

Estimating Worst-Case Carbon Monoxide Exposure Uncertainty Using Deterministic and Monte Carlo Methods Southward from UPN Seturan Intersection, Yogyakarta

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Abstract

Carbon Monoxide (CO) is a critical urban pollutant with severe health implications, primarily driven by vehicular emissions in high-density traffic zones. This study investigates the spatial dispersion of CO along the main road located towards the south of the Universitas Pembangunan Nasional (UPN) Seturan Depok intersection, extending 150 meters to the south (Jalan Seturan Raya) in Condongcatur Sleman Yogyakarta, aligning with specific sampling positions located directly amidst the traffic stream to capture immediate exposure levels. This research addresses the limitations of deterministic approaches based on the advection-diffusion equation, which often fail to fully account for the random fluctuations of atmospheric turbulence inherent in complex urban environments. To address this, the study integrates direct field measurements with a probabilistic algorithm that treats the diffusivity coefficient as a random variable governed by the Peclet number. The results demonstrate that the Monte Carlo simulation achieves a predictive accuracy ($R^2 = 0.9393$) which, while slightly lower than the analytical model ($R^2 = 0.9522$), remains highly robust as it successfully accounts for the chaotic, random nature of real world atmospheric turbulence. Furthermore, the simulation identifies a critical high-risk zone within 40 meters of the source where concentrations consistently exceed 35 mg/m^3 due to diffusion-dominated transport.

Keywords: *air dispersion, carbon monoxide, monte carlo simulation, stochastic modelling, urban air quality*

Abstrak

Karbon Monoksida (CO) merupakan polutan perkotaan dengan dampak kesehatan serius yang utamanya dipicu oleh emisi kendaraan di zona lalu lintas padat. Penelitian ini mengkaji dispersi spasial CO di sepanjang jalan utama yang terletak ke arah selatan perempatan Universitas Pembangunan Nasional (UPN) Seturan Depok, meluas sejauh 150 meter ke selatan (Jalan Seturan Raya), Condongcatur Sleman Yogyakarta, untuk menangkap tingkat paparan langsung di tengah arus lalu lintas. Pendekatan stokastik digunakan untuk mengatasi keterbatasan model deterministik dalam memperhitungkan fluktuasi acak turbulensi atmosfer di lingkungan perkotaan yang kompleks. Untuk mengatasi hal tersebut, studi ini mengintegrasikan pengukuran lapangan langsung dengan algoritma probabilitas yang memperlakukan koefisien difusivitas sebagai variabel acak yang dikendalikan oleh bilangan Peclet. Hasil penelitian menunjukkan bahwa simulasi Monte Carlo menghasilkan akurasi prediktif ($R^2 = 0.9393$) yang sedikit lebih rendah dibandingkan model analitis ($R^2 = 0.9522$), namun tetap sangat andal karena berhasil memperhitungkan sifat acak dari turbulensi atmosfer di lapangan. Simulasi tersebut mengidentifikasi zona risiko tinggi dalam radius 40 meter dari sumber, dengan konsentrasi melebihi 35 mg/m^3 akibat transport yang didominasi oleh difusi.

Kata Kunci: *dispersi udara, karbon monoksida, simulasi monte carlo, pemodelan stokastik, kualitas udara perkotaan*

1. Introduction

As cities grow and people travel more, the number of vehicles on the road has increased, leading to serious concerns about air quality [1]. The transportation sector is now the biggest source of urban pollution, responsible for nearly 60% of emissions, with CO making up a large part of this [2]. This gas is often called

a "silent killer" because it is colorless and odorless, making it a major danger to public health and the environment, especially in busy traffic areas [2], [3]. Since CO can travel long distances depending on the weather, we need effective simulation methods to predict where it goes and how to manage it [4], [5].

To understand how pollution spreads, scientists use mathematical models that simulate air movement [6]. These models use equations to calculate how pollutants disperse from their source [7] [8]. However, standard models like the Gaussian Plume often assume that wind and weather conditions are constant. This is a limitation because, in reality, the atmosphere changes randomly (stochastically). This issue is especially important in complex city environments, such as the road towards the south of the UPN Seturan Depok intersection, where standard models may not fully capture the unpredictable nature of the wind.

Previous research has attempted to analyze these patterns using various methods. Gusrianti et al. analyzed CO from traffic in Medan using the Finite Length Line Source (FLLS) model and GIS. They found that pollution was highest at the roadside and generally decreased with distance, though nearby housing complexes caused unexpected spikes [9]. Similarly, AERMOD software (based on the Gaussian Plume model) to simulate dispersion in Yogyakarta [10]. Their simulation identified specific high-pollution streets, but the results did not always match real field measurements because the model could not account for external pollution sources. [11] measured CO levels on the Mojokerto Bypass. Using statistical tests, they found that traffic volume strongly increased pollution, while wind speed slightly decreased it [11].

Despite these contributions, a significant gap remains. All these studies relied on deterministic model's formulas that give the exact same result every time or simple statistical observations. They do not account for the random (stochastic) nature of atmospheric turbulence. Furthermore, no study has yet used the Peclet number to model these random patterns specifically towards the south of the UPN Seturan Depok intersection. This study aims to fill this gap by introducing a probability-based model. To solve this problem, this study uses a statistical method called Monte Carlo simulation, which is designed to handle uncertainty and random changes in the atmosphere. The scientific novelty of this research is the use of the Peclet number to better represent how gas disperses in a changing urban environment. The objectives of this study are to build a mathematical algorithm using Python to simulate CO distribution, determine the uncertainty of CO concentration to estimate worst-case exposure scenarios experienced by people directly amidst the crowded traffic, analyse how distance affect pollution levels, and conduct a comparative analysis of the proposed stochastic Monte Carlo model against a traditional deterministic analytical model, validating both against real field measurements.

2. Material and Methods

This study integrates field measurements with mathematical modeling to analyze CO dispersion. The methodology follows three stages: (i) data acquisition, (ii) Python-based analytical and stochastic modeling, and (iii) statistical validation against observed data. This method ensures that the results are based on real-world data while also accounting for the unpredictable nature of the atmosphere [12]. The dispersion modeling provides a crucial analysis of air quality, offering a broader spatial perspective than in-situ measurements alone [13].

The computational framework developed for this study is systematically outlined in the programming flowchart shown in **Figure 1**. The process begins with the input of observation data, followed by the parallel execution of both the deterministic analytical solution and the stochastic Monte Carlo simulation. A critical decision node evaluates the model's accuracy; if the coefficient of determination (R^2) exceeds the threshold of 0.9, the results are considered valid for curve fitting and final visualization. This rigorous logic ensures that the generated models are not only theoretically sound but also empirically reliable before any conclusions are drawn.

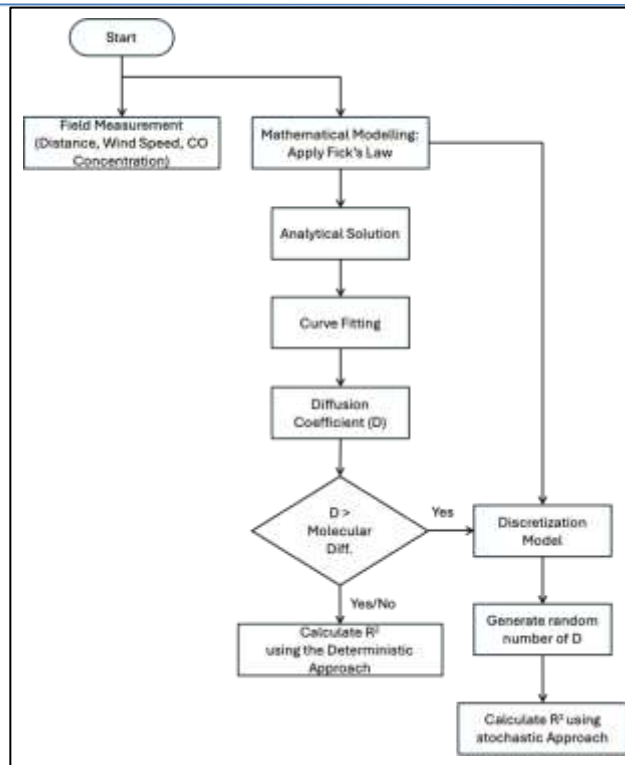


Figure 1. Flowchart of the Simulation and Model Validation Process

Study Area and Equipment

The research was conducted along the main road located towards the south of the UPN Seturan Depok Intersection (Jalan Seturan Raya), extending 150 meters to the south of the intersection, and the map of the sampling area is shown in **Figure 2**. This specific location was selected because it is close to a major intersection where traffic congestion frequently causes high accumulation of vehicle emissions.

To collect the necessary data, two primary instruments were used, as presented in **Figure 3**: a CO Meter (Smart Sensor AS8700A) to measure gas concentration and a Digital Anemometer (Benetech GM816) to measure wind speed and direction. These factors are critical as meteorological conditions like wind speed and direction significantly influence pollutant distribution [14]. All mathematical modeling and simulations were performed using the Python 3.12 programming language via the Spyder software. Python was chosen for its flexibility, simplicity, and extensive library support for data analysis and visualization [15] [16].



Figure 2. Sampling Location



Figure 3. (a) Carbon Monoxide Meter (smart Sensor AS8700A) (b) Digital Anemometer (Benetech GM816)

Data Collection Procedure

Field measurements were taken over three days (May 20, 21, and 26, 2025) during the peak afternoon hours of 16:00 to 17:35 WIB. This specific time frame was chosen to capture consistent high-traffic conditions. The data collection followed a systematic process:

1. Source Measurement: The concentration of CO was first measured at a designated starting point ($x=0$). This point corresponds to the road intersection, which is assumed to be the location of heaviest traffic congestion and the primary source of emissions, although significant traffic congestion persists as one move away from this intersection.
2. Sampling Position: The sampling was explicitly conducted in the middle of the traffic stream, directly amidst the crowded vehicles, rather than on the pedestrian walkway. This positioning was chosen to estimate the direct CO exposure levels. Measurements were chosen to estimate the direct CO exposure levels. Measurements were restricted to a duration of 45 to 60 seconds per point; extending this duration was not feasible due to the rapid changes in the traffic conditions once the traffic light turned green.
3. Interval Sampling: Measurements were taken at six subsequent points starting from the intersection (0m) which is considered the most polluted zone due to traffic accumulation and continuing at 30-meter intervals (30m, 60m, 90m, 120m, 150m) following the direction of the wind towards the south of the UPN Seturan Depok intersection. The data from the three days were averaged to minimize daily fluctuations and provide a reliable baseline for the simulation.
4. Wind Analysis: Wind speed and direction were recorded to determine the path of dispersion. The average wind speed recorded during the study was 1.1 m/s.

Mathematical Modeling (Analytical Approach)

To establish a baseline description of how gas spreads in space, a deterministic mathematical approach based on the advection–diffusion equation can be used. This approach combines the concept of advection (transport due to bulk fluid motion, such as wind) with molecular diffusion as described by Fick's law. Under a steady-state assumption, the concentration does not change with time but varies only with position. In this condition, the driving force for mass transfer is the concentration gradient, causing the substance to move from regions of higher concentration to regions of lower concentration.

For one-dimensional transport with constant velocity and constant diffusivity, the governing equation is:

$$v_x \frac{dC_A}{dx} = D_{AB} \frac{d^2C_A}{dx^2} \quad (1)$$

Where v_x represents the wind velocity and D_{AB} represents the diffusivity coefficient. Solving this steady-state equation gives an exponential concentration profile:

$$C_A = C_{A0} e^{-\frac{v_x x}{D}} \quad (2)$$

The equation-2 was used to calculate the theoretical concentration of CO at each distance point along the sampling route.

Stochastic Simulation (Monte Carlo Method)

Since real atmospheric conditions involve complex turbulence that fixed, deterministic formulas cannot fully capture, this study utilized a modified approach incorporating the Peclet number. The Peclet number represents the ratio between advective and diffusive transport, a value greater than 1 indicates that advection dominates [17], which is typical in open atmosphere environments.

To represent the stochastic nature of these conditions, the Monte Carlo method is employed. This method assumes that pollutant particles move via a combination of mean flow and random fluctuations caused by turbulence. In this simulation, the macroscopic dispersion at any downwind distance x is represented as an aggregate of n discrete stochastic states. The CO concentration for a specific state k is calculated using the following equation-3:

$$C_{A(x,k)} = C_{A0} e^{-Pe(k)} = C_{A0} e^{\frac{-vx}{D_{mol} + D_{tur(k)}}} \quad (3)$$

In equation-3, $D_{tur}(k)$ represent the turbulent diffusion coefficient. It is treated as a random variable to capture the heterogeneity of the system and is generated by taking the inverse of equation-4 using a random number input (γ_k). $D_{tur,k}$ is assumed to follow a normal (Gaussian) distribution.

$$\gamma(k) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{D_{tur(k)} - \mu}{\sigma}\right)^2} \quad (4)$$

To set the standard deviation (σ) and mean (μ), the shape of this distribution must be defined, a specific algorithm was employed to ensure physically realistic results. The turbulent diffusion values were constrained within a valid range defined by specific boundary conditions. Here, v_0 represents the lower bound of diffusivity, set to 0 to prevent physically impossible negative diffusion, while v_f represents the upper bound, set to approximately twice the mean to capture extreme turbulent events.

The cumulative probabilities p_0 and p_f correspond to these bounds, set to 10^{-6} and ~ 1 respectively. These values were chosen to avoid mathematical singularities while covering nearly the entire probability space. To determine the distribution parameters, the algorithm utilizes the inverse error function erf^{-1} to map these boundary conditions to the corresponding statistical properties. Finally standard deviation (σ) and mean (μ) are derived s shown in equation-5 and 6.

$$\sigma = \frac{v_f - v_0}{\sqrt{2}[erf^{-1}(2p_f - 1) - erf^{-1}(2p_0 - 1)]} \quad (5)$$

$$\mu = v_0 - \sigma\sqrt{2} \cdot erf^{-1}(2p_0 - 1) \quad (6)$$

To determine the final concentration profile, the simulation aggregates the results from multiple iterations. The concentration $C_{A(x)}$ at a given distance x is computed as the arithmetic mean of the concentrations derived from $n = 10$ discrete stochastic states. This sample size was selected as a robust computational threshold to sufficiently capture the statistical variance of atmospheric turbulence while preserving the representative heterogeneity of the local micro-environment. This averaging process, which smooths out the random fluctuations to reveal the macroscopic dispersion trend, is expressed mathematically as shown in Equation-7.

$$C_{A(x)} = \frac{1}{n} \sum_{k=1}^n C_{A(x,k)} \quad (7)$$

Data Analysis

Finally, the results from both the analytical math model and the Monte Carlo simulation were compared with the actual field data. The accuracy of the algorithms was tested using the Coefficient of Determination (R^2). A high R^2 value (close to 1.0) indicates that the model successfully predicts the real-world dispersion patterns.

3. Results and Discussion

This section presents the findings from the field observations and the subsequent mathematical modelling. It begins by analyzing the actual CO concentration trends measured at the study site, followed by a comparison between the deterministic analytical model and the stochastic Monte Carlo simulation.

The discussion highlights how atmospheric turbulence influences the dispersion process and demonstrates why a probabilistic approach provides a more accurate representation of real-world conditions.

Field Measurement Results and Dispersion Trends

The field data collected over three days reveals a clear trend in pollutant dispersion. As shown in the observation data in

Table 1, the concentration of CO decreases significantly as the distance from the source increases. At the starting point ($x=0$), the average concentration was recorded at 50.407 mg/m³. This value dropped progressively to 29.404 mg/m³ at 30 meters and continued to decline, reaching 12.983 mg/m³ at a distance of 150 meters.

This pattern confirms the fundamental principle of dispersion, where pollutants are diluted as they mix with the surrounding air. The consistent decrease in concentration indicates that the wind effectively transports and spreads the gas away from the high-traffic source. However, the rate of this decrease is not perfectly smooth, which suggests that environmental factors such as wind fluctuations and physical obstacles (like buildings or trees) play a role in how the gas spreads.

To accurately capture the real-world dispersion of CO, field measurements were conducted over a period of three days at consistent afternoon peak hours (16:00 - 17:35 WIB). The data collection focused on recording CO concentrations at fixed intervals downwind from the primary source point.

Table 1 summarizes the detailed coordinate data, daily measurements, and the calculated average concentrations for each distance interval, providing the empirical basis for the subsequent modelling. It is important to note that the recorded concentrations are relatively high; this is a direct consequence of the sampling procedure described in Section 2.2, where measurements were taken in immediate proximity to vehicle emissions as the pedestrian walkway is situated directly adjacent to the road traffic.

Table 1. Observed Carbon Monoxide (CO) Concentrations

| No of Samples | Distances (m) | Coordinates | CO Concentration (mg/m ³) | | | |
|---------------|---------------|----------------------------|---------------------------------------|----------------|----------------|----------------|
| | | | Day 1 | Day 2 | Day 3 | Average |
| 1 | 0 | -7.7619542, 110.4119727 | 45.824 | 50.407 | 54.989 | 50.407 |
| 2 | 30 | -7.762216, 110.41192717 | 30.931 | 27.495 | 29.786 | 29.404 |
| 3 | 60 | -7.762492, 110.4118651 | 26.349 | 25.203 | 20.621 | 24.058 |
| 4 | 90 | -7.7627485, 110.4117994 | 17.184 | 16.039 | 18.330 | 17.184 |
| 5 | 120 | -7.7763013, 110.411734 | 14.893 | 12.602 | 12.602 | 13.366 |
| 6 | 150 | -7.7632727, 110.4116632 | 13.747 | 12.602 | 12.602 | 12.983 |
| Σ | 450 | | 148.928 | 144.348 | 148.930 | 147.402 |

The field data collected over three days reveals a clear trend in pollutant dispersion. As shown in the observation data in

Table 1 and visualized in **Figure 4**, the concentration of Carbon Monoxide (CO) decreases significantly as the distance from the source increases. At the starting point ($x=0$), the average concentration was recorded at 50.407 mg/m³. This value dropped progressively to 29.404 mg/m³ at 30 meters and continued to decline, reaching 12.983 mg/m³ at a distance of 150 meters.

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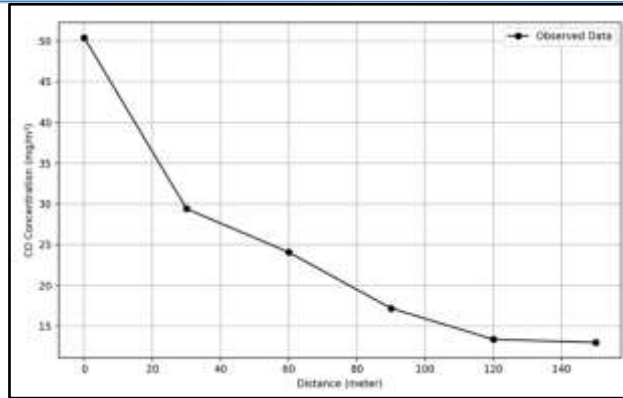


Figure 4. Observed Concentration vs Distance

Analytical Modeling and the Role of Turbulence

The mathematical simulation was first executed using the deterministic analytical approach, solving the differential equation presented in Equation (1) to obtain the concentration profile defined by Equation (2). As illustrated in Figure 5, the model produces a decay curve that generally follows the downward trend of the observed field data. This finding aligns with previous study [18], [19], these results confirm that atmospheric pollutant concentrations naturally decrease with distance from the source due to dilution processes. From a mass transport perspective, this movement is driven by the concentration gradient, where pollutant naturally migrate from high-density to low-density region[20].

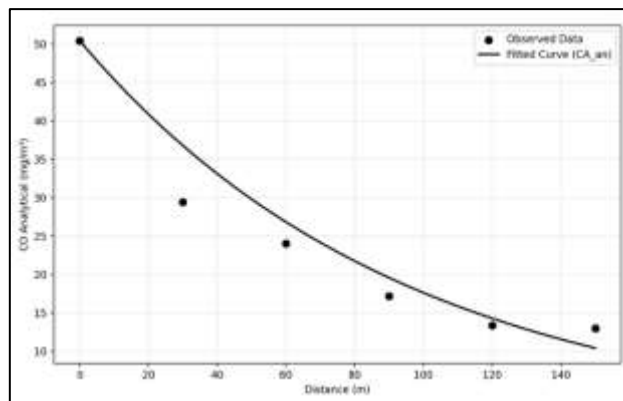


Figure 5. Distance vs Analytical CO Concentration

To quantify this fit, a linear regression validation was performed. The initial attempt to model this data using the deterministic analytical equation showed a strong correlation with the field measurements, achieving a Coefficient of Determination (R^2) of 0.9522, as presented in Figure 6. While this indicates a good fit, a deeper analysis of the diffusivity coefficient (D) reveals a significant anomaly.

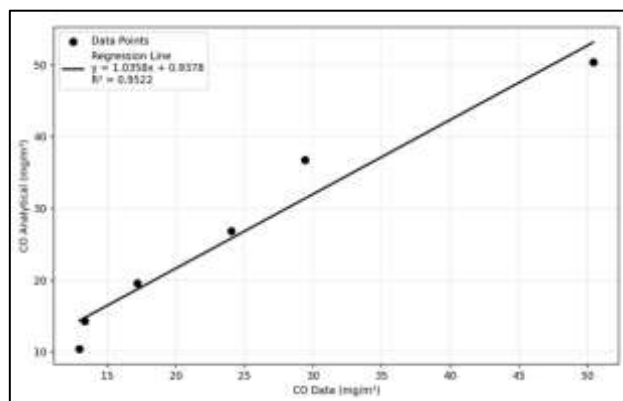


Figure 6. Correlation Between Measured and Analytical CO Concentration Data

The mathematical calculation yielded a diffusivity coefficient of approximately 104.678 m²/s. This value is drastically higher than the standard molecular diffusivity of CO in air found in scientific literature,

which is typically very small, on the order of $1.9 \text{ cm}^2/\text{s}$ [21]. This massive difference where the calculated value is thousands of times larger cannot be explained by simple molecular movement. Instead, it highlights the dominance of atmospheric turbulence. Modern dispersion models demonstrate that turbulent eddies are capable of transporting pollutants in a mass and rapidly, creating effective diffusion rates that far exceed the capabilities of basic molecular diffusion [22]. Therefore, the "high" diffusivity found in the model actually represents turbulent diffusion. This significant margin in values is a direct consequence of the heterogeneity of atmospheric conditions at the site. It confirms that a static, deterministic model is fundamentally limited in capturing the physical reality of turbulent urban airflow, thereby highlighting the necessity for a stochastic modeling approach.

Stochastic Modelling using Monte Carlo Simulation

To address the limitations of the deterministic model and better represent the chaotic nature of turbulence, the Monte Carlo simulation was applied. This approach introduces stochasticity by varying the Peclet number (Pe), allowing the model to simulate multiple dispersion scenarios rather than relying on a single fixed value. As visualized in **Figure 7**, the Monte Carlo realizations of the Peclet number show significant variability across the sampling distances, capturing the dynamic and random nature of atmospheric transport.

For this simulation, the mean turbulent diffusivity (μ) was set to $104.676 \text{ m}^2/\text{s}$, a value derived from the fitted diffusivity coefficient (D_{AB}) obtained in the analytical Fick's law model (equation-2). The standard deviation (σ) was established as a tunable parameter to represent atmospheric variability, refined through an iterative optimization process to best match the field data dispersion. The simulation generates 10 random samples for every distance interval. The final concentration $C_{A(x)}$ is then determined by averaging these 10 stochastic states, providing a result that accounts for the natural variability of the atmosphere.

As visualized in **Figure 7**, the Monte Carlo realizations of the Peclet number show significant variability across the sampling distances, capturing the dynamic and random nature of atmospheric transport. The scatter plot reveals that at shorter distances (specifically below 60 meters), the Peclet numbers generally remain below 1, signifying a diffusion-dominated regime. This dominance of diffusion implies that the dispersion process is relatively slow compared to advection, leading to the local accumulation of pollutants. Consequently, this near-field area acts as a potential hotspot for CO, where concentrations remain dangerously high due to the lack of effective wind flushing, posing significant health risks to road users. In contrast, at distances greater than 60 meters, the Peclet number begins to frequently exceed 1, indicating that advection starts to contribute more significantly to the transport process, eventually dominating over diffusion as the distance increases. This widening dispersion of red dots signifies increasing uncertainty and stronger influence of turbulent eddies further downwind. Instead of a single deterministic line, this probabilistic cloud demonstrates that the ratio of advection to diffusion is not constant but fluctuates due to atmospheric instability, validating the need for a stochastic approach to model real-world conditions.

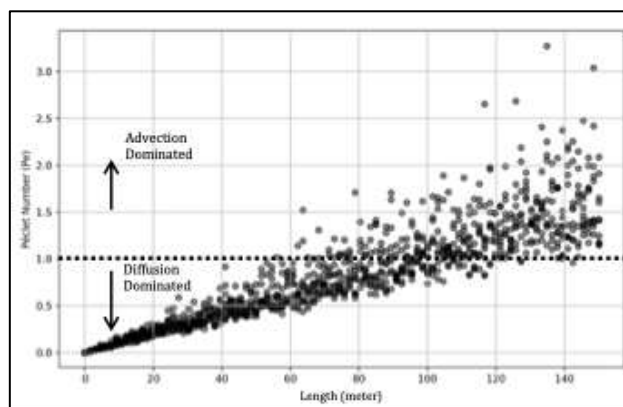


Figure 7. Monte Carlo Realizations of Peclet Number

Using these probabilistic inputs, the simulation produced a refined dispersion curve. **Figure 8** illustrates the Monte Carlo curve fit against the observed data, demonstrating a smoother and more representative decay pattern compared to the deterministic model. The stochastic approach effectively smoothed out the "noise" inherent in field data while adhering to the physical laws of dispersion.

The statistical validation of this method yielded a predictive accuracy that remains highly competitive with the deterministic analytical approach. As presented in **Figure 9**, the Monte Carlo simulation achieved a Coefficient of Determination (R^2) of 0.9393. While this value is marginally lower than the analytical models of 0.9522, the stochastic results are significant they successfully incorporate the inherent probability and variability of atmospheric transport. This robustness indicates that treating the diffusivity coefficient as a random variable allows the model to better account for real world urban complexities, such as sudden wind gusts and physical obstacles, providing a more realistic representation of the uncertainty involved in pollutant dispersion.

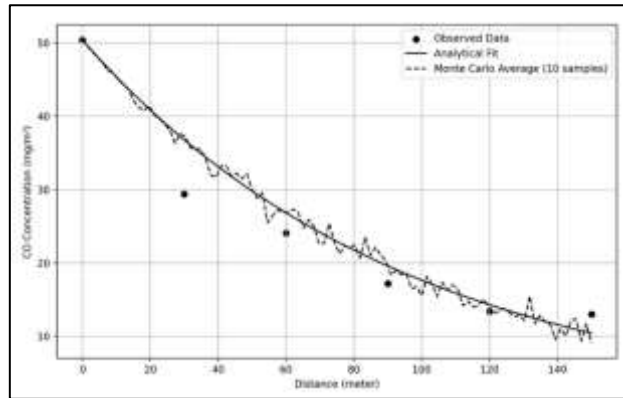


Figure 8. Analytical vs Monte Carlo Model Comparison

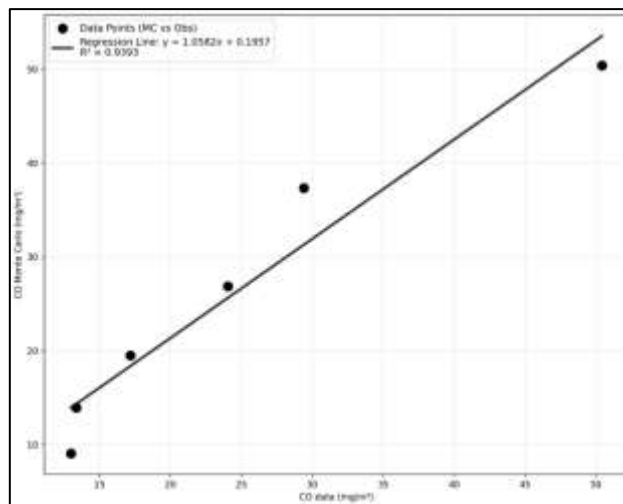


Figure 9. Monte Carlo Simulation vs Observed CO

The detailed comparison of the results is summarized in **Table 2**. At a distance of 30 meters, the Monte Carlo model predicted a concentration of 35.327 mg/m³, which is closer to the observed field data (29.404 mg/m³) compared to the Analytical model (36.777 mg/m³). This trend of improved proximity to real data demonstrates the superiority of the stochastic approach in near-field dispersion. By effectively modeling the randomness of the environment, the Monte Carlo method proves to be a robust tool for air quality prediction in heterogeneous urban settings.

Table 2. Observed CO vs. Analytical & Monte Carlo Models

| x (m) | CO Concentration (mg/m ³) | | |
|-------|---------------------------------------|------------|-------------|
| | Observed | Analytical | Monte Carlo |
| 0 | 50.407 | 50.407 | 50.407 |
| 30 | 29.404 | 36.777 | 35.327 |
| 60 | 24.058 | 26.833 | 27.853 |
| 90 | 17.184 | 19.577 | 18.407 |
| 120 | 13.366 | 14.284 | 13.869 |
| 150 | 12.983 | 10.421 | 9.879 |

Probabilistic Analysis of Dispersion Zones

When observing the dispersion of CO over distance, distinct zones of probability emerge from the Monte Carlo simulation (as visualized in **Figure 10**) that reflect the changing behavior of the gas plume. In the immediate vicinity of the source (0 to 40 meters), the simulation reveals a scenario of high certainty. The data points here are tightly packed, forming a narrow, linear path. That indicates a very high probability nearly a guarantee that CO concentrations will remain critically high, consistently falling between 35 and 50 mg/m³. At this short range, the influence of random variable is minimal, the model predicts a severe exposure risk with very little deviation.

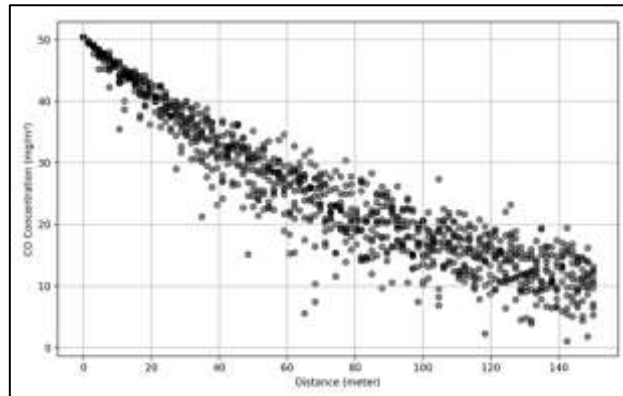


Figure 10. CO Concentration Variability and Uncertainty over Distance

As the plume moves into the transition zone (40 to 90 meters), the narrative changes from certainty to variability. The tight clustering of data points begins to fan out vertically, signaling that stochastic factors perhaps wind gusts or turbulence are starting to disrupt the plume structure. In this interval, predicting an exact value becomes more difficult. While the overall trend is decreasing, the probability distribution widens, meaning an observer at 60 meters could just likely encounter a concentration of 25 mg/m³ as they could 35 mg/m³.

Finally, in the far-field zone (90 to 150 meters), the dispersion becomes highly unpredictable in terms of precise values, but predictable in term of safety. The data points scatter significantly, showing the highest level of uncertainty in the simulation. However, the probability of high exposure drops dramatically. Despite the ‘noise’ in the data, there is a strong statistical likelihood that concentrations in this zone will settle below 20 mg/m³, as the plume effectively dilutes into surrounding environment. The distinct characteristics of these dispersion zones, including the predicting concentration ranges and the associated probability of exposure, are summarized in **Table 3**. The classification of "High Risk" is defined by concentrations exceeding 35 mg/m³. Although the WHO Air Quality Guidelines [23] recommended a limit of 35 mg/m³ for a 1-hour exposure, the field measurements in this study were strictly limited to 45-60 seconds to isolate the peak accumulation phase before traffic conditions changed with the green light (as detailed in Section 2.2). Therefore, detecting concentrations that approach or exceed the hourly standard within this brief, worst-case window serves as a robust indicator of acute exposure risk.

Table 3. Summary of Dispersion Zones and Probabilistic Risk

| Distance | CO Range | High Exposure (>35 mg/m ³) | Reliability |
|------------|---------------------------|--|----------------------------|
| 0 – 40 m | 35 - 50 mg/m ³ | High | High (Low Variance) |
| 40 – 90 m | 15 - 35 mg/m ³ | Moderate | Medium (Increasing Spread) |
| 90 – 150 m | 0 - 20 mg/m ³ | Low | Low (High Variance) |

4. Conclusion

This study developed and implemented a Python-based computational framework to evaluate Carbon Monoxide (CO) dispersion south of the UPN Seturan Depok intersection. By comparing a deterministic analytical approach with a stochastic Monte Carlo simulation, the research highlights the critical importance of accounting for atmospheric turbulence in urban environments.

Although the analytical model achieved a high correlation (R²=0.9522), it required an unrealistically high diffusivity coefficient (104.678 m²/s), confirming that turbulent eddies not simple molecular motion

drive dispersion in this corridor. Conversely, the Monte Carlo simulation treated diffusivity as a stochastic variable governed by the Peclet number. Despite a marginally lower accuracy ($R^2=0.9393$), this probabilistic approach proved vastly superior at capturing the chaotic physical variability of real world urban airflow.

The simulation identified a potential high-risk, diffusion-dominated zone within 40 meters of the intersection. Because field measurements were restricted to brief sampling intervals, these concentrations exceeding 35 mg/m^3 serve as a potential high-risk indicator for acute exposure during instantaneous (worst case scenarios). Beyond 60 meters, advection dominates, scattering the plume and increasing concentration uncertainty. Based on these findings, it is recommended that local authorities implement dense vegetation barriers within 80 meters of major intersections to serve as natural bio-filters

5. Acknowledgment

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