Methane gas concentration prediction in underground coal mines as a sustainable mining approach

J. Diaz[1], Z. Agioutantis[1], D.T. Hristopulos[2], and S. Schafrik[1]

[1]University of Kentucky, Kentucky, USA
[2]Technical University of Crete, Crete

INTRODUCTION

Coal is the most affordable energy fuel and the most significant commodity market worldwide for electricity generation. Despite all the environmental concerns around coal extraction and processing, coal production increased by around 6% (450 million tonnes) in 2021. Furthermore, coal provides more than 36% of global electricity and accounts for around 25% of the domestic electricity in the United States (US) [1,2]. Therefore, coal is considered crucial to relieving energy poverty due to its reliability and affordability. However, as coal is mined, methane gas is emitted, which is considered a significant threat to underground coal mine operations. Thousands of miners have lost their lives due to methane explosions in underground coal mines worldwide [3,4,5]. This paper discusses different univariate and multivariate methane gas forecasting models that have been developed. The models allow mine operators to accurately predict changes in methane concentrations as a function of weather conditions as well as production. As operators can prepare for methane concentration changes, mine operations can become safer and more sustainable.

PROCEDURE

The data that were used to develop the univariate and multivariate methane gas forecasting models can be classified into two main categories; (i) mine data (methane gas time series) and (ii) weather data (barometric pressure time series). The mine data were collected from the Atmospheric Monitoring System (AMS) of three active underground coal mines in the US, referred to as Mines A, B, and C. Furthermore, the weather data were retrieved from the closest weather stations to each mine, automatically downloaded from a free commercial weather service, known as the Weather Underground Commercial Company (WU). More detailed information concerning the characteristics (e.g., source, frequency, length, and units) of the data collected can be found in Diaz *et al.*, [6,7].

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The main steps of the data collection, management and analysis process implemented in this research are as follows:

a) Collect the mine and weather data.
b) Store the methane gas and barometric pressure time series data in a custom relational database, Atmospheric Monitoring Analysis and Database Management (AMANDA).
c) Pre-process the data which includes data cleaning and filtering.
d) Homogenise the data to ensure that data points from different time series share a common date/time stamp. Furthermore, data homogenisation can create a 12-hour or daily average time series for every data stream.
e) Process the data by (i) determining the potential autocorrelation of the methane gas time series to identify the univariate forecast model(s) and (ii) establishing the cross-correlation between methane gas and barometric pressure to select the multivariate forecasting models.
f) Develop time series models for forecasting.
g) Select the best methane gas forecast model (univariate or multivariate) based on validation data and metrics.

Three forecasting approaches, the univariate model ARIMA(p,d,q) and the multivariate models, VAR(p) and ARIMAX(p,d,q), were developed to predict future levels of methane gas concentrations. The performance of these models was assessed using cross-validation (CV) and validation metrics (e.g., Linear Correlation Coefficient (R) and the Root Mean Squared Error (RMSE)), which calculates how well the predicted values compare with the true values. Furthermore, the optimal model is determined based on the Akaike Information Criterium. The optimal model is then employed to forecast methane concentrations in advance, and the forecast is compared to the measured value. Finally, the RMSE generates 95% confidence intervals (CI) for the forecasts.

SUMMARY OF RESULTS

The dataset used includes two time series; (i) the methane gas time series (dependent variable) and (ii) the barometric pressure time series (independent variable); both time series were used to feed the multivariate approaches (VAR and ARIMAX), but only the methane gas time series was implemented to run the univariate model (ARIMA). Moreover, the methane gas time series data used were retrieved from the first case study (Mine A) and the barometric pressure time series data from the nearest weather station of Mine A using the WU. Additionally, the time series were homogenised and averaged at 12-hour values; both comprise one year of data with approximately 730 records each.

Figure 1 consists of four plots (a to d). Graph (a) represents the time series employed to feed the forecasting models. The green line represents the barometric pressure time series (InWG), and the red line represents the methane gas concentration time series (%). Furthermore, graphs (b), (c), and (d) are the forecasts obtained using the ARIMA, VAR, and ARIMAX techniques, respectively. The black dashed lines indicate the upper and lower 95% confidence interval for the forecasts. The red line denotes the forecast, and the blue line inside the C.I. signifies the validation data. The forecast and the validation periods correspond to 5% of the methane time series. Moreover, the gray line in Figure 1b and 1c and the blue line in the white background of Figure 1d denote the training data that include 95% of the records in the methane time series.

Figures 1b, 1c and 1d show that the forecasts (red line) closely follow the validation data (blue line); the forecast matches the changes (increase/decrease) in the validation data. Furthermore, the linear correlation coefficient calculated for the ARIMA, VAR, and ARIMAX forecast models was 0.90, 0.91, and 0.91, and the root mean square error obtained was 0.47, 0.46, and 0.46, respectively. The linear correlation achieved by the three forecast models indicates a strong positive correlation between the validation data and the forecast. Finally, the 95% confidence interval boundaries consistently contained the forecast and validation data.

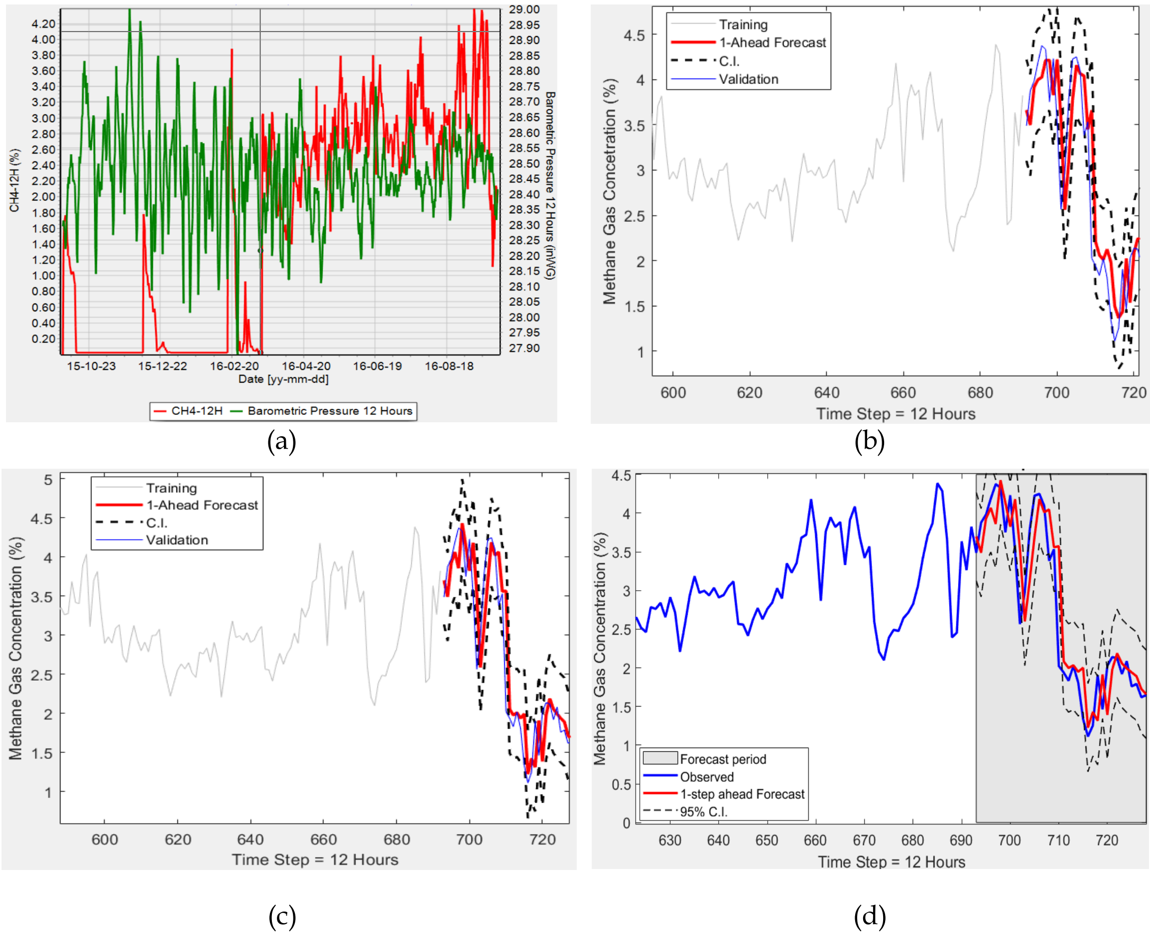

Figure 1. Univariate and multivariate forecast results using 12-hour average values time series: (a) barometric pressure and methane gas time series employed to feed the models; (b) results from the ARIMA model; (c) results from the VAR model; (d) results from the ARIMAX model.

CONCLUSIONS

The proposed methane gas forecasting models (ARIMA, VAR, and ARIMAX) offer an excellent solution complementing the suite of reliable available methodologies capable of accurately forecasting methane gas concentrations to improve the safety and health conditions of the workforce in the underground coal mining industry. Furthermore, it was found that none of the forecasting models proposed could uniformly outperform the other forecasting approaches for all datasets. Consequently, a methodology for selecting the best (univariate or multivariate) forecast model based on cross-validation analysis should be developed.

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Juan Carlos Diaz Martinez

Postdoctoral Researcher
University of Kentucky

Detail-oriented Bilingual Mining Engineer with five years of experience and enthusiasm for solving complex problems. Experienced in Artisan Small Scale Mining, Mine Ventilation, and Health & Safety Management with a strong background in conducting research in state-of-the-art mining engineering challenges. I hold a PhD in Mining Engineering from the University of Kentucky (US), a master's degree in Advanced Mineral Resources Development from TU Bergakademie Freiberg (Germany) and Montanuniversitaet Leoben (Austria) and a bachelor's degree in mining and Metallurgical Engineering from La Universidad Nacional de Colombia.