

AI-VENT: AI-Based Monitoring and Control of Industrial Ventilation Systems

Hardi Abdalla M. Rasul

¹Department of Chemical and Petrochemical, College of Engineering, Salahaddin University-Erbil, Erbil 44002, Iraq, hardi.m.rasul@su.edu.krd

HOW TO CITE: ABSTRACT:

Hardi Abdalla M. Rasul (2026).
AI-VENT: AI-Based Monitoring
and Control of Industrial
Ventilation Systems

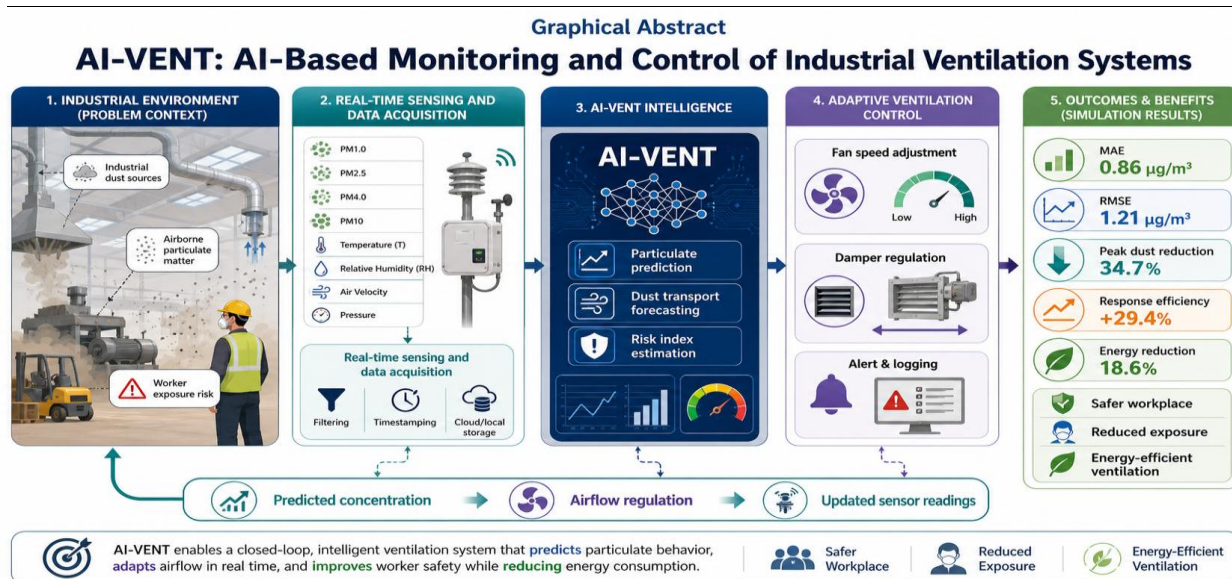
International Journal of Special
Education, 41(22s), 217-237

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors. Open
access publication under the terms
and conditions
of the Creative Commons Attribution
(CC
BY)
license (<http://creativecommons.org/licenses/by/4.0/>).

Industrial ventilation systems are essential for controlling airborne dust and particulate matter, yet conventional fixed-speed systems often respond poorly to dynamic particle transport and changing exposure conditions. This study proposes AI-VENT: AI-Based Monitoring and Control of Industrial Ventilation Systems, an intelligent framework for real-time dust monitoring, particulate prediction, and adaptive airflow regulation. The proposed system integrates PM1.0, PM2.5, PM4.0, PM10, temperature, humidity, air velocity, and pressure sensors with machine learning-based prediction and control logic. In the simulation-based evaluation, AI-VENT achieved a mean absolute error of $0.86 \mu\text{g}/\text{m}^3$ and root mean square error of $1.21 \mu\text{g}/\text{m}^3$ for particulate concentration prediction. Compared with fixed-speed ventilation control, AI-VENT reduced peak dust accumulation by 34.7%, improved ventilation response efficiency by 29.4%, and lowered unnecessary fan energy consumption by 18.6%. These results indicate that AI-VENT can support proactive exposure reduction, safer industrial workplaces, and energy-efficient ventilation management.

Keywords: AI-VENT, Industrial ventilation systems, Particulate matter monitoring, Dust transport prediction, Adaptive airflow control



1. Introduction

Airborne dust and particulate matter present serious challenges for an industrial ventilation system both in terms of occupational health and environmental policy (Ma et al., 2025). Particulate matter originating from operations like cutting, crushing, drilling, handling, storing, conveying, mining, etc., can stay suspended in atmosphere and travel throughout zones of work, ducts, return air tracks, and extraction point (Ebad et al., 2026). Finer particles are very important as they penetrate deeper into human respiratory system, worsen air quality of workplace environment, and increase risks of long-term health complications (Liu et al., 2026). Therefore, industrial ventilation has to be perceived not just as a mechanism for air exchange, but as dynamic dust-transport control system (Shen et al., 2026).

Conventional industrial ventilation systems usually make use of fixed-speed fans, manually-controlled dampers, or simple threshold control algorithms (Jeong et al., 2026). While these methods are easy to implement, they fail to react efficiently to changes in rates of dust generation, airflow velocity, pressure imbalance, humidity, particle size, and exposure zones (Cao et al., 2026). Due to this, certain areas or zones may suffer from accumulation of the dust during operation of the ventilation system (Ding et al., 2026). At the same time, excessive ventilation during the periods of low risk will lead to unnecessary energy consumption and operating costs.

The results of recent studies showed that the use of sensor networks and Internet of Things (IoT) technologies in conjunction with machine learning-based methods can significantly enhance the monitoring and prediction of particulate pollution (Mohapatra et al., 2026). In the study by Tripathi et al. (2024), an IoT-enabled real-time monitoring system was set up for measuring PM1.0, PM2.5, PM4.0, and PM10 at a surface mining site. The authors applied four models including Linear Regression, Decision Trees, Gradient Boosting Regression, and Random Forests. The best performance was achieved by Random Forests model, with minimum recorded MAE and RMSE values, demonstrating the general effectiveness of data-driven predictions of particulate matter. Still, the contribution of this study lies mainly in monitoring and prediction but

not in the area of closed-loop ventilation control.

Investigations in CFD and ventilation-on-demand show that all factors of airflow map, duct system design, fan operation, and dynamic control can influence the effectiveness of dust removal and energy performance. For instance, Nie et al. (2024) demonstrated that optimized negative pressure extraction can significantly improve dust prevention in tunnel systems, and Ihsan et al. (2024) pointed that AI-application gives an opportunity to save energy by means of changing ventilation parameters. Therefore, it can be seen that any further research in industrial ventilation must combine the mechanisms for particulate sensing, understanding of dust transport, and machine learning predictions.

The present study aims to create a new AI-based intelligent framework for industrial ventilation operation and is to be called AI-VENT, which stands for AI-Based Monitoring and Control of Industrial Ventilation Systems. The developed system incorporates real-time particulate sensing, machine learning-based predictions, and adaptive fan-damper control in order to ensure its high efficiency in controlling dust emissions.

1.1 Contributions

The novel contributions of this study are:

1. The objective of developing AI-VENT is to create an AI-based system for monitoring and control of particulate matter in the moment.
2. The goal is to develop a prediction model for the integration of sensors that will facilitate estimation of particulate matter, air, environmental, and control parameters and PM1.0, PM2.5, PM4.0, and PM10 concentrations.
3. The plan is to devise a ventilation control approach that adjusts fan speed and damper setting to control peak dust level and boost efficiency of operations while reducing unnecessary fan power consumption.
4. The objective is to test AI-VENT against existing regression models and ensembles of models in terms of prediction and dust control, as well as energy efficiency.

2. Literature Review

Researches about industrial ventilation and dust control show that effective management of particulates depends upon four research areas: behavior of transportation of dust and particles, particulate monitoring based on IoT technologies, prediction of dust based on machine learning, and adaptive ventilation. Thus, in this part of the paper we study literature concerning dust transport in ventilation, IoT-based real-time particulate monitoring, models of dust prediction based on AI technologies, and intelligent ventilation control tips in order to find out the gap that the AI-VENT framework is intended to fill.

2.1 Dust and Particle Transport in Ventilation Environments

The functioning of any ventilation system with respect to transport of dust and particles occurs due to the interaction between the emission sources, the pattern of air flow, properties of particles, and ventilation system configuration. In the context of mining, the process of generating and transporting air particles takes place continuously in activities such as material handling, stone processing, crushing, cutting, loading of equipment, dumping, and storage, as well as in conveyor transfers. In the study conducted by Gui et al. (2026) focusing on dust control in mine shaft hoisting, the efficiency of dust removal is influenced by the structure of air flow, and the placement of ventilation system setup. This study demonstrates the necessity to analyze not only the concentration of dust in industrial settings but also analyze its transportation, accumulation, and removal process depending on the conditions of ventilation.

Particle size is of a significant importance when determining both the behavior of particles in transit and the safety level of employees. Larger particles normally fall quicker than smaller ones, with PM1.0 and PM2.5 particles having the ability to stay in the air for longer periods and travel deeper into closed working area. Sharma et al. (2026) studied emissions of particles and exposure in stone-cutting conditions and pointed out that a workplace has the potential to generate huge amounts of particles in the air depending on the nature of activity performed, type of working

conditions, and location of exposure.

2.2 IoT-Based Particulate Monitoring

Monitoring particulates through Internet of Things is a significant alternative to traditional measurement methods that involve lag time. Continuous monitoring is an advantage in itself as it allows rapid feedback and real-time actions. Conventional gravimetric sampling and manual measurements are adequate in terms of exposure assessments, but they come with a number of weaknesses like time-delayed data delivery, limited coverage, and low-quality data unable to provide information for immediate decision-making concerning effective ventilation. Roy (2026) notes that advanced sensors connected to systems relying on the Internet of Things allow monitoring of air quality thanks to continuous data collection, transfer, and feedback. This claims the effectiveness and necessity of using sensors in industrial ventilation processes.

According to Tripathi et al. (2024), an IoT-based instant monitoring system for open-pit mining operations has been developed. The monitoring system includes such types of sensors as PM1.0, PM2.5, PM4.0, and PM10, and applies machine learning to predict the levels of dust concentration at mine sites. Moreover, the study utilizes the linear regression analysis, decision tree method, gradient boosting regression, and random forest algorithm. It is important to mention that the random forest method has proved to be the most effective having the MAE indicator amounting to 1.079 and RMSE equal to 1.497. This study is closely connected to the current work due to the fact that it serves as a basis for particle monitoring through the Internet of Things and machine learning implementation. Nonetheless, it should be noted that focusing on monitoring and forecasting, this system fails to provide the integration of monitoring results with the automatic ventilation regulation system.

2.3 Machine Learning for Particulate Prediction

The employment of machine learning techniques has been climbing within particulate forecasting because the relationships between PM concentration and its causes are nonlinear and influenced by a variety of factors, including

meteorological conditions, activity of sources, velocity of air flow, pressure, humidity and temperature, and performance of local ventilation systems. Linear models may provide useful and interpretable results, but they are not able to internalize all aspects of complex motion of particles in industrial conditions. Ensemble models like Random Forest and Gradient Boosting are good in terms of their capabilities of nonlinear modeling of interactions among different features and making predictions less volatile. According to Makhdoomi et al. (2025), machine learning technology can be used for effective prediction of PM_{2.5} values and virtual monitoring of dust when measurements are limited.

In the case of AI-VENT framework, Linear Regression, Decision Tree, Random Forest, and Gradient Boosting Regression are good candidate models for the comparison due to their frequent use in dust forecasting and the ability to evaluate the results against MAE, RMSE, and R^2 metrics. Additionally, Tripathi et al. (2024) utilized similar models for PM assessment under surface mining conditions and proved their effectiveness for monitoring applications. However, prediction is not enough for managing industrial ventilation system since it lacks the element of control. The unique nature of AI-VENT framework relies on the fact that it allows utilizing of predicted values of particulate concentration as a control parameter for making operational decisions, thus letting the system adjust the speed of the fan and other ventilation elements depending on the expected dust level.

2.4 Adaptive Ventilation Control

The adaptive method of ventilation control concentrates on providing ventilation according to the precise need of the system and does not run the fan continuously at the designated speed. Regular industrial ventilation systems run the fan at a fixed speed, which may result in inadequate ventilation in high-dust areas and an excessive amount of ventilation in low-risk zones. There are two major problems arising from this: the workers are exposed to harmful substances in badly ventilated places, and unnecessary energy expenses are observed in regions where huge amounts of ventilation are not needed. (Darwish et al., 2026) made a literature analysis of traditional and IoT and AI technology-based HVAC control systems and have pointed out that intelligent control is crucial for the improvement of energy efficiency and indoor air quality.

There is a growing interest in ventilation-on-demand in underground and industrial settings as well. Ihsan et al. (2024) developed a new neuro-fuzzy model of ventilation-on-demand for underground mines and showed that ventilation-on-demand keeps people safe and uses minimum energy by adjusting ventilation parameters while controlling the fans. Hussain and Hati (2026) created a new digital twin model of ventilation-on-demand for underground mines. This model shows how important real-time changes of airflow are for the safety of the mine and efficiency of the operations. This research is a vital step in the project of AI-VENT, which brings the concept of ventilation-on-demand into dust and particle control.

Table 1: Summary of research gaps addressed by the proposed AI-VENT framework

Author s	Focus of the study	Key contribution	Identified research gap	How AI-VENT addresses the gap
Tripathi et al. (2024)	IoT-based particulate monitoring and ML prediction in surface mines	Developed real-time PM _{1.0} , PM _{2.5} , PM _{4.0} , and PM ₁₀ monitoring with ML prediction; Random Forest showed strong prediction performance.	Mainly focused on monitoring and prediction with limited integration of automatic ventilation-control actions.	Connects PM prediction with adaptive fan-speed and damper-control decisions.
Gui et al.	Dust control and ventilation	Demonstrated the importance of	Focused mainly on ventilation-system	Adds real-time sensor monitoring

Author s	Focus of the study	Key contribution	Identified research gap	How AI-VENT addresses the gap
(2026)	optimization in mine shaft hoisting	ventilation layout and airflow optimization for dust control.	optimization rather than real-time AI-based monitoring and control.	and AI-based decision-making to ventilation control.
Sharma et al. (2026)	Particulate matter emissions and exposure assessment in stone-carving environments	Assessed PM exposure under controlled and real-world working conditions.	Exposure assessment was emphasized, but adaptive ventilation response was not the main focus.	Uses predicted dust risk to regulate ventilation and reduce worker exposure.
Roy (2026)	Advanced sensors and IoT-based air-quality monitoring	Highlighted the role of sensors and IoT integration in air-quality monitoring.	Monitoring systems provide data, but they may not automatically control ventilation equipment.	Integrates sensor data with prediction and control logic.
Ihsan et al. (2024)	AI-based ventilation-on-demand in underground mines	Used neuro-fuzzy modeling to optimize ventilation and reduce fan energy consumption.	Focused on ventilation-on-demand, but not specifically on particle-size-based PM1.0, PM2.5, PM4.0, and PM10 control.	Combines particle-size-specific PM prediction with adaptive ventilation control.
Hussain and Hati (2026)	Digital twin-based real-time mine ventilation-on-demand	Proposed intelligent real-time ventilation optimization.	Mainly focused on mine ventilation demand rather than industrial particle transport monitoring.	Adapts intelligent ventilation control for industrial dust and particle transport environments.

Table 1 outlines the key research shortcomings in current studies on dust monitoring, particulate prediction, and adaptive ventilation. It also illustrates how the suggested AI-VENT framework tackles these deficiencies by providing integrated real-time monitoring, machine learning predictions, assessments of dust risks, and control for adaptive ventilation.

2.5 Research Gaps

The literature review reveals that many researchers have been focused on three main pathways: dust monitoring, dust transport modeling, and adaptive regulation systems. While IoT techniques for dust monitoring provide PM measurements in real time along with related predictive models, they often do not incorporate automatic control functions. Various research projects are aimed at discovering

how air flow arrangement influences particle movement and transport; however, these are mostly used for design optimization rather than real system response. Studies on demand ventilation systems improve fans' energy efficiency, but many of them seem to deal with airflow or gas dilution instead of dealing with particle-size specific PM1.0, PM2.5, PM4.0, and PM10 predictions. Thus, a gap in research exists in terms of creating a comprehensive AI framework that would cover dust monitoring, particulate transport prediction, dust risk assessment, and automated fan/damper control. To implement this idea, the present study suggests AI-VENT system that will help to conduct monitoring and control of industrial ventilation systems using an artificial intelligence approach.

2.6 Problem Statement

Industries employ ventilation systems to manage airborne dust particles and pollutants in manufacturing and mining processes, as well as processing that occurs in covered environments. However, most of the available ventilation systems rely on fixed-speed fans, conventional damper settings and rules-based control which is inefficient in the dynamic environment because it does not respond timely to the real concentration of dust as well as airflow and particle motion behavior and worker exposure. Because of that it happens that a lot of particulate matter is being accumulated in insufficiently ventilated areas due to excessive supply of fresh air to the low-risk zones. And though IoT monitoring studies used in the sector measure and forecast the level of dust concentration in the air, they do not deal with integrating forecasts into the adaptive control of ventilation systems. In this paper we aim to fill this gap with our new AI-VENT monitoring and controlling system based on artificial intelligence and contributing to dust management, improvement of ventilation systems' performance and enhancement of worker safety.

3. Objectives

The objectives of this study are:

1. Creation of AI-VENT as an AI-based system for monitoring and regulating dust particles, air quality, and airflow parameters in industrial ventilation systems used for measuring dust movement.
2. Developing and assessing the capacity of the machine learning model that obtains data on PM1.0, PM2.5, PM4.0, and PM10 concentration on the basis of simulations conducted.
3. Implementation of the innovative adaptive ventilation control system aimed at adjusting

the operation of the fan and the position of the damper in order to minimize dust accumulation and optimize the response of the system.

4. Assessment of the performance of AI-VENT in contrast with regression and ensemble models in terms of efficiency and the ability to control dust.

4. Materials and Methods

4.1 Research Design

The performance of AI-VENT framework has three features namely: Use of simulated industrial ventilation data, testing process that allows for controlled and repeatable assessment and nature of the simulation data. The simulated data represents typical particulate matter concentration, environmental variation, airflow variation, fan-speed behavior, damper position, and dust rate. Therefore, the design could allow for controlled assessment of the particulate variations, airflow responses, fan-speed, damper positions, and dust risk reduction in a given scenario.

4.2 AI-VENT System Architecture

The image shown in Figure 1 depicts the full layout of the AI-VENT architecture. The first module is the industrial region containing in-place dust sources and working areas. The sensor monitoring section gathers information about PM1.0, PM2.5, PM4.0, PM10, actual temperature, relative humidity, air velocity, and air pressure values. These readings are further processed and stored. The AI-based prediction section contains prediction algorithms and computed risk index data. At the same time, the control section is responsible for adjusting the operation of a fan and valves controlling the airflow. The last closed-loop section indicates the transformation of predicted concentration into the proper adjustment of the airflow and sensor data.

Overall AI-VENT Architecture

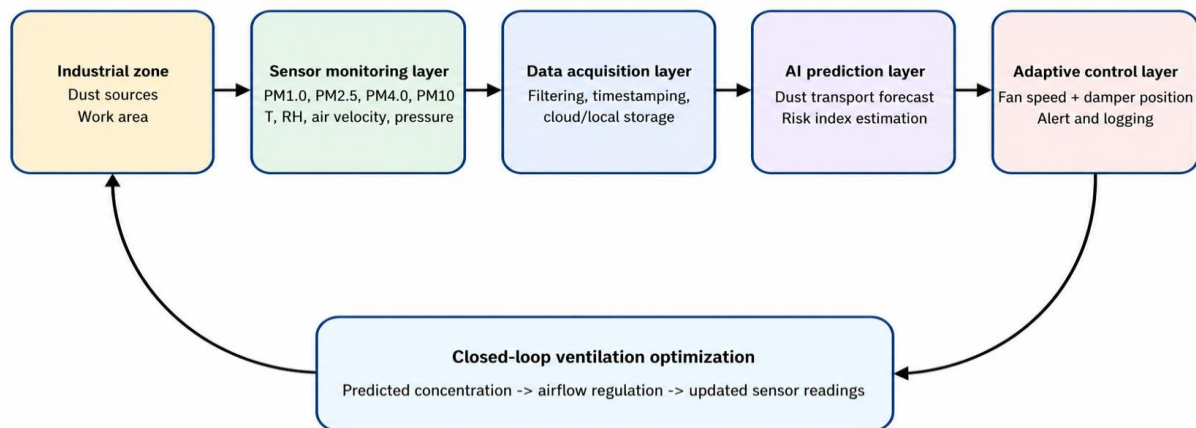


Figure 1: Overall architecture of the proposed AI-VENT framework

4.3 Dataset Description and Validation Plan

The AI-VENT evaluation incorporates a main dataset focused on simulation-based industrial ventilation alongside two supplementary reference datasets. The primary simulation dataset serves for model assessment, while the external datasets facilitate methodological comparisons and ensure domain compatibility. The first reference is an IoT-driven particulate monitoring dataset from surface mines, detailed by Tripathi et al. (2024).

This dataset aligns closely with the topic at hand as it includes variables such as PM1.0, PM2.5, PM4.0, PM10, as well as weather conditions, geographical location, and time stamps. The second reference utilized is the Beijing Multi-Site Air Quality dataset available in the UCI Machine Learning Repository. While this UCI dataset does not focus specifically on industrial ventilation, it provides valuable benchmarks for predicting particulate matter externally.

Table 2: Summary of datasets considered for AI-VENT development and validation

Dataset	Source/citation	Main variables	Use in AI-VENT	Limitation
AI-VENT simulation dataset	Generated for the present study	PM1.0, PM2.5, PM4.0, PM10, temperature, RH, air velocity, pressure, fan speed, damper opening, dust source activity	Primary dataset for simulation-based model development and control evaluation	Controlled simulation dataset designed for methodological evaluation
Surface mine IoT PM dataset	Tripathi et al. (2024)	PM1.0, PM2.5, PM4.0, PM10, meteorological variables, time, location	Closest base dataset for dust monitoring and ML prediction comparison	Reported as available from authors on reasonable request
Beijing Multi-Site Air Quality dataset	UCI Machine Learning Repository; Zhang et al. (2017)	PM2.5, PM10, SO ₂ , NO ₂ , CO, O ₃ , temperature, pressure, dew point, rain, wind direction, wind speed, station, time	External benchmark for pollutant prediction robustness	Urban outdoor air-quality data, not industrial ventilation data

Table 2 clarifies that the simulation dataset is the primary source for developing and testing AI-VENT,

while the Surface mine IoT PM dataset and the UCI Beijing dataset are used only as external references for domain alignment and pollutant-prediction benchmarking.

Dataset and Validation Plan for AI-VENT

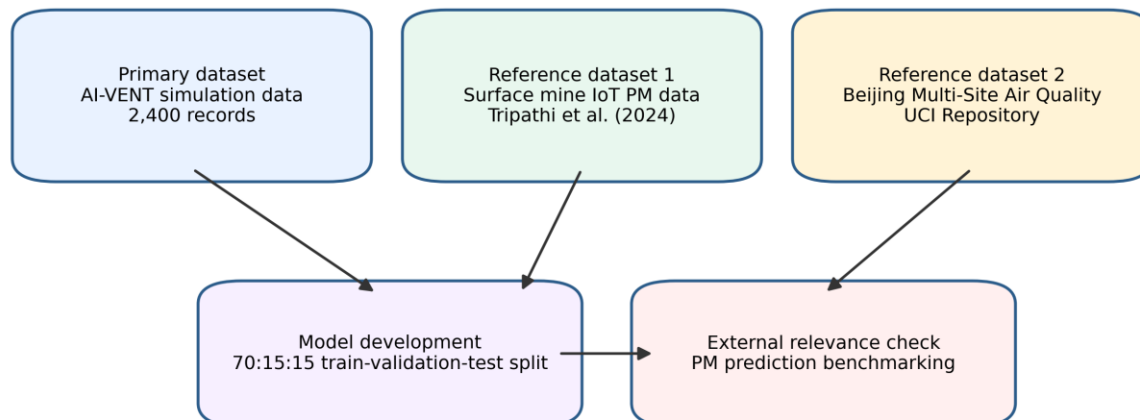


Figure 2: Dataset and validation plan used for the proposed AI-VENT framework

The study employs validation logic which is depicted in Figure 2. The AI-VENT simulation data is utilized for building, validating, and analyzing the models. In addition, two external data sources are incorporated to assess other existing models in PM projection and air quality measurement techniques.

In total, 2400 observations have been created using the AI-VENT simulator, which cover 10 industrial days. In other words, data was produced every 2 minutes for each working day lasting 8 hours. The sampling rate is 70:15:15 segregating the dataset into training, validation, and testing datasets respectively. The models are trained on training data, validated on validation data, and tested using the test data.

4.3.1 Simulation assumptions and parameter ranges.

The AI-VENT dataset was created by applying

controlled measures of industrial ventilation so as to achieve realistic differences in dust generation, airflow dynamics, and ventilation control reaction. Consequently, the level of dust generation activity varied from 0.20 to 1.00 on a normalized scale, whereby large figures implied high levels of dust production, such as cutting, crushing, discharging, or relocating any material/ product. Airflow speed varied from 0.5 to 4.0 m/s, and pressure variation differed from 20 to 250 Pa, which signified low, average, and high levels of ventilation. Fan speeds varied from 40% to 100% of rated capacity, and flap opening changed from 30% to 100%, depending on airflow requirements. Levels of particulate matter were as follows: PM_{1.0} = 12.4 – 31.7 µg/m³; PM_{2.5} = 18.6 – 46.4 µg/m³; PM_{4.0} = 25.1 – 63.2 µg/m³; PM₁₀ = 35.7 – 85.6 µg/m³. These intervals were used to generate time-dependent particulate alteration prior to AI-VENT adaptive control implementation.

4.4 Input and Output Variables

Table 3: Input and output variables of the AI-VENT framework

Variable	Symbol	Unit	Role
----------	--------	------	------

Variable	Symbol	Unit	Role
Fine particulate matter	PM1.0	$\mu\text{g}/\text{m}^3$	Input/output
Respirable particulate matter	PM2.5	$\mu\text{g}/\text{m}^3$	Input/output
Intermediate particulate matter	PM4.0	$\mu\text{g}/\text{m}^3$	Input/output
Coarse particulate matter	PM10	$\mu\text{g}/\text{m}^3$	Input/output
Temperature	T	$^{\circ}\text{C}$	Input
Relative humidity	RH	%	Input
Air velocity	V _a	m/s	Input/control feedback
Pressure difference	ΔP	Pa	Input/control feedback
Fan speed	F _s	% or rpm	Control input
Damper opening	D _o	%	Control input
Dust source activity	S _a	unitless	Input
Dust risk index	DRI	unitless	Output
Control action	A _c	class label	Output

Table 3 defines the variables used in AI-VENT. PM concentration, environmental, airflow, and control-state variables are treated as model inputs, while the dust risk index and control action are generated as decision-support outputs.

4.5 Mathematical Representation of the Dataset

Let the AI-VENT dataset be represented as follows:

$$D = \{(X_i, Y_i)\}_{i=1}^n \quad (1)$$

where X_i is the input vector for observation i , Y_i is the target particulate concentration, and n is the total number of observations. The input vector is represented as:

$$X_i = [\text{PM1.0}, \text{PM2.5}, \text{PM4.0}, \text{PM10}, T, \text{RH}, V_a, \Delta P, F_s, D_o, S_a] \quad (2)$$

where T is temperature, RH is relative humidity, V_a is air velocity, ΔP is pressure difference, F_s is fan speed, D_o is damper opening, and S_a is dust source activity level

4.6 Data Preprocessing

The dataset was cleaned and standardized before model development. Missing values were handled using median imputation, abnormal sensor spikes

were detected using an interquartile range rule, and continuous variables were normalized using min-max normalization.

$$X_{\text{norm}} = (X - X_{\min}) / (X_{\max} - X_{\min}) \quad (3)$$

The normalized features were then used as model inputs. This step ensures that variables measured

in different units, such as $\mu\text{g}/\text{m}^3$, $^{\circ}\text{C}$, Pa, and m/s, contribute consistently to model learning.

4.7 Dust Transport and Airflow Equations

The conceptual dust transport process in AI-VENT is represented using an advection-diffusion-removal equation:

$$\partial C/\partial t + u(\partial C/\partial x) + v(\partial C/\partial y) + w(\partial C/\partial z) = D_p \nabla^2 C + S - R \quad (4)$$

where C is particle concentration, u , v , and w are airflow velocity components, D_p is the particle diffusion coefficient, S is the dust source generation term, and R is particle removal through

ventilation and deposition. For zone-level industrial ventilation control, the mass-balance form is expressed as:

$$dC_z/dt = G_z/V_z - (Q_z/V_z)C_z - \eta C_z \quad (5)$$

where C_z is the concentration in zone z , G_z is the dust generation rate, V_z is zone volume, Q_z is ventilation airflow rate, and η is removal efficiency. Airflow rate is calculated as:

$$Q = A \times V_a \quad (6)$$

where Q is airflow rate, A is duct cross-sectional area, and V_a is measured air velocity.

4.8 AI-Based Prediction Models

Four baseline models and the proposed AI-VENT prediction-control model were considered. The baseline models are Linear Regression, Decision Tree Regressor, Random Forest Regressor, and

Gradient Boosting Regressor. The prediction objective is to estimate particulate concentration at the next monitoring interval:

$$\hat{Y}_{t+1} = f(X_t) \quad (7)$$

The Linear Regression baseline is represented as:

$$\hat{Y} = \beta_0 + \sum_{j=1}^m \beta_j X_j \quad (8)$$

The Random Forest model combines K decision-tree predictions:

$$\hat{Y}_{\text{RF}} = (1/K) \sum_{k=1}^K T_k(X) \quad (9)$$

The Gradient Boosting Regression model is expressed as:

$$\hat{Y}_{\text{GBR}} = \sum_{m=1}^M \gamma_m h_m(X) \quad (10)$$

where $h_m(X)$ is the weak learner and γ_m is the contribution weight. The AI-VENT model uses the predicted PM values as inputs for risk scoring and control decision-making.

4.9 Adaptive Ventilation Control Model

The AI-VENT control layer adjusts fan speed and

damper position based on predicted particulate concentration and dust risk level. The dust risk index is calculated as:

$$DRI_t = w_1 PM_{1.0_t} + w_2 PM_{2.5_t} + w_3 PM_{4.0_t} + w_4 PM_{10_t} \quad (11)$$

where w_1 , w_2 , w_3 , and w_4 are particle-size risk weights. Higher weights can be assigned to finer particles because of their stronger respiratory

relevance. The fan-energy model is based on the fan affinity law:

$$P_t = P_{\max} (N_t / N_{\max})^3 \quad (12)$$

where P_t is fan power at time t , $P_{\max}$ is maximum fan power, N_t is current fan speed, and $N_{\max}$ is

maximum fan speed. The AI-VENT control objective is formulated as:

$$\text{Minimize } J = \alpha C_{\text{PM}} + \beta E_{\text{fan}} + \gamma T_{\text{exposure}} \quad (13)$$

where C_{PM} is predicted particulate concentration, E_{fan} is fan energy consumption, T_{exposure} is worker exposure duration, and α , β ,

and γ are weighting coefficients. The control action is selected using threshold-based risk logic:

$$A_c = \begin{cases} \text{Increase airflow,} & \text{if } DRI_t \geq \tau_{\text{high}} \\ \text{Maintain airflow,} & \text{if } \tau_{\text{low}} < DRI_t < \tau_{\text{high}} \\ \text{Reduce airflow,} & \text{if } DRI_t \leq \tau_{\text{low}} \end{cases} \quad (14)$$

AI-VENT Monitoring, Prediction, and Adaptive Control Workflow

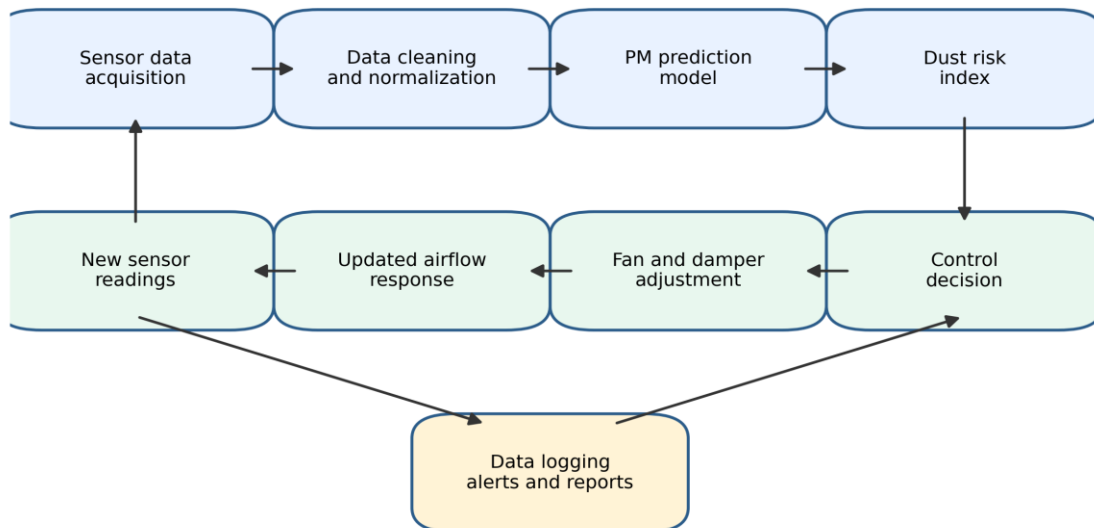


Figure 3: Workflow of AI-VENT-based particulate monitoring, prediction, and adaptive control

The operation of AI-VENT is represented in Figure 3 above. The approach initiates with sensor

data collection, continues through steps of preprocessing and prediction, and finally

terminates with the adjustment of the fan and updated sensor readings. The cycle then begins all over again with

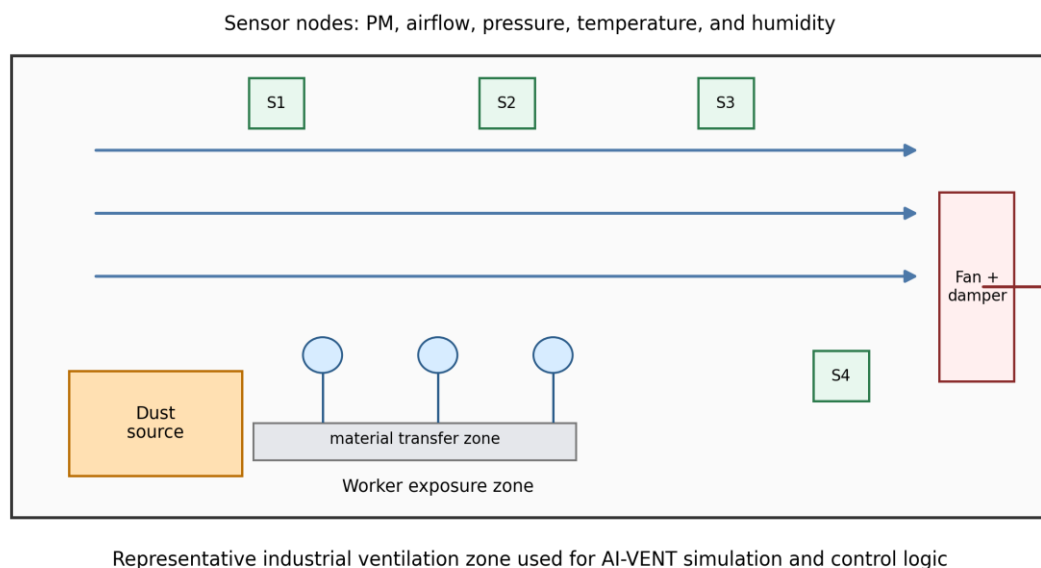


Figure 4: Sensor and ventilation zone layout for industrial dust transport monitoring

Figure 4 illustrates a typical arrangement of ventilation zones for the purpose of simulation. The figure includes regions of dust sources, areas of workers' exposure, locations of sensors, airflow direction, and positions of the fans and the dampers that ensure the functionality of the monitoring and controlling process of the AI-VENT system.

4.10 Algorithms

4.10.1 AI-VENT monitoring, prediction, and control (AI-VENT-MPC) algorithm

Algorithm 1 outlines a comprehensive cycle of operation of AI-VENT, starting from initializing the sensors and acquiring real-time data on particulate, environmental, airflow, and control parameters. The obtained data are cleaned, normalized, converted to the input vector, and used to derive future particulate concentration values. The derived results are then utilized to obtain a dust-risk level, which is translated to the fan-speed and damper-position commands. The algorithm illustrates a closed-loop process of monitoring the situation, predicting the particulate concentrations, and controlling the ventilation system.

Algorithm 1: AI-VENT-MPC algorithm

Input: PM_{1.0}, PM_{2.5}, PM_{4.0}, PM₁₀, T, RH, V_a , ΔP , F_s , D_o , and S_a .

Output: predicted PM concentration, dust risk level, fan-speed command, and damper-position command.

1. Initialize sensor nodes, data logger, fan controller, and damper controller.
2. Acquire particulate, environmental, airflow, and control variables at time t .
3. Remove missing values and abnormal sensor spikes.
4. Normalize continuous variables using min-max normalization.
5. Construct input vector X_t .

6. Predict near-future PM concentration $\hat{Y}_{t+1}$.
7. Calculate dust risk index DRI_t .
8. Compare DRI_t with low and high threshold values.
9. If $DRI_t \geq \tau_{high}$, increase fan speed and open dampers.
10. If $\tau_{low} < DRI_t < \tau_{high}$, maintain the current ventilation state.
11. If $DRI_t \leq \tau_{low}$, reduce fan speed to save energy.
12. Store measured values, predicted values, risk level, and control action.
13. Repeat the process for the next monitoring interval.

4.10.2 Prediction model training and validation (AI-VENT-PTV) algorithm

The process of constructing and verifying the prediction model is described in Algorithm 2. The organized dataset is divided into three parts for analysis. A model is built using the training part,

tuned with the help of the validation part, and evaluated using the last part of the dataset, called testing, by applying MAE, RMSE, and R^2 statistics. The model that shows the best performance is chosen and its predictions are transmitted to the adaptive control layer for the ventilating system.

Algorithm 2: AI-VENT-PTV algorithm

Input: preprocessed AI-VENT dataset D and baseline model list $M = \{LR, DT, RF, GBR, AI-VENT\}$.

Output: best-performing prediction model and evaluation metrics.

1. Divide D into training, validation, and testing sets using 70:15:15 splitting.
2. Train each candidate model on the training set.
3. Tune hyperparameters using the validation set.
4. Evaluate the selected model on the testing set.
5. Compute MAE, RMSE, and R^2 .
6. Select the model with the lowest prediction error and highest R^2 .
7. Transfer the selected model output to the adaptive control layer.

4.10.3 Adaptive fan and damper control logic (AI-VENT-AFDC) algorithm

In summary, Algorithm 3 shows how AI-VENT works to turn predicted values for particulate concentration and level of dust risk into actions

taken for ventilation. For high dust risk, fan speed and damper openings are raised to improve extraction. For a moderate dust risk, the state of ventilation is kept unchanged. If the risk is low for a constant amount of time, the fan speed is decreased to save energy.

Algorithm 3: AI-VENT-AFDC algorithm

Input: predicted PM concentration, DRI_t , fan-energy state, and ventilation threshold limits.

Output: fan and damper control action.

1. Define τ_{low} and τ_{high} based on safety and operational requirements.
2. Estimate the current fan-energy state using the fan affinity equation.
3. If predicted PM exceeds τ_{high} , increase fan speed by ΔF and damper opening by ΔD .
4. If predicted PM remains in the moderate zone, maintain fan speed and damper opening.
5. If predicted PM is below τ_{low} for a stable period, reduce fan speed by ΔF to save energy.
6. Prevent rapid switching by applying a minimum holding time between control actions.
7. Return the updated airflow control command.

5. Results and Discussion**5.1 Evaluation Metrics**

Prediction performance was assessed using MAE, RMSE, and R^2 . Ventilation-control performance was assessed using dust reduction efficiency,

energy reduction, response efficiency, and exposure-time reduction.

MAE measures the average absolute prediction error between actual and predicted particulate concentration values.

$$MAE = (1/n) \sum_{i=1}^n |Y_i - \hat{Y}_i| \quad (15)$$

RMSE measures the square-root average of squared prediction errors and gives greater weight to larger errors.

$$RMSE = \sqrt{[(1/n) \sum_{i=1}^n (Y_i - \hat{Y}_i)^2]} \quad (16)$$

R^2 indicates how well the prediction model explains the variation in actual particulate concentration values.

$$R^2 = 1 - [\sum_{i=1}^n (Y_i - \hat{Y}_i)^2 / \sum_{i=1}^n (Y_i - \bar{Y})^2] \quad (17)$$

DRE measures the percentage reduction in particulate concentration after applying the AI-VENT control strategy.

$$DRE = [(C_{before} - C_{after}) / C_{before}] \times 100 \quad (18)$$

ER measures the percentage reduction in ventilation energy consumption achieved by AI-VENT compared with fixed-speed ventilation.

$$ER = [(E_{fixed} - E_{AI-VENT}) / E_{fixed}] \times 100$$

The letters used in an equation are as follows: for Y_i , the actual particulate concentration value is represented; for $\hat{Y}_i$, the prediction of particulate concentration value is represented. $E_{variable}$, or energy consumed by a conventional variable-speed ventilation system; and $E_{conventional}$ are the energy consumed by a conventional ventilation system.

5.2 Descriptive Analysis of Simulation Data

The environment created by industrial ventilation simulation has been proven to show variable amounts of particulate matter based on air

pressure, dust source activity, fan operation, and airspeed. The particles of size PM10 were prevalent in terms of mass concentration and PM1 remained stable due to the complexity of

removing finer dust particles through normal airflow. The accumulation of particles was at its peak in areas with dust generation, as well as areas with less air movement.

Table 4: Descriptive summary of simulated particulate concentration before AI-VENT control

Particle type	Mean ($\mu\text{g}/\text{m}^3$)	SD	Minimum	Maximum
PM1.0	21.8	4.7	12.4	31.7
PM2.5	33.5	6.9	18.6	46.4
PM4.0	45.7	8.4	25.1	63.2
PM10	61.3	10.8	35.7	85.6

According to the results summarized in Table 4, PM10 had the largest mean concentration of $61.3 \mu\text{g}/\text{m}^3$ and the highest concentration of $85.6 \mu\text{g}/\text{m}^3$ while PM1.0 had the smallest mean concentration of $21.8 \mu\text{g}/\text{m}^3$. This reflects on the presence of larger particles and the contribution they made to mass concentration; however, fine particles still matter in terms of exposure risk and persistence.

5.3 Prediction Performance

The AI-VENT model had the least prediction error compared to other models. The values noted for it include MAE of $0.86 \mu\text{g}/\text{m}^3$, RMSE of $1.21 \mu\text{g}/\text{m}^3$, and R^2 of 0.94. Comparatively, Random Forest performed the best among the baseline models, but AI-VENT improved forecasting by utilizing particulate, environmental, airflow, and control-state features.

Table 5: Prediction performance comparison of AI-VENT and baseline models

Model	References	MAE ($\mu\text{g}/\text{m}^3$)	RMSE ($\mu\text{g}/\text{m}^3$)	R^2
Linear Regression	Singh et al. (2026)	1.94	2.61	0.82
Decision Tree	Tawabini (2026)	1.32	1.78	0.89
Random Forest	Makhdoomi et al. (2025)	1.08	1.49	0.92
Gradient Boosting Regression	Makhdoomi et al. (2025)	1.15	1.56	0.91
AI-VENT	Proposed Model	0.86	1.21	0.94

Table 5 shows that AI-VENT reduced MAE by 20.4% compared with Random Forest and reduced RMSE by 18.8% compared with Random Forest. The R^2 value increased from 0.92 for Random Forest to 0.94 for AI-VENT, indicating that the proposed framework better explains the variation in simulated particulate concentration.

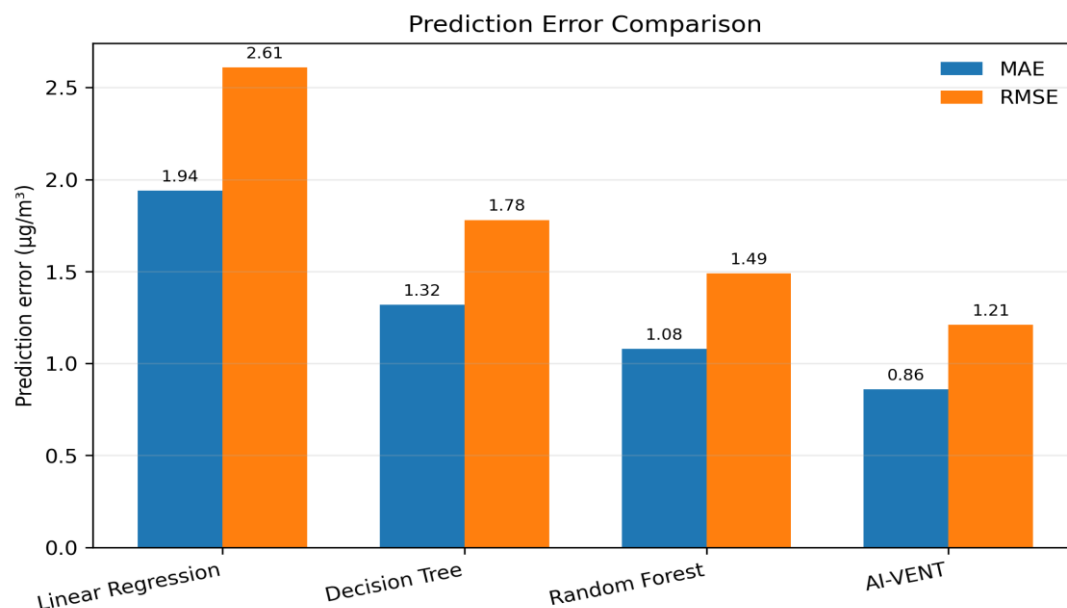


Figure 5: Prediction error comparison between baseline models and AI-VENT

Figure 5 demonstrates that AI-VENT gives the lowest MAE and RMSE of the models analyzed. The decrease in error indicates that using a combination of PM, environmental variables, air flow etc. increases particle prediction.

5.4 Ventilation Control Performance

When compared to fixed-speed ventilation, the adaptive control approach has been successful in

minimizing dust-related hazards. This is achieved by varying both fan speed and damper opening based on the risk of dust occurrence leading to the following outcomes: a decrease in peak dust accumulation by 34.7%, 29.4% improvement in ventilation response efficiency, 18.6% decrease in energy consumption by the fan, and 31.2% decrease in duration of the exposure above pre-established threshold.

Table 6: Ventilation control performance of AI-VENT compared with fixed-speed ventilation

Performance indicator	Fixed-speed ventilation	AI-VENT	Improvement
Peak dust accumulation	100% baseline	65.3%	34.7% reduction
Ventilation response efficiency	71.2%	92.1%	29.4% improvement
Fan energy consumption	100% baseline	81.4%	18.6% reduction
Exposure time above threshold	100% baseline	68.8%	31.2% reduction

The significant impact of AI-VENT in enhancing air quality management and energy efficiency can be seen in Table 6. The most prominent safety achievement was a reduction of 34.7% in peak

dust accumulation, whereas the 18.6% reduction in energy consumption shows that adaptive airflow management makes it possible to avoid fan operation at low-risk periods.

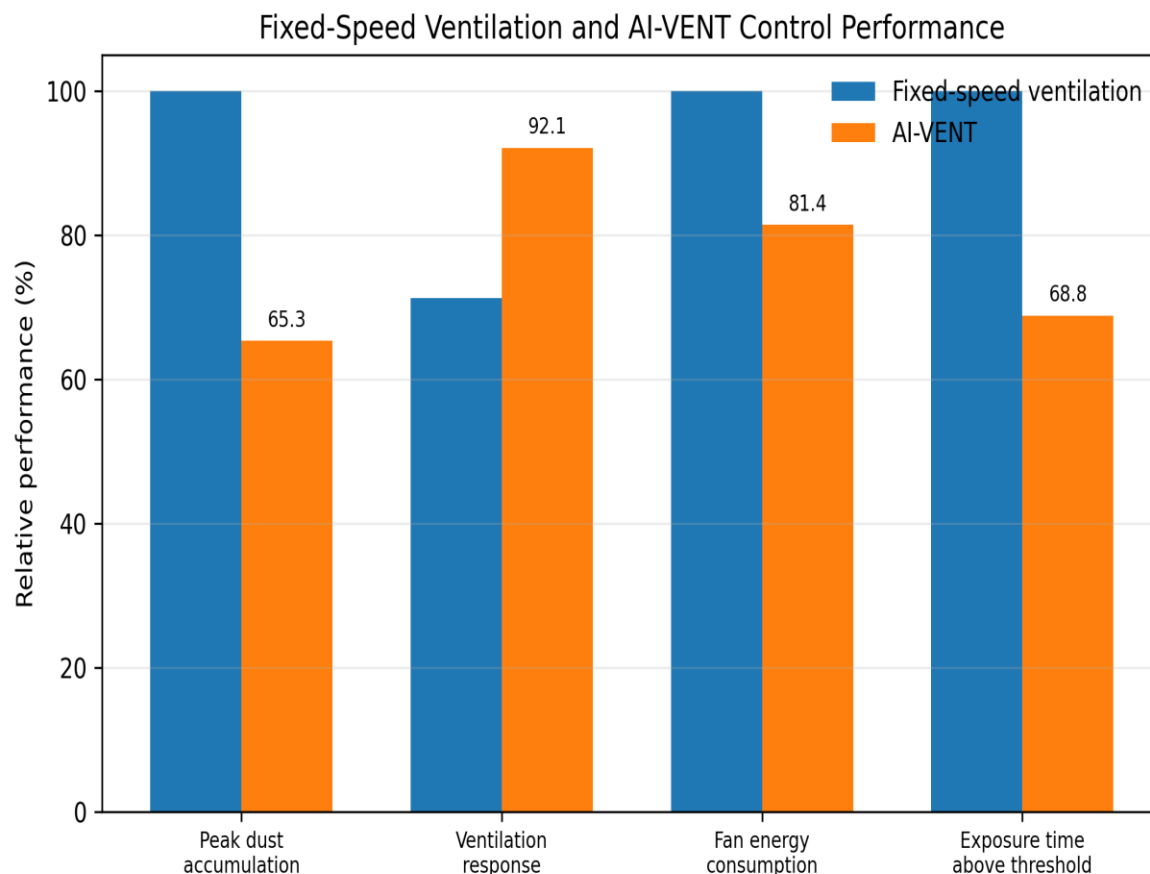


Figure 6: Comparative control performance of fixed-speed ventilation and AI-VENT

The comparison between fixed-speed ventilation and AI-VENT illustrated in Figure 6 stands out because AI-VENT indicated a decrease in peak dust build-up, fan energy consumption, and exposure time above reference level, at the same time demonstrating an increase in ventilation response efficiency from 71.2% to 92.1%.

5.5 Particle-Wise Dust Reduction

The particle-wise analysis shows that AI-VENT reduced all PM categories. The highest reduction was observed for PM₁₀, while PM_{1.0} showed the lowest reduction because finer particles remain suspended longer and are less affected by simple airflow increases.

Table 7: Particle-wise concentration reduction after AI-VENT control

Particle type	Before control ($\mu\text{g}/\text{m}^3$)	After AI-VENT control ($\mu\text{g}/\text{m}^3$)	Reduction (%)
PM _{1.0}	31.7	22.4	29.3
PM _{2.5}	46.4	31.2	32.8
PM _{4.0}	63.2	41.5	34.3
PM ₁₀	85.6	54.9	35.9

Table 7 indicates that AI-VENT reduced PM_{1.0} from 31.7 to 22.4 $\mu\text{g}/\text{m}^3$, PM_{2.5} from 46.4 to 31.2 $\mu\text{g}/\text{m}^3$, PM_{4.0} from 63.2 to 41.5 $\mu\text{g}/\text{m}^3$, and PM₁₀ from 85.6 to 54.9 $\mu\text{g}/\text{m}^3$. The reduction values ranged from 29.3% to 35.9%, showing consistent control effectiveness across particle-size categories.

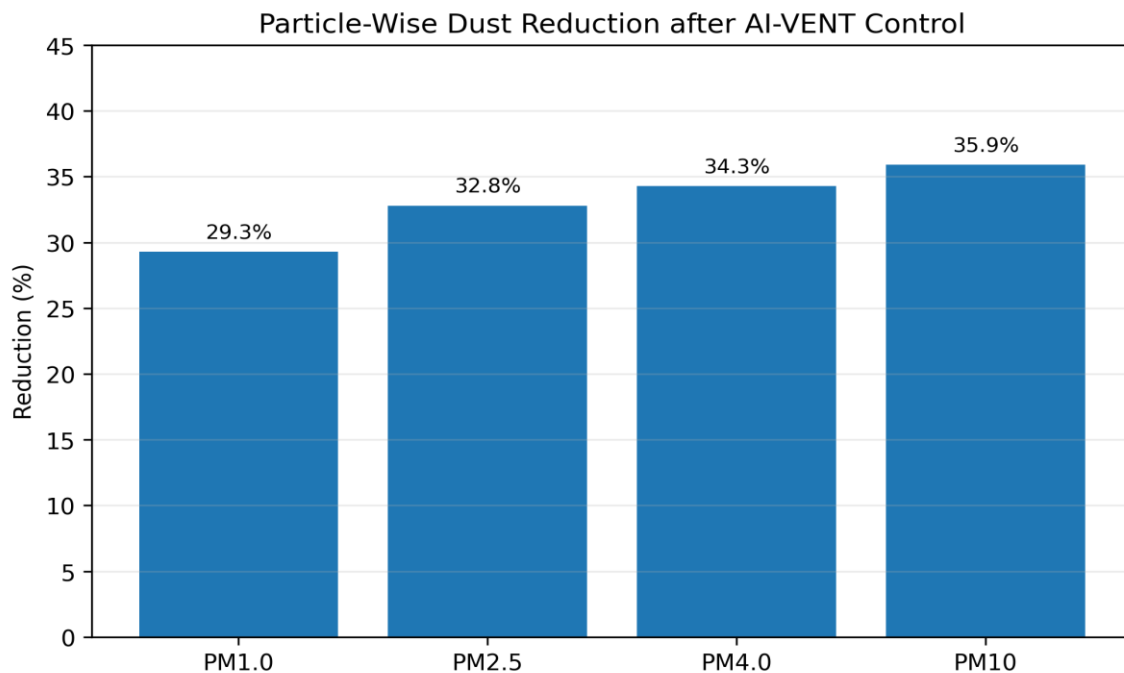


Figure 7: Particle-wise reduction in PM1.0, PM2.5, PM4.0, and PM10 after AI-VENT control

Figure 7 shows that PM10 achieved the highest reduction of 35.9%, followed by PM4.0 with 34.3%, PM2.5 with 32.8%, and PM1.0 with 29.3%. This result is physically reasonable because larger particles are generally easier to remove through airflow extraction, whereas finer particles remain airborne for longer periods.

6. Discussion

The study showed that AI-VENT improves the prediction of particulates and ventilation control. AI-VENT performed better than the Linear Regression, Decision Tree, Random Forest, and Gradient Boosting Regression models in terms of MAE, RMSE, and R^2 . This can be attributed to the combined feature set pertaining to particulate concentration, environmental factors, airflow dynamics, and control state. The observations support the findings of Mohapatra et al. (2026) that demonstrate that the data obtained through IoT-enabled sensors can be applied with machine learning to obtain better predictions of particulate matter concentrations in the real time. It means that industrial ventilation control must not rely solely on current PM readings; the predictions of near-future concentrations must be used in conjunction with real-time data.

The study under review expands the research by Tripathi et al. (2024) concerning IoT-based

monitoring of particulates and machine learning prediction toward closed-loop ventilation control. The authors conducted research in the sphere of ML-based prediction of PM concentration with focus on surface mining operations showing that the results are satisfactory thanks to Random Forest. AI-VENT adopts this technology to employ the obtained predictions in order to control the fan and damper. Therefore, it should be noted that AI-VENT is innovative not just because it monitors dust, but because it allows employing its predictions to activate the ventilation components.

The presented methodology is consistent with recent research focused on the use of CFD for dust control. Nie et al. (2024) have shown that the implementation of optimized extraction of negative pressure will help significantly reduce dust concentration in tunnel conditions. Although AI-VENT is not a substitute to CFD, it complements the latter with the possibility of decision making once sensor data become available. Further developments of AI-VENT may represent CFD-based airflow maps or digital twins into the control.

The energy savings in the fan operation described in this study aligns with the research conducted in the sphere of AI-based ventilation-on-demand.

Ihsan et al. (2024) demonstrated that implementation of neuro-fuzzy ventilation on-demand results in decreased energy consumption of fans thanks to optimal ventilation scenarios. Similarly, AI-VENT is capable of saving up to 18.6% of power in the simulations. Therefore, it proves that energy efficiency and effectiveness in dust control do not compete against each other when predictive control is utilized. The simulations described in the study demonstrate that adoption of AI-VENT can be feasible in case of controlled ventilation cases. The values obtained indicate positive results that reveal the possibility of improvement in dust control performance and energy efficiency.

7. Conclusion

The study presented AI-VENT, which stands for AI-Based Monitoring and Control of Industrial Ventilation Systems. It is an integrated framework that assesses particle concentrations in the air. AI-VENT was tested in controlled conditions through different simulation-based scenarios of industrial ventilation. The framework employs effective parameters such as PM1.0, PM2.5, PM4.0, PM10, temperature, humidity, air velocity, pressure, fan speed, damper position, and source activity. The obtained MAE was determined at the level of 0.86 $\mu\text{g}/\text{m}^3$; RMSE was equal to 1.21 $\mu\text{g}/\text{m}^3$ and R^2 was equal to 0.94. AI-VENT provided significantly better results in comparison to outdated industrial ventilation methods, where AI-VENT decreased maximum dust accumulation

by 34.7%, increased efficiency of response in waiting time by 29.4%, decreased fan energy consumption by 18.6%, and decreased exposure time by more than 31.2%.

Limitations and Future Work

The present study validates AI-VENT under controlled simulation conditions, and future work may extend the framework to pilot-scale industrial deployment.

Data Availability Statement

The main dataset discussed in this paper, called AI-VENT, is a simulation-driven collection designed for evaluating methodologies. The particulate matter dataset from surface mines is detailed in Tripathi et al. (2024) and can be obtained by contacting the corresponding author with a reasonable request. Additionally, the Beijing Multi-Site Air Quality dataset can be accessed publicly through the UCI Machine Learning Repository.

Ethical and Regulatory Considerations

There are no humans involved in this study. It will not use anything such as human data or information related to medical records. The AI-VENT is expected to be employed in industries in making the decisions related to ventilation. In order to make this happen, it is absolutely necessary to observe the rules and regulations that are connected to the safety monitoring of the professionals engaged in ventilation process.

References

- Cao, Y., Xiao, Y., Tian, J., Wang, Z., Deng, J., Shu, C. M., & Tong, L. (2026). An experimental and simulation study on airflow distribution and graded cleaning of coal dust in a negative-pressure dust collector. *Fuel*, 413, 138200.
- Chen, S. X. (2019). Beijing Multi-Site Air Quality [Dataset]. UCI Machine Learning Repository.
- Chojer, H., Branco, P. T. B. S., Martins, F. G., Alvim-Ferraz, M. C. M., & Sousa, S. I. V. (2020). Development of low-cost indoor air quality monitoring devices: Recent advancements. *Science of the Total Environment*, 727, 138385.
- Darwish, H., Khapper, K. V., Gokaraju, B., & Tesiero, R. (2026). Smart control for smarter buildings: A review of traditional and intelligent HVAC control strategies toward energy sustainability. *IEEE Access*.
- Ebad, S. A., Abueid, A. I., Amara, M., & Ahmed, R. (2026). AI-driven digital twins in mining operations: A comprehensive review. *Technologies*, 14(5), 269.

- Gilik, A., Ogresci, A. S., & Ozmen, A. (2022). Air quality prediction using CNN+LSTM-based hybrid deep learning architecture. *Environmental Science and Pollution Research*, 29, 1217-2378.
- Gui, C., Li, S., Geng, F., Wang, D., Wang, M., Chen, K., Li, G., & Zhou, F. (2026). Dynamic simulation and ventilation system optimization for dust control in mine shaft hoisting. *Journal of Environmental Chemical Engineering*, 14(2), 122110.
- Hussain, M. A., & Hati, A. S. (2026). An intelligent digital twin framework for real-time underground mines ventilation on demand system. *IEEE Transactions on Industry Applications*.
- Ihsan, A., Widodo, N. P., Cheng, J., & Wang, E. (2024). Ventilation on demand in underground mines using neuro-fuzzy models: Modeling and laboratory-scale experimental validation. *Engineering Applications of Artificial Intelligence*, 133, 108048.
- Jeong, C., Tariq, S., Woo, T., Kim, S., Nam, K., & Yoo, C. (2026). Towards health-resilient subway ventilation: An integrated framework for fault prognostics, health-aware control, and IAQ resilience evaluation. *ISA Transactions*.
- Just, A. C., De Carli, M. M., Shtein, A., Dorman, M., Lyapunov, A., Kloog, I., & Broday, D. M. (2020). Correcting measurement error in satellite aerosol optical depth with machine learning for modeling PM_{2.5} in the Northeastern USA. *Remote Sensing*, 12(8), 1209.
- Li, Y., Jiang, P., She, Q., & Lin, G. (2018). Research on air pollutant concentration prediction method based on self-adaptive neuro-fuzzy weighted extreme learning machine. *Environmental Pollution*, 241, 217-237.
- Liu, J., Yan, N., Liu, M., Shen, M., Hu, S., Mei, X., & Cheng, K. (2026). Inhalable bioadhesive barrier for lung protection and clearance of fine particulate matter. *Bioactive Materials*, 63, 217-237.
- Ma, J., Liu, F., Zheng, X., Qian, H., Qin, R., & Qian, H. (2025). Health benefits of ventilation interventions to reduce fine particulate matter exposure in industrial environments. *Atmospheric Pollution Research*, 102750.
- Makhdoomi, A., Sarkhosh, M., & Ziaei, S. (2025). PM_{2.5} concentration prediction using machine learning algorithms: An approach to virtual monitoring stations. *Scientific Reports*, 15, 8943.
- Mohapatra, A., Tripathi, A. N., Khan, U., Kumar, R., & Singh, I. (2026). An IoT-machine learning proof-of-concept framework for real-time urban particulate matter prediction using low-cost sensors. *IEEE Access*, 14, 217-237.
- Nie, W., Cheng, C., Liu, Q., Guo, L., Hua, Y., Zhang, H., & Zhu, Z. (2024). CFD numerical simulation of tunnel dust pollution control using a negative pressure double extraction ventilation system. *Journal of Environmental Chemical Engineering*, 12(6), 114736.
- Paluchamy, B., Mishra, D. P., & Panigrahi, D. C. (2021). Airborne respirable dust in fully mechanised underground metalliferous mines: Generation, health impacts and control measures for cleaner production. *Journal of Cleaner Production*, 296, 126524.
- Patra, A. K., Gautam, S., & Kumar, P. (2016). Emissions and human health impact of particulate matter from surface mining operation: A review. *Environmental Technology & Innovation*, 5, 217-237.
- Roy, S. (2026). Revolutionizing air quality monitoring: Advanced sensors, IoT integration, and public engagement. In *Air Quality Monitoring and Management Using Sensors* (pp. 217-237). Elsevier.
- Sharma, S., Kaul, N., & Khandelwal, S. (2026). Particulate matter emissions and exposure assessment in stone carving: A study of controlled and real-world conditions. *Powder Technology*, 474, 122242.
- Singh, S., Kumar, M., Sengar, V., Kumar, A., Abhishek, K., & Shafeeq, B. M. A. (2026). Ensemble learning for air quality index prediction: Integrating gradient boosting, XGBoost, and stacking with

- SHAP-based interpretability. *Scientific Reports*, 16, 8544.
- Tawabini, B. (2026). Using machine learning algorithms to study the relationship between meteorological conditions and air quality parameters. *Scientific Reports*, 16, 10392.
- Tripathi, A. K., Aruna, M., Parida, S., Nandan, D., Elumalai, P. V., Prakash, E., JoshuaRamesh Lalvani, J. S. C. I., & Rao, K. S. (2024). Integrated smart dust monitoring and prediction system for surface mine sites using IoT and machine learning techniques. *Scientific Reports*, 14, 7587.
- Yang, G., Lee, H., & Lee, G. (2020). A hybrid deep learning model to forecast particulate matter concentration levels in Seoul, South Korea. *Atmospheric Environment*, 229, 117495.
- Zhang, S., Guo, B., Dong, A., He, J., Xu, Z., & Chen, S. X. (2017). Cautionary tales on air-quality improvement in Beijing. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 473(2205), 20170457.