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SELLO MATHATHO, Tshwane University of Technology, Pretoria, Gauteng, South Africa

PIUS ADEWALE OWOLAWI, Tshwane University of Technology, Pretoria, Gauteng, South Africa

CHUNLING TU, Tshwane University of Technology, Pretoria, Gauteng, South Africa

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PDF Download
3415088.3415106.pdf
25 December 2025
Total Citations: 2
Total Downloads: 76

Published: 24 September 2020

Citation in BibTeX format

ICONIC: 2020 International Conference
on Intelligent and Innovative Computing
Applications

September 24 - 25, 2020
Plaine Magnien, Mauritius

An Artificial Neural Network and Principle Component Analysis Based Model for Methane Level Prediction in Underground Coal Mines

Sello Mathatho
Dept. Computer Systems
Engineering
Tshwane University of
Technology
Tshwane South Africa
zilla.mathatho@gmail.com

Pius Adewale Owolawi
Dept. Computer Systems
Engineering
Tshwane University of
Technology
Tshwane South Africa
owolawipa@tut.ac.za

Chunling Tu
Dept. Computer Systems
Engineering
Tshwane University of
Technology
Tshwane South Africa
duc@tut.ac.za

ABSTRACT

High methane levels in underground coal mines interfere with mining activities and increase the risk of fires and explosions. Therefore, early warning and predicting systems are imperative in ongoing underground coal mining exploitation areas. In this paper, a hierarchical approach made of the principal component analysis (PCA) and the artificial neural network (ANN) model is proposed to improve the prediction accuracy of methane levels. The PCA was used to evaluate those factors most influencing methane levels. The variables extracted by the PCA were used as inputs parameters to the artificial neural network ANN model. An ideal number of neurons was developed for both conventional inputs and PCA-extracted variables. To train the model four algorithms were employed. The algorithm which proved to have the highest accuracy was Levenberg-Marquardt, with a supervised method of learning adopted. The study demonstrates that the hierarchical model achieved better performance and slightly improved prediction accuracy than the ANN model with original input parameters. It is also proven that a higher prediction is dependent on the variables derived from the PCA and the training algorithm adopted.

CCS CONCEPTS

•Computing methodologies~Machine learning~Machine learning approaches~Neural networks

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ICONIC, September 24–25, 2020, Plaine Magnien, Mauritius

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ACM ISBN 978-1-4503-7558-0/20/09...\$15.00

<https://doi.org/10.1145/3415088.3415106>

KEYWORDS

Prediction, PCA, ANN

ACM Reference format:

Sello Mathatho, Pius Owolawi and Chunling Tu. 2020. An Artificial Neural Network and Principle Component Analysis Based Model for Methane Level Prediction in Underground Coal Mines. In *Proceedings of 2nd International Conference on Intelligent and Innovative Computing Applications (ICONIC'20)*. ACM, Plaine Magnien, Mauritius, 7 pages. <https://doi.org/10.1145/3415088.3415106>

1 Introduction

Underground coal mines are subjected to many natural hazards, including the methane hazard. Currently, 60% of the world's coal production is acquired through underground exploitation [1], which is known to be very hazardous owing to many risks. The coal exploitation phase triggers the methane release, this results in methane becoming flammable and explosive when it reaches certain levels of concentration. Methane gas explosions are the most prevalent causes of mining accidents, especially in coal mines. As coal is manufactured from compressed plant material, methane is generated as a by-product that is released into the local atmosphere with potentially lethal effects, especially when rocks are excavated [2].

The awareness of the effects of methane in underground coal mines is important [3]. In most cases, unexpected geological changes, insufficient ventilation, and increased coal mining production rates can overwhelm ventilation capabilities and result in significant rises in methane levels. This can lead to interruptions of coal mining operations and compromise the safety of coal miners. Studies of ventilation at coal mine faces show that methane concentrations in the underground should always be kept below 1%, any value above this can be explosive. Thus, accurate prediction of methane levels is essential in providing early detection and safety measures such as adequate

ventilation air supply to reduce methane levels, power supply cut-offs, and early warning alarms [4]. However, the complex and nonlinear nature of methane levels in coal mines is beyond the capability of a simple mathematical prediction model. Thus, in recent years several modeling and statistical methods such as Multiple Linear Regression (MLR) [5], Artificial Neural Network (ANN), Fuzzy Time Series[6], and Principal Component Analysis (PCA) have been used. Some of these models have shown reasonable results for evaluating factors and predicting methane levels in coal mines. To optimize the efficiency of methane level prediction models, it is essential to develop an understanding of key parameters that influence the rise in methane.

This study aims to evaluate the effectiveness of artificial neural networks (ANN) and principal component analysis (PCA) in predicting methane levels in coal mines.

Key objectives of this paper are as follows:

- Identification of key factors most influencing the levels of methane in coal mines, which in effect will reduce the dimension of the data set.
- Improve model performance and accuracy of the results using variables extracted through the PCA to accurately predict methane levels.

The paper is structured as follows: 1. Related Work of the PCA-based ANN model, 2. Hybrid model integration and evaluation. 3. Results of the proposed model. 4. A conclusion that also outlines future work

2 Related Works

Several researchers have proposed related methods for predicting methane levels using the MLP-ANN network while others also incorporated statistical techniques such as PCA. The fusion of ANN and PCA has proved to be the most prevailing and simplest hybrid model for predicting gas prone environments like underground coal mines. Azid et al. [7] developed a fusion of a PCA and ANN model that seeks to predict air quality mine. The findings revealed that the PCA better identified the most influencing parameters from all of the parameters in the dataset. The PCA based ANN model demonstrated high accuracy in predicting air quality with fewer input variables. A similar model was proposed by Jo et al. [8] with the aim of monitoring and forecasting mine air quality. A PCA-based MLP-ANN model was developed, in which the PCA extracted variables were fed to the model as input parameters. The PCA was able to accurately indicate the input parameters that have significance in the prediction of mine air quality. The results of the model showed greater accuracy than other regression models. Mathatho et al. [9] proposed another similar method that predicts methane in underground coal mines using ANN, without using any statistical tool for identifying key parameters that influence methane. The model achieved good prediction accuracy and can be further improved by adding statistical tools such as PCA. Thus, it can be expected that a Hybrid PCA-based ANN model will be able to improve prediction accuracy and performance of methane predictions.

3 Methodology

3.1 Dataset

The data used in this study was obtained publicly from the knowledge pit mining competition containing sensor data recorded in 2014 from the month March to June. The data set is made of a set number of time periods, every period consisting of 600 input values, all recorded over a 10-minute long period [10]. The parameters in this data set include methane, humidity, pressure, wind (speed and current), and temperature.

3.2 Principal Component Analysis

The PCA is a tool that is used for reducing the dimensions of a large number of variables to an acceptable small number that contains more of the data found in the larger set [11]. Mathematically it can be described as a method that converts (potentially) several correlated variables into (lower) uncorrelated variables called principal components [12]. The process starts by identifying the main component variables that are linear variations of the initial variables, where the data sets are prioritized depending on the highest variability; in other words, the original dataset with the greatest possible variability is characterized by the first main component.

3.2.1 Objectives of principal component analysis

The PCA reduces the space of the attribute from a larger number of variables to a lower-dimensional attribute space via a non-dependent procedure (i.e. it does not assume that a dependent variable is specified). PCA is a technique for reducing dimensionality or compressing data. The aim is to reduce dimensions and identify significant variables. From a bigger set, a subset of variables is selected in such a way that the principal components are generated by combining initial variables having the greatest correlations.

3.2.2 Input source identification

Like other prediction models, the selection of appropriate input parameters and the input space dimension is very important. The key aspect is to identify and select correct input parameters based on the understanding of causal variables and familiarity of the modeling method. Identifying Principal Components (PCs) helps to reduce the data set's dimension while ensuring variation in the data set is preserved as much as possible [13]. To reduce these dimensions, initial variables have to be turned into orthogonal PCs that are not correlated to one another. In most cases, the variance that is preserved in the data set is usually in the initial components that prove to have a significant contribution to the variance. Elimination of PCs that do not result in data volatility reduces the size of the data set and therefore discloses information on the discrepancies found between these variables and their weights in the respective PCs [13].

3.3 Artificial Neural Networks

Artificial Neural Network (ANN) is an adaptable system capable of determining the relationships between various data sets [14]. ANN models were designed to address issues for cases where

traditional computing models are proving to be inefficient. These inefficiencies range from having no polynomial relationship or being too complex to even explain mathematically [15]. Various statistical techniques one being the multiple regression analysis were utilized on several occasions to address such related problems but often fall short in the prediction accuracy, especially in cases of extreme non-linear relationships. The main advantages of ANN models are their learning ability, pattern recognition between input and output spaces, and generalizing solutions [16].

ANN is made up of three layers. Firstly the input layer, secondly the hidden layer and lastly the output layer. Figure 1 illustrates a simple structure of an artificial neural network, mathematically $x(m)$ represents different inputs to the network. Every input represented is multiplied by a weight connection. The weights are denoted by $w(m)$.

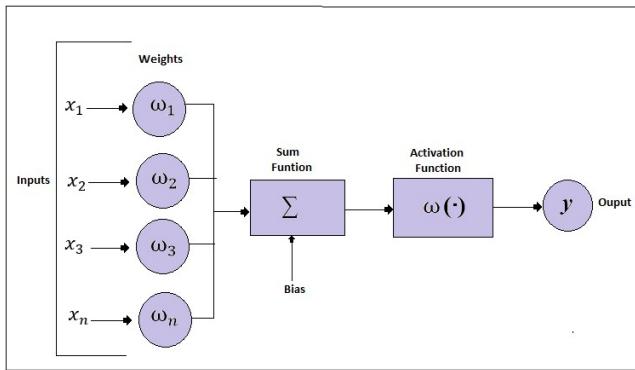


Figure 1: Simple structure of an artificial neural network.

In the simplest case, to produce a result, the products are added up, fed into an activation function (transfer function), and the outcome is sent out as the output. The ANN model's mathematical description[17] can be seen in (1), the φ is the transfer function, and is also known as the major unknown variable. That it is because it defines the network's features.

$$o_j = \varphi \left(\sum_{i=1}^n w_{ij} \cdot x_i + \theta_j \right) \quad (1)$$

3.3.1 ANN learning rates

The rate at which ANN models learn depends on a variety of controllable factors. A slower rate typically means an increased time in developing a model that's trained properly. However, in cases of high learning rates, there is always a great probability of the network being unable to adequate distinctions which are very common in slower learning models.

Most learning functions have a way of providing for a learning rate. The term is generally a positive one, in the range of 0 and 1. In cases where the learning rate has a value more than 1, typically the learning algorithm will easily overfit in weight correction and the network will oscillate. Small learning rate values don't have

the ability to correct current error indefinitely but if incremental steps are taken to correct errors, there is a strong probability that the best minimum convergence will be achieved [18].

3.3.2 ANN training algorithms

The training of input and output data collection in an ANN model is very important, it ensures that an accurate prediction of the value of output is achieved. The algorithms that are widely known for adequately training ANN models are Gradient Descent (GD), Scaled Conjugate Gradient (SCG), Resilient Back Propagation (SCG), and Levenberg–Marquardt (LM). Back Propagation algorithm is mostly the commonly adopted training method in the backward pass and forward pass networks [19].

3.4 Proposed Hierarchal Model

This section presents the implementation of the PCA and the ANN to build the proposed hierachal methane level prediction system in underground coal mines.

Developing an ANN makes use of structure recognition and parameter estimation as essential steps. PCA as previously described offers a clear insight as to which key input parameters could be utilized in models that predict methane levels in ongoing underground coal mines. Figure 2 depicts the diagram of the PCA based ANN model.

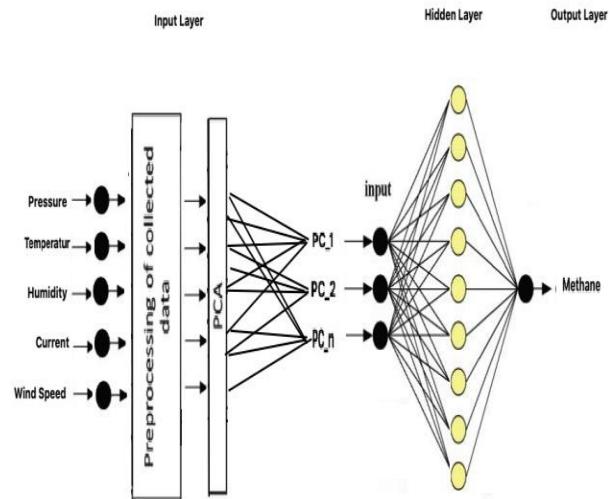


Figure 2: PCA based artificial neural network model diagram

In this proposed model, the outputs of the PCA and the original normalized input parameters are separately fed to the ANN model as inputs. Tasks such as model performance evaluation and data preprocessing are carried out using MATLAB 2018. For data preprocessing, the normalization technique was applied through a realistic approach of managing the neural network weights, this enables the ANN model to effectively predict new data with a limited error.

3.4.1 Identification and Selection of Appropriate Input parameters via PCA

The PCA is used in this study to evaluate and select the most acceptable input variables from all of the parameters (temperature, pressure, humidity, wind speed and current). PCA evaluates numerous variables, known as main components which are obtained as linear pairings of the initial variables in order to achieve model reduction. Each principal component as defined in (2), is a linear combination of the original variables [10].

$$PC_p = W_{1p} x_1 + W_{2p} x_2 + \dots + W_{np} x_n \quad (2)$$

Where PC_p is the p-th order principal component notation for the total n number of results, W_{np} is the regression coefficient as defined by PCA (or weight), while x_n is the mean adjusted matrix. In a PCA, most of the variance in the data set is reserved in the initial components which results in a better degree of variance, leading to the elimination of PCs that don't have much significance to the variance in the data. This study shows that the variables are in a way correlated and not orthogonal. The two most important parts of the five selected PCs have more than one eigenvalue. The values of each variable (Component) extracted and the percentages of variance are summarized and illustrated in Table I.

Table I. Eigenvalues and the variances described by the principal components derived observations of 5 variables.

	F1	F2	F3	F4	F5
Eigenvalue	2,625	1,055	0,768	0,369	0,183
Variability (%)	52,508	21,091	15,363	7,386	3,652
Cumulative %	52,508	73,599	88,962	96,348	100,000

The variables (components) that have a value of less than 1 are subsequently ignored because their presence has no significant relationship with the more important factors. Table I and Figure 2 indicates that the first two variables (components) have eigenvalues that are greater than 1 and the value of their cumulative variances constitutes 73,599 %. Dimensions with the highest correlation in the dataset are expressed by the eigenvectors with the largest values. It therefore explicitly shown that the strongest correlations are found in the first two components, the most effective being the first PC followed by the second PC.

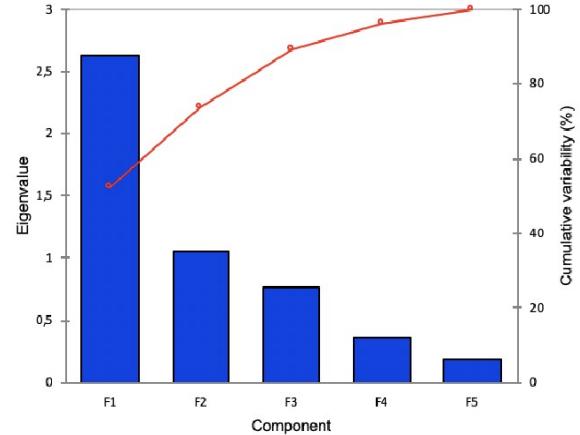


Figure 3: PCA scree plot with eigenvalues

These components were therefore selected for the matrix of the principal component. It can be seen that the positive values suggest positive correlations, while negative values show negative correlations. Values close to 1 also show stronger correlations.

Table II displays the loadings that display the influence of the variables in Principal components (PCs). It further indicates elements that are regarded as key influencing factors of methane levels in underground coal mines. In these influencing factors, PC (F1) contributes 55,508% to loading factors of temperature, humidity, and pressure. In PCA (F2) wind speed is only the loading factor.

Table II. Loadings of variables for the principal components matrix.

	PC (F1)	PC (F2)	PC (F3)	PC(F4)	PC(F5)
Wind Speed	0,154	0,894	-0,418	0,029	0,020
Temperature	0,859	-0,037	0,088	0,496	-0,087
Humidity	0,918	0,021	0,181	-0,122	0,330
Pressure	0,880	0,132	0,203	-0,319	-0,257
Current	-0,497	0,485	0,715	0,077	0,012

3.5 ANN Model

To train the ANN model, four training algorithms were adopted. The data set [15] was divided into two, with 70% reserved for training, and the remaining 30 % for testing. The Levenberg-Marquardt training algorithm turned out to be the best reliable algorithm mainly because of its high competence, speed, and capability of training a network at standardized ranges of [0 -1].

The normalization equation [20] is indicated in (3).

$$z = 0.7 \left(\frac{x - \min(x)}{\max(x) - \min(x)} \right) + 0.3 \quad (3)$$

To get a suitable number of neurons in the hidden layer, the ANN model training was done by increasing the number of neurons by an incremental value of one till it converges into a minimum average square error. This was done on both the original normalized parameters and PCA extracted components. For the PCA extracted components, the minimum MSE and maximum coefficient of determination (R^2) for both training and testing were obtained at 6 hidden neurons and 15 hidden neurons for the original normalized parameters. This proves that the PCA-based ANN model is more effective in both training and testing more the ANN model fed with original data. Table III and IV respectfully display the training and test values of R for each of the four algorithms, based on the original normalized parameters and PCA extracted components.

Table III. OPTIMAL NUMBER OF NEURONS FOR ORIGINAL AND PCA BASED DATA

	Training Algorithm	LM-Algorithm		GD-Algorithm	
		No of neurons	R training	R test	R training
Original dataset	15	0.9315	0.9331	0.5517	0.5370
PCA Components	6	0.92717	0.9479	0.46	0.6370

Table IV OPTIMAL NUMBER OF NEURONS FOR ORIGINAL AND PCA BASED DATA

	Training Algorithm	RP-Algorithm		SGD-Algorithm	
		No of neurons	R trainin g	R test	R trainin g
Original dataset	15	0.8974	0.8875	0.9120	0.5370
PCA Components	6	0.8209	0.8970	0.7272	0.8893

The above findings indicate that the Levenberg-Marquardt (LM) training algorithm applied to a PCA based ANN model, achieved better results with fewer neurons in a hidden layer than the ANN model fed with input parameters from the original dataset. This demonstrates that the adoption of the PCA based ANN model was worth it, as the model still managed to get good prediction results with fewer input parameters.

3.6 Model performance evaluation

To adequately evaluate the performance of the ANN model based on both the original dataset and the extracted components of the PCA, an error analysis [21] technique was performed to compare predicted methane values with real values. Both the MSE and RMSE were used as methods of comparison to determine model performance. To obtain the amount of scatter produced by the ANN model, the RMSE value was used. A low RMSE score results in a higher prediction accuracy. MSE values were used to check if target and performance values converged. Both MSE and RMSE [22] equations are defined in (4) and (5).

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_i - y_i)^2}{N}} \quad (4)$$

$$MSE = \left(\frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2 \right) \quad (5)$$

Table V. Performance of ANN model based on the original dataset

Algorithm	MSE	RMSE
GD	0.0087	0.0933
SCG	0.0023	0.0881
LM	0.0022	0.0469
RP	0.0058	0.0548

Table VI. Performance of ANN model based on PCA Components

Algorithm	MSE	RMSE
GD	0.0072	0.0849
SCG	0.0023	0.0881
LM	0.0019	0.0426
RP	0.0048	0.0693

4 Results and Discussion

As shown in Table V and Table VI, the PCA-based ANN obtained a minimum mean square error using the LM algorithm [19]. The performance plot of the PCA based ANN model is displayed in Figure 4. It can further be seen that when there's an increase in epochs, the values of MSE and RMSE decreases. To validate that there are no overfitting problems, the performance plot indicates that the validation error and test error sets are similar. This validates that the PCA has improved the ANN model prediction accuracy. Additionally, the results show that the PCA combined with ANN increases model performance.

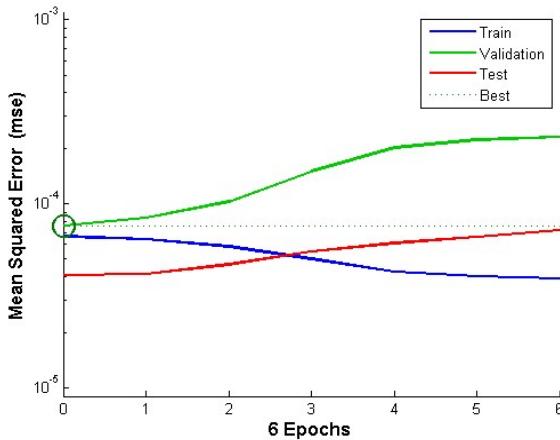


Figure 4: Performance plot of a PCA based ANN model

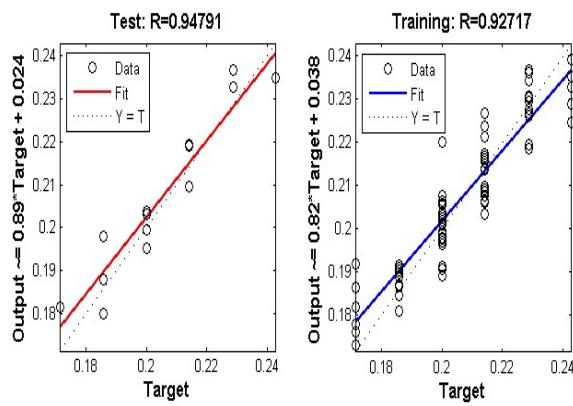


Figure 5: Training and testing regression plot for PCA-based ANN model

As shown in Figure 5, the values of R for testing was 0.947 and 0.92717 for training on a PCA-based Ann model. The value of R is regarded as the correlation coefficient that always has to be equal to 1 in order to validate the relationship between the predicted values and calculated values. The value of R for both testing and training from this experiment depicts a high relationship between the predicted values and calculated values.

5 Conclusion

In this paper, a hybrid ANN model made of a PCA and an ANN model was developed. The PCA was used to evaluate and select input variables (factors) most affecting methane levels. The most significant inputs variables identified by the PCA were humidity, temperature, and pressure. The variables extracted through the PCA were fed to the ANN model as input parameters. The PCA based ANN model was then compared to the ANN model with input parameters from the original dataset. The results depicted that the PCA based model achieved an improved performance and prediction accuracy, using fewer neurons in the hidden layer and reduced input variables than the ANN model fed with input

parameters from the original dataset. The values of R for testing was 0.947 and 0.92717 for training. This developed PCA-based ANN model has proven to be a good alternative for identifying key influencing factors and improving the performance of methane prediction models. Future proposed work would be to integrate and compare the PCA with other regression models besides the ANN model. Furthermore, an element of IoT could be looked at, to test the model with real-time data.

ACKNOWLEDGMENTS

The Tshwane University of Technology has provided research and development support towards this research work.

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