Potential Methane concentration forward prediction methodology using artificial intelligence from measurements in underground mines

T. Dias[1], *B. Belle*[2], *G.L. Danko*[3]

1.Graduate Research Assistant, University of Nevada, Reno, NV, 89502.
tdiasdealmeida@nevada.unr.edu

2. Ph.D., Lead Ventilation and Gas Manager, Anglo American Coal, Australia; Adj. Prof of Mining, UNSW, Australia; Adj. Prof of Mining UQ, Australia.

3. Ph.D. Professor, University of Nevada, Reno, NV, 89502.

danko@unr.edu

Keywords: Neural Network, smart system, safety, transport model.

Abstract

A well-known problem in underground mines is the release of hazardous gases. The main sources most often are strata fractures due to high extraction in longwall and room and pillar mines. The fractures created can let methane escape into the mine workings. A problem associated with the unmanaged gases inside the mine airways are hazards to health and explosions, especially methane (CH_4) in coal mines. Another factor that may harm the health and safety of workers in underground mines is heat release from the strata and machinery, causing temperature rise. High temperature near a working face may also be due to poor localized ventilation management (airflow conditions) or inadequate mine cooling systems. Therefore, continuously monitoring the in-situ conditions as well as the amount of contaminant gases, especially methane, are important factors for predicting the necessary actions for keeping the mine a safe and healthy place for workers. This paper studies methods for predicting ahead of time methane concentration inside underground mines using long-short-term memory (LSTM) neural network (NN) model, as well as transport model-based model applications. Different combinations of the variables are tested in NN models to find best results for accuracy and applicability. The training method uses a sliding time window, where data from 1 to 5-time steps are used for training and data from 6 to 10 time-steps are predicted. Continuing with this training, time steps from 2 to 6 are trained and 7 to 11 are predicted. The results show that the NN predicting power is sensitive to sliding window sizes and the number of forward-step predictions. Recommendations are discussed for transport model-based solutions for forward predictions combining their parameter identification with those used for NN model training.