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Development of a Machine Learning Model to Estimate Refrigeration in an Underground Mine

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Abstract

The rise in temperature in an underground mine is one of the critical challenges. The main causes of increasing mine air temperature include geothermal gradients, machinery operation, depth, width of the airway, and limited natural ventilation. High temperatures cause discomfort and adverse health effects among miners and also reduce worker efficiency, impair equipment performance, increase energy consumption, and lower overall productivity. Efficient cooling or refrigeration and ventilation systems are key to maintaining safe and sustainable working conditions. The study deals with the simulation-based parametric study and machine learning techniques that can be used in order to reduce heat in underground mine air. The air velocity, mine depths, and width of airways have been considered for understanding air circulation and heat transfer in varying conditions. Simulation-based data were gathered from a number of cases to study variations in airflow, heat buildup, and cooling demand. These datasets were then processed using machine-learning algorithms to develop predictive models that estimate cooling demand and determine optimal ventilation strategies. Using machine learning, thermal behaviour can be forecast from past data; hence, it is a smart and efficient method for improving ventilation design. The machine learning model takes into consideration several input parameters simultaneously and can give indications about the cooling methods that consume the lowest amount of energy while keeping air temperature within acceptable limits. It is also observed that simulation-based analysis and machine learning form a powerful framework for understanding and determining the refrigeration to control heat in underground mines. The results of this study evidence that data-driven prediction can be highly effective in improving cooling efficiency by providing proper refrigeration, decreasing operational costs, and contributing to a safer, more sustainable deep mining environment.

Major Findings: *Simulation results showed that refrigeration demand increases significantly with higher air velocity, airway width, and initial mine temperature, while depth has comparatively less influence on cooling requirements. The developed XGBoost model predicted refrigeration demand with high accuracy, achieving an R^2 of 0.985, RMSE of 3008.64, and MAE of 579.32, demonstrating strong agreement with simulation data. Validation against VentSim outputs showed excellent correlation (R^2 = 0.9998) and low prediction error (MAE = 159.427), confirming that the machine learning model can reliably estimate refrigeration requirements for underground mines.*

Keywords: *Machine Learning, Refrigeration, Temperature in Underground, Underground Mine, Velocity of Air, Ventilation*

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1.0 Introduction

The control of heat in underground mines is an imperative part of mine safety and efficient operation. Increased temperatures in underground mining conditions may adversely affect employee health, minimise productivity, and raise cooling expenses. Providing a thermally acceptable working environment, thus, represents a basic priority for mine managers and ventilation experts[1]. Effective heat management practices are necessary to reduce the hazards of prolonged exposure to high temperatures and to meet occupational health and safety regulations. Ventilation systems are the main mechanism for managing thermal conditions in underground mining environments, handling key heat sources such as geothermal gradient, auto-compression, equipment operation, and human activity[2,3].

Efficient ventilation has direct implications on employee health and safety by avoiding heat stress and cognitive impairment[4], while at the same time providing compliance with regulatory requirements for temperature and air velocity levels[5]. Studies show that at temperatures above 27 °C, Wet Bulb Globe Temperature (WBGT), worker efficiency declines, and at temperatures above 32 °C, WBGT, there is a significant risk of heat-related illnesses[6]. It is also known that the worker efficiency decreases as the WBGT goes beyond 21 °C, and above 30 °C WBGT, the velocity requirements have to be increased[7,8]. In deep mines, high temperatures also increase physiological strain, heart rate, and thermal discomfort, making proper ventilation and cooling essential for maintaining worker health and productivity[1].

The examination of heat reduction in underground mine air using VentSim3D is of significant importance to engineering projects, particularly mining and environmental engineering. Underground mining operations are typically beset by excessive heat produced by geological structures, equipment, and working conditions in closed spaces[9]. Elevated temperatures can pose health risks to workers, including heat stress, dehydration, and reduced physical and mental performance[10]. Using the powerful 3D ventilation simulation tool VentSim3D, engineers can simulate airflow patterns, temperature distribution, and the effectiveness of various cooling methods such as refrigerated air, chilled water systems, and increased airflow rates[11]. This makes it possible to design effective and cost-efficient ventilation systems that enhance thermal comfort and safety among mine workers[12].

Besides, the optimisation of measures to reduce heat not only increases occupational health and safety but also contributes to enhanced worker productivity, improved equipment performance, and compliance with regulations[9]. The results of such a study can guide engineering choices in new mine development and retrofitting old operations, contributing to more sustainable and operationally effective underground environments[11].

Traditional ventilation and cooling methods, such as increasing airflow or using refrigeration systems, can be costly and inefficient if not properly designed and optimised[4]. The complexity of underground mine ventilation networks requires advanced simulation tools to predict airflow patterns, temperature distribution, and the effectiveness of heat reduction measures. To address these challenges, this study employs VentSim3D, a sophisticated ventilation simulation software, to model heat distribution and test various cooling and ventilation systems[13].

2.0 Simulation-Based Parametric Study

The simulation-based approach is particularly beneficial for deep and hot mines, where the cost and complexity of cooling solutions are significantly higher. Heat is another critical factor affecting underground mine environments, particularly in deep mines where rock temperature, auto-compression of air, and equipment heat contribute to thermal load. Excessive heat reduces worker efficiency and increases health and safety risks, making temperature control essential for safe mining operations. VentSim provides advanced heat simulation by modelling the sources of heat, such as rock strata, machinery, and auto-compression, and predicting how these factors influence air temperature distribution throughout the mine. By adjusting ventilation and refrigeration parameters, VentSim helps maintain thermal comfort levels, improve energy efficiency, and ensure compliance with occupational health and safety

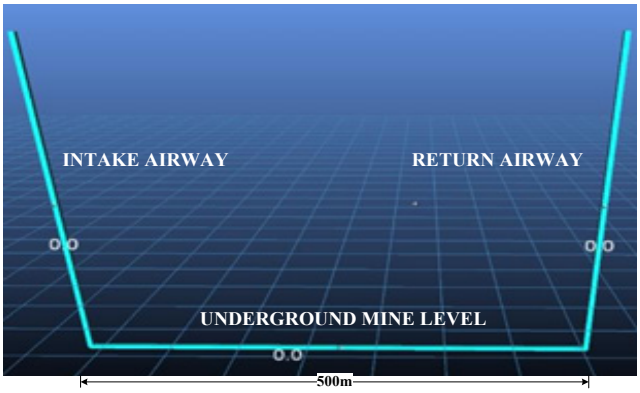


Figure 1. A model of simulated airway in ventsim software.

standards[14]. Hence, VentSim is considered in the study to determine the optimum refrigeration for an underground mine. An ideal underground condition is simulated by considering the intake airway, underground mine level, and return airway, suggesting a simple U-shaped model to study the various factors on refrigeration, as shown in Figure 1.

The parameters considered in the study i.e., width of the airway ranging from 3 to 6 m[3,10] with an interval of 0.5m, velocity of airway ranging from 1-7 m/s[5,8] with an interval of 1 m/s, depth of the intake and return airways ranging from 250 to 850m[4,6] with an interval of 100m and temperature of the mine ranging from 30 – 50 °C [4,6] with an interval of 10°C whereas length of the airway restricted to 500m and height of the airway is restricted to 3m[3,10], based on the available literature are used to simulate the model is listed as in the Table 1. In the study, the initial temperature of the air was considered at 50°C, 40 °C, or 30°C, and it was lowered to 21°C using refrigeration under different airway conditions[1,7].

3.0 Results of Simulated Study

The influence of air velocity, width of the opening, temperature, and depth of the opening on refrigeration is given.

3.1 Effect of Air Velocity on Refrigeration

Refrigeration demand is directly influenced by airflow velocity. At higher air velocities, the moving air absorbs greater quantities of heat from the surrounding rock and machinery, leading to an increase in cooling requirements. Higher airflow increases heat transfer from the rock walls and equipment to the air. This relationship is reflected in Figure 2 (a-d), where refrigeration demand rises consistently with air velocity.

Table 1. List of parameters affecting ventilation considered in the study

Parameters	Specified Range
Length of the airway	500m
Width of the airway	3-6 m
Height of the airway	3m
Geothermal Gradient	2.5°C/100m
Velocity of Air	1-7m/s
Depth	250-850 m
Temperature	30-50 °C

3.2 Effect of Width on Refrigeration

Increasing airway width increases the cross-sectional area available for airflow. A wider airway allows more air to flow at the same velocity.

With greater volume, more heat is transported into the system, which requires higher refrigeration. Wider airways also have more exposed surface area of rock, which contributes additional heat transfer to the air. Thus, refrigeration demand increases almost proportionally with airway width. The refrigeration requirement grows with airway width, as shown in Figure 2 (a-d)

3.3 Effect of Temperature on Refrigeration

The temperature increase in an underground mine is the cumulative effect of all parameters contributing for increase in heat. Increasing the airway temperature in the mine resulted in excess consumption of refrigeration. The trend from the simulated study suggests that the refrigeration demand increases almost proportionally with an increase in temperature, as shown in Figure 3 (a-d).

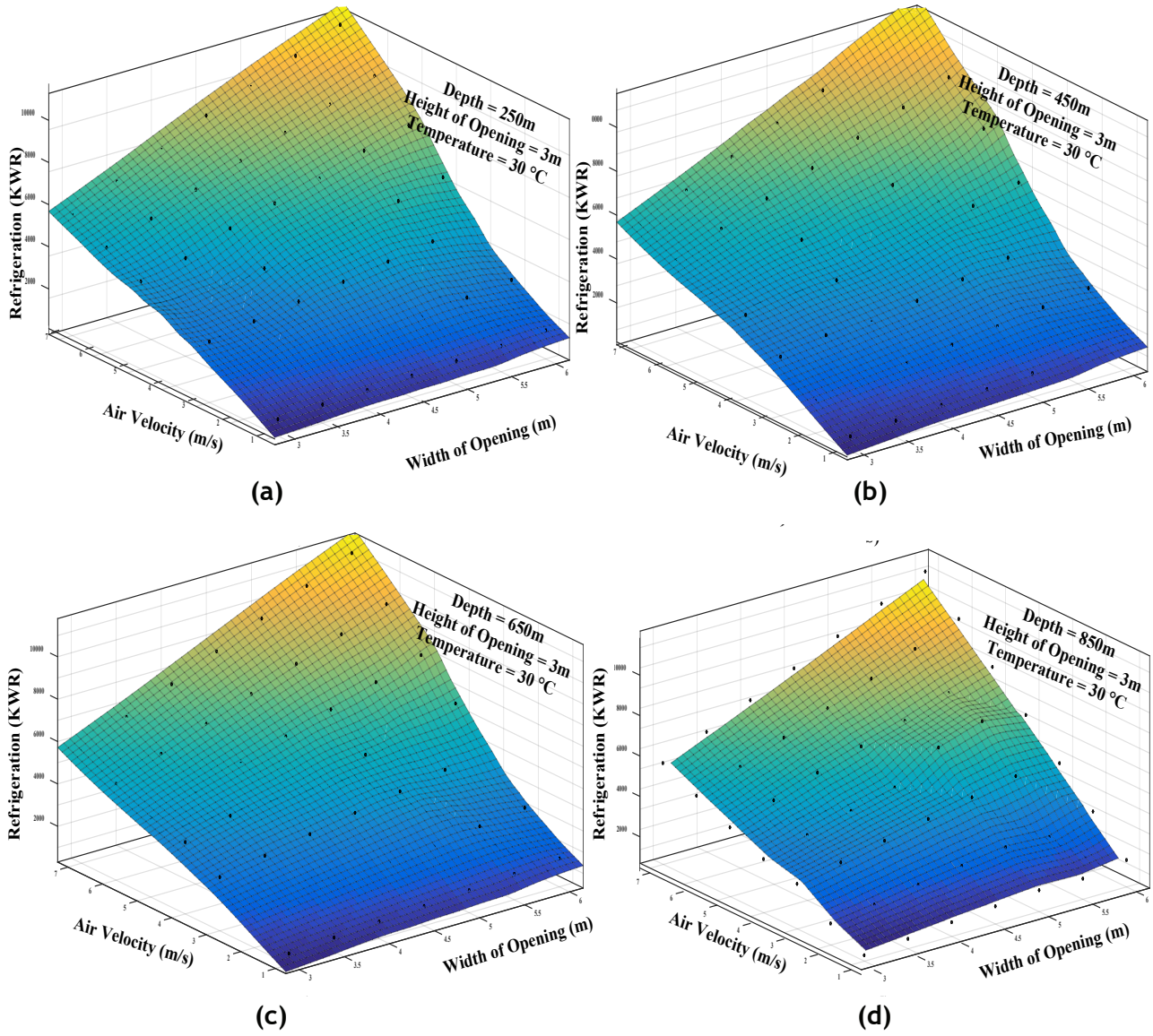


Figure 2. **(a-d).** A trend of the effect of air velocity and width of opening on refrigeration.

3.4 Effect of Depth of the Opening on Refrigeration

An increase in heat in deeper underground mines is usually attributed to the geothermal gradient. But, in the study, it is revealed that the effect of depth on rise in temperature is limited compared to the other affecting parameters like velocity of airway and width of opening, resulting in limited change in refrigeration as shown in Figure 3 (a-d).

4.0 Development of Machine Learning Model

A Machine Learning (ML) model based on the XGBoost algorithm in order to predict refrigeration demand related to underground mine environments is used in the study based on the literature. The dataset from the simulation-based study is used in training and testing the model. Data were standardised and then split into both training and testing subsets to ensure

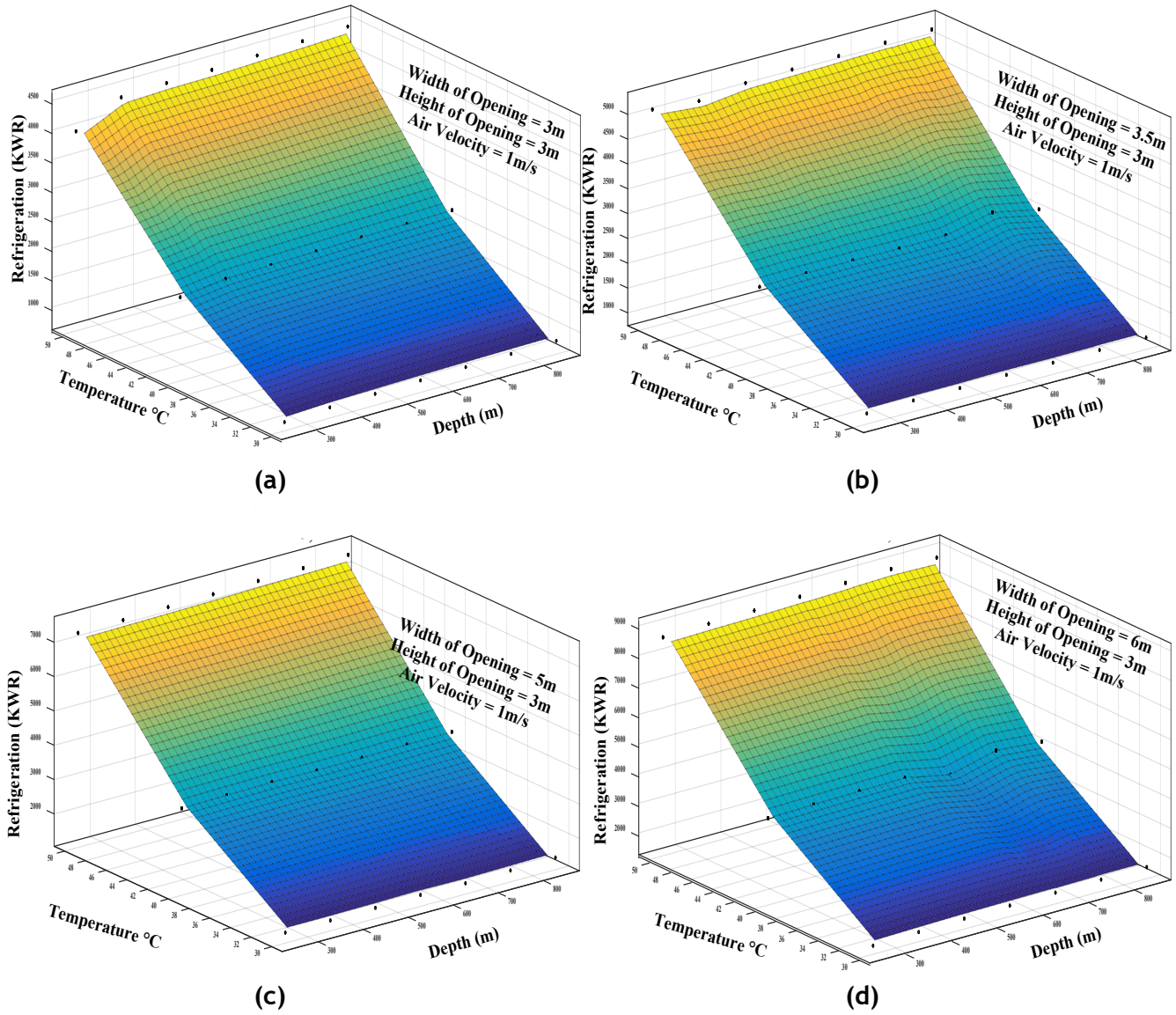


Figure 3. A trend of the effect of temperature and depth on refrigeration.

model generalisation and stability. Even though the simulated study suggested that the effect of selected parameters (air velocity and width of opening) on refrigeration is linear and depth is excluded because the trend in the simulation showed a minimum on refrigeration, the XGBoost machine learning algorithm was selected, because it treats linear and nonlinear relationships robustly and is computationally efficient in regression-based prediction problems[15], as shown in Figure 4.

The sample results obtained from the trained XGBoost ML model are shown in Table 2. The table displays a subset of the predicted refrigeration demand values corresponding to selected input parameters. These results demonstrate the model's ability to predict refrigeration requirements accurately across varying conditions.

The performance of the model in making a prediction was determined through the use of the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). The low RMSE value

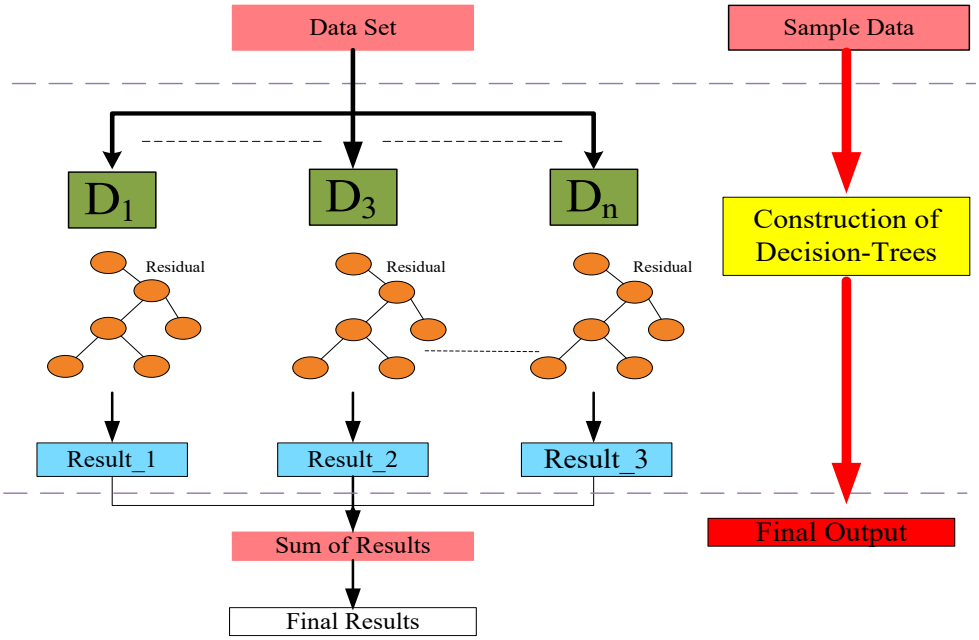


Figure 4. XGB booster algorithm used in the study[16].

Table 2. Predicted results sample from ML model to bring the temperature

Air Velocity (M/S)	Depth (M)	Width (M)	Temperature (°C)	Refrigeration (KWR)
6	750	5	40	21443.123
4	450	4.5	30	4530.5425
7	250	6	50	61373.945
4	550	5	40	14351.904
3	350	5.5	30	4297.035

of 3008.64 and low MAE value of 579.32, with a high R^2 value of 0.985, suggested that the model performed well in terms of the accuracy of prediction. The results from the predictions showed the same tendency that would have been expected from the simulation dataset, thereby proving the model to be reliable in estimating the refrigeration requirements. It also suggests that a lower RMSE and MAE demonstrate that the model predictions are very close to the actual values, ensuring minimal error in the output. An R^2 close to 1.0 signifies a very high degree of correlation between the predicted and actual values,

Table 3. Performance metrics of the prediction model

Sl. No.	Performance Metrics	Values
1.	Root Mean Squared Error (RMSE)	3008.64
2.	Mean Absolute Error (MAE)	579.32
3.	Coefficient of Determination (R^2)	0.985

confirming that the model possesses strong predictive capability[17]. The performance metrics of the model are mentioned in Table 3.

5.0 Validation

Validation of the developed machine learning model is done by comparing predictive results with the outputs from VentSim, i.e., mine ventilation simulation software. A comparison between the results of the machine learning predictions and those obtained from VentSim is carried out to establish the reliability and predictive strength of the ML model.

The validation analysis was conducted by considering a random 39 test cases. The 39 test cases were modelled in VentSim software, and the same input parameters

Table 4. Simulated and predicted refrigeration results

Air Velocity (M/S)	Depth (M)	Width (M)	Temperature (°C)	Refrigeration Simulated In Ventsim (KWR)	Refrigeration Predicted By Ml Model (KWR)	Variation In Results (%)
6	750	5	40	21510	21443.123	0.31
4	450	4.5	30	4291	4530.5425	5.58
7	250	6	50	61010	61373.945	0.60
4	550	5	40	14320	14351.904	0.22
3	350	5.5	30	4820	4297.035	10.85
2	250	3	30	1617	1546.8104	4.34
2	250	3.5	30	1885	1949.0956	3.40
2	250	4	30	2160	2155.7458	0.20
2	250	4.5	30	2420	2493.628	3.04
2	250	5	30	2700	2724.5486	0.91
2	250	5.5	30	2970	2899.484	2.37
2	250	6	30	3220	3089.2356	4.06
2	350	3	30	1621	1801.6328	11.14
4	750	5.5	40	15820	15723.171	0.61
4	750	6	40	17210	17174.438	0.21
4	850	3	40	8660	8612.755	0.55
4	850	3.5	40	10090	10233.267	1.42
4	850	4	40	11520	11671.408	1.31
4	850	4.5	40	12950	13334.221	2.97
4	850	5	40	14380	14950.384	3.97
4	850	5.5	40	15810	16109.219	1.89
4	850	6	40	17250	17032.848	1.26
5	250	3	40	10710	10748.288	0.36

Table 4 Continued

5	250	3.5	40	12465	12220.854	1.96
5	250	4	40	14235	14504.134	1.89
5	250	4.5	40	16010	15967.549	0.27
5	250	5	40	17780	17516.828	1.48
5	250	5.5	40	19555	19690.027	0.69
5	250	6	40	21330	21425.49	0.45
5	350	3	40	10710	10806.151	0.90
5	350	3.5	40	12490	12392.718	0.78
4	850	4	50	23620	23479.008	0.60
4	850	4.5	50	26425	26442.047	0.06
4	850	5	50	29650	29603.053	0.16
4	850	5.5	50	32620	32516.043	0.32
4	850	6	50	35,350	35103.72	0.70
5	250	3.5	50	24,650	24858.725	0.23
5	250	4	50	29,180	28955.99	0.85

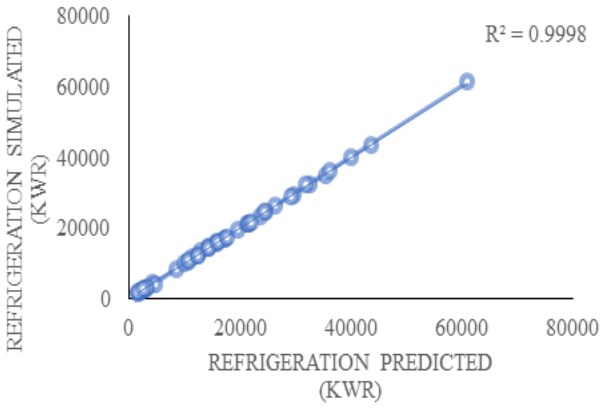


Figure 5. A correlation of results obtained using ventsim and machine learning model.

were used for the machine learning model. The input parameters used are air velocity and the width of the opening that predominantly drive the refrigeration demand in underground mine environments, as per the parametric study.

Figure 5 and Table 4 illustrate the relationship between the VentSim-simulated refrigeration demand and the predicted refrigeration demand required to reduce the mine air temperature to 21 °C. Each data point represents a comparison between simulated and predicted values under different operating conditions. The points are closely aligned along a straight line, indicating a strong linear relationship and minimal deviation between the two datasets. This close agreement shows that the predicted values accurately follow the trend of the simulated results across the entire range of refrigeration demand. Overall, the graph demonstrates the consistency and reliability of the prediction model when compared with VentSim simulation outputs. The machine learning model's predictions were very close to the simulated values, and an R^2 near unity indicates that the model captures more than 99.9% of the variation in refrigeration demand. A summary of the comparison between VentSim outputs and machine-learning predictions to bring the temperature to 21°C is shown in Table 5.

Table 5. Performance metrics of simulated and predicted results

Sl. No.	Performance Metrics	Values
1.	Coefficient of Determination (R^2)	0.9998
2.	Mean Absolute Error (MAE)	159.427

A MAE value of 159.427 indicates the average difference between the predicted refrigeration demand and the VentSim-simulated values. This implies that the model predictions deviate from the simulated results by approximately 159 units on average. When compared with the overall range of refrigeration demand considered in the study, this level of error is relatively small and acceptable. The low MAE value demonstrates that the prediction model provides accurate and consistent estimates of refrigeration requirements. Therefore, the MAE result supports the reliability of the model in predicting refrigeration demand for reducing the mine air temperature to 21 °C.

6.0 Conclusion

The following conclusions were observed from this study: An underground mine model is simulated in VentSim to study the effect of airway velocity, depth of the opening, temperature, and width of the opening on refrigeration. It is found that as the air velocity, width of the opening, and temperature increase, the refrigeration demand increases, whereas the depth does not have a noticeable impact compared to other influencing factors. With the datasets generated from VentSim simulations, the XGBoost ML model has been trained to learn the relationship between key ventilation parameters, including airflow, airway area, and sensible heat load, to determine cooling requirements in underground environments. An XGBoost-based machine learning model proved very effective for the prediction of refrigeration demand in underground mine air systems, providing quite accurate results while reducing the time and effort needed in traditional simulation-based analyses by a great extent. The validation is done by comparing machine learning predictions against the results from the VentSim test cases. The results suggest that the ML model is in good agreement with VentSim results. The developed ML model has an R^2 value of 0.985 and an RMSE of 3008.64, and an MAE of 579.32, hence proving that it can closely match the outcomes from VentSim results. These results confirmed that the model is reliable, consistent, and can produce realistic predictions even under different simulated conditions. Hence, it can be concluded that data-driven approaches such as XGBoost can effectively complement conventional simulation methods. The advantages that the proposed model has are its speed and flexibility: Once trained, it can instantaneously predict refrigeration demand for any given set of conditions, making it a practical tool for quick analysis and ventilation planning in underground mines. The study has emphasised that the integration of machine learning techniques with conventional mine ventilation systems can help in improving energy consumption, enhancing cooling efficiency, and maintaining a safe and comfortable work area for miners.

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8.0 Conflict of Interest

The authors declare that they have no conflict of interest.

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Conceptualization: Dr. Raja S. and Dr. Manjunath A. **Methodology:** Dr. Raja S. and Dr. Manjunath A. **Data Collection:** Mr.Gokul, Mr.Deepak, Mr. B Dhanush, Mr. Makesh Vishwanath P. **Data Analysis:** Dr. Raja S, Dr. Manjunath A, Mr.Gokul, Mr.Deepak, Mr. B Dhanush, Mr. Makesh Vishwanath P. **Manuscript Drafting:** Dr. Raja S. **Manuscript Review & Editing:** Dr. Raja S. and Dr. Manjunath A. **Supervision:** Dr. Raja S. and Dr. Manjunath A.

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