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Assessment of the Environmental Impact for Any Industrial or Nuclear Facility by Using Artificial Intelligence Software

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Abstract

This study uses a Gaussian plume model of airborne contaminants and artificial intelligence (AI) tools to evaluate the environmental impact of industrial emissions. It focuses on determining the major variables affecting the dispersion of airborne pollutants and calculating their concentrations downwind from the source of emissions. The study made use of hypothetical data from the NOAA website, which included a variety of physical and atmospheric variables like temperature, wind speed, emission rate, and chimney features. The Pasquill-Gifford classification was combined with a rule-based artificial intelligence tool to compute the dispersion coefficients (σ_y, σ_z) and assess atmospheric stability. The results showed that wind speed, distance from the emission source, and atmospheric stability all had a major impact on pollutant concentration. Additionally, the findings of the AI tool and well-established conventional methodologies were shown to be in good agreement. This work is important to be used as a training program for students.

Subject Areas

Artificial Intelligence Software

Keywords

Artificial Intelligence Software, Dispersion Factors, Ground-Level Concentration

1. Introduction

An essential component of industrial facilities' environmental impact assessment is atmospheric dispersion modeling. In order to accurately estimate ground-level concentrations from continuous discharges, air turbulence, source characteristics, and weather conditions are crucial. Because of their ease of analysis and physical interpretability, Gaussian plume models are still commonly utilized. However, accurately determining climatic and dispersion parameters is essential to the dependability of such models. Recently, industries have shown concerning trends, particularly in the complexity and diversity of industrial operations. The biosphere has deteriorated, and natural environmental processes have been disrupted as a result of the extreme pollution that has resulted from this. The exact meaning of environmental pollution has been contested by environmental experts. In general, pollution refers to changes in environmental components, either quantitative or qualitative, that damage ecosystems. It is brought on by unfavorable alterations to the natural world that have a negative impact on the atmosphere and its constituent elements. Pollutants are substances that exist in liquid, solid, or gaseous form and become contaminants when their levels exceed natural limits [1]-[3]. Due to industrial growth fueled by contemporary technology, air pollution—a serious concern—contributes to soil degradation. Energy-generating facilities are one of the main sources of pollution. Animal extinction and plant destruction result from the disruption of ecological equilibrium caused by increasing environmental pollution. Understanding the connection between environmental contaminants and health is necessary to address this problem [4]-[7]. Research organizations and international organizations have established acceptable limits for heavy metals and other substances in soil, water, food, and air as a result of multiple experiments and studies. All physical properties, as well as those of the surrounding atmosphere, regulate the movement and dispersion of polluting gas or aerosol when it enters the atmosphere. It is useful to consider how effluent typically acts after being released in order to visualize the features of this motion, as shown in **Figure 1**. The atmosphere is an important channel to consider when assessing the environmental impact of pollutant escapes from any facilities. The Gaussian plume model is the fundamental component of air dispersion models used to assess the effects of air pollution. By defining several parameters, such as the classification of the atmospheric stability class, the Gaussian plume dispersion calculation makes it possible to calculate the potential concentration of a pollutant downwind of a source [8]-[14]. The vertical profile of wind speed, as well as the rise and dispersion of plumes, parameters for downwind, σ_y, and σ_z. The concentration of pollutant produced by effluent emissions in the air during normal operation or accident conditions from a industrial facility is a crucial component of risk analysis and emergency planning for the regulatory safety assessment. Artificial intelligence (AI) is regarded as one of the most disruptive technologies of the century due to its numerous applications. This study attempted to apply artificial intelligence (AI) in air dispersion models (the Gaussian plume dispersion) for determining the possible concentration of a pollutant downwind of a source by establishing several parameters, including the identification of the atmospheric stability class. The vertical wind speed profile, downwind radioactivity concentration, plume rise,

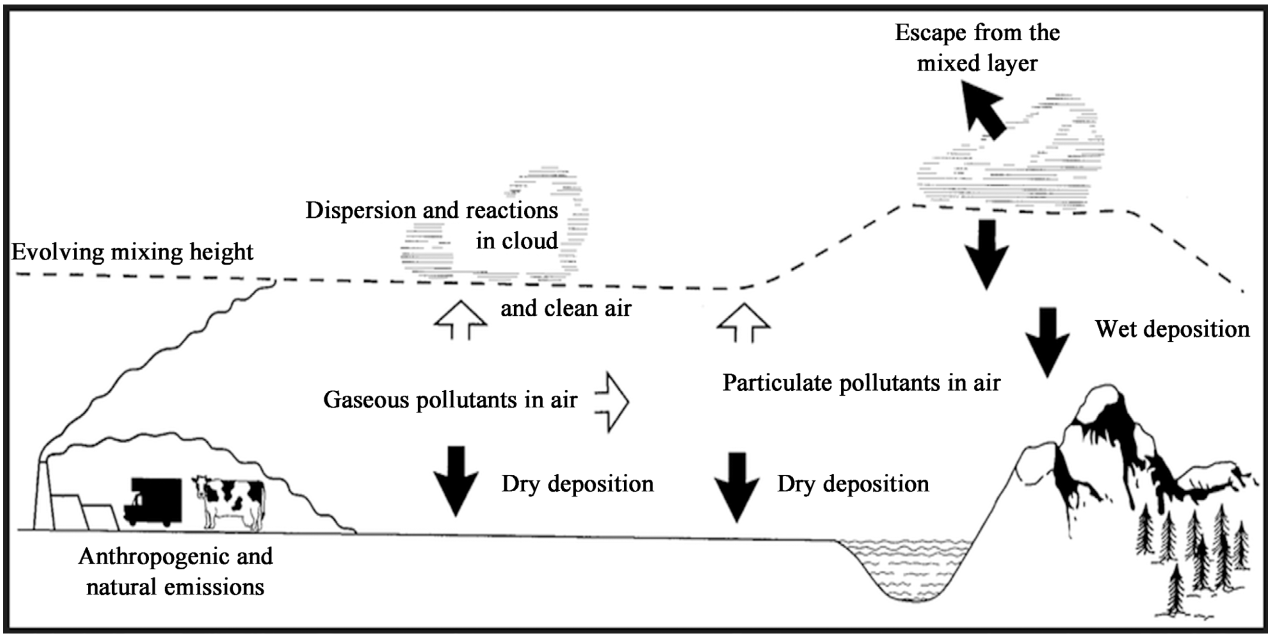

Figure 1. Behavior of effluents released to the atmosphere.

and dispersion σ_y and σ_z parameters This could also help us create suitable regulations to preserve a healthy and balanced ecosystem and protect human health and safeguard human health [15]-[18].

2. Methodology

In order to more precisely estimate pollutant concentrations (particularly radioactive elements) downwind, this study combines artificial intelligence (AI) approaches with conventional physics models of atmospheric pollutant dispersion. The following is how the methodology was applied [19].

2.1. Study Framework

The main mathematical framework for explaining the behavior of pollution dispersion in the atmosphere was the Gaussian Plume model. This model estimates pollutant concentrations at various locations by connecting the physical characteristics of the source with atmospheric conditions. Additionally, an AI-based tool was used to enhance forecast accuracy and examine the variables affecting dispersion.

2.2. Defining Model Inputs

The NOAA website provided hypothetical data of an industrial facility for a number of environmental and physical factors influencing pollutant dispersal. Emission rate (Q), wind speed at source height (U), chimney height (h_s), chimney diameter (d), gas exit velocity (V_s), ambient air temperature (T_a), horizontal distance (x), vertical distance (y), ground elevation (z), and emitted gas temperature (T_s) are some of these factors.

3. Theoretical Background

The Gaussian plume model, which determines the possible concentration of a pollutant downwind of a source by defining many parameters, is one of the fundamental air dispersion models used to evaluate the impacts of air pollution. These parameters include stack diameter, stack gas exit velocity, stack gas exit temperature, ambient temperature, height above ground for any industrial facility, emission rate, and the receptor's distance from the source downwind, as shown in Equation (1):

$$X(x,y,z) = \frac{Q}{2\Pi\sigma_y\sigma_z U}\exp\left[-\left(\frac{Y^2}{2\sigma_y^2}\right)\right]\left(\exp\left[-\left(\frac{-(z-h)^2}{2\sigma_z^2}\right)\right]+\exp\left[-\left(\frac{-(z+h)^2}{2\sigma_z^2}\right)\right]\right) \quad (1)$$

where:

$X(x,y,z)$: air concentration ($Bq.m^{-3}$) at a point with coordinates *x*, *y*, *z*;

x: downwind distance(m);

y: crosswind distance (m);

z: height above the ground (m);

Q: release rate ($Bq.s^{-1}$);

U: mean wind speed ($m.s^{-1}$);

h: effective release height (m);

$\sigma_y \sigma_z$: Diffusion parameters (m), which are a function of downwind distance, *x*, and atmospheric stability.

3.1. Determination of Atmospheric Stability Class

Atmospheric stability refers to the atmosphere's propensity to either facilitate or obstruct the buoyant upward movement. Because heat flow and thermal turbulence are associated, neutral conditions are observed when there is a lot of cloud cover, because, depending on the time of day, the amount of cloud cover decreases, leading to heating or cooling. Strong winds frequently create unbiased Conditions. While low winds and clear skies at night usually lead to minimal dispersion (stable conditions), good dispersion happens during the day, as shown in Table 1. According to the Pasquill-Gifford scheme, we choose the atmospheric stability class using the selection tool.

Table 1. Pasquill stability class.

Speed of Wind U ($m \cdot s^{-1}$) at 10 m	Class of Stability, Day, with Solar Radiation R_D (langleys·h^{-1})				Class of Stability, Night, with Net Radiation R_N (langleys·h^{-1})		
	$R_D \geq 50$	$50 > R_D \geq 25$	$25 > R_D \geq 12.5$	$12.5 > R_D$	$R_N > -1.8$	$-1.8 \geq R_N > -3.6$	$-3.6 \geq R_N$
$U < 2$	A	A-B	B	D	D	-	-
$2 \leq U < 3$	A-B	B	C	D	D	E	F
$3 \leq U < 4$	B	B-C	C	D	D	D	E
$4 \leq U < 6$	C	C-D	D	D	D	D	D
$6 \leq U$	C	D	D	D	D	D	D

Note: A: extremely unstable; B: moderately unstable; C: slightly unstable; D: neutral; E: slightly stable; F: moderately stable.

3.2. The Vertical Wind Speed at Stack Height Due to Surface/Terrain Friction

How to calculate wind speed at stack height: The tendency for wind speeds at higher elevations to be higher than those at lower elevations, due to surface/terrain friction, is known as the vertical wind speed profile, as shown in Equation (2):

$$u_s = u_a \left(h_s / h_a \right)^p \tag{2}$$

where:

u_s = speed of wind at stack height (m/s);

u_a = speed of wind at anemometer height (m/s);

h_a = height of anemometer (m);

h_s = height of stack (m);

p = exponent dependent on stability class and environment classification, which can be determined in accordance with the ISC3 Dispersion Models user guide.

3.3. Calculation Plume Rise

Plume rise is primarily caused by two factors: momentum and thermal buoyancy. Plume buoyancy is determined by the temperature and density difference between the exhaust gas and the ambient air. The exhaust gas's mass and velocity as it exits the stack establish momentum. Many methods have been developed to estimate the plume increase based on these two mechanisms. This calculator uses the Davidson-Bryant formula because it integrates thermal buoyancy and momentum into a single formula (3):

$$\Delta H = d \left(V_s / u_s \right)^{1/4} \left(1 + \left(\Delta T / T_s \right) \right) \tag{3}$$

where:

ΔH = rise of plume above stack (m);

d = stack diameter (m);

V_s = stack gas exit speed (m/s);

u_s = speed of wind (m/s);

ΔT = temperature of the stack gas relative to the surrounding air (K);

T_s = temperature of stack gas (K).

3.4. Calculate Dispersion Parameters σ_y and σ_z

With the dispersion parameters σ_y and σ_z being the standard deviations in y and z directions, respectively, the Gaussian dispersion model basically proposes that gas dispersion and the resulting concentration are normally distributed in the lateral directions (perpendicular to the wind direction). The dispersion parameters of the Gaussian dispersion model depend on atmospheric stability and the source's distance downwind. This step automatically chooses the appropriate constants and equations from the Pasquill-Guifford method in order to compute the dispersion parameters. Simply enter the receptor's downwind distance from the source. The dispersion parameters σ_y and σ_z are given as functions of stability and downwind distance (x) based on a combination of theory and experimental evidence. The most widely used plan was developed by Pasquill (1961) and slightly modified by Turner (1967). The horizontal (σ_y) and vertical (σ_z) dispersion coefficients are calculated using constants based on x (m) distances and Pasquill-Gifford atmospheric stability conditions [19].

3.5. Calculate the Downwind Concentration

The pollutant concentration downwind of a source can be calculated using the Gaussian dispersion equation in the following:

$$X(x,y,z) = (Q/U_s)\cdot(1/2\pi\sigma_x\sigma_y)\exp\left[-y^2/2\sigma_y\right] \cdot\left(\exp\left[-(z+H_s)^2/2\sigma_z^2\right]+\exp\left[-(z+H_s)^2/2\sigma_z^2\right]\right) \quad (4)$$

where:

X = concentration (μg/m^3);

Q = emission rate (g/s);

π = 3.141593;

U_s = stack height wind speed (m/s);

σ_y = lateral dispersion parameter (m);

σ_z = vertical dispersion parameter (m);

y = crosswind distance (m);

z = elevation of receptor (m);

H_s = effective stack height (h_s + ΔH).

4. Results and Discussion

By specifying certain parameters, the Gaussian plume dispersion calculation enables you to determine the possible concentration of a pollutant downwind of a source [19]:

- Identify the class of atmospheric stability
- Determine the wind speed at the height of the stack
- Determine the plume rise
- Find the σ_y and σ_z dispersion parameters.
- Determine the concentration of downwind pollutants.

Step 1: Determine the atmospheric stability class

Use the selection tool to determine the atmospheric stability class in accordance with the Pasquill-Gifford scheme, and a case-determination atmospheric stability class (day, with solar radiation). The equilibrium between thermal turbulence driven by solar heating of the Earth's surface and mechanical turbulence induced by wind shear is the main factor controlling atmospheric stability during the day. While modest sun radiation reduces turbulent motion, strong solar radiation increases buoyant convection, leading to robust vertical mixing. Based on combinations of wind speed and solar radiation intensity, Pasquill-Gifford stability classes (A - F) are assigned by the stability classification table. Because air stability directly regulates the dispersion coefficients σ_y and σ_z, which influence the plume's horizontal and vertical spread [20]-[25], respectively, these categories are important, as shown in Table 2.

Table 2. Determination of the atmospheric stability class (day, with solar radiation) using the selection tool.

Wind Speed at the Surface (m/s)	Day-Time Insolation (Solar Radiation)	Time of Day	The Type of Atmospheric Stability that Is Produced
$U < 2$	Strong ($R_D \geq 50$)	Day	A (Very Unstable)
$2 \leq U < 3$	Moderate ($50 > R_D \geq 25$)	Day	B (Moderately Unstable)
$3 \leq U < 5$	Slight ($25 > R_D \geq 12.5$)	Day	C (Slightly Unstable)
$U \geq 5$	Weak ($R_D < 12.5$)	Day	D (Neutral)

In determining the atmospheric stability class (night, with net radiation), because there is no solar radiation throughout the night, the ground surface cools. Temperature inversions induced by this cooling restrict vertical mixing and drastically alter plume behavior. The atmosphere becomes extremely stable (Class F) under clear-sky, low-wind conditions, leading to restricted plume dispersal and high ground-level concentrations. Wind speed and cloud cover are included in the nighttime stability chart to account for heat loss. Because cloud cover traps long-wave radiation, it lessens surface cooling and moderates stability. Since stable conditions frequently correlate with the worst-case exposure outcomes, these stability regimes are especially important for accident scenarios [26]-[29] (Table 3).

Table 3. Determination of atmospheric stability class (night, with net radiation) using the selection tool.

Wind Speed at the Surface (m/s)	Cloud Cover (Nighttime)	Net Radiation (R_N)	Time of Day	The Type of Atmospheric Stability that Is Produced
$U < 2$	Clear Sky	$R_N < -3.6$	Night	F (Stable)
$2 \leq U < 3$	Partial	$-3.6 \leq R_N < -1.8$	Night	E (Slightly Stable)
$3 \leq U < 5$	Cloudy	$R_N > -1.8$	Night	D (Neutral)

Step 2: Calculate the speed of wind at the stack height due to surface/terrain friction

Table 4 illustrates that although the stability class, anemometer height, wind speed at anemometer height, and stack height are all the same, the wind speed in the urban scenario is higher than that in the rural case due to the urban area's lack of impediments.

Step 3: Calculate plume rise

In Table 5, when the stack gas exit velocity decreases at a constant stack diameter and ambient temperature, plume rise decreases due to two mechanisms: momentum-driven rise (due to exit velocity) and buoyancy-driven rise (due to temperature or density differences). Otherwise, when the stack gas exit velocity decreases, and the stack diameter increases, plume rise increases, because Plume rise depends more strongly on diameter than on velocity.

Step 4: Determine dispersion parameters σ_y and σ_z

In Table 6, it's observed that as the distance downwind increases, the dispersion parameters σy and σz increase, because the longer the plume travels, the greater the time available for random turbulent motions to act, resulting in an ever-widening plume both horizontally and vertically.

Table 4. Speed of wind calculated at stack height due to surface/terrain friction.

Stability Category	Environment (Urban-Rural)	Anemometer Height (h_a) (Measured Wind Speed Height) (m)	Speed of Wind at Anemometer Height ((m/s)	Stack Height hs (m)	Speed of Wind at Stack Height(m/s)
A	Urban	3	4	5	4.47
B	Urban				4.66
C	Rural				4.87
D	Rural				5.10
E	Urban				5.35
F	Rural				5.61

Table 5. Plume rise calculated above the stack tip.

Diameter of Stack (d) (m)	Stack Gas Exit Velocity (m/s)	Temperature of Stack Gas Exit (T_s) (K)	Temperature of the Surrounding Air (T_a) (K)	Plume Rise above Stack Tip (ΔH) (m)	Speed of Wind at Effective Stack Height ($H_s = h_s + \Delta H$) (m)
5	8	200	298	2.92	7.92
	3			2.28	7.27
10	8			5.84	10.84
	3			4.75	9.57

Table 6. Dispersion parameters σ_y and σ_z.

Distance Downwind (x) (m)	Distance Downwind (km)	σ_y (Urban) (m)	σ_z (Urban) (m)
5	0.01	0.54	0.39
10		1.09	0.79

Step 5: Calculate pollutant concentration downwind

Figure 2 shows that the pollutant concentration decreases as crosswind distance increases because of the lateral dispersion (spreading) of the plume caused by atmospheric turbulence and diffusion. This behavior is fundamental in air-pollution dispersion theory, especially in the Gaussian plume model, and Figure 3 shows the pollutant concentration follows a Gaussian distribution with height above ground because: The motions of vertical turbulence are random, Normal distributions are the result of random diffusion, Vertical motion is reflected in the earth and the spread is shaped by air stability and mass conservation [30]-[35].

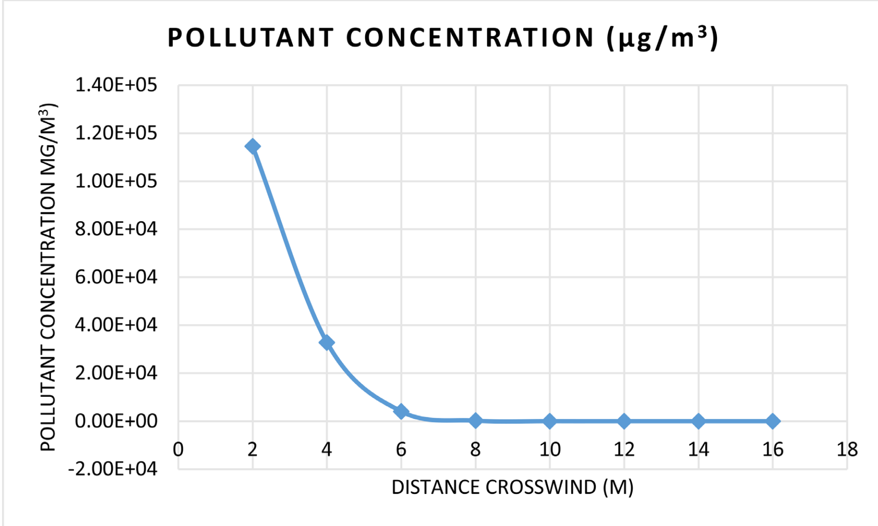

Figure 2. Pollutant concentration and distance crosswind.

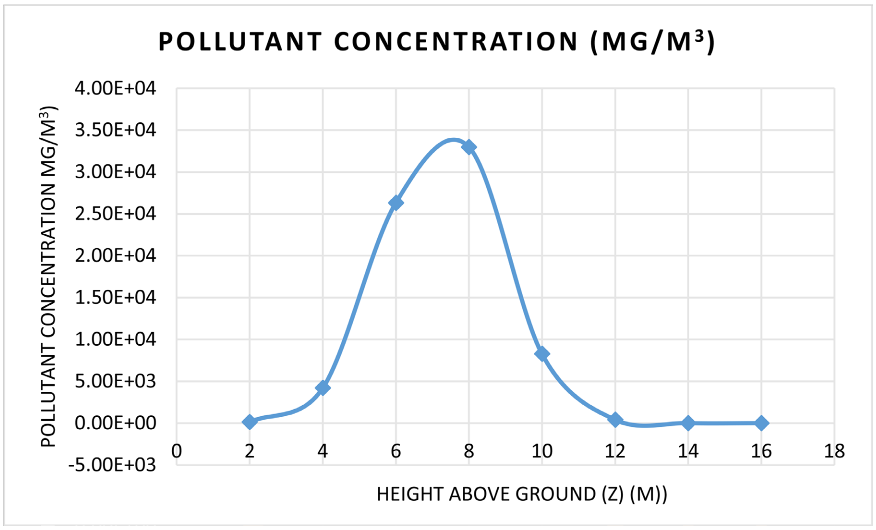

Figure 3. Pollutant concentration and height above ground.

5. Literature Review

- **Samir Lemeš** [36]**:** Through applications like climate modeling, artificial intelligence (AI), and digital technology are already being employed to address environmental concerns. AI-powered solutions help with energy grid optimization and climate forecasting. Real-time environmental monitoring is made possible by IoT devices and satellite imagery. The environmental impact of AI and IT infrastructure is simultaneously increased by these promising applications. High-performance computing data centers need a lot of energy because of their massive carbon emissions. The necessity to extract essential minerals, which are rarely ecologically favorable, is greatly increased by the expanding quantity of gear in data centers and IT infrastructure. The purpose of this analysis is to look at the dual nature of digital technologies and how they relate to environmental protection, as well as whether the advantages and disadvantages of these technologies can be balanced. Are "GreenAI" and "SustainableIT" feasible, and do the advantages of Industry 4.0 and societal advancement outweigh the environmental costs associated with these technologies?

- **Jyoti Kataria *et al.* [37]:** In light of Sustainable Development Goals (SDGs) 13, 14, and 15, this study improves understanding of how artificial intelligence (AI) can either help or hinder the progress of environmental sustainability. Policymakers, scholars, and practitioners looking for practical ways to achieve sustainable development goals might benefit greatly from its insights.
- **Ibrahim Alnafrah [38]:** According to this study, there is a critical threshold beyond which the environmental impact of AI increases, especially in upper-middle-income nations. In contrast, lower-middle-income countries face a technological leapfrogging conundrum, where adoption exceeds regulatory capability. However, these negative effects have been found to be mitigated by strict environmental regulations, a diverse energy mix, and robust digital infrastructure. Our results show that the environmental impact of AI depends on both productive capacities and national policy. We make the case for integrated environmental-digital governance to guarantee that AI promotes sustainability rather than increases ecological dangers.
- **Noemi Luna Carmen *et al.* [39]:** The world is changing due to artificial intelligence (AI), but its effects on the environment and human welfare are still unknown. In order to determine the primary effects of AI and how they are evaluated, we carried out a comprehensive literature analysis of 1,291 studies that were chosen from 6,655 records. The data shows an uneven terrain: only 11% of environmental studies take systemic consequences into account, whereas 72% concentrate primarily on energy use and CO_2 emissions. The majority of research on well-being is conceptual and ignores subjective aspects. Remarkably, well-being assessments show a nearly equal split (44% positive; 46% negative), while environmental studies depict AI's effects as beneficial in 83% of cases. This division, however, obscures variations in several aspects of well-being.
- **Juan Yu *et al.* [40]:** With an emphasis on the long-term effects on sustainable development, the study looks at the social, economic, and environmental advantages of AI optimization. The study examines the environmental effects of wastewater treatment throughout its lifecycle, from the procurement of raw materials to the disposal of finished waste, by building a thorough life cycle assessment (LCA) model. By simulating dynamic feedback mechanisms, the integration of the SD model forecasts the long-term impacts of AI optimization on environmental performance and resource efficiency.

6. Conclusions

An essential technique to improve environmental safety and air pollution studies near industrial facilities is to use artificial intelligence (AI) to determine the factors driving atmospheric pollution dispersion. Artificial intelligence (AI) models analyze key meteorological variables, such as temperature gradients, wind direction, wind speed, and air stability, to predict the potential concentration of pollutants downwind of a release location. This enhances catastrophe planning, contaminated zone forecasts, and population exposure assessment. Combining traditional dispersion methodologies with artificial intelligence (AI)-based modeling ultimately leads to more precise, real-time decision-making, lowering potential risks associated with industrial site operations. The use of artificial intelligence systems tools has shown that, with constant parameters such as emission rate and height above ground, the concentration of pollutants reduces as the distance above ground increases. According to a review of earlier research, artificial intelligence (AI) has emerged as a key instrument for promoting environmental sustainability and increasing the effectiveness of resource management. While many studies have concentrated on AI's role in forecasting climate change, improving energy efficiency, and advancing the attainment of the Sustainable Development Goals (SDGs), some have also addressed the dual impact of AI, showing that while it can improve environmental performance, it may also increase environmental burdens due to energy consumption and the strain on digital infrastructure. Additionally, recent research has emphasized the significance of environmental laws and regulatory frameworks in directing the application of AI towards attaining sustainability, stressing that its environmental impact differs depending on a nation's infrastructure and technological capabilities. In keeping with the expanding trend of comprehending the long-term implications of these technologies, some research has also concentrated on evaluating the environmental impact of AI using sophisticated analytical models like lifecycle assessment (LCA).

In order to improve the estimation of atmospheric pollutant concentrations and increase the accuracy of environmental risk assessments, especially in the context of industrial and nuclear facilities, this study intends to close this research gap by utilizing artificial intelligence techniques in addition to conventional atmospheric diffusion models.

7. Recommendations

1) Integration with Decision Support Systems: Creating a system that can be incorporated into environmental decision support systems to help industrial facility decision-makers with emergency planning and crisis management.

2) Strengthening Regulatory Frameworks: In order to lower pollutant emissions, especially in nations that use nuclear technology, the outcomes of these models must be used to support environmental policies and create more accurate regulatory requirements.

3) Increasing Energy Efficiency in AI Applications: It is advised to create "Green AI" solutions to lower the carbon footprint of the models utilized, given the environmental impact of AI connected to energy consumption.

4) Creating Training and Educational Programs: Using this model as a teaching tool in colleges to teach students how to utilize AI for atmospheric diffusion anal-

ysis, while creating interactive user interfaces that make it easier to use.

Conflicts of Interest

The author declares no conflicts of interest.

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