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Development of Vehicular Emission Inventory using Traffic-Type-Road Classification: A Case Study of Nashik, India

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Vehicular emissions are a major contributor to deteriorating urban air quality; conventional bottom-up emission inventories apply a uniform citywide average Vehicle Kilometre Travelled (VKT) derived from limited manual counts. This oversimplification overlooks the heterogeneous composition of traffic and diurnal activity, leading to inflated and poorly resolved emission estimates. This study estimates a traffic-type-based road categorisation framework to generate link-specific VKT and quantify vehicular emissions for Nashik city, India. Classified vehicle count, dominant traffic category, road hierarchy and hourly activity duration were integrated across a 24-hour cycle, and emissions of PM, NOx, CO and HC were estimated using category-specific emission factors. Relative to the uniform VKT method, the proposed framework estimated 69% lower PM, 63% lower NOx, 53% lower CO and 55% lower HC and a more realistic emission load. Temporal assessment revealed that two-wheelers dominated daytime (internal road activity), contributing 63.1% of CO and 46.6% of HC, while Light-Duty Vehicles (LDV) and Heavy-Duty Vehicles (HDV) dominated the early hours, contributing 45.4% of NOx and 29% of PM. Unlike the conventional methods that yielded consistent patterns, the proposed emission inventory method highlighted spatial output with distinct emission hotspots along the freight corridors. The novelty of this methodology lies in traffic-type-based estimation of vehicle kilometre travelled, enabling explicit quantification of intra-urban and diurnal heterogeneity. This framework offers practicability for urban local bodies, transport planners and pollution regulatory authorities by providing an adaptable, data-efficient and policy-relevant methodology for air pollution control, emission hotspots identification, and city traffic management in rapidly motorising Indian cities.

Keywords: Bottom-up approach, Source emission inventory, Source apportionment, Vehicle kilometre travelled, Urban air quality

Introduction

Emission inventories are commonly developed using either top-down or bottom-up approaches. The top-down approach aggregates emission data or fuel consumption data to spatial units using surrogate parameters such as vehicle population, fuel sales, or socio-economic indicators. While suitable at national or regional scales, top-down methods lack spatial detail and are inadequate for city-scale or corridor-level assessment. The bottom-up approach, in contrast, calculates emissions from road-level vehicle activity, usually expressed as Vehicle Kilometre Travelled (VKT), multiplied by vehicle category emission factors, enabling the higher spatial resolution required for policy-oriented urban inventories.[1]

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Literature Review

In bottom-up inventories, VKT is the most widely used activity metric, and its estimation has a strong influence on emission results, regardless of the emission model employed.[2,3] A careful review of published studies shows that authors predominantly rely on average VKT values derived from traffic counts, vehicle registration statistics, or fuel consumption datasets.[4–7] City-scale studies employ bottom-up methods, typically estimating VKT by multiplying manual traffic counts at selected intersections or links by segment lengths, and then applying uniform or average VKT values across broader functional road classes, such as arterial, sub-arterial, and collector roads.[8–10] GIS-based vehicular emission inventories have used similar traffic counts to assign average VKT inputs with spatial grids, demonstrating that VKT remains the dominant activity indicator even when spatial resolution increases.[11,12]

Studies using advanced emission models such as MOBILE, MOVES or COPERT also require VKT inputs and typically rely on externally estimated average VKT values due to the absence of continuous traffic datasets.[13–16] In the absence of vehicle volume data, several gridded emission inventories treat available road length as a proxy for VKT, distributing emissions in proportion to road network density rather than observed traffic demand.[17] In such cases, VKT is effectively reduced to a supply-side infrastructure metric (road length per grid cell), which causes emission hotspots to align with denser networks. Collectively, existing literature shows that urban vehicular emission inventories have relied on average VKT, functional classification and road length proxies to operationalise bottom-up emission inventory in data-scarce environments.

Research Gap

From the literature review, it is clear that methodological limitations have direct consequences on emission accuracy. The average VKT-based inventories assume spatially uniform travel behaviour, ignoring heterogeneity in fleet composition and mobility patterns across different road links. The road classification does not reflect dominant traffic types or fleet behaviour. As a result, an internal road dominated by two-wheelers is treated similarly to a freight corridor dominated by Heavy-Duty Vehicles (HDV). The diurnal variation in fleet activity is rarely incorporated, even though mixed traffic systems exhibit distinct commuter peaks and freight windows that influence emission load. Using road length as a proxy for VKT transforms a demand metric into a supply metric and masks actual emission hotspots.[18]

Most critically, the reviewed literature does not report any operational framework that uses a traffic-type-based road categorisation as the basis for VKT estimation in bottom-up vehicular emission inventory for mixed-traffic urban environments. Consequently, existing inventories are unable to explicitly represent road-level traffic heterogeneity and its influence on spatial and temporal emission patterns.

Proposed Study

To address the above limitation, this study proposes a traffic-type-based road categorisation framework that replaces conventional uniform or average VKT assumptions with road-category-specific VKT derived from observed fleet composition, dominant traffic type and hourly activity duration. The present study develops and demonstrates a traffic-type-based road categorisation framework for VKT estimation and bottom-up vehicular emission inventory development in an Indian mixed-traffic urban context. The approach demonstrated in this study offers a scalable and practical solution for data-scarce Indian cities, enabling improved hotspot identification, temporal emission profiling and policy-oriented air quality management.

Study Area

The proposed methodology is demonstrated for Nashik city, located at 19° 59' 50.8344" N and 73° 47' 23.2908" E (Fig. 1). Nashik is one of the fastest growing tier-II urban centres in the state and serves as a vital economic and transportation hub connecting Mumbai and Pune. The city lies on the western Deccan plateau at an elevation of approximately 560 meters above MSL and experiences a tropical Savannah climate characterised by hot, dry summers, monsoon rainfall from June to September, and mild winters. The city of Nashik has low wind speeds, and frequent temperature inversions are seen during winter, which leads to the accumulation of pollution. According to Census 2011, Nashik’s population surpassed 1.5 million, and recent estimates denote that it has now crossed 2.3 million, reflecting the rapid motorisation; registered vehicles increased from about 0.38 million in 2010 to more than 1.1 million by 2024.

Nashik exhibits diverse road typologies, from dense urban cores and narrow internal streets to high-speed freight corridors, allowing for a comprehensive evaluation of vehicular emission patterns under varied traffic conditions.

Methodology

A comprehensive spatial database of Nashik’s Road network was digitised using the OSM map. Vehicular fleet was classified into 2W, 3W, 4W, LDV and HDV categories with Bharat Stage (BS-I to BS-VI) emission norms to represent fuel and technology variability. One week of traffic activity data for 24 hours was collected through manual vehicle counting at mid-link sections, toll-plaza records from National and State Highways and registered vehicle statistics obtained from RTO/VAHAN.[19]

Road segments exhibiting similar traffic-type characteristics were aggregated into sixteen distinct categories, designated as R1 to R16, which are described in Table 1. This traffic-type-based road grouping provides a foundation for mapping emission

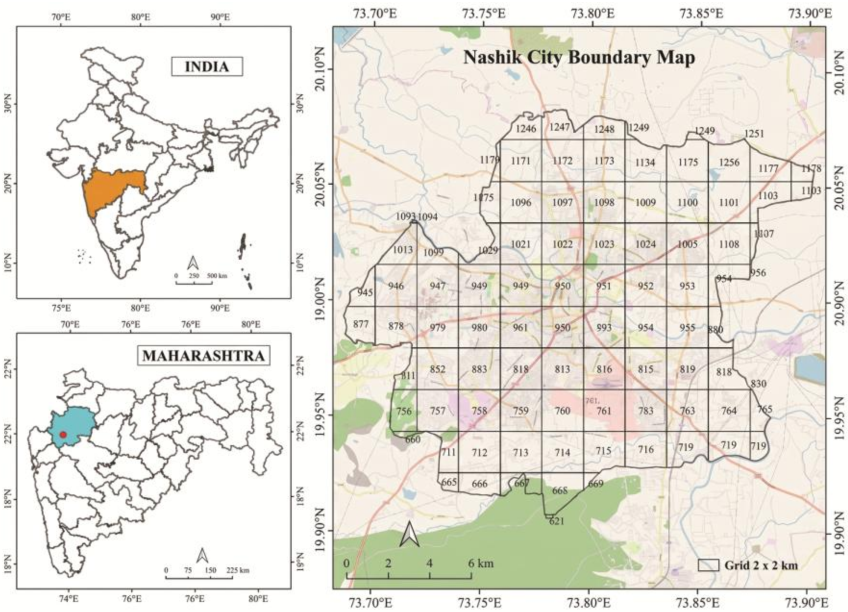

Fig. 1 — Location of study area (Nashik) with a 2 km × 2 km grid

Table 1 — Vehicular traffic-type-based road categorisation

Traffic Type	Dominant vehicle class/Category
R1	Two-wheelers only
R2	Two and three-wheelers
R3	Three-wheelers (passenger) and light-duty (P&C) vehicles
R4	Two, three, four wheelers
R5	Two-wheelers, four-wheelers and institutional buses (LDV)
R6	Heavy-duty vehicles, two-wheelers
R7	Three-wheelers, light-duty vehicles (LDV), along with agricultural vehicles
R8	Two and four wheelers
R9	All types of vehicles with high LDV and HDV
R10	Three wheelers and LDV
R11	All types of vehicles, with a high count of 2 and 4-wheelers
R12	Passenger vehicles (LDV and HDV)
R13	Cars, LDV and transport vehicles
R14	Two-wheelers, three-wheelers with a carriage
R15	LDV & HDV
R16	Mixed traffic with major two-wheelers and cars

factors and developing a bottom-up mobile emission inventory and is presented in Fig. 2. Emission factors (EFs) quantify the amount of pollutant emitted per kilometre travelled (g/km) and are used for emission inventory development.[20]

Conventional Emission Inventory Approach

The conventional mobile emission inventory for Nashik city was developed using a bottom-up approach.[1,21] Vehicle counts were derived from both manual and CCTV-based observations, and the total length (in km) was computed within each grid cell using GIS tools.[21] For grid cells lacking direct traffic observations, vehicle activity data were spatially interpolated using the road density and functional road class correlations.[22] Emission load was estimated using:

$$EL = Ni \ x \ VKTi \ x \ EFi \qquad \dots (1)$$

where, EL is emission load (kg/d); Ni is the number of vehicles in category i; VKTi is the average daily distance travelled per day for vehicle category i, and EFi is the emission factor for vehicle category i (g/km or g/km/vehicle)

Emission Inventory based on Traffic-Type based Road (TTR) Categorisation

In this approach, the overall road network of the city was categorised into sixteen traffic-type categories (R1 to R16) based on vehicle composition and traffic density derived from field surveys and traffic counts. Each traffic-type category represented a distinct traffic pattern, such as two-wheeler-dominated, mixed traffic or heavy commercial corridors, capturing the real variability in vehicular activity across the road network. Within each grid cell, every traffic-type road segment was assigned a vehicle kilometre travelled (VKT) specific to its vehicle category, rather than applying a single averaged VKT value across the grids. This refinement ensured that roads primarily used by two-wheelers or light commercial vehicles have distinct VKT assignments compared with highways dominated by heavy-duty traffic.

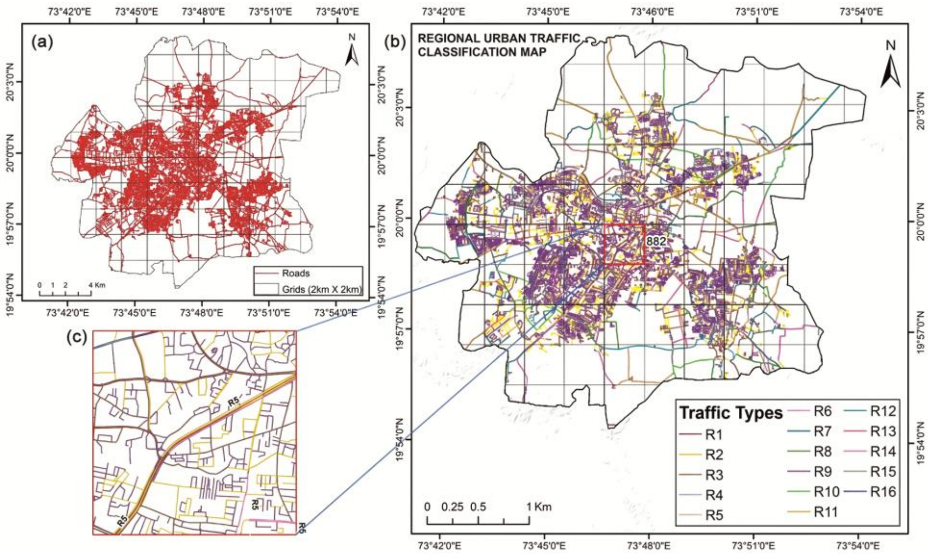

Fig. 2 — Spatial depiction of the roads and traffic-type-based road categorisation utilised in the line source emission inventory for the study area: **(a)** Overall road network distribution overlaid with a 2 km × 2 km grid, **(b)** Classification of roads into different traffic types (R1–R16) across the study area, **(c)** Enlarged visualisation of the traffic-type road categorisation with colour differentiation

For the complete city, road segments belonging to each traffic-type category were identified, and vehicle counts were conducted on representative road links within each category. The obtained traffic counts were then used to represent other roads of similar traffic type, ensuring coverage of the entire network even in areas lacking direct vehicle counts.

Subsequently, emission load for each grid was estimated by multiplying the traffic-type-based-VKT with the corresponding emission factor, fuel, and engine technology distributing factor and then summing the contributions across all road segments within the grid. This approach integrated real traffic composition and spatial variability into the emission load estimation process, leading to a more realistic and spatially resolved mobile source emission inventory.[23] The emission load for every single grid was calculated using Eq. 2. The reformed equation, which captures this added dimensionality, is formulated as:

$$EL = \sum_{r}^{n} \sum_{i}^{n} \left(VKT_{r,i} \times EF_{r,i} \times F_{r,i} \right) \quad \ldots (2)$$

where,

EL: Emission load; $VKT_{r,i}$: VKT for every vehicular category ‘i’ on traffic-type-based-road category ‘r’
($VKT_{r,i} = N_{r,i} \times L_{r,i}$).

$N_{r,i}$: Vehicular count for every category i seen on traffic-type-based-road category r.

$L_{r,i}$: Total length (km) of road segments belonging to the traffic-type-based-road category r.

$EF_{r,i}$: Emission factor for vehicle category i on traffic-type-based-road category r (g/km).

$F_{r,i}$: Fuel and engine technology distribution factor for vehicle category i on traffic-type-based-road category r.

This traffic-type road-based framework enhanced the mobile emission inventory by introducing technology-specific and temporally resolved estimation. Unlike conventional emission inventory that relies on static annual averages, this approach allows hourly and diurnal emissions profiling, reflecting real traffic variability across time. This higher temporal determination assisted the dynamic monitoring of automobile emissions and reinforced the linkage between emission load, traffic flow movement and ambient air quality. This gridded high-resolution spatiotemporal emission inventory data provided a robust footing for city-level air quality action plans and documentation-based policy interventions.

Results and Discussion

A clear dominance of two-wheelers (2W) in engine technology and fuel categories can be observed from Fig. 3. The fleet is largely composed of BS-III and BS-IV vehicles, along with petrol dominance by two-wheelers and cars, while diesel fuel is used in four-wheelers and HDV. Major three-wheelers are seen on CNG.[24]

Comparison of Emission Load (Conventional and Proposed)

Emission loads estimated using the conventional average VKT-based approach were compared with the traffic-type road categorisation.[25] The comparative analysis was performed for four key pollutants, particulate matter (PM), Nitrogen oxides (NOx), Carbon monoxide (CO) and hydrocarbons (HCs), aggregated at both city-wide and 2 × 2 km grid level.

Under the conventional emission inventory, uniform average VKTs were applied across all the road segments. This approach yielded total emission loads of 3007 kg/d, 33885 kg/d, 17226 kg/d and 55332 kg/d for PM, NOx, HC and CO, respectively (Table 2). However, such city-wide totals are insufficient to characterise temporal peaks or to attribute high emission load to a specific vehicle category, fuel types or engine technologies.[26]

In contrast, the traffic-type-based-road-categorisation approach yielded emission estimates that aligned more closely with observed traffic realities. The incorporation of traffic-type-road-specific VKTs and vehicle composition data reduced spatial bias and allowed the detection of distinct emission hotspots along freight and commuter corridors. The proposed method estimates showed a decrease of 63%, 69%, 53% and 55% emission load for NOx, PM, CO and HC (Table 2).

In the conventional approach, a uniform emission load was distributed across the complete road network, failing to capture localised congestion or variations in traffic activity. In contrast, the proposed method displayed distinguishable spatial patterns, hotspots closely aligned with the industrial estates (Satpur and Ambad), highway intersections (NH-60 and NH-848), and dense commercial corridors (Mumbai Naka and College Road). The roads that had a lower vehicular count exhibited a reduction in emission load intensities. This advanced spatial differentiation emphasizes the incorporation of traffic-type-based road categorisation and realistic VKT allocation results in a more accurate and policy-relevant representation of urban vehicular emissions.

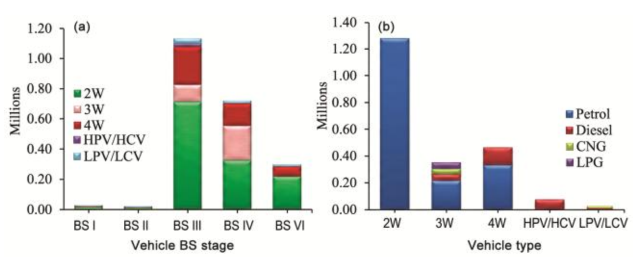

Fig. 3 — Registered Bharat Stage (BS) and fuel-wise Vehicles in Nashik District

The gridded map evidently indicates both spatial redistribution and change in total emission load across different vehicle categories and pollutants.[19] Carbon monoxide (CO) and hydrocarbon (HC) emission load shave mostly intensified the central and western areas of the city, where two-wheelers and cars are mostly operational. These vehicular types are generally petrol-fuelled and emit high amounts of CO and HC emissions due to frequent traffic congestion conditions.[27] In contrast, the emission load for nitrogen oxides (NOx) and Particulate Matter (PM) is seen at the north east side, where freight movement is dominated by light and heavy-duty commercial vehicles, which are mostly diesel powered. The spatial patterns suggest that freight corridors contribute disproportionately to NOx and PM, while commuter corridors are the key emitters of CO and HC.[28]

In addition to spatial redistribution, the total emission load also varied between the two approaches. Compared to the traditional uniform VKT-based method, the proposed traffic-type-based framework estimated 69% lower PM, 63% lower NOx, 53% lower CO and 55% lower HC emissions, respectively.

Spatial-Temporal Traffic and Emission Load Distribution

The spatio-temporal analysis revealed pronounced variations in traffic intensity and composition across the 24-hour cycle and among traffic-type-based road

Table 2 — Comparison of conventional and proposed emission load (kg/d)

Vehicle Category	Conventional Method (Kg/d)				Proposed Method (Kg/d)			
	PM	NOx	CO	HC	PM	NOx	CO	HC
Two-wheeler (2W)	124	2478	16455	4685	130	3219	14339	5053
Three-wheeler (3W)	1016	4611	10001	8603	168	2254	4064	2119
Four-wheeler (4W)	211	2810	9670	1925	87	1001	2119	246
Light Duty Vehicles (LDV)	419	2602	3432	1093	61	312	338	94
Heavy-Duty Vehicles (HDV)	1237	21384	15774	920	485	5725	5076	259
Total emission load	3007	33885	55332	17226	931	12511	25936	7771

categories (R1-R16).[29] The hourly distribution of five vehicle categories, i.e., two-wheelers, three-wheelers, four-wheelers, LDVs and HDVs across all traffic-type-based road classes is illustrated in Fig. 4. Two-wheelers dominated overall traffic flow, particularly between 08:00 and 18:00 h, on internal and commercial roads (R1, R2, R5 and R12), corresponding to work commutes, educational trips and intra-city errands. Three-wheelers exhibited extended operation from 06:00 to 22:00 h on R3, R4, R6, R12 and R13, reflecting their role as shared public transport. Four-wheelers displayed distinct morning 09:00 to 11:00 h and evening 17:00 to 20:00 h peaks along R9, R11 and R13, coinciding with office and return tips. LDVs were active from 07:00 to 19:00 h along R6, R12 and R14, aligning with delivery and logistics operations, whereas HDVs dominated the early-morning 03:00 to 08:00 h and late evening 20:00 to 24:00 h on R9, R13, R15 and R16, consistent with urban freight restrictions and long-haul transit on outer corridors.

These temporal patterns align with observations from Indian metropolitan contexts such as Delhi and Mumbai, and other developing cities with mixed traffic modes.[30] The clear road-use specialisation by vehicle class highlights the dominance of two-wheelers in internal and connective networks and the concentration of freight vehicles on peripheral and industrial routes. Such patterns emphasise the need for vehicle-class-specific road management and zoning in emission reduction planning.[31]

The emission load distribution followed these traffic dynamics closely. Daytime emissions were dominated by CO and HC, largely emitted by petrol-driven two and four wheelers experiencing frequent acceleration, idling and cold starts in congested cores.[27] NOx and PM exhibited elevated levels during early morning and late-night hours, coinciding with diesel-powered LDV and HDV operations on freight and ring corridors. Gridded emission maps reveal that CO and HC hotspots are concentrated in central and commercial areas, while NOx and PM intensities are higher along freight-dominated peripheries (R9, R13, R15, R16). Compared to the traditional uniform VKT approach, the traffic-type-based method calculated a more realistic spatial redistribution of emissions, reflecting actual traffic intensity and vehicle composition at different times of the day.[18]

The integration of temporal traffic profiles with traffic-type-VKTs and road classification provides a more accurate representation of both total emission load and its hourly variability. Two-wheelers emerged as the dominant contributors to daytime CO and HC emissions, whereas freight vehicles were responsible for nocturnal NOx and PM. This temporal alternation underscores the necessity of incorporating hourly fleet composition into vehicular emission inventories to improve the precision of spatially resolved emission assessments and support time-targeted mitigation

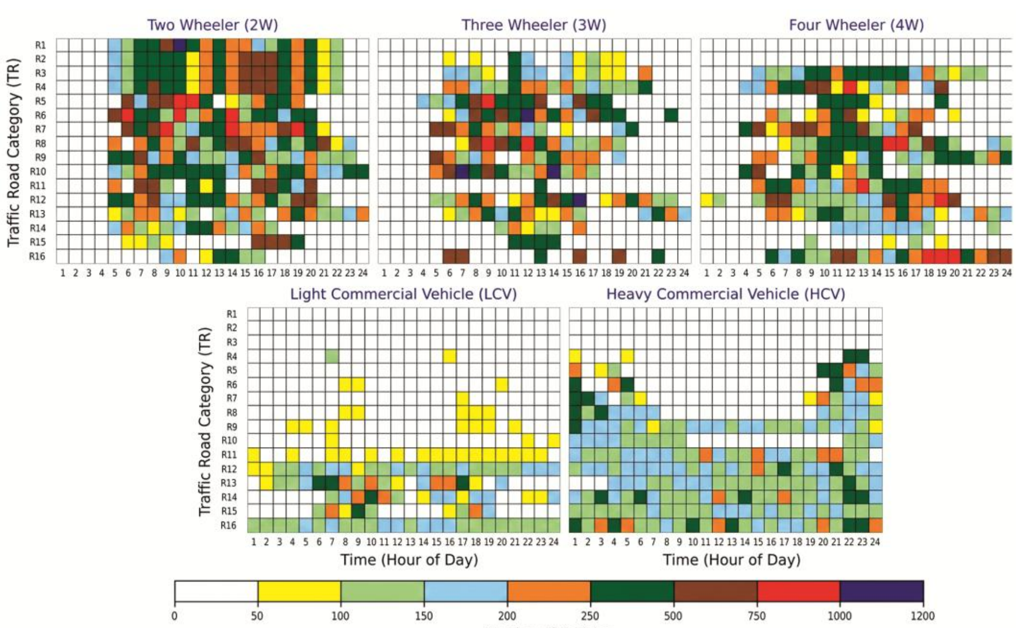

Fig. 4 — Hourly traffic volume on different traffic-type-road categories

strategies such as dynamic traffic control and low-emissions zone scheduling.[32]

Estimation of Emission Load (kg/h) based on Vehicle Category

The hourly emission load across vehicular categories, fuel types, and engine stages is illustrated in Fig. 5. The total pollution load emitted from these vehicles is 63.1% for CO and 22.2% for HC. Higher emission load is seen during morning and evening rush hours, due to frequent stopping, idling at traffic signals and cold start, as this leads to rise-up the CO and HC emissions.[33] Typical of small-capacity engines, despite newer BS-IV and BS-VI vehicles showing reduced emission intensities, the persistence of BS-III and older models continues to influence total urban CO emission load, particularly during morning (06:00 – 10:00 h) and evening (17:00 – 21:00 h) peaks.[34]

Three-wheelers (3Ws) exhibit higher CO and NOx emissions, contributing approximately 47.2% of the CO and 26.2% of the NOx emission load, with clear bimodal peaks corresponding to passenger demand cycles. A large portion of three-wheelers operate on CNG and LPG, which reduces particulate emissions but still produces CO and HC.[35]

Four-wheelers (4Ws) in Nashik city are petrol-driven for private use and diesel-driven for taxi purposes, contributing substantially to both CO and NOx emissions, accounting for 29% of NOx and 61.4% of CO. This pattern reflects the mixed presence of petrol and diesel vehicles, where petrol cars emit CO and diesel cars emit NOx. The hourly pattern shows peaks during morning and evening office commuting hours.

LDVs exhibit a relatively balanced emission pattern across pollutants, with CO (42%) and NOx (38.7%). These vehicles are widely used for urban goods transportation and delivery services, resulting in higher emissions during daytime commercial activity hours. Their emission characteristics reflect a mix of petrol and diesel engines, contributing to both CO and NOx emissions.[36]

Heavy-Duty Vehicles show the highest contribution of NOx (49.6%), followed by CO (44%). These vehicles are predominantly diesel-powered, and high combustion temperatures in diesel engines lead to significant NOx formation. Unlike passenger vehicles, their emission load remains relatively high throughout the day due to continuous freight movement and logistics activities. The emission load standard distribution highlights that HDV dominate the emission load across several Bharat Stage technologies, contributing 67.6%, 69.4% and 45.4% under BS-II, BS-III and BS-VI, respectively.[28]

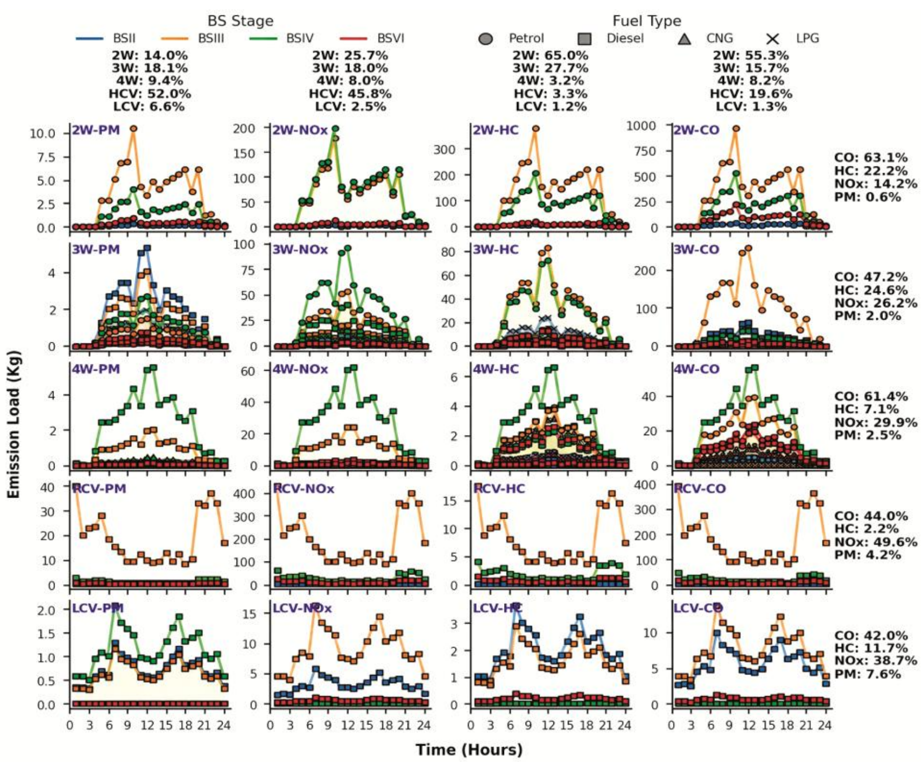

Fig. 5 — Hourly emission load (in Kg) of pollutant (PM, NOx, HC, and CO) for each vehicle category

The emission load analysis underscores the importance of considering both temporal and vehicular heterogeneity in emission modelling. Unlike conventional inventories that rely on aggregated daily or monthly traffic data, the present approach captures the dynamic hourly variation of emission loads across different vehicle categories, fuels and BS stages. This temporal resolution allows identification of critical emission windows and pollutant-specific dominant sources, providing a stronger foundation for real-time emission management and short-term air quality forecasting.[37]

Hourly Emission Load (kg/h) on Traffic-Type-based Road Category

The hourly estimation of emission load (kg/h) across multiple traffic-type-based road categories, illustrated in Fig. 6, presents a refined spatiotemporal understanding of how different vehicle categories and pollutants interact with the city's road network.[38] This new approach incorporates real-time vehicular activities along with count and fleet composition to provide real-time emission patterns. The heat map clearly depicts the intensity variation of emission pollutants along the road category and hourly emissions, offering spatio-temporal emission visualisation that conventional emission inventories fail to showcase.

Emission load from two-wheelers is localised but highly intense, reflecting incomplete combustion in small-capacity engines under stop-go traffic conditions.[39] In contrast, NOx and PM emissions from 2Ws remain limited due to the absence of diesel combustion. Three-wheelers exhibit moderate CO and HC emissions, representing their role as a short-

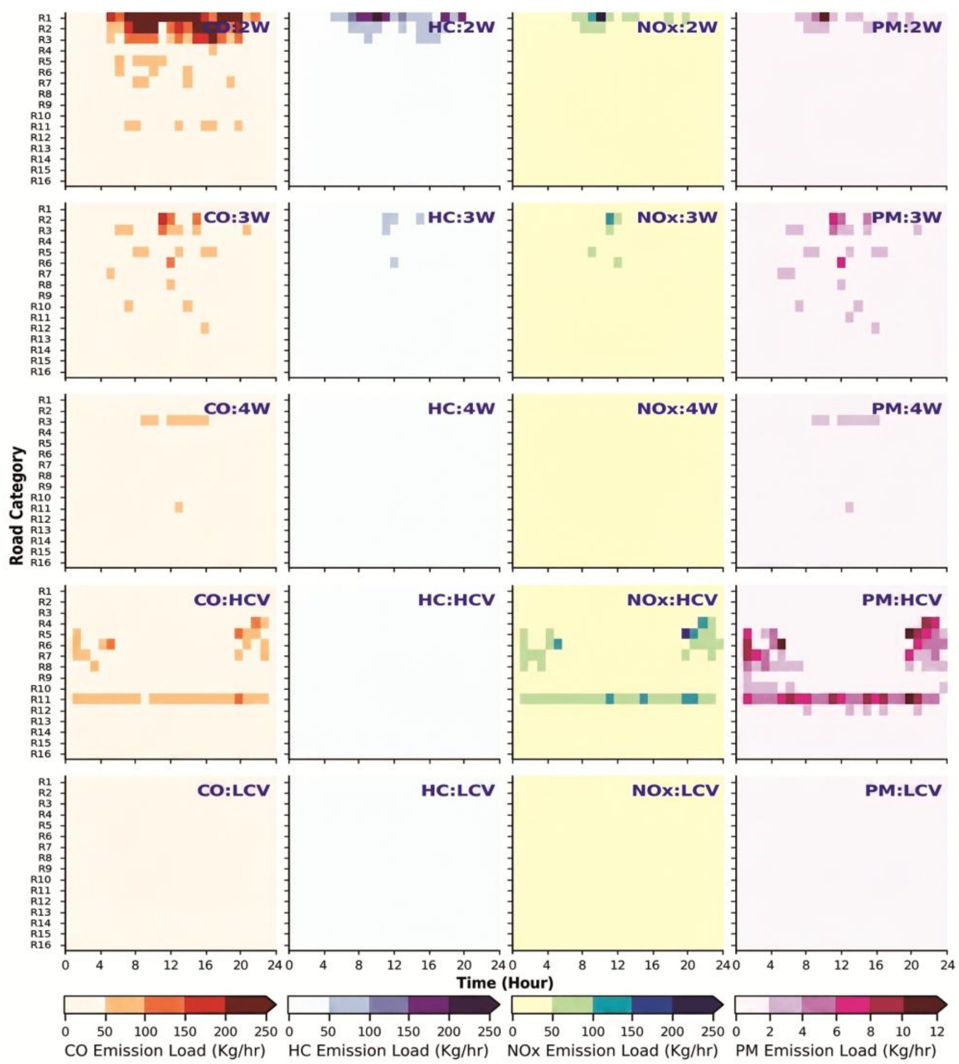

Fig. 6 — Hourly emission load (Kg/h) of pollutants (PM, NOx, HC, and CO) for each vehicle category on different road categories

distance passenger carrier. Nitrogen oxides (NOx) and PM emissions from 4Ws, especially diesel taxis, persist through daylight hours, reflecting the effect of prolonged engine load during peak traffic conditions. The strong emission bands are observed from HDVs, indicating the concentrated movement of goods, long-distance freight, and passenger movement during off-peak hours.[28] Carbon monoxide emissions from HDVs also appear during early hours, confirming their significant nocturnal impact on local air quality. The operational uniformity of LDVs across the day, linked to intra-city goods and passenger transport, maintains consistent NOx and CO levels throughout the daytime hours, with marginal PM contributions.

The heat maps, through their discrete and colour-intensity patterns, clearly demarcate time and location-specific emission peaks that the conventional model smoothens out. The early-morning dominance of emission load from HDVs to daytime surges in CO and HC from two and three-wheeler vehicles portrays a realistic temporal alternation. Such a detailed differentiation is critical for designing time-specific control strategies, such as restricting HDV movement during pre-dawn hours or encouraging alternative work timings to flatten commuter peaks.

This proposed traffic-type-based emission framework outperforms earlier approaches by directly integrating observed traffic composition through traffic-type-based road categorisation, which captures road-specific traffic dynamics and vehicle activity patterns with the emission estimation process. Traditional bottom-up inventories generally assume uniform vehicle activity and static average VKT across entire road classes, leading to spatially averaged and temporally aggregated results. In contrast, the present method dynamically categorises roads according to real-world traffic density, dominant vehicle category and activity duration. This enables the emission inventory to reflect intra-urban heterogeneity and time-resolved conditions with high precision. As a result, the observed emission load peaks and pollutant dominance patterns closely correspond to actual traffic cycles, thereby eliminating the over-smoothing effect typically seen in conventional methods.

The present framework advances beyond the earlier studies by providing an hourly and road-type-resolved emission matrix, which directly links emission peaks to specific urban corridors and time periods. This high-resolution temporal-spatial disaggregation represents a methodological leap in emission inventory development for Indian cities, facilitating improved calibration of dispersion and exposure models, as well as more informed urban transport and air quality policy designs.

This approach of emission estimation not only increases the accuracy but also helps in interpretation for decision-making. It enables the decision makers to pinpoint the control measures or alternatives to reduce emissions with adaptive interventions, like traffic-flow management and fleet modernisation. The advantage of this framework lies in its integration with temporal, spatial and traffic-type-based road categorisation, transforming emission inventory estimates from a static accounting exercise to a real-time analytical tool for substantial urban air quality management.

The uncertainty in the emission inventory arises from the secondary datasets used in the estimation. Vehicle registration data obtained from the VAHAN portal may not exactly represent the active on-road fleet in terms of engine technology and fuel-wise vehicle categorisation. Also, emission factors adopted from the ARAI database may not fully capture real-world driving conditions, vehicle maintenance status and traffic characteristics typical of Indian cities. Despite these limitations, the adopted methodology provides a reasonable estimate of vehicular emission load for the study area.

Conclusions

The findings show that traffic-type-based road categorisation VKT estimation improves the bottom-up line source emission inventories. This approach enables near real-time estimation of on-road exhaust emissions. Unlike conventional methods, it captures both spatial and temporal variations in traffic activity. The framework identifies road-specific traffic patterns and hourly changes in emission load. Such spatial differentiation is important for effective air quality management. It supports targeted mitigation measures instead of broad city-wide policies. The study shows daytime dominance of CO and HC emissions from petrol-driven two- and four-wheelers. In contrast, NOx and PM emissions peak during night-time and early morning due to diesel-powered freight and commercial vehicles. These findings will help to develop time-specific mitigation strategies.

The methodology has strong potential for adoption across Indian cities. It can support cleaner mobility planning, evidence-based air quality management, and dispersion modelling to estimate ground-level pollutant concentrations.

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