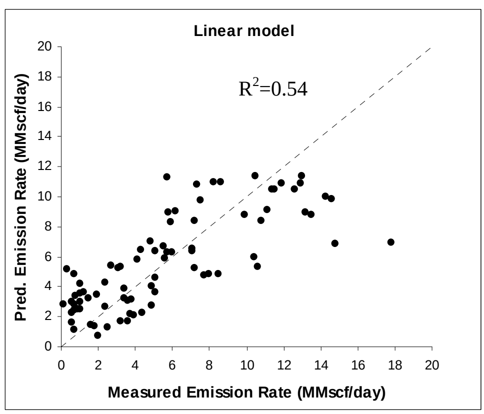


Figure 6. A scatter plot of measured methane emissions and multilinear model (Eqn. 2) predictions of the "testing" data set.

4.2 ANN Modeling of Degasification System Selection for U.S. Longwall Mines Using Classification Mapping.

A similar initial model search was performed for

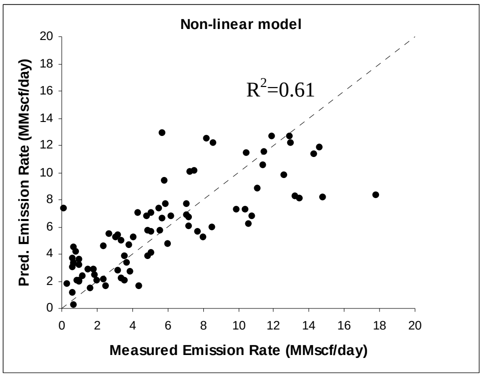


Figure 7. A scatter plot of measured methane emissions and second-order non-linear model (Eqn. 3) predictions of the "testing" data set.

degasification system selection. Again, the strategy was to start with an ANN structure common to all models and to change the input variables to find the model that would yield the best results. For this phase, 9 different models were tested (Table 6). In all models, the ANN training and network options were the same so that all models and results could be compared. A two-hidden layer ANN model with 50 and 30 processing elements for the first and second layers, respectively, was constructed. The number of nodes in the output layer was four, each corresponding to a degasification scheme, namely no degasification (N), gob vent borehole (G), horizontal boreholes and gob vent boreholes (HG), and vertical, horizontal, and gob vent boreholes (VHG).

Table 6. Different models and variables tested in the ANN for degasification system selection for U.S. longwall mines.

Model number	Input variables*
1	Total Gas, Panel W, Entries, State, Seam H.
2	Total Gas, Panel W, Panel L., State, Seam H.
3	Total Gas, Panel W, State, Seam H., Cut H.
4	Total Gas, Panel W, State, Seam H., Rank
5	Total Gas, Panel W, State, Seam H., Cut D.
6	Total Gas, Panel W, Coal P., State, Seam H., Vent E.
7	Total Gas, Panel W, Coal P., State, Seam H., Vent E., Cut H.
8	Total Gas, Panel W, Coal P., State, Seam H., Vent E., Cut H., OB.
9	Total Gas, Panel W, Coal P., State, Seam H., Vent E., Cut H., Entries

* OB: Overburden; Panel W: Panel width; Panel L.: Panel length; Seam H.: Seam height; Cut H.: Cut height; Cut D.: Cut depth; Coal P.: Coal production; Vent E.: Ventilation emission; Entries: Number of entries

The results of the initial input parameters search resulted in "model 8" of Table 6, producing the least MSE training error (0.004). The cross-validation error was the second lowest after "model 7." The degasification system in the testing set was more correctly identified using "model 8" than "model 7." Testing of "model 8" produced 86.4%, 93.8%, 80.0% and 91.7% correct identifications for HG, N, G, and VHG classes, respectively. Thus, the input variables for "model 8," namely total gas content, panel width, coal production, and state, seam height, cut height, overburden thickness, and ventilation emissions were selected as the input variables for the degasification system identification model.

The optimization of network parameters for degasification system selection by changing various network parameters resulted in a two-hidden-layer network, with the best results given by 48 and 28 processing elements, hyperbolic tangent and softmax axon as the transfer functions, a momentum term of 0.7, and 1500 training epochs. Table 7 shows the performance of the network using testing data. As can be seen from these data, the network incorrectly identified 1 case out of 22 samples for the HG-type degasification system for an accuracy of 95%. The model correctly identified 29 mines without any degasification system (N) out of 32 samples. It identified 3 of them incorrectly and recommended an "HG" system instead. For gob vent borehole identification (G), out of 15 samples, the model identified 12 of them correctly and recommended one of them incorrectly as HG and two of them incorrectly as N. The highest score was obtained for the VHG system. The ANN identified all 12 cases correctly.

Table 7. Performance of the ANN network used for identification of a suitable degasification system (N: None; G: Gob vent boreholes; HG: Horizontal boreholes and gob vent boreholes; VHG: Vertical, horizontal and gob vent ventholes) for U.S. longwall mines.

ANN Output	HG (Hor+GVB)	N (None)	G (GVB)	VHG (Vert+Hor.+GVB)
HG	21 (True)	3 (False)	1 (False)	0
N	0	29 (True)	2 (False)	0
G	1 (False)	0	12 (True)	0
VHG	0	0	0	12 (True)
% Correct	95.5	90.6	80.0	100.0

5 Summary and Conclusions

The results of the PCA and initial ANN model search process showed that ventilation emissions and degasification system selection could be defined by a number of variables, each representing a particular emission contributor and degasification system selection criterion.

In this study, PCA and preliminary test models showed that state, total gas content of coalbed, seam and cut heights, panel width, face conveyor speed, stage loader speed, number of entries, and coal productions were the most effective parameters to predict ventilation emissions. The ANN algorithm yielded good results for predicting emissions. A two-hidden layer model with 56 and 38 processing elements in each layer was found to be sufficient.

Comparison of the ANN model with the linear and non-linear statistical models showed that the ANN model performed better using the testing data due to its flexibility and highly non-linear nature. A regression coefficient of 0.92 was obtained from the ANN as compared to 0.54 and 0.61 for linear and non-linear models, respectively.

The presented approach using PCA and ANN is one of the more accurate and generalized models to predict methane emissions from longwall mines. Based on the results, the best combination of variables for selecting a degasification system using the ANN approach was determined. The parameters of the ANN were optimized to improve the classification performance of the model. The final model had two-hidden layers with 48 and 28 processing elements in each layer. Results showed that degasification systems that are commonly used at U.S. longwall mines can be classified effectively using only a few variables. This study showed that using the variables of state, total gas content of coalbed, seam and cut heights, panel width, coal productions, overburden depths of the mines, and ventilation emissions resulted in high accuracies for correctly identifying the use of no degasification, gob vent boreholes (GVB), horizontal and GVB, and horizontal, vertical, and GVB designs. The approach and the results suggest that, by incorporating the critical stratigraphic features in place of geographical information, this model may be applicable to other mines in different locations.

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