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Posted Date: 23 March 2026

doi: 10.20944/preprints202603.1733.v1

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Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 23 March 2026 doi:10.20944/preprints202603.1733.v1

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# CFD-Based and Experimental Investigation of Indoor Air Quality: Particulate Matter Dispersion and Exposure in Library Buildings

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## Abstract

Indoor air quality (IAQ) is a critical determinant of occupant health, comfort, and cognitive performance, particularly in densely occupied indoor environments such as libraries. This study aims to quantify particulate matter (PM) dispersion dynamics and exposure characteristics through an integrated experimental and computational framework. Three-dimensional CFD simulations were conducted using Flow-3D to resolve the transient transport behavior of multiple PM fractions (PM0.3–PM10) under realistic indoor conditions, and the results were validated against in situ measurements obtained from two library buildings. The findings demonstrate that fine particles (PM0.3–PM1.0) remain suspended at occupant breathing height for extended durations, whereas coarse particles (PM5–PM10) predominantly undergo gravitational settling and accumulate near floor regions. A strong agreement between numerical predictions and experimental data was achieved for PM2.5 and PM10, while discrepancies for ultrafine particles were attributed to turbulence-induced diffusion and Brownian motion. Furthermore, the results highlight the critical role of airflow distribution, ventilation configuration, and spatial obstructions in governing particle transport and the formation of localized high-concentration zones. These findings underscore that ventilation effectiveness is primarily controlled by airflow patterns rather than airflow rate alone. The study confirms that CFD, when supported by experimental validation, provides a robust tool for assessing IAQ and informing ventilation design strategies to mitigate occupant exposure in indoor environments.

**Keywords:** indoor air quality; particulate matter; computational fluid dynamics; ventilation; exposure; CFD validation; indoor environments

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## 1. Introduction

The indoor air quality (IAQ) has become a critical determinant of human health, well-being, and cognitive performance in contemporary built environments, particularly as individuals spend the majority of their time indoors [1]. The increasing awareness of exposure to airborne pollutants has led to substantial research efforts aimed at understanding contaminant transport mechanisms and optimizing ventilation performance in enclosed spaces [2]. In this context, computational and experimental investigations have gained prominence, with recent review studies emphasizing the central role of computational fluid dynamics (CFD) in analyzing airborne contaminant dispersion and transport phenomena in indoor environments [3]. Among various indoor pollutants, particulate matter (PM) represents one of the most significant concerns due to its persistence in the air, complex transport behavior, and well-documented adverse health effects [4,5].

Ventilation systems are widely recognized as the primary mechanism for controlling indoor pollutant concentrations; however, their effectiveness is not solely dependent on airflow rates but is strongly governed by airflow distribution patterns, building geometry, and boundary conditions [6]. Experimental studies have demonstrated that even well-designed systems may fail to provide uniform contaminant removal if airflow organization is not properly addressed [7]. Furthermore, numerical investigations across different indoor environments have shown that pollutant transport is highly sensitive to enclosure configuration and ventilation strategy, leading to spatially heterogeneous concentration fields [8]. Ensuring the reliability of such numerical predictions requires rigorous verification and validation procedures, as highlighted in studies focusing on CFD accuracy and quality control in indoor airflow simulations [9].

In addition to airflow-driven transport, recent research has increasingly focused on the interaction between indoor and outdoor pollutant sources. Multi-zone modeling approaches have demonstrated that outdoor particulate matter can significantly contribute to indoor concentrations depending on building characteristics and ventilation conditions [10]. Parallel advances in sensing technologies have enabled high-resolution monitoring of IAQ, facilitating more accurate characterization of pollutant dynamics and improving the validation of numerical models [11]. Moreover, the effectiveness of emerging air-cleaning technologies, including ionization systems and portable filtration devices, has been investigated, revealing that removal efficiency varies considerably with system design and operating conditions [12].

The transport and fate of particulate matter within indoor environments are governed by a complex interplay of physical processes, including advection, diffusion, gravitational settling, and particle–surface interactions. Recent case studies have demonstrated that ventilation strategies play a decisive role in controlling particle dispersion and accumulation patterns in indoor spaces [13]. Measurement uncertainties, particularly those associated with humidity and aerosol optical properties, further complicate the accurate assessment of particulate concentrations [14]. Field investigations conducted in densely occupied public environments have also highlighted the potential for elevated inhalation exposure risks under certain indoor conditions [15]. Similarly, studies examining building retrofit strategies have shown that the combined implementation of ventilation and filtration measures can significantly improve IAQ performance [16], while experimental evaluations of portable air-cleaning systems have confirmed their potential to reduce airborne particle concentrations under controlled conditions [17].

Exposure variability across indoor environments has been further documented in residential microenvironments, where particulate matter concentrations exhibit substantial spatial and temporal variability depending on occupant activities and ventilation conditions [18]. In occupational settings, real-time monitoring of bioaerosols and particulate matter has revealed the complexity of indoor pollutant mixtures and their dynamic behavior [19]. CFD-based analyses of complex building layouts, such as dormitory structures, have demonstrated that airflow pathways and inter-unit interactions can significantly influence contaminant dispersion [20]. Comparable findings have been reported in office-type environments, where localized airflow structures determine pollutant transport and exposure levels [21].

Despite these advances, certain indoor environments remain insufficiently investigated. Libraries, in particular, represent a unique case due to prolonged occupancy durations, relatively stable seating arrangements, dense interior layouts, and often limited airflow variability. A recent study focusing on library group study rooms has emphasized the importance of simultaneously addressing IAQ and occupant comfort in such environments [22]. However, comprehensive analyses integrating both experimental measurements and high-resolution CFD simulations in library settings remain limited.

Recent research has also explored broader aspects of particulate matter behavior and IAQ assessment in specialized contexts, including combined experimental–numerical thermal systems [23], toxicological impacts of fine particulate matter [24], and the influence of heating source positioning on indoor pollutant distribution [25]. Additionally, the development of low-cost sensor networks has expanded the capabilities for real-time indoor air quality monitoring [26]. These contemporary contributions build upon foundational studies that established quantitative relationships between indoor environmental quality and human performance [27], as well as the fundamental links between fine particulate matter exposure and adverse health outcomes [28]. Long-term analyses of indoor pollutant evolution have further enriched the understanding of indoor environmental processes [29], while CFD has been firmly established as a mature and indispensable tool for modeling indoor airflow and contaminant transport [30]. More recently, global research efforts have reinforced the importance of minimizing airborne exposure in indoor environments through effective ventilation and control strategies [31].

Notwithstanding the substantial body of literature, there remains a critical need for integrated studies that combine experimental measurements with validated CFD simulations under realistic indoor conditions. This need is particularly evident in environments such as libraries, where prolonged exposure and specific airflow characteristics may significantly influence occupant risk. Therefore, the present study aims to investigate particulate matter dispersion and exposure characteristics using a combined experimental and CFD-based approach. By integrating field measurements with high-resolution numerical simulations, this research seeks to provide a comprehensive assessment of IAQ and to support the development of more effective ventilation strategies for reducing occupant exposure in indoor environments.

Despite the substantial body of literature on indoor air quality and CFD-based analyses, important gaps remain in the integrated assessment of particulate matter dynamics under realistic occupancy conditions, particularly in library environments characterized by prolonged exposure durations and relatively stable airflow patterns. Existing studies have largely focused either on experimental measurements or numerical simulations, with limited efforts to systematically combine both approaches for validation and comprehensive interpretation. In this context, the present study aims to provide a comparative and integrated analysis of indoor particulate matter behavior by combining field measurements with high-resolution CFD simulations in two different library buildings. The results demonstrate that while CFD modeling provides high accuracy for larger particle fractions (PM2.5–PM10), deviations are more pronounced for ultrafine particles due to turbulence and stochastic effects. Furthermore, the findings reveal that ventilation effectiveness is strongly influenced by spatial airflow distribution, leading to localized accumulation zones and potential exposure risks at the occupant level. These results contribute to a deeper understanding of particle transport mechanisms in indoor environments and offer practical insights for optimizing ventilation design and improving occupant health in public buildings.

## 2. Materials and Methods

The methodology of this study is based on a combined experimental and numerical approach to investigate indoor air quality in library environments. Field measurements were conducted to determine particulate matter and $CO_2$ concentrations under real operating conditions, while computational fluid dynamics (CFD) simulations were employed to analyze the spatial and temporal distribution of particles. Statistical analyses were performed to evaluate differences between buildings and measurement heights, as well as relationships among variables. The overall approach enables a comprehensive assessment of indoor air quality and supports the validation of numerical modeling results.

### *2.1. Study Area and Measurement Design*

This study was conducted in two distinct library buildings located in Antalya, Türkiye, selected to represent different architectural configurations, occupancy characteristics, and ventilation conditions. The selection of these two case studies enables a comparative assessment of indoor air quality (IAQ) under varying spatial and operational scenarios, thereby enhancing the generalizability of the findings.

The Antalya Public Library is a large-scale public facility characterized by high occupancy density and diverse functional zones, including group study areas, individual reading sections, and archival storage spaces. The building exhibits a relatively large internal volume, with maximum floor dimensions of approximately 50.60 m × 41.40 m on the first floor and 50.60 m × 38.85 m on the second floor. Such volumetric characteristics are expected to influence airflow patterns, particle dispersion, and dilution capacity. In contrast, the Akdeniz University Central Library represents a more compact academic environment with a two-story configuration and maximum floor dimensions of 32.25 m × 31.65 m. The relatively smaller volume and different spatial organization of this building provide an opportunity to investigate how geometric constraints affect pollutant distribution and ventilation efficiency.

To ensure a representative and spatially resolved dataset, measurement locations were systematically determined based on architectural layout, occupancy zones, and expected airflow pathways. A total of 18 sampling points were established, comprising 11 locations in the Antalya Public Library and 7 locations in the Akdeniz University Library. These points were strategically distributed to capture variations across high-occupancy areas, circulation zones, and relatively stagnant regions, where pollutant accumulation is more likely to occur.

At each measurement location, data were collected at three vertical levels: 0.5 m, representing the seated breathing zone; 1.2 m, corresponding to the average human breathing height; and 1.8 m, representing the upper breathing zone and near-ceiling region. This multi-level measurement strategy was adopted to capture the vertical stratification of particulate matter and $CO_2$ concentrations, which is particularly relevant in indoor environments where buoyancy-driven flows, thermal gradients, and ventilation characteristics can significantly influence pollutant distribution.

Furthermore, measurements were conducted under typical usage conditions to reflect realistic indoor environments, including normal occupancy levels and routine ventilation operation. This approach ensures that the collected data accurately represent actual exposure scenarios and can be reliably used for both statistical evaluation and CFD model validation. By integrating spatially distributed and vertically resolved measurements, the study provides a comprehensive dataset for analyzing indoor pollutant dynamics and supporting high-resolution numerical simulations.

### *2.2 Instrumentation and Data Collection*

Particulate matter (PM) concentrations were measured using a PCE-PCO 2 optical particle counter, which is capable of detecting six particle size fractions, namely PM0.3, PM0.5, PM1, PM2.5, PM5, and PM10. The instrument operates with a constant sampling flow rate of 2.83 L/min and a measurement duration ranging between 10 and 15 seconds per sampling cycle. The device is factory-calibrated, ensuring reliable and consistent measurements across different sampling locations. The use of multi-size particle detection enables a comprehensive assessment of particle size distribution, which is essential for understanding transport dynamics, deposition behavior, and potential health impacts.

Carbon dioxide ($CO_2$) concentration and air temperature were simultaneously measured using a JD-3002 monitoring device. The instrument provides a measurement range of 0–5000 ppm for $CO_2$ and 0–50°C for temperature, with reported accuracies of ±50 ppm and ±0.5°C, respectively. $CO_2$ concentration was used as an indicator of occupancy-related emissions and ventilation performance, providing additional insight into indoor air quality conditions and air exchange effectiveness.

To ensure data reliability and representativeness, measurements were conducted under typical operational conditions, including standard occupancy levels and routine ventilation scenarios. At each sampling point, multiple consecutive readings were taken and averaged to minimize the influence of short-term fluctuations and measurement noise. Care was taken to avoid direct interference from localized sources (e.g., immediate exhalation or proximity to emission points), thereby ensuring that the recorded values reflect the general indoor environment.

All measurements were systematically recorded and organized for further statistical analysis and model validation. The collected dataset provides both spatial and vertical resolution, enabling a detailed evaluation of indoor pollutant distribution patterns and supporting the calibration and validation of the CFD simulations.

doi:10.20944/preprints202603.1733.v1

### *2.3 Statistical Analysis*

Statistical analyses were conducted using IBM SPSS Statistics 26.0 (IBM Corp., Armonk, NY, USA). Descriptive statistics, including mean, median, and standard deviation, were calculated to summarize the central tendency and dispersion of all measured parameters.

Prior to inferential analysis, the normality of the data distribution was assessed using the Kolmogorov–Smirnov test. The results indicated that the majority of the variables did not satisfy the assumption of normality ($p < 0.05$). This finding was further supported by skewness and kurtosis values, confirming the non-Gaussian nature of the dataset. Consequently, non-parametric statistical methods were adopted to ensure robust and reliable analysis without violating underlying test assumptions.

To evaluate differences between the two library environments, the Mann–Whitney U test was applied, as it is suitable for comparing two independent groups with non-normally distributed data. Variations across measurement heights (0.5 m, 1.2 m, and 1.8 m) were analyzed using the Kruskal–Wallis test, which allows for comparison among more than two independent groups. When applicable, median values were used as the primary measure of central tendency due to the non-normal distribution of the data.

Relationships between particulate matter fractions and $CO_2$ concentrations were examined using Spearman's rho correlation coefficient, which is appropriate for identifying monotonic relationships in non-parametric datasets. Correlation strength was interpreted based on standard thresholds, enabling classification into low, moderate, and high relationships.

A significance level of $p < 0.05$ was adopted for all statistical tests. This statistical framework ensures a consistent and reliable evaluation of differences and relationships within the dataset, providing a solid basis for interpreting indoor air quality patterns and supporting subsequent CFD validation.

### *2.4 CFD Modeling and Validation*

To investigate the spatial and temporal evolution of particulate matter within indoor environments, computational fluid dynamics (CFD) simulations were performed using FLOW-3D software. The simulations were designed to replicate realistic indoor conditions based on the experimental measurement setup. A total simulation duration of 3600 seconds was defined to capture both transient and quasi-steady-state particle behavior. The simulation results were analyzed at five representative time steps (324 s, 900 s, 1800 s, 2700 s, and 3600 s) to evaluate the progression of particle dispersion, accumulation, and stabilization within the indoor space.

A structured, volume-based mesh was employed to discretize the computational domain, ensuring adequate resolution of airflow and particle transport phenomena. The airflow field was modeled using the Reynolds-Averaged Navier–Stokes (RANS) approach with the RNG $k–\varepsilon$ turbulence model, which is widely recognized for its robustness and suitability in indoor airflow simulations involving recirculation and low-Reynolds-number effects. The governing physical parameters included an air density of $1.225\ kg/m^3$, dynamic viscosity of $1.81 \times 10^{-5}\ Pa{\cdot}s$, gravitational acceleration of $9.81\ m/s^2$, and particle density of $1000\ kg/m^3$.

Particle transport was simulated using the Euler–Lagrange framework, in which the airflow phase was treated as a continuous medium, while particles were tracked individually as discrete entities. This approach allows for accurate representation of particle trajectories under the combined influence of drag force, gravity, and turbulent dispersion. Separate simulations were conducted for different particle size fractions (PM0.3–PM10), enabling a detailed assessment of size-dependent transport mechanisms, including suspension, sedimentation, and spatial redistribution.

Boundary conditions were defined based on the physical characteristics of the study areas, including airflow inlets, outlets, and wall interactions. The simulations accounted for gravitational settling and inertial effects, which are particularly significant for larger particle fractions. The temporal evolution of particle concentration fields was analyzed through sectional contour visualizations, allowing identification of accumulation zones, airflow-driven transport paths, and regions of limited ventilation efficiency.

Model validation was carried out by comparing CFD-derived average particle concentrations with experimentally measured values obtained from field observations. The results indicated a strong agreement between numerical and experimental data, particularly for coarse particles (PM2.5–PM10), confirming the reliability of the modeling approach. However, larger discrepancies were observed for ultrafine particles (PM0.3–PM0.5), which can be attributed to increased sensitivity to turbulent fluctuations and Brownian motion effects, phenomena that are inherently more challenging to resolve within RANS-based CFD frameworks.

Overall, the combined use of experimental data and CFD simulations provides a robust framework for analyzing indoor particle dynamics, enabling both validation of numerical predictions and enhanced interpretation of pollutant transport behavior under realistic indoor conditions.

## 3. Results

The results of the study are presented through a combination of statistical analyses and numerical simulations to provide a comprehensive evaluation of indoor air quality conditions. This section first summarizes the descriptive statistics of the measured parameters, followed by comparative analyses between different environments and measurement heights. Subsequently, the relationships among variables are examined, and the findings from CFD simulations are presented and validated against experimental data.

### *3.1. Descriptive Statistics of IAQ Parameters*

Table 1 summarizes the statistical distribution of all measured indoor air quality parameters. A pronounced size-dependent gradient is evident, with particle concentrations decreasing systematically as particle diameter increases. Fine particles dominate the indoor environment, with PM0.3 and PM0.5 exhibiting substantially higher concentrations compared to coarse fractions.

The dispersion of fine particles is also markedly higher, as reflected by their large standard deviations and wide concentration ranges (e.g., PM0.3: 4,066–232,103), indicating strong spatial variability and the influence of localized emission and resuspension processes. In contrast, coarse particles (PM5 and PM10) display lower variability and more constrained distributions, suggesting stronger gravitational settling and reduced airborne persistence.

$CO_2$ concentrations remain relatively stable across all measurements, with limited dispersion around the mean value (~408 ppm), implying consistent ventilation performance and the absence of significant accumulation under the observed conditions.

The normality assessment reported in Table 1 confirms that all variables deviate from Gaussian behavior ($p < 0.05$), which is consistent with the observed skewed distributions of particulate matter. This non-normal structure reflects the inherently heterogeneous nature of indoor particle dynamics, driven by intermittent sources, airflow patterns, and spatial constraints.

**Table 1.** Descriptive statistics of measured IAQ parameters.

| **Parameter** | **Mean** | **Std. Dev.** | **Median** | **Min** | **Max** |
|---|---|---|---|---|---|
| $CO_2$ | 407.62 | 33.94 | 400 | 400 | 819 |
| PM0.3 | 21024.18 | 20059.82 | 17443 | 4066 | 232103 |
| PM0.5 | 9317.80 | 8969.47 | 7676 | 1667 | 108767 |
| PM1 | 1908.89 | 1417.41 | 1529 | 278 | 15184 |
| PM2.5 | 443.92 | 260.67 | 370 | 90 | 2322 |
| PM5 | 59.33 | 36.12 | 51 | 6 | 201 |
| PM10 | 29.61 | 19.51 | 25 | 2 | 128 |

### 3.2. Comparison between Libraries and Measurement Heights

The comparative analysis of indoor air quality parameters between the two libraries and across different measurement heights is presented in **Table 2**. As shown in Table 2, none of the measured variables exhibited statistically significant differences between the Antalya Public Library and the Akdeniz University Library (Mann–Whitney U test, $p > 0.05$ for all parameters). Despite differences in building size and spatial configuration, median values for all particulate matter fractions and $CO_2$ concentrations remained comparable between the two environments.

Similarly, the Kruskal–Wallis test results summarized in Table 2 indicate that variations across measurement heights (0.5 m, 1.2 m, and 1.8 m) were not statistically significant ($p > 0.05$). This suggests that vertical stratification of particulate matter and $CO_2$ concentrations is limited, and that the indoor air is relatively well mixed within the studied environments.

However, Table 2 also reveals notable variability in the minimum–maximum ranges, particularly for fine particle fractions such as PM0.3 and PM0.5. These wide ranges indicate localized fluctuations that are not captured by median-based statistical comparisons alone. Slight differences in median values across heights, although not statistically significant, may reflect the influence of occupant activity, airflow heterogeneity, and particle resuspension mechanisms.

The absence of statistically significant differences between the two buildings, as observed in Table 2, suggests that indoor air quality is governed more by airflow distribution and ventilation effectiveness than by building size alone. This finding highlights the importance of detailed airflow analysis, as localized pollutant accumulation zones may exist even in environments that appear statistically similar.

**Table 2.** Comparison of IAQ parameters between libraries and measurement heights

| Parameter | Height (m) | Akdeniz Univ. Library Median (Min–Max) | Antalya Library Median (Min–Max) | Z | p | KW (height) | p |
|---|---|---|---|---|---|---|---|
| $CO_2$ | 0.5 | 400 (400–600) | 400 (400–578) | 0.309 | 0.758 | 5.278 | 0.071 |
| | 1.2 | 400 (400–819) | 400 (400–572) | -0.699 | 0.485 | | |
| | 1.8 | 400 (400–676) | 400 (400–580) | -0.588 | 0.577 | | |
| PM0.3 | 0.5 | 19132 (4944–232103) | 17877 (5178–185795) | -0.396 | 0.692 | 0.326 | 0.849 |
| | 1.2 | 16963 (5421–79304) | 14733 (5083–75196) | -0.769 | 0.442 | | |
| | 1.8 | 19328 (4874–59015) | 17022 (4066–68377) | -0.757 | 0.449 | | |

doi:10.20944/preprints202603.1733.v1

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| PM0.5 | 0.5 | 7572 (2079–108767) | 7762 (2268–81448) | 0.040 | 0.968 | 0.741 | 0.690 |
| | 1.2 | 7200 (2611–33371) | 6924 (2226–31580) | -0.327 | 0.744 | | |
| | 1.8 | 8674 (2356–25387) | 8311 (1667–30863) | -0.098 | 0.922 | | |
| PM1 | 0.5 | 1340 (554–15184) | 1627 (479–11132) | 0.546 | 0.585 | 0.166 | 0.920 |
| PM2.5 | 0.5 | 336 (157–2322) | 384 (153–1779) | 0.922 | 0.357 | 0.379 | 0.828 |
| PM5 | 0.5 | 54 (11–201) | 52 (19–156) | -0.639 | 0.523 | 0.837 | 0.658 |
| PM10 | 0.5 | 30 (7–128) | 26 (6–80) | -0.750 | 0.453 | 1.924 | 0.382 |

### *3.3. Correlation Analysis*

The relationships between indoor air quality parameters were examined using Spearman's rho correlation analysis, and the results are presented in **Table 3**. The analysis reveals a clear structural pattern in the dataset, characterized by strong interdependence among particulate matter fractions and weak associations with $CO_2$ concentrations.

As shown in Table 3, no meaningful correlation is observed between $CO_2$ and any particulate matter fraction, with correlation coefficients remaining close to zero. This indicates that particle concentrations are not directly driven by occupancy-related $CO_2$ levels under the studied conditions, but are instead governed by independent physical processes.

In contrast, particulate matter fractions exhibit strong and consistent positive correlations, particularly among fine particles. The highest correlation is observed between PM0.3 and PM0.5 ($r = 0.977$), followed by PM0.5–PM1 ($r = 0.918$) and PM1–PM2.5 ($r = 0.901$). This pattern suggests that fine particles share common sources and are transported through similar airflow mechanisms within the indoor environment.

A gradual decline in correlation strength is observed with increasing particle size differences. For instance, the relatively weak relationship between PM0.3 and PM10 ($r = 0.192$) indicates that coarse particles are influenced by different governing mechanisms, such as gravitational settling and localized resuspension, rather than uniform transport processes.

Strong correlations among larger particle fractions, such as PM5–PM10 ($r = 0.892$) and PM2.5–PM5 ($r = 0.840$), further highlight the role of size-dependent physical behavior in particle dynamics. These findings indicate that while fine particles tend to behave coherently within airflow structures, coarse particles exhibit more localized and deposition-driven characteristics.

Overall, the correlation structure presented in Table 3 demonstrates that indoor particulate matter dynamics are primarily controlled by particle size and transport physics rather than occupancy indicators such as $CO_2$. This reinforces the importance of airflow distribution and particle behavior modeling, supporting the use of CFD simulations for a more detailed interpretation of indoor air quality patterns.

**Table 3.** Spearman correlation coefficients between IAQ parameters

| Parameter | $CO_2$ | PM0.3 | PM0.5 | PM1 | PM2.5 | PM5 | PM10 |
|---|---|---|---|---|---|---|---|
| $CO_2$ | 1 | 0.084 | 0.057 | 0.002 | -0.035 | -0.095 | -0.104 |
| PM0.3 | 0.084 | 1 | 0.977 | 0.854 | 0.683 | 0.377 | 0.192 |
| PM0.5 | 0.057 | 0.977 | 1 | 0.918 | 0.773 | 0.462 | 0.270 |
| PM1 | 0.002 | 0.854 | 0.918 | 1 | 0.901 | 0.649 | 0.464 |
| PM2.5 | -0.035 | 0.683 | 0.773 | 0.901 | 1 | 0.840 | 0.688 |
| PM5 | -0.095 | 0.377 | 0.462 | 0.649 | 0.840 | 1 | 0.892 |
| PM10 | -0.104 | 0.192 | 0.270 | 0.464 | 0.688 | 0.892 | 1 |

### *3.4. CFD Results and Model Validation*

The spatial and temporal evolution of particulate matter within the indoor environments was analyzed using CFD simulations, and the results are illustrated through representative contour plots in Figures 1–3. These visualizations provide a detailed understanding of particle transport mechanisms, accumulation zones, and time-dependent dispersion behavior.

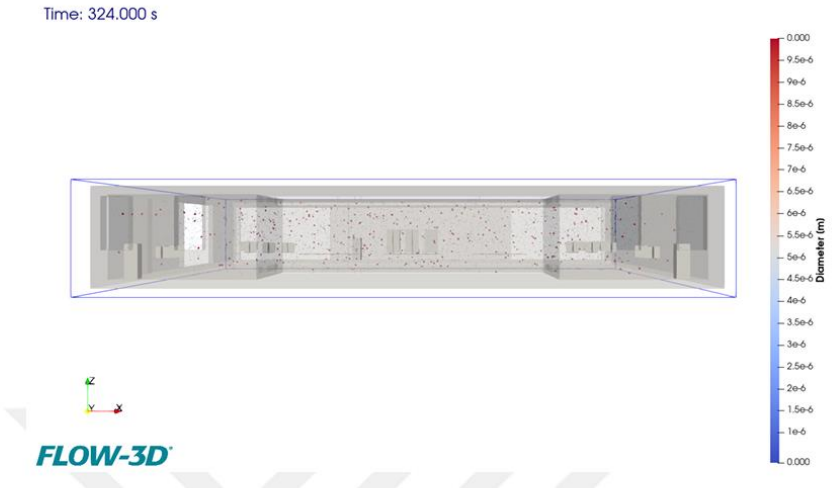
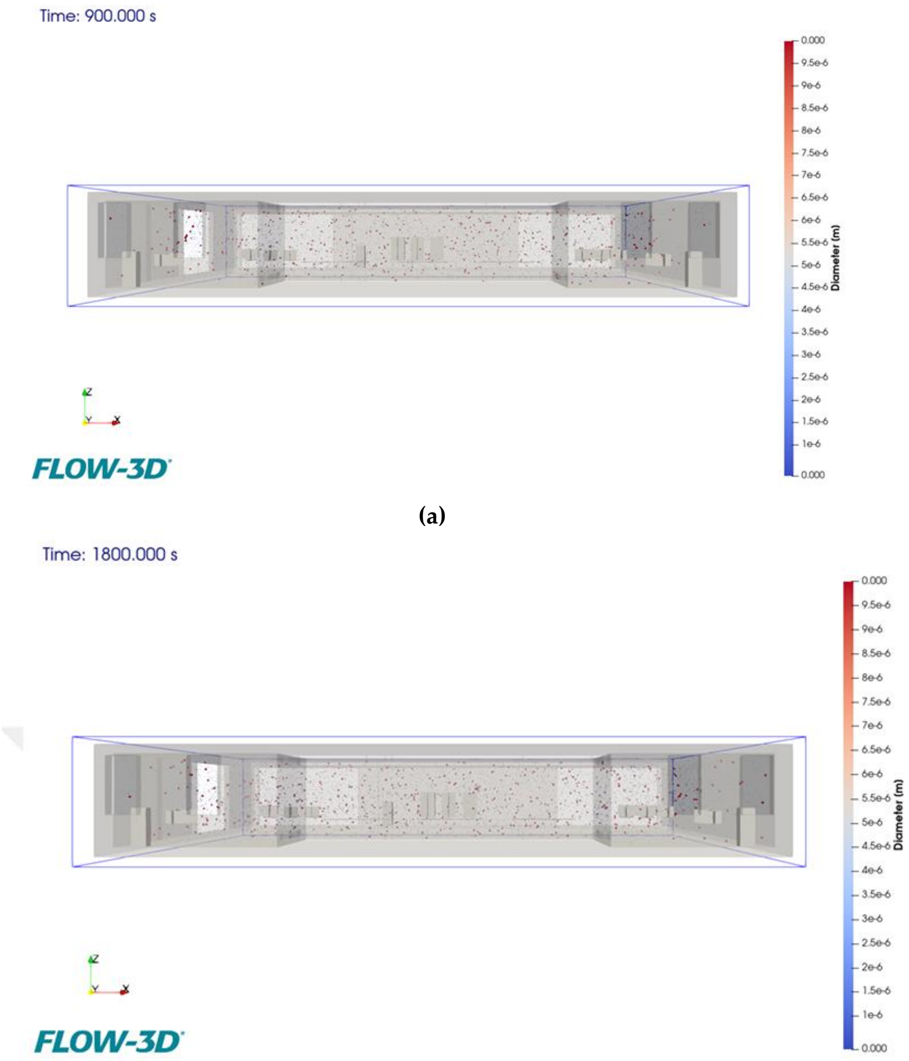


**Figure 1.** Spatial distribution of particulate matter at the initial stage of the simulation (t = 324 s), illustrating the early-phase dispersion behavior dominated by airflow-induced transport. Fine particles remain predominantly suspended in the upper regions of the domain due to low settling velocities and limited vertical mixing.

At the early simulation stage (324 s), particles are primarily concentrated in the upper regions of the indoor space, as shown in Figure 1. This initial distribution is governed by upward airflow structures and the low settling velocity of fine particles. As a result, smaller particles (PM0.3–PM1.0) remain suspended near the ceiling and exhibit limited vertical mixing during this phase.

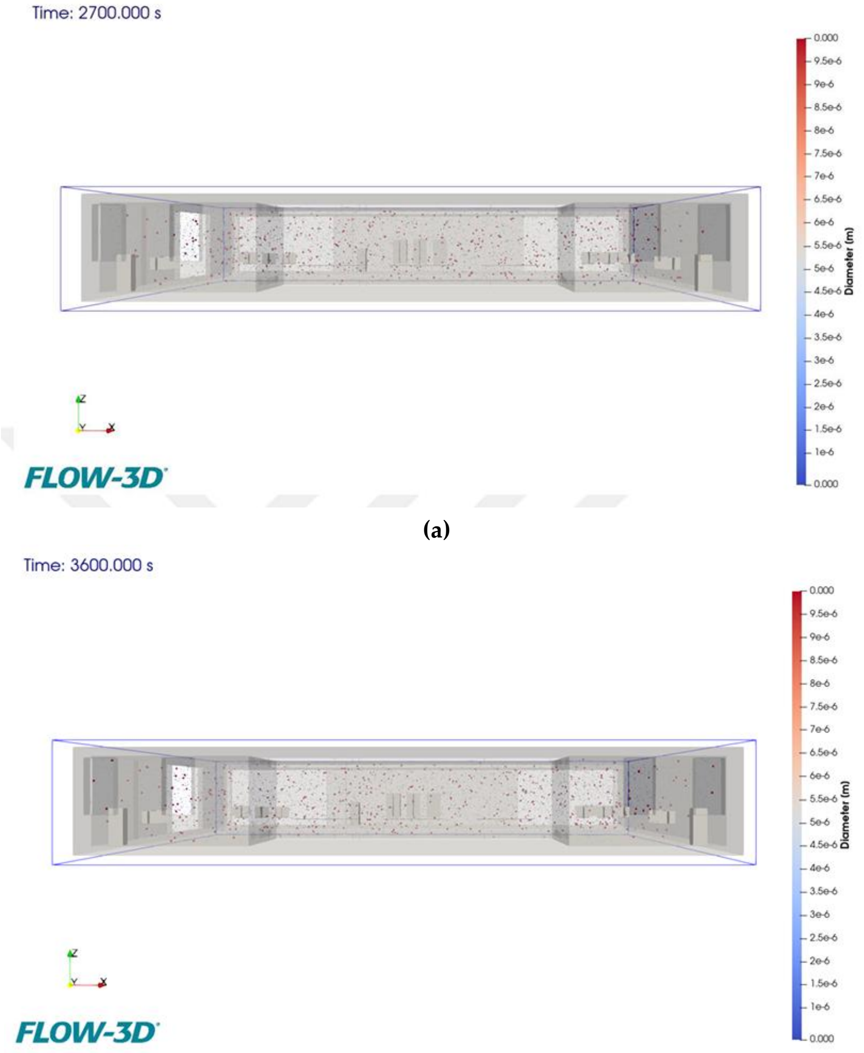


**(a)**

**(b)**

**Figure 2.** Temporal evolution of particulate matter dispersion within the indoor environment: (a) particle distribution at t = 900 s, showing enhanced spatial spreading and the onset of downward transport due to gravitational effects; (b) particle distribution at t = 1800 s, indicating increased mixing and the penetration of particles into the occupant breathing zone, resulting in more homogeneous concentration fields.

As the simulation progresses (900 s and 1800 s), particle dispersion becomes more spatially distributed across the indoor volume (Figure 2). A gradual downward transport is observed, driven by gravitational settling and weak convective air movements. During this stage, increased concentrations appear within the occupant breathing zone (~1.2 m), indicating a transition toward exposure-relevant conditions.



**(a)**

**(b)**

**Figure 3.** Particle distribution at later simulation stages approaching quasi-steady conditions: (a) particle distribution at t = 2700 s, demonstrating stabilization of airflow patterns and increased deposition of coarse particles; (b) particle distribution at t = 3600 s, illustrating quasi-equilibrium conditions characterized by particle accumulation near floor regions and sustained suspension of fine particles within the indoor volume.

At later stages (2700 s and 3600 s), the system approaches a quasi-steady state, as illustrated in Figure 3. Larger particles (PM2.5–PM10) show clear deposition behavior and accumulate near the floor due to gravitational effects. In contrast, smaller particles remain suspended and continue to circulate within the indoor environment, maintaining noticeable concentrations at occupant height. This highlights the persistence of fine particles and their potential contribution to prolonged exposure.

The simulations also reveal localized accumulation zones in regions with low airflow velocity, particularly near geometric constraints and poorly ventilated areas. These zones are not easily detectable through point-based measurements, demonstrating the added value of CFD in identifying spatial heterogeneity in indoor air quality.

Model validation was performed by comparing CFD-predicted average concentrations with experimental measurements, as summarized in Tables 4–6. The comparison indicates strong agreement for larger particle fractions (PM2.5–PM10), confirming that the model accurately captures dominant physical processes such as advection and gravitational settling. However, greater deviations are observed for ultrafine particles (PM0.3–PM0.5), which can be attributed to turbulence-

doi:10.20944/preprints202603.1733.v1

induced dispersion and stochastic particle motion, effects that are not fully resolved within the RANS-based modeling framework.

Overall, the CFD results demonstrate that indoor particle dynamics are strongly size-dependent and governed by the interaction between airflow patterns and gravitational forces. The integration of experimental data with numerical simulations provides a robust framework for evaluating indoor air quality and identifying high-exposure zones in complex indoor environments.

## 4. Discussion

The results of this study provide a comprehensive assessment of indoor particulate matter dynamics by integrating experimental measurements with CFD simulations. The findings reveal that particle behavior is strongly governed by size-dependent physical mechanisms, airflow patterns, and indoor environmental conditions.

One of the most significant outcomes is the strong correlation observed among fine particulate fractions (PM0.3–PM2.5), which suggests a common origin and similar transport behavior. This is consistent with previous studies emphasizing that fine particles tend to follow airflow streamlines and remain suspended for extended periods due to their low settling velocities [3,6,30]. In contrast, weaker correlations between fine and coarse particles indicate that larger particles are more influenced by gravitational settling and localized resuspension processes, as also reported in the literature [4,8].

The absence of a meaningful relationship between $CO_2$ concentrations and particulate matter levels highlights the complexity of indoor air quality dynamics. While $CO_2$ is widely used as an indicator of occupancy and ventilation efficiency, it does not adequately represent particulate behavior, which is influenced by additional factors such as particle sources, deposition mechanisms, and airflow distribution [5,31]. This finding reinforces the need to evaluate indoor air quality using multi-parameter approaches rather than relying solely on $CO_2$ levels.

CFD simulations provided further insight into spatial heterogeneity and temporal evolution of particle distribution. The results demonstrated that fine particles remain suspended at occupant level even at later simulation stages, posing a potential long-term exposure risk. Similar observations have been reported in CFD-based studies, where ultrafine particles exhibit prolonged residence times and complex dispersion patterns due to turbulence and Brownian motion effects [1,2,9]. In contrast, coarse particles showed clear deposition behavior, accumulating near floor regions, which aligns with established sedimentation theories [6,30].

Another important finding is the identification of localized accumulation zones associated with low airflow regions. These areas, often influenced by room geometry and ventilation design, can lead to elevated exposure levels despite overall acceptable average conditions. Previous studies have similarly highlighted the role of ventilation effectiveness and airflow distribution in controlling indoor pollutant dispersion [2,7].

From an engineering perspective, these results emphasize the critical importance of ventilation system design in controlling indoor air quality. Optimizing air distribution, minimizing stagnant zones, and enhancing mixing efficiency are essential strategies for reducing particle concentration levels. In this context, CFD modeling proves to be a powerful decision-support tool, enabling the evaluation of different ventilation scenarios and the identification of high-risk zones that are not easily captured through experimental measurements alone.

Despite these contributions, several limitations should be acknowledged. The simulations were conducted using a RANS-based turbulence model, which may not fully capture small-scale turbulent structures affecting ultrafine particle dynamics. Additionally, dynamic indoor factors such as occupant movement and transient source variations were not explicitly modeled. Future studies should consider advanced turbulence models such as LES and incorporate real-time occupancy behavior and environmental variability to improve model accuracy and applicability.

## 5. Conclusions

This study investigated indoor particulate matter distribution in library environments through a combined experimental and CFD-based approach. The results demonstrate that indoor particle behavior is strongly influenced by particle size, airflow patterns, and ventilation characteristics.

Fine particles (PM0.3–PM2.5) were found to remain suspended within the indoor environment and accumulate within the occupant breathing zone, indicating a potential long-term exposure risk. In contrast, coarse particles (PM5–PM10) exhibited clear deposition behavior, primarily accumulating near floor regions due to gravitational settling. These findings highlight the importance of considering particle size distribution in indoor air quality assessments.

The statistical analysis revealed strong correlations among particulate fractions, while $CO_2$ concentrations showed weak relationships with particle levels, suggesting that $CO_2$ alone is not a sufficient indicator of indoor particulate pollution. This underscores the need for multi-parameter monitoring strategies in indoor environments.

CFD simulations successfully captured the temporal evolution and spatial distribution of particles, demonstrating good agreement with experimental measurements, particularly for larger particle fractions. The simulations also identified localized accumulation zones associated with poor airflow conditions, emphasizing the importance of ventilation design in minimizing exposure risks.

Overall, the integration of experimental measurements and CFD modeling provides a robust framework for evaluating indoor air quality and optimizing ventilation strategies. The findings of this study contribute to the development of healthier indoor environments by supporting evidence-based design and operation of HVAC systems.

Future work should focus on incorporating dynamic indoor conditions, advanced turbulence modeling approaches, and real-time monitoring systems to further enhance the accuracy and applicability of CFD-based indoor air quality assessments.

**Author Contributions:** Conceptualization, A.U.D. and A.Ç.; methodology, A.U.D.; software, A.U.D.; validation, A.U.D., A.Ç. and L.A.; formal analysis, A.U.D.; investigation, A.U.D.; resources, A.U.D.; data curation, A.U.D.; writing—original draft preparation, A.U.D.; writing—review and editing, A.Ç. and L.A.; visualization, A.U.D.; supervision, A.Ç. and L.A.; project administration, A.Ç.; funding acquisition, none. All authors have read and agreed to the published version of the manuscript.

**Funding:** The APC was funded by the authors.

**Data Availability Statement:** The data presented in this study are available on reasonable request from the corresponding author.

**Acknowledgments:** During the preparation of this manuscript, the authors used AI-based language tools for language refinement. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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