A Real-Time Air Quality and Public Health Monitoring and Management Model

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KEYWORDS

Air Quality, Public Health, Management, Health Risk

ABSTRACT

Inhalation of air contaminants leads to various detrimental health consequences. These harmful effects happen whenever people are directly exposed to air pollution. Health Risks (HR) lowers the intensity, duration, and regularity of exposure to air pollution. The system provides customized Air Quality (AQ) data and related HR information. This system depends on pollution, the city layout, the weather, and the chemical and physical processes that affect the pollutant's mobility. It measures the AQ levels in many places, like homes, schools, businesses, and transportation for Public Health (PH). It uses Big Data (BD) and a surveillance system to monitor the street-level AQ. The street-level AQ modeling shows higher accuracy than reference data [17]. The PH and prediction of HR are parts of the ongoing process. It shares knowledge about air pollution and its impact on PH.

1. Introduction

The World Health Organization (WHO) found that poor Air Quality (AQ) caused 4.8 million deaths in 2020 [1]. Strokes, Chronic Obstructive Pulmonary Disease (COPD), and lung illnesses were responsible for 19%, 25%, and 27%, respectively. The air pollutants in the indoor environment are two to four times higher than those outside[3]. In the United States, people spend 24.72 hours indoors and 2.31 hours in cars or other forms of transportation. Indoor Air Quality (IAQ) is a significant environmental Health Risk (HR) due to the higher pollution inside buildings [2].

The indoor environment can impact Public Health (PH), which can be categorized as Building-Related Illness (BRI) or Sick Building Syndrome (SBS) [16]. BRI pertains to symptoms that are characterized based on clinical criteria and are diagnosed through the presence of airborne pollutants in buildings. SBS is a constellation of symptoms of unknown etiology. It should be emphasized that SBS results from inadequate indoor AQ.

Current PH research indicates noticeable differences in the PH impacts caused by exposure to air pollution at the individual level [12]. These effects are evident in symptoms such as wheezing, difficulty breathing, coughing, etc. An investigation involving 300 individuals in suitable PH in Taipei demonstrated that closing windows decreased the entry of surrounding particles into households while enhancing the participants' Coronary Heart Disease (CHD). A further study involving 95 individuals diagnosed with CHD revealed that the application of effective face masks resulted in a reduction of symptoms. This reduction occurred during a deteriorated AQ in Beijing, where the masks were employed to minimize personal contact with ambient particulates.

The typical daily individual contact in the surrounding environment varied by a factor of 10 throughout a 92% frequency range among a modeled population of 0.2 million people living in Philadelphia [4]. Offering individuals customized air pollutant exposure information and guidance on how to minimize these exposures can assist them in identifying the specific locations and times when they are most exposed to significant amounts of pollutants [14]. This will ultimately improve their overall well-being. The susceptibility of individuals to the negative impacts of AQ varies, and those who are more susceptible are likely to experience more significant benefits from initiatives aimed at reducing their exposure [13]. Individuals can enhance their ability to manage personal hazards and advantages by understanding if they are more susceptible than the average person to the detrimental impacts of specific AQ and being aware of when and where these exposures are more severe [6]. Accurately measuring the variation in exposure to AQ requires detailed information about the concentration of contaminants in specific locations and at certain times, as well as data on individual movement.

The obstacles to measuring the differences in exposure between individuals are being eliminated due to the progress in intelligent technology [19]. Urban AQ designs, like the atmospheric dispersion modeling, allow the monitoring of city AQ [10]. These models provide detailed information about the movement of pollutants from their origins to the places where they are detected, with a high level of accuracy in terms of time and location, even at the street level [18]. Using Big Data (BD) technologies enables the integration of data from diverse sources and styles to capture real-time fluctuations in traffic and other variables that impact AQ levels inside an urban area [9]. Recent advancements in AQ detection have made it possible to create portable sensor bundles that can measure levels of AQ in various settings where people commonly spend their time, including indoor spaces and during transportation [5]. Smartphones provide effective data gathering on individual movement, which is valuable for obtaining individual time-use statistics for exposure assessment [15].

The system provides people with personalized data on their popularity to AQ and helps them oversee their HR [11]. This system takes advantage of technological advances that make it easier to provide this information [8]. The latest iteration of the suggested approach can offer real-time estimations of concentrations of AQ at street level for numerous contaminants [7]. It can forecast these levels for 48 hours. The system gathered comprehensive data on AQ levels in typical indoor, in-vehicle, and outdoor settings. This data will expand the suggested structure and predict individual exposure levels.

The aims of this article are: (1) to determine the most advanced methods associated with estimating personal contact; (2) to create a system that combines these methods to offer real-time AQ intensity predicts at the street levels; and (3) to verify the accuracy of the system using real-world observational information.

2. Methodology

The introduction of the several technologies and data sources mentioned earlier establishes a basis for creating a system of data that combines them to offer individuals customized information regarding their particular exposures and strategies for handling them. However, the technique can be applied to other cases. Figure 1 depicts the suggested system for AQ monitoring and its main elements.

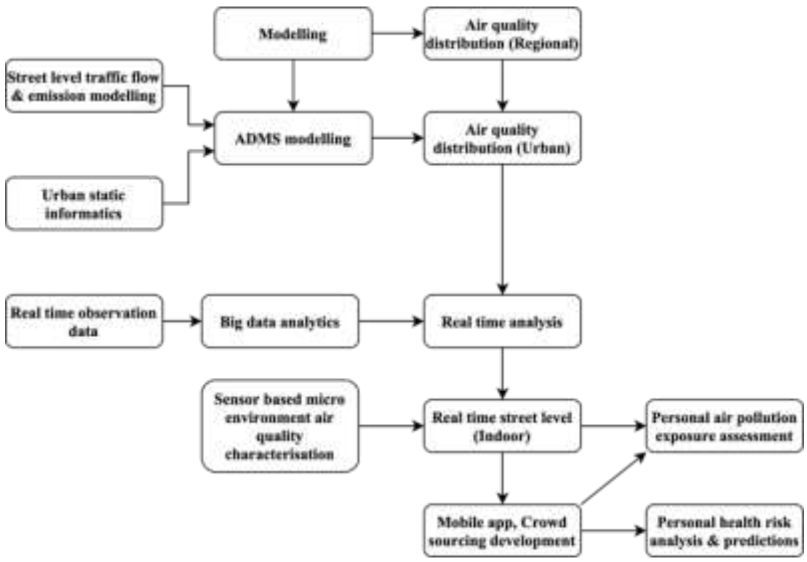

Figure 1. The architecture of the proposed AQ monitoring system

The present stage of the suggested system relies on quantifying pollutants at regional-to-local scales, modeling AQ at the street level, using Big Data Analytics (BDA) to enhance AQ predictions, and conducting extensive field tests to determine quantities of AQ in microenvironments. The planned project is being developed to include location monitoring, crowdsourcing, measurement of personal contact, linking AQ complaints with contact, and providing consumers with suggestions for reducing exposure. The proposed system is composed of seven subsystems, namely: (1) integrated Urban AQ monitoring; (2) street-level circulation and release simulation; (3) BDA; (4) sensor-based microenvironmental AQ description; (5) mobile application and crowdsourcing growth; (6) particular AQ exposure evaluation; and (7) particular PH-response evaluation and forecasting. This proposal aims to furnish data regarding individual susceptibility to AQ from the surrounding environment. The existing method does not explicitly account for pollutants produced by indoor pursuits or lifestyle choices, such as cooking and smoking. Indoor pollutants are considered when estimating the indoor-to-outdoor proportion of atmospheric AQ based on microenvironmental measures.

- AQ forecasting

The efficacy of the suggested AQ forecasting is reviewed by comparing it with the observed AQ concentrations from measuring locations. The hourly mean forecasts are assessed using three different combinations of modeling methods: (1) the local Congestion Mitigation & Air Quality (CMAQ) system, (2) the combined CMAQ/ Atmospheric Dispersion Modelling System (ADMS)-Urban method, and (3) the combined Urban modeling enhanced with BD fusion, which is commonly referred to as the proposed method.

To maintain consistency throughout all three methods, only monitoring locations not used in model synthesis or BD fusion are employed for verification. The testing sites consist of four generic sites used to evaluate the intensity forecast over a vast region (general verification sites) and three roadside sites utilized to assess the AQ intensity estimates at street level (roadside testing websites). For evaluation purposes, February (winter) and June (summer) 2023 have been chosen as an illustration. Various air pollutants, such as $PM_{2.5}$, PM_{10}, NO_2, and O_3, are assessed with PH measures. The hourly data match the hourly model findings. An Index Of Agreement (IOA) assesses the concordance between the measured and expected values. The IOA measures the degree to which the differences between hourly measurements and the overall average correlate to the differences between hourly forecasts and the overall average. IOA is employed in the assessment of AQ models.

3. Results and discussion

The initial iteration of the suggested application underwent a soft launch in February 2022, followed by an official release in June 2022. Before the official launch, the app downloading varied between 145 and 255 monthly. After the formal launch in June, there was a significant increase, reaching a peak of over 1800 downloads. The number of downloads kept increasing steadily, reaching 6500 as of November 15, 2023.

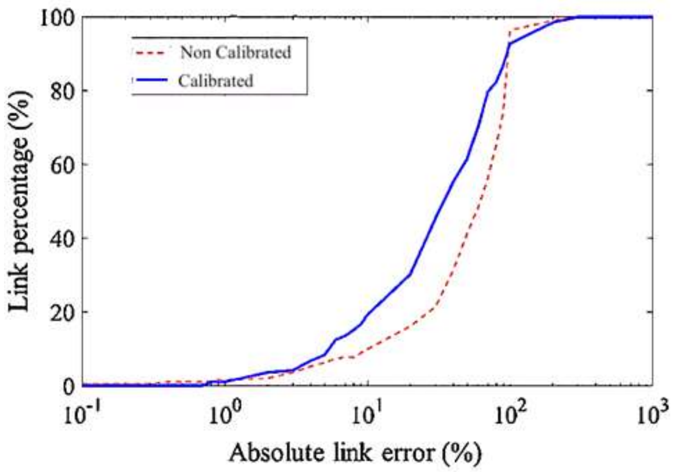

Figure 2. Air quality analysis

Figure 2 displays the cumulative dispersion of link defects between the annual peak-time modeling and the measured link counts, both before and after measurement. The term link error pertains to the exact percentage difference between the simulated and actual traffic counts for all vehicles on a specific link. The mean link error fell from over 60% before calibrating to less than 30% post-normalization. The calibration process enhanced the accuracy of the traffic simulations on links experiencing high traffic volumes.

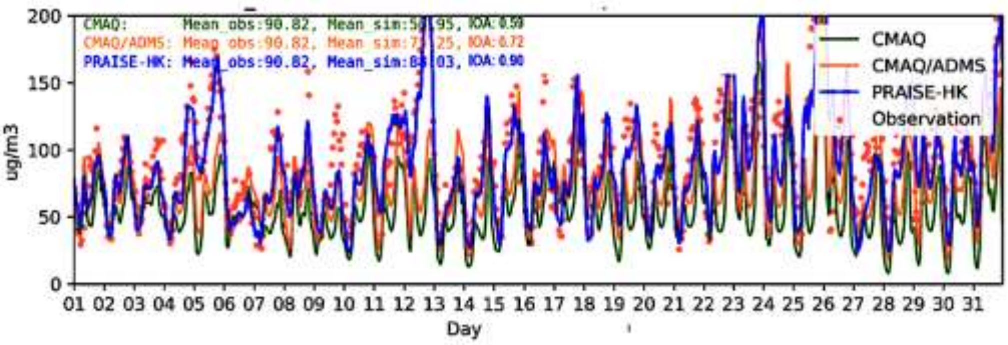

Figure 3(a). Air quality data in February 2023

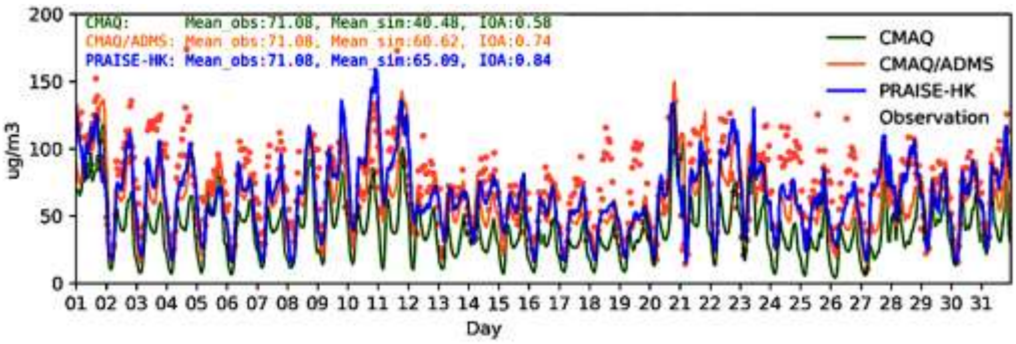

Figure 3(b). Air quality data in June 2023

Figures 3(a) and 3(b) display time series and association plots of hourly simulated and measured NO_2 emissions at a roadside location for February and June 2023. The findings demonstrated constant model efficiency for both the summer and winter seasons. The local CMAQ approach's coarse granularity led to underestimating roadside AQ. This indicates that the algorithm could be more effective in accurately representing street-level AQ, assuming pollution is evenly distributed inside each grid cell. CMAQ-ADMS-Urban improved AQ prediction accuracy by incorporating an evolving traffic simulation framework to quantify vehicle emissions. The IOA values for CMAQ-ADMS-Urban are 0.68 and 0.61 for February and June, respectively, but the IOA values for CMAQ alone are 0.42 and 0.49. The suggested AQ forecasts demonstrated the highest level of concurrence with the data, achieving IOA values of 0.87 and 0.79 for February and June, respectively. This can be credited to integrating data fusion with BDA using the CMAQ-ADMS-Urban framework.

4. Conclusion and future scope

The impact of AQ on PH and quality of life is significant. Supplying individuals with personal AQ data is crucial in helping them control their exposure and associated HR. A system is presented that combines technology and information from several fields to facilitate the calculation of individual exposure. The system was developed using data on emission-producing action and detailed urban morphology, advanced modeling of physical and chemical processes in pollution transportation, and incorporating BD from sensor surveillance, tracking of movements, and crowdsourcing. It aims to analyze and predict AQ, personal contact, and PH outcomes at a high-resolution urban scale.

The AQ forecast by the combined system demonstrated enhanced agreement with roadside AQ tracks, with the IOA for NO2 improving by 25%–35% compared to conventional local AQ modeling. The proposed approach, merging BD with real-time data in the Urban modeling structure, demonstrated the highest concordance with measurements. It achieved IOA values exceeding 0.78 for all modeled contaminants and the corresponding HR in winter and summer. The proposed examination of contact and self-reported impact enhances the capacity to assess the effects of air pollution on PH, particularly the correlations between exposure and diseases, as well as the interplay between genetic and ecological elements in the incidence of diseases.

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