Integrating Agent-Based Traffic Modeling with Pollution Emission and Dispersion Models: A Comprehensive Approach to Simulate Urban Air Pollution

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***Abstract*—Traffic and air pollution are two of the most connected aspects that contribute to climate change especially in third world countries. Being one of the most populated countries, Bangladesh had an average AQI rating of 156 in the year 2022. The lack of traffic regulations and threshold of vehicle emissions asks for a more decisive and accurate representation of traffic simulation coupled with an air pollution simulation system. To facilitate investigations evaluating this situation, a more comprehensive approach is required in simulating traffic related air pollution. Regular traffic simulations carried out using driving cycles or patterns often provide inaccurate and unrealistic results. This paper introduces agent based simulation which have provided promising results in modelling traffic and transport systems. The aim of this study is to provide a more realistic simulation connecting traffic with air quality index in urban areas. We show how agent based simulation can be properly connected with emission and dispersion models. We then evaluate the results generated from the simulation and contrast them against real-world information.**

***Index Terms*—traffic simulation, agent-based modeling, emissions modeling, air pollution, air quality index, vehicle emissions, traffic congestion, dynamic simulation, transportation systems, dispersion models**

I. Introduction

The process of urbanization, accompanied by the growing needs of contemporary societies, has led to intricate challenges, with urban air pollution emerging as a significant issue. The negative impacts of the endangered air quality on public health, environmental well-being, and the overall standard of living highlight the pressing need for the creation of sophisticated and holistic methodologies to analyze and address urban air pollution. A research inquiry delves into the intricate connection between urbanization and air pollution, with a specific emphasis on global-scale PM2.5 pollutants [6]. The results indicate that demographic urbanization consistently leads to elevated PM2.5 concentrations observed in different income based sub panels, encompassing average, below average, middle higher and higher income categories. Conversely, spatial urbanization demonstrates a detrimental impact on air pollution in high-income countries but exerts a positive influence in other contexts. Furthermore, there is a continuous intensification of air pollution in Bangladesh. The significant attention given to Dhaka, recognized as one of the most polluted cities worldwide based on the Air Quality Index, emphasizes the seriousness of the situation [5]. Major contributors to hazardous airborne particles are identified as vehicle emissions, industrial activities, and unplanned urbanization. The negative impacts of air pollution on human health encompass a spectrum from respiratory diseases to cancer, cardiovascular issues, immunologic disorders, hematologic complications, and reproductive system disorders. The gravity of the issue is further underscored by the alarming statistic that approximately 9 million deaths globally each year are attributed to anthropogenic air pollution, with Bangladesh experiencing a significant share of this burden [5]. Conventional methods such as the use of box models, gaussian models, eulerian models and cfd models are employed for air quality assessment [7]. However, these established techniques often employ oversimplified representations of traffic flow and emission sources, limiting their capacity to capture the complex spatial and temporal dynamics of urban air pollution. While different studies in open environments exhibit diverse correlations between gas and particle concentrations, the situation becomes considerably more intricate in urban environments characterized by turbulence and dispersed emissions [7]. In such complex environments, the shortcomings of employing simplistic box models for air quality modeling become evident. Moreover, an alternative investigation suggested a hybrid agent-based modeling framework that combines the sophisticated cognitive capacities of agents with a macroscopic traffic flow model. This integration enables authentic behavioral depictions of a population while maintaining computational efficiency [8]. In our study, we propose enhancing the comprehension of the intricate relationship between urban traffic and air pollution by integrating agent-based traffic modeling with dispersion models. This integration provides valuable insights for promoting sustainable urban development and effective pollution control. Agent-based traffic modeling captures individual drivers' behaviors, including route choices, vehicle interactions, and decision-making, offering a more authentic representation of traffic dynamics in urban environments. Additionally, dispersion models, within the realm of environmental science and air quality management, are computational tools used to simulate the movement and spread of pollutants in the atmosphere. These models aid in predicting how pollutants emitted from diverse sources disperse, mix, and ultimately reach different locations in the surrounding air. Hence, the goals of our research extend beyond simple integration; they strive to establish a comprehensive framework with the capability to simulate urban air pollution with a high level of accuracy. In the following sections, we illustrate the methodology used to integrate these modeling components, present significant findings, and examine the consequences of our comprehensive approach for investigating urban air pollution.

II. Related Research

[1] presents an integrated modelling system called SIMTRAP which simulates traffic flow, emissions, and the dispersion of air pollution. The key components include: (i) a mesoscopic dynamic traffic flow model called DYNEMO that uses parameters like speed and acceleration to simulate vehicle behaviors; (ii) a statistical model to estimate vehicle emissions based on vehicle types and driving patterns; (iii) DYMOS, an air pollution transport and chemistry model, simulates pollutant dispersion; (iv) these models are connected in sequence to simulate the effect in pollutant concentrations due to traffic conditions. An application case study modelling air pollution in Berlin has been demonstrated using this integrated model workflow. In summary, traffic flow and emissions were simulated using DYNEMO; emissions were input to DYMOS to calculate pollutant transport and ozone chemistry. This system generated estimates of spatial emissions and concentration fields which were then used for scenario analysis. Overall, they demonstrate a promising modelling framework integrating traffic, emissions, and air quality models to assess the impacts of urban transportation on air pollution. One of the notable limitations is that the emission model is not directly coupled with the dynamic vehicle activities, rather it uses the driving patterns making it less realistic. Another limitation is that the simulation has been run only once over the case study limiting its validity over other real-world measurements.

In another study [2], a different approach, such as taking real-world measurements, was taken in order to achieve more valid results. The key components proposed in this study included: (i) taking measurements from air quality monitoring stations to measure pollutant concentrations; (ii) monitoring traffic at different stations to measure emissions and vehicle flows; (iii) a data management system to connect these elements. Their models estimate emissions from traffic patterns observed from the traffic monitoring stations and compare these modeled concentrations to real-time measurements for validation. Another case study in Beijing was used to demonstrate the applicability of this concept and further evaluate the needs for improving the transportation system. The results highlighted the benefits of coupling real-time measurements with emission models. Their approach is more closely aligned with an agent based approach where the monitoring stations are not required.

In a study [3] related to agent based traffic simulators, an open source agent based traffic simulator, MATSim, has some key features enabling direct communication with an emission model. MATSim provides a co-evolutionary optimization process that is automated once configured and its modelling fits emissions analysis across full trips of an individual vehicle. Custom extensions allow it to be coupled with emissions modelling components from third parties making it highly modular. [4] describes a dynamic network simulation methodology carried out using route-based microscopic simulation in AIMSUN. Vehicles are assigned origins and destinations where they follow user-defined paths or dynamic shortest paths that are periodically recalculated based on updated link travel times. The overall simulation process works in steps: (i) initial shortest paths are calculated using predefined link costs from origin to destination; (ii) demand is simulated for a short period to collect link statistics; (iii) updated route information is then provided to all vehicles; (iv) steps (ii) and (iii) are repeated in order to simulate a dynamic environment.

Building on these insights, this study aims to link agent based simulation with traditional methods of modelling traffic and emissions. In order to address the limitations observed in previous studies and contribute to the existing research on this topic, we have implemented a new approach that combines agent based traffic simulation with emission models.

III. Methodology

In this section, the methodology employed to integrate an emission model with a microscopic dynamic traffic model is outlined. It is essential to note that the simulation discussed herein was not conducted as part of the current study but is based on findings derived from an existing work [4]. The chosen methodology involves synthesizing and adapting information from this source to address the research objectives outlined in this paper.

A. Data Synthesis from AIMSUN Traffic Model

In order to integrate the traffic model and emissions model properly, valid data should be collected that can be directly connected to the emission model. The following are synthesized data collected from a simulation study [4] that uses AIMSUN traffic model.

a) Time-dependent link speeds: In this microscopic traffic simulation, the individual vehicles are represented as entities with certain characteristics that include speed among other important factors. The simulation uses car-following and lane changing models to determine each vehicle speed on each link representing a road over time. An average speed of specific vehicle types in each specific link can be calculated from the simulation providing insights into changes in speeds of traffic dynamically.

b) Time-dependent link travel times: Detailed vehicle paths across the links are simulated to model the time it takes for an individual vehicle to travel a specific link. Using the acceleration, deceleration and lane changes data, the travel times for a specific vehicle type can be calculated. The results can then be summed up to get information about the total travel time over a specific link for a vehicle type. We can repeat the same steps for all the segments of the road network, thus obtaining travel durations ordered by vehicle type along with link id.

c) Time-dependent path flows: As the simulation assigns vehicles to specific routes and therefore tracking the movement along these paths, the flow of vehicles can be understood in each link. This provides insight into the number of vehicles on each route which is helpful for analyzing and identifying busy routes at a particular time.

d) Queues: Tracking the detailed vehicle positions allows proper identification of queues (buildups of vehicles waiting in specific road links). Some key information can be obtained from these information such as: length of queues, duration spent in queues and the locations of the queues (link id). Queues are essential for assessing congestion in different areas and identifying potential flaws in road networks/traffic regulations.

B. CMEM Architecture Integration

Building upon the collected data, we integrate Comprehensive Modal Emissions Model (CMEM) [9] architecture to introduce emissions modelling. In this study, we will use a simplified model with assumptions such as: constant vehicle trip parameters over a certain link with varying speed. The vehicles defined in this study are divided into three categories: light, medium and heavy weight. Each of this class will have some common parameters as well as some vehicle specific parameters as employed by [10].

We have synthesized the typical vehicle common data provided by [10] to fit third world country vehicle information. Some of the data are obtained from the traffic model previously stated. The vehicle specific parameters for light, medium and heavy duty vehicles are also adapted to fit vehicle types in third world countries. Parameters such as engine speed, engine friction factor and curb weight uses average of those vehicle types with respect to their classes. One of the key components of this model is that it calculates second by second emissions profiles thus enabling direct input from the traffic model once obtaining the vehicle specific parameters. With the time-dependent outputs from the AIMSUN traffic model, the CMEM model is able to provide numerical values for a number of things providing insight into the air pollution:

a) Emission estimates: Quantitative values for emissions that represent the majority of air pollution, such as particulate matter (PM), nitrogen oxides (NOx), sulfur dioxide (SO2), carbon monoxide (CO), and volatile organic compounds (VOCs) are obtained.

b) Temporal Analysis: The CMEM model architecture allows us to obtain time-dependent emission profiles. This time-dependency coupled with the traffic model allows continuous data on emission profiles.

c) Geographic distribution of emissions: Using information from specific links in a road network allows us to locate the areas or segments where higher emissions are expected.

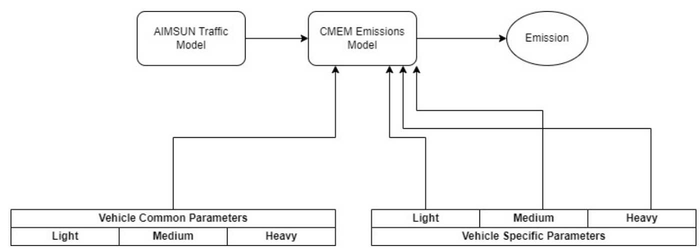

Fig. 1. Integration of sub-models

The key components and parameters for integrating a dynamic traffic model with an emissions model has been outlined in this methodology. Developing and implementing a simulation to obtain emissions result in third world countries due to traffic remains as a next step for follow-on research.

IV. Implementation

In this study, the synthesized data that we obtained from the AIMSUN model will be used to establish a mathematical model that estimates the emissions from the CMEM architecture. The time-dependent values found in the AIMSUN model are given the following notations: n_i, the number of vehicles in the i^{th} link; d_i, the length of the i^{th} link; $t_{i,j}$, time taken for vehicle j in the i^{th} link; $v_{i,j}$, velocity of vehicle j in the i^{th} link; $f(i,j)$, load for vehicle j in the i^{th} link. For simplicity, we will use the average of j vehicles for time (t_i), velocity (v_i), and load (f_i).

According to [10], the CMEM architecture employs a mathematical model that requires alpha, beta, gamma and lambda constants to calculate the fuel consumption rate for each vehicle type, h. To calculate these constants, specific vehicle data is required.

$$\lambda = \frac{\epsilon}{\kappa\psi} \tag{1}$$

where:

$$\epsilon = \text{fuel to air ratio},$$
$$\kappa = \text{heating value of typical diesel fuel},$$
$$\psi = \text{conversion factor (g/s to L/s)}$$

$$\gamma^h = \frac{1}{1000 N_{tf} \eta} \tag{2}$$

where:

$$N_{tf} = \text{vehicle drive train efficiency},$$
$$\eta = \text{efficiency parameters for diesel engines}$$

$$\beta^h = 0.5 C_d^h \rho A^h \tag{3}$$

where:

$$C_d^h = \text{coefficient for aerodynamics drag},$$
$$\rho = \text{air density},$$
$$A^h = \text{frontal surface area}$$

$$\alpha = \tau + g \sin(\theta) + g C_r \tag{4}$$

where:

$$g = \text{gravitational acceleration}$$
$$C_r = \text{Coefficient of rotational resistance}$$
$$\theta = \text{Road angle}$$

The CMEM architecture uses three modules to model the fuel emission rate for each vehicle type. The engine module, weight module and speed module are combined together to estimate the fuel consumption according to the following formula:

$$FR_i^h = \lambda \left(k^h N^h V^h t_i + M^h \gamma^h \alpha d_i + \beta^h \gamma^h d_i v_i^2 \right) \tag{5}$$

where:

$$FR_i^h = \text{fuel consumption rate},$$
$$k^h = \text{engine friction factor},$$
$$N^h = \text{engine speed},$$
$$V^h = \text{engine displacement},$$
$$M^h = \text{total vehicle weight}$$

According to [11], the following three formulas can be used to estimate the engine-out CO, HC, and NO_x emission rates:

$$\text{ECO} \approx \left[C_0 \left(1 - \phi^{-1}\right) + a_{\text{CO}} \right] \text{FR}$$
$$\text{EHC} \approx a_{\text{HC}} \text{FR} + r_{\text{HC}}$$
$$\text{ENO}_x = a_{\text{NO}_x} (\text{FR} - \text{FR}_{\text{NO}_x})$$

where ϕ is the fuel-to-air ratio, typically between 0.8 and 1.02; C_0, a_{CO}, a_{HC}, and r_{HC} are constants that differ from vehicle to vehicle; however, this difference does not affect the proportionality of emission rate with consumption rate.

Therefore, from these emission rate equations, we can deduce that fuel consumption rate is directly proportional to engine-out CO, HC, and NO_x emission rates. This enables us to simulate the general trend for emissions with the help of fuel consumption rate. Finally, we get the following equation using the fuel consumption rate for each link and vehicle type:

$$\text{ENO}_x \propto \text{EHC} \propto \text{ECO} \propto FR_i^h \tag{6}$$

In order to simulate vehicles in third world country, we assume that some coefficients and factors deteriorate by a certain percentage with vehicle age.

V. Result Analysis and Future Research

In this study, the simulation has been carried out using estimated values of d_i, t_i, f_i, and v_i. The calculation of fuel consumption rate values has been solely based on the CMEM model. While the integration of the AIMSUN model for this simulation is crucial, for simplicity, different fuel consumption rate relationships, with variable data that would otherwise come from the AIMSUN model, have been explored in our research. Two of the most significant factors have been v_i and d_i. The following are the results:

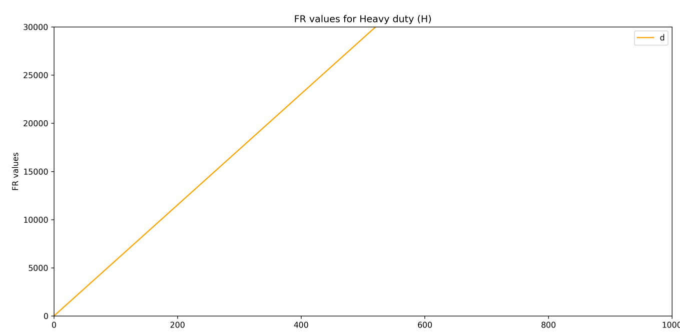

Fig. 2. FR against distance graph for Heavy duty vehicle with $t_i = 100s$, $f_i = 500kg$, and $v_i = 60m/s$

All three types of vehicles has a constant relationship between the fuel consumption rate and the distance in each link. As distance in link i increases, Heavy duty vehicles has the highest gradient indicating the highest emission according to the proportionality as explained earlier.

The following are the relationships between the fuel consumption rate and the average velocity in the i^{th} link:

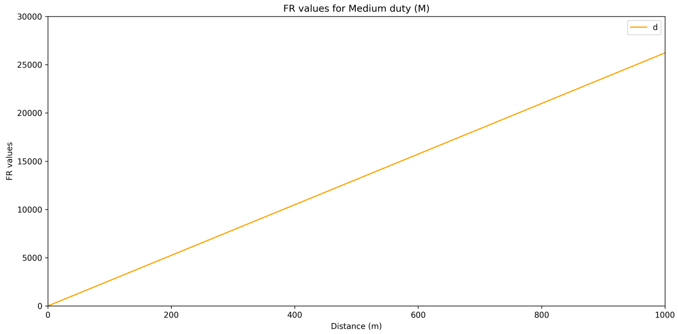

Fig. 3. FR against distance graph for Medium duty vehicle with $t_i = 100s$, $f_i = 500kg$, and $v_i = 60m/s$

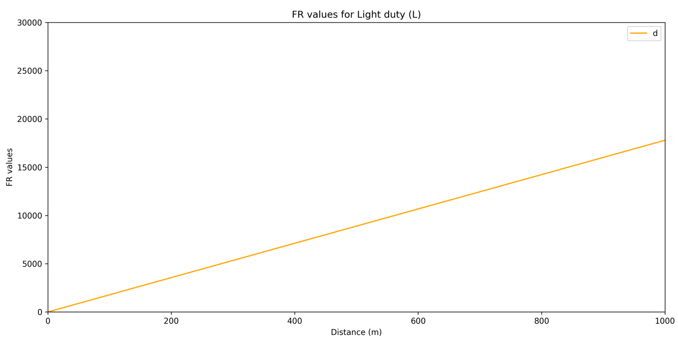

Fig. 4. FR against distance graph for Light duty vehicle with $t_i = 100s$, $f_i = 500kg$, and $v_i = 60m/s$

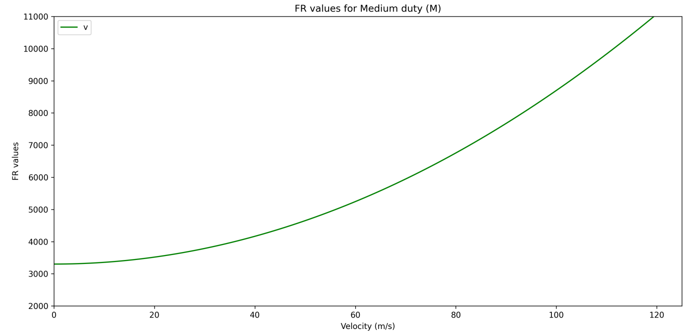

Fig. 6. FR against velocity graph for Medium duty vehicle with $t_i = 100s$, $f_i = 500kg$, and $d_i = 200m$

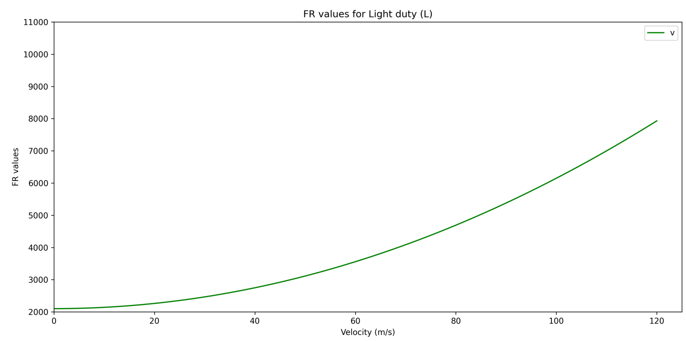

Fig. 7. FR against velocity graph for Medium duty vehicle with $t_i = 100s$, $f_i = 500kg$, and $d_i = 200m$

In this simulation run, a link of distance 200 meters has been selected from the road network with varying velocity. Again, all three vehicle types shows an increase in fuel consumption rate with an increasing gradient. It is essential to note that some of the parameters in the CMEM model has been adapted to fit third-world country vehicle data.

The analysis of the simulation results demonstrates the capabilities of linking a dynamic traffic model with an emissions model to evaluate vehicle impacts on air pollution. As shown through the adaptations made in this methodology, the Comprehensive Modal Emissions Model (CMEM) architecture provides a flexible framework that can be integrated with various traffic models that generate time-dependent vehicle activities and speeds. Models such as AIMSUN can output driving parameters at the vehicle level to feed into CMEM for emissions calculations. The model linkages presented thus provide a pathway for comprehensive analysis of traffic conditions on emissions and air quality for urban planning needs especially in developing countries.

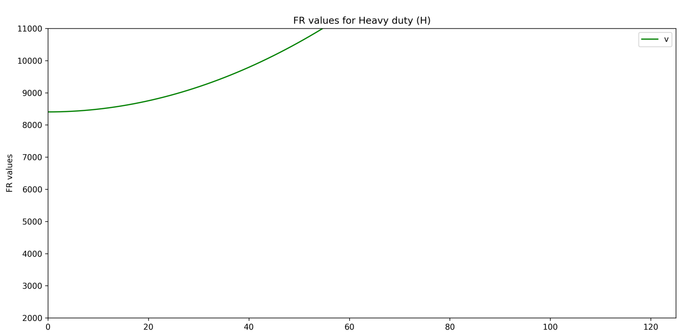

Fig. 5. FR against velocity graph for Heavy duty vehicle with $t_i = 100s$, $f_i = 500kg$, and $d_i = 200m$

Acknowledgment

In this study, we have used the dataset provided by [10] extensively to mathematically model the CMEM architecture. We would also like to acknowledge the developers of the AIMSUN simulation software for providing the resources to conduct robust microscopic traffic modeling which supplied the foundational inputs to the integrated methodology presented here.

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