Chapter 1

Introduction

1.1 Background

India's rapid urbanization has profoundly reshaped its spatial, demographic and infrastructural fabric, placing critical structural and operational pressures on urban mobility and infrastructure systems. Metropolitan cities such as Delhi, Mumbai, Bengaluru and Chennai are witnessing sharp increases in population density, vehicular ownership and infrastructure stress. As per estimates by the Ministry of Housing and Urban Affairs (MoHUA) and the International Institute for Population Sciences (IIPS), India's urban population increased from approximately 286 million in 2001 to about 488 million in 2020, with the UN-Habitat World Cities Report 2022 projecting a rise beyond 675 million by 2035 [1–3]. This demographic surge has not been met with proportional infrastructure growth, resulting in severe transportation bottlenecks, rising congestion levels and heightened exposure to traffic-induced environmental stressors, including air pollution, noise and ground-borne vibrations (TIV). These conditions are further aggravated by non-uniform road development and inadequate design margins in urban corridors, emphasizing the urgent need for integrated, vibration-sensitive planning approaches.

Quantitatively, this imbalance is stark. According to PRS Legislative Research, India's road network expanded by 39% since the early 2000s, while the number of registered vehicles surged by over 158% during the same period [4]. The total road length increased from approximately 0.4 million kilometers in the 1950s to more than 5.5 million kilometers by 2015. However, the structural quality, load-bearing capacity and maintenance of these roadways have not scaled accordingly, particularly in Tier II and Tier III cities. This asymmetry has led to the overloading of urban corridors, degraded pavement conditions and intensified vehicle-road interaction dynamics, key contributors to mechanical vibrations transmitted through the ground.

India's high dependency on road-based transportation further exacerbates the problem. While countries such as China and the United States carry only 30% and 37% of transport via roads, respectively, India transports more than 60% of its freight and passenger load on roadways [5]. This road-centric model results in high axle repetitions per lane and concentrated stress cycles, especially on arterial and sub-arterial roads in congested urban settings. The continuous passage of diverse vehicle classes over imperfect pavements and geometrically abrupt features induces vertical and lateral ground vibrations, which propagate into adjacent substructures and built environments.

Unlike many developed countries with homogeneous and lane-disciplined traffic systems, Indian urban roads present highly heterogeneous traffic streams. These include a broad spectrum of vehicle types, from two-wheelers, three-wheelers, passenger cars and LCVs, to buses, trucks, e-rickshaws and non-motorized traffic sharing limited carriageway space without formal segregation. This lack of structural separation, combined with non-lane-based, opportunistic maneuvering behavior such as zigzag driving and irregular overtaking, results in chaotic vehicle dynamics. Sudden braking, unregulated lane shifts, uneven load distributions and variable speeds collectively generate complex and non-stationary vibrational responses at the pavement vehicle interface [6, 7]. Traditional models fail to characterize these conditions, necessitating advanced traffic and vibration modeling frameworks rooted in empirical field data and dynamic signal analysis.

Urban congestion is one of the most prominent consequences of this unregulated growth [8, 9]. Overloaded intersections, suboptimal signal phasing, poor driver compliance and insufficient infrastructure lead to severe delays and traffic spillovers. This congestion contributes not only to economic inefficiency and emissions but also to elevated ground vibrations due to intensified braking and acceleration cycles. Vehicles operating under stop-and-go conditions induce transient, high-frequency vibrations, particularly harmful to nearby infrastructure with low dynamic tolerance. Critically, smoother traffic enabled by route optimization reduces these events, thereby passively mitigating vibration levels. Hence, traffic planning tools considering vehicle types and congestion levels can serve a dual purpose, improving throughput and reducing vibration exposure.

In parallel, the environmental and societal consequences of escalating traffic congestion are profound [10]. Excessive vehicular density and prolonged idling contribute significantly to urban air pollution, with transportation sources emitting high levels of particulate matter ($PM_{2.5}$, PM_{10}), nitrogen oxides (NO_x), sulfur dioxide (SO_2), carbon monoxide (CO) and volatile organic compounds (VOCs). According to the Central Pollution Control Board (CPCB) and the International Council on Clean Transportation (ICCT), the transportation sector accounts for nearly 20–35% of ambient air pollution in India's major cities [11]. Simultaneously, traffic-generated noise pollution frequently exceeds permissible thresholds, impairing auditory health and increasing the risk of cardiovascular disease. Chronic exposure to traffic congestion has also been linked to elevated stress levels, anxiety, sleep disturbances and hypertension among urban residents [12]. Moreover, congestion-induced time losses directly translate into decreased productivity, increased fuel consumption and rising socio-economic costs. These multifaceted impacts underscore the urgency of designing holistic traffic management strategies that address congestion and its secondary effects on health, environment and infrastructure integrity.

Speed-control measures such as humps, rumble strips and raised pedestrian crossings are widely used in India to regulate vehicular speed. However, their placement often lacks technical standardization and context-sensitive planning. Rigid hump materials, excessive heights, or abrupt geometries frequently result in sharp vertical accelerations and impulsive ground excitations when heavy vehicles traverse them [13]. In the absence of geometric design tailored to the expected vehicle mix and traffic volume, such features act as unintended vibration sources, affecting sensitive zones including hospitals, educational campuses and historical precincts. However, in many Indian urban contexts, the selection of hump profiles and materials lacks technical standardization or consideration of traffic characteristics such as vehicle type or peak hour load. There is a need for context-sensitive hump design that balances traffic calming with potential vibration impacts, especially near sensitive zones such as hospitals, educational institutions and heritage sites.

From an infrastructure degradation perspective, chronic exposure to traffic-induced vibrations leads to cumulative damage, especially in buildings not designed for dynamic excitations. Vibrations propagate through subsoil layers depending on stiffness, stratification and damping characteristics, often resulting in amplification or resonance at specific structural frequencies. This is particularly critical for heritage buildings with unreinforced masonry, poorly connected joints, or high slenderness ratios [14]. Existing vibration standards such as ISO 2631-1 [15] and BS 6472 [16] provide exposure thresholds but do not adequately account for frequency-specific responses in varying soil and structural conditions typical of Indian cities.

The ability to control and manage TIV depends critically on accurate, real-time identification of vehicle types contributing to vibration emissions. Conventional classification systems based on axle-load sensors or video analytics often face practical limitations in Indian urban settings due to high infrastructure costs, environmental sensitivity and complex maintenance requirements [17]. These challenges are further exacerbated in heterogeneous and mixed-traffic environments, where occlusion, variable lighting and informal vehicle behavior compromise the performance of vision-based systems. As a result, there is a growing interest in alternative, non-intrusive, data-driven classification approaches that can reliably capture vehicle-road interaction dynamics across varied operating conditions.

Following vehicle identification, quantifying vibrational impact from different vehicle types is essential for effective infrastructure planning and regulatory intervention. While the Passenger Car Unit (PCU) is widely used in traffic flow modeling to standardize vehicle impacts, there is currently no established equivalent for characterizing vibration emissions across vehicle classes. To address this gap, the development of vibration-based comparative indices, analogous to PCU, has been conceptually proposed. Hypothetical metrics such as Passenger Car Vibration Equivalence (PCVE) and Reference Vibration Emission Level (RVEL) can potentially normalize the vibrational footprint of various vehicle types over different speed and surface conditions. When integrated with real-time traffic analytics, such indices could inform vibration-sensitive route planning, zoning policies and speed regulation frameworks, especially in structurally vulnerable or sensitive urban zones.

Addressing TIV in Indian cities requires an integrated multidisciplinary framework combining empirical ground vibration measurements, advanced signal analysis, real-time traffic classification and forecasting models. Additionally, the framework should account for geometric elements such as speed-control devices (e.g., humps, rumble strips), whose designs often act as unintended sources of impulsive vibrations. Such a holistic approach would support vibration-aware traffic management, infrastructure planning and sustainable urban policy. The subsequent sections examine the physical mechanisms of TIV, existing research limitations and the motivation for a methodological framework suitable for heterogeneous urban environments.

1.2 Traffic-Induced Vibrations (TIV): Mechanisms, Impacts and System-Level Perspectives

While the background highlights the broader urban dynamics and the need for integrated solutions, a foundational understanding of the physical mechanisms and effects of TIV is critical for addressing its urban implications. Traffic-induced vibrations (TIV) have emerged as a critical yet often underestimated environmental phenomenon in rapidly urbanizing cities, particularly within the context of heterogeneous and congested traffic systems. Unlike more perceptible forms of environmental degradation, such as air and noise pollution [18], TIV is characterized by its subtler physical manifestation and cumulative impact. It remains mainly unmonitored in existing urban frameworks, despite its demonstrated influence on structural degradation, human well-being and infrastructure serviceability in vibration-sensitive zones [19, 20].

Mechanistically, TIV originates from complex dynamic interactions between moving vehicles and the roadway structure. As vehicles traverse the pavement, they impart transient and cyclic loads that generate elastic and inelastic responses within the surface and the underlying soil layers [21]. Vehicle-specific parameters heavily modulate these interactions, including axle configuration, gross weight, suspension characteristics and operational speed. Heavy vehicles such as multi-axle trucks, buses and freight carriers produce significantly higher amplitude and lower-frequency vibrations. In contrast, lighter vehicles contribute to higher-frequency but lower-energy excitations [22]. Significantly, the presence of surface irregularities such as potholes, patch joints, geometric transitions and speed control measures like humps and rumble strips amplifies these responses by introducing discontinuities in force transmission [23, 24].

In real-world urban contexts, particularly in Indian cities, such amplification is further exacerbated by inconsistent pavement maintenance, non-standardized hump design and unpredictable vehicle behaviors due to mixed traffic conditions [25]. These issues are especially pronounced in Tier-II and Tier-III cities, where rapid urban growth has outpaced infrastructure regulation. As a result, vibration waveforms transmitted from roadways propagate into subgrades, foundations and adjacent structures through surface and body wave mechanisms, with spatial reach and severity influenced by soil stiffness, damping properties and structural resonances [26].

From a structural standpoint, the effects of TIV are cumulative and manifest as long-term degradation. Repeated vibratory excitation contributes to fatigue damage, loss of material integrity and micro-crack evolution, particularly in masonry or lightly reinforced concrete structures not designed for dynamic loads. Heritage buildings, old residential blocks, educational institutions and low-rise commercial facilities are especially vulnerable due to poor dynamic resistance and the absence of seismic or vibrational design considerations. Studies have documented modal drift, dynamic amplification and serviceability loss in structures within high-traffic corridors exposed to persistent vehicular vibration [14, 19]. These degradation mechanisms are susceptible to the frequency content of ground vibrations, further underscoring the importance of spectral analysis in vibration studies.

Beyond structural concerns, TIV has notable implications for functionality and quality of life. Ground-borne vibrations are known to interfere with the performance of vibration-sensitive equipment in hospitals, research laboratories and data centers. In such environments, even sub-millimeter ground displacements can degrade the accuracy of medical diagnostics, precision testing and scientific instrumentation [27]. Moreover, prolonged human exposure to vibration stimuli has been associated with psychological stress, sleep disturbance, reduced productivity and in some cases, cardiovascular risks [20].

Despite these diverse and documented effects, India's current urban and infrastructure policies lack dedicated regulatory mechanisms to assess, monitor, or mitigate TIV. Most existing standards, such as ISO 2631-1 [15] and BS 6472 [16], provide generalized guidelines for human exposure and structural response to vibration. However, as these codes are designed for broad applicability, they do not directly account for site-specific factors such as soil properties, traffic heterogeneity, and urban land-use conditions. It is therefore the responsibility of practitioners to correctly interpret and apply these guidelines within the context of local geotechnical and environmental conditions.

Recent advances in urban traffic sensing, vehicle classification and predictive modeling have opened new pathways to more effective TIV management. By integrating classified vehicle flow data with localized vibration forecasting and intelligent infrastructure planning, urban authorities can proactively identify high-risk corridors, enforce zoning protections and implement vehicle rerouting in vibration-sensitive areas. Furthermore, the emergence of comparative vibration metrics, such as the Passenger Car Vibration Equivalence (PCVE) and the Reference Vibration Emission (RVEL), allows for standardized quantification of vibrational impacts across vehicle types and road conditions, providing a robust basis for regulatory intervention and design optimization.

This section has established the physical drivers, structural and social impacts and system-level complexities associated with traffic-induced vibrations in heterogeneous urban settings. It has also highlighted the limitations of current regulatory standards and underscored the need for integrated approaches that combine vehicle classification, vibration quantification and predictive traffic control. The following section systematically identifies the methodological and policy gaps that constrain existing solutions and sets the stage for a unified framework capable of addressing TIV through real-time sensing, spectral analytics and planning-aware mitigation strategies.

1.3 Critical Gaps and Limitations of Existing Approaches

Despite growing recognition of traffic-induced vibrations (TIV) as a significant environmental and infrastructural concern, the current frameworks for assessing, predicting and mitigating TIV remain fragmented, non-contextual and vastly inadequate for complex urban settings such as those in India. These limitations are especially pronounced in environments characterized by heterogeneous traffic flow, inconsistent pavement quality and informal speed-regulating measures. Despite established knowledge of TIV mechanisms and their consequences, real-world mitigation efforts remain ineffective due to several methodological and institutional limitations.

Firstly, the existing international vibration standards, including ISO 2631-1 [15] and BS 6472 [16], were primarily developed under assumptions of homogeneous traffic flow, smooth pavement conditions and standardized infrastructure. These standards provide generalized exposure limits for human comfort and structural safety but fail to capture the stochastic and amplified vibration patterns typical of mixed urban traffic operating over discontinuous road geometries. Their applicability becomes questionable in Indian contexts, where unplanned speed humps, deteriorated road segments and abrupt elevation changes act as localized sources of transient, high-energy vibrations that propagate into adjacent structures.

Secondly, most vibration prediction models rely on deterministic or semi-empirical formulations assuming steady-state vehicle motion over idealized pavement profiles [28]. These models typically exclude the effects of traffic-induced load variability, unsignalized intersections and impulsive excitation caused by repeated braking or acceleration events. The inability of such frameworks to simulate dynamic vehicle-pavement interactions, especially across speed-controlling elements like humps, leads to substantial deviations between predicted and observed vibration levels. Moreover, there exists a lack of standardized procedures for incorporating real-time surface irregularities and speed hump geometries into vibration modeling protocols, despite their well-documented influence on vibration amplification.

Thirdly, vehicle classification systems, essential for source identification in TIV studies, remain dependent on either manual counts, intrusive axle-load sensors, or image-based detection algorithms [29]. These approaches are often impractical in dense urban settings due to high costs, environmental sensitivity and maintenance overhead. More critically, they fail to capture the dynamic interaction characteristics that govern vibration generation. The potential of tri-axial ground vibration signals as a robust, non-intrusive data source for classification remains underexplored in current literature. There is an absence of scalable, machine-learning-driven frameworks that leverage these signals to distinguish between vehicle types based on their vibrational signatures under field conditions.

Fourthly, existing route optimization systems predominantly rely on GPS-based trajectory data to estimate congestion and travel time [30]. These tools, however, treat all GPS signals equally, ignoring vehicle type, occupancy and vibration potential. As a result, a truck and a bus are indistinguishable despite vastly different spatial and vibrational footprints. Such models fail to incorporate classified traffic volume or zone-specific sensitivity, often routing high-vibration vehicles through heritage areas, hospitals, or labs. The absence of vibration-aware routing based on vehicle class and road sensitivity restricts effective traffic management in vibration-critical corridors.

Fifthly, existing urban traffic frameworks lack universally accepted, vibration-specific comparative indices for regulatory and planning applications. While traffic flow theory adopts standardized measures such as Passenger Car Units (PCU) to normalize space and time occupancy, no equivalent standard exists for characterizing the vibration impact of different vehicle classes. This absence of a reference vibration metric prevents quantitative comparison, limiting the development of vibration-based policies, speed regulation and infrastructure zoning guidelines. Without such metrics, enforcing design or operational modifications in areas prone to chronic vibration exposure becomes difficult.

Lastly, a systemic regulatory gap persists in formally recognizing TIV as a critical planning and infrastructure parameter. National urban transport policies and municipal development codes currently do not mandate the assessment of vibrational impacts during road planning, infrastructure retrofitting, or zoning policy design. As a result, vibration mitigation is rarely embedded into traffic design workflows, even in proximity to vibration-sensitive facilities. The lack of institutional mandates constrains the adoption of vibration-sensitive infrastructure planning practices across Indian cities.

In summary, critical limitations persist across five domains: (i) inadequacy of existing vibration exposure standards under mixed-traffic and irregular roadway conditions, (ii) oversimplification in vibration prediction models lacking vehicle-road interaction realism, (iii) lack of scalable, non-intrusive vehicle classification frameworks utilizing vibration signals, (iv) reliance on GPS-based routing systems that ignore vehicle-specific vibration emission profiles and (v) non-availability of standardized comparative vibration indices for regulatory use. These deficiencies necessitate the development of an integrated, multidisciplinary framework that fuses empirical vibration data, advanced signal decomposition, machine-learning-based classification and context-aware forecasting. The subsequent sections outline the methodological structure adopted in this research to systematically address these interconnected challenges.

1.4 Need for an Integrated Multidisciplinary Framework

Addressing traffic-induced vibrations (TIV) in complex, heterogeneous urban environments, particularly those in India, requires a departure from fragmented, single-domain approaches toward a unified, multidisciplinary framework [31]. Existing practices developed under assumptions of homogeneous traffic and consistent infrastructure fail to account for the stochastic dynamics, variable surface conditions and infrastructural vulnerabilities characteristic of Indian road networks. Effective mitigation of TIV thus mandates the integration of civil engineering, signal processing, machine learning and traffic modeling within a context-aware, data-driven framework.

At the core of this integrated strategy lies the empirical quantification of ground-borne vibrations under realistic traffic conditions. High-resolution tri-axial vibration signals acquired from urban corridors provide essential insight into the directionality, intensity and frequency content of traffic-induced vibration events. These measurements capture the interplay between vehicle characteristics, pavement geometry and structural boundaries, particularly in response to surface discontinuities such as humps or degraded pavement sections without relying on controlled or laboratory conditions.

Advanced signal decomposition methods are essential for analyzing complex vibration responses, particularly when assessing the influence of speed-control structures such as humps. Techniques like Variational Mode Decomposition (VMD) [32] isolate frequency bands associated with different vehicle-pavement interactions, allowing characterization of vibration amplification under varying geometries and speeds. These insights are critical for infrastructure-responsive speed hump design and form the analytical foundation for quantifying vibrational severity in uncontrolled urban environments.

This research further extends the framework by introducing a non-intrusive, vibration-based vehicle classification system. Conventional classification tools such as axle-count sensors or video analytics are intrusive or environmentally constrained [33]. In contrast, the approach adopted here leverages machine learning to classify vehicle types using features extracted from ground vibration signatures, enabling scalable and weather-independent identification in mixed traffic.

Beyond classification, the framework incorporates predictive traffic volume modeling based on historically classified vehicle count data. Unlike traditional GPS-only models that overlook vehicle heterogeneity [34], the proposed forecasting approach emphasizes vehicle-specific flow and its relationship to future congestion and vibrational load. This enables proactive planning by predicting when and where high-vibration vehicle types may dominate the flow and allows for rerouting or regulatory intervention.

A key innovation within this framework is the introduction of comparative vibration indices, namely, Passenger Car Vibration Equivalence (PCVE) and Reference Vibration Emission Level (RVEL). These metrics standardize the vibrational footprint of different vehicle classes across speeds and road conditions, analogous to PCU in traffic engineering [35]. This enables urban planners to evaluate the cumulative vibrational impact of traffic flows and enforce zoning or routing regulations for vibration-sensitive areas.

Importantly, this framework aligns with broader urban sustainability goals by linking TIV to public health, livability and infrastructure resilience. Prolonged exposure to low-level vibrations affects structural durability and human well-being. Thus, integrating TIV considerations into policy, traffic control and infrastructure planning is a technical necessity and a public health imperative.

The proposed multidisciplinary framework bridges empirical vibration monitoring, signal decomposition, vehicle classification and forecasting within a unified system. It equips urban planners and engineers with tools to make informed, vibration-aware decisions for traffic management, infrastructure design and urban zoning, especially critical for cities with heterogeneous traffic, fragile infrastructure and limited regulatory controls. The following section outlines the specific objectives and scope of this research built upon this integrated framework.

1.5 Research Objectives and Scope of the Doctoral Research

This doctoral research aims to develop an empirically grounded and operationally scalable framework for the characterization, classification and governance of traffic-induced vibrations (TIV) in urban environments. The framework synthesizes field-based vibration sensing, signal decomposition, vehicle classification and forecasting techniques to address critical limitations in existing standards, predictive models and regulatory mechanisms. The specific research objectives are delineated as follows:

1. **To empirically characterize and evaluate the design implications of speed hump-induced ground vibrations across multidirectional components (X, Y, Z)** using triaxial accelerometers under real-world traffic conditions. The study applies Variational Mode Decomposition (VMD) to extract dominant modal characteristics and assesses how variations in hump material and geometry influence vibration profiles, supporting data-driven design recommendations.

2. **To formulate and validate standardized vibration emission metrics**, namely, *Passenger Car Vibration Equivalence (PCVE)* and *Reference Vibration Emission Level (RVEL)*, for comparative evaluation of vibrational impacts across vehicle categories and operational speeds. Among these, PCVE serves as a vibration-based analogue to the Passenger Car Unit (PCU) used in traffic engineering. At the same time, RVEL defines vehicle and speed-specific reference thresholds for emission-level regulation and zoning guidance.

3. **To develop a vibration-based vehicle classification framework** that leverages statistical and energy-based features derived from tri-axial vibration signals, enabling non-intrusive, weather-resilient identification of vehicle types. The classification

system is designed to operate under real-world conditions, using ensemble machine learning models to overcome limitations of vision-based and sensor-intrusive techniques.

4. **To construct a forecasting and route optimization framework** by integrating classified vehicle count data with time-series and machine learning models (ARIMA, SVM, XGBoost), augmented with GPS-based trajectory data. The goal is to enhance travel-time efficiency in congested urban corridors, indirectly supporting vibration mitigation by promoting smoother vehicle flow.

The scope of this research encompasses the following key components:

- **Field Vibration Data Collection:** Installation of tri-axial accelerometers at selected urban corridors, including those with speed-control devices such as humps and rumble strips, to capture authentic directional vibration signals under varying traffic and surface conditions.

- **Advanced Signal Processing and Frequency-Based Decomposition:** Application of Variational Mode Decomposition (VMD) to analyze vibration characteristics induced by geometric discontinuities such as speed humps, enabling frequency-resolved assessment of energy distribution and modal contributions.

- **Vibration Emission Metric Development and Normalization:** Formulation of standardized indices, Passenger Car Vibration Equivalence (PCVE) and Reference Vibration Emission Level (RVEL), to compare vehicle-induced vibrations across different vehicle types and speeds.

- **Vibration-Based Vehicle Classification:** Development of a non-intrusive machine learning framework using statistical and energy-based features extracted from ground vibration signals allows accurate vehicle category identification in real-time under mixed-traffic conditions.

- **Traffic Forecasting and GPS-Augmented Route Optimization:** Integration of classified vehicle count data with time-series and machine learning models (ARIMA, SVM, XGBoost), supported by GPS-based trajectory inputs, to enable congestion-aware, travel-time optimized routing.

- **Unified Framework Deployment for Vibration-Aware Governance:** Integrating field sensing, PCVE/RVEL metrics, vibration-based vehicle classification and GPS-augmented traffic forecasting into an operational system for real-time vibration monitoring, impact-sensitive traffic rerouting and risk-informed infrastructure governance.

This cohesive methodological structure establishes a robust foundation for vibration-sensitive transportation planning, supporting infrastructure-responsive design, real-time vehicle classification and data-informed regulatory decision-making for managing traffic-induced ground vibrations via data-driven infrastructure design and evidence-based regulatory interventions in urban environments.

1.6 Significance and Novel Contributions

This doctoral research proposes and validates a comprehensive, field-integrated framework for the assessment, classification and proactive management of traffic-induced vibrations (TIV) in heterogeneous urban settings. The study is situated within the complex context of Indian roadways, where mixed-traffic conditions, irregular surface geometries and infrastructural vulnerabilities complicate the assessment and mitigation of ground-borne vibrations. While previous studies have examined TIV phenomena in isolation, this work unifies empirical data collection, signal analysis, machine learning and predictive traffic modeling into a coherent system capable of informing real-time decision-making.

The significance of this research lies in its capacity to bridge the domains of vibration science, traffic engineering and data-driven urban management. Existing approaches in traffic planning often overlook the vibrational implications of vehicle movement and vibration studies seldom integrate vehicle-specific data or traffic forecasting. This thesis addresses these gaps by developing a unified methodology that enables the monitoring, classification and prediction of traffic-induced ground vibrations using real-world datasets and scalable computational models.

The major contributions of the research are outlined as follows:

- **Empirical Characterization and Design Guidance for Speed Humps:** A detailed in-situ experimental investigation was conducted using tri-axial accelerometers across urban corridors equipped with speed control devices constructed from bitumen, fiber composites and rumble strips. Vibration responses from multiple vehicle categories were analyzed using Variational Mode Decomposition (VMD) to extract dominant frequency bands, energy profiles and modal amplitudes. The findings demonstrate material- and geometry-dependent variations in vibration intensity and provide evidence-based recommendations for selecting speed hump types in vibration-sensitive and enforcement-priority zones.

- **Standardization of Vibration Quantification Metrics:** Two novel vibration-based metrics were developed: Passenger Car Vibration Equivalence (PCVE), which serves as a normalized unit for comparing the vibration contributions of various vehicle types and Reference Vibration Emission Level (RVEL), which defines expected emission levels based on vehicle type and speed. These metrics enable objective evaluation and zoning regulations sensitive to vibration intensity.

- **Machine Learning-Based Vehicle Classification Using Vibration Data:** A vibration-based vehicle classification system was developed using statistical and energy-domain features extracted from tri-axial ground vibration signals. Ensemble learning models were trained and validated for the reliable identification of vehicle categories under field conditions. This non-intrusive system overcomes the environmental and infrastructural limitations of image-based and axle-load sensor methods.

- **Forecasting Framework for Traffic Volume and Flow Composition:** The study introduces a forecasting model based on classified vehicle volume counts and augmented GPS-based trajectory inputs. By integrating ARIMA, SVM and XGBoost models, the framework predicts short-term traffic flow patterns across urban corridors. While travel-time optimization is the primary goal, smoother vehicle movements inherently reduce impulsive vibration events.

- **Integrated Framework for Vibration-Aware Traffic Management:** A unified, modular framework was developed that seamlessly integrates tri-axial vibration sensing, PCVE and RVEL-based quantification, machine learning-driven vehicle classification and predictive traffic forecasting into an operational architecture. The system enables real-time vibration-aware route optimization, dynamic zoning of vibration-sensitive corridors and infrastructure risk mitigation. It supports regulatory enforcement by translating empirical vibration signals into actionable traffic control and planning decisions, thereby bridging the gap between field measurements and urban governance.

By combining empirical fieldwork with computational intelligence and transportation analytics, this research offers a new paradigm for managing the vibrational impacts of urban road traffic. It provides planners, engineers and policymakers with a technically rigorous toolkit for sustainable, vibration-conscious infrastructure development and transportation regulation.

1.7 Structure of the Thesis

This thesis is structured into nine technically cohesive chapters. Each chapter addresses a critical component in developing a comprehensive, field-validated framework for analyzing, quantifying, classifying and forecasting traffic-induced vibrations (TIV) in urban transport systems.

- **Chapter 1: Introduction** Defines the research problem, contextualizes the importance of TIV in infrastructure planning and articulates the multi-objective goals of this doctoral investigation, establishing its interdisciplinary scope.

- **Chapter 2: Literature Review** Critically evaluates previous work related to vibration generation, speed hump impacts, signal decomposition methodologies, vehicle classification from vibration signals and limitations of GPS-based traffic prediction. A synthesis of gaps is used to frame the research agenda.

- **Chapter 3: Methodology** Outlines the complete methodological framework covering vibration sensing, signal preprocessing, Variational Mode Decomposition (VMD), machine learning for classification and the development of standardized vibration indices (PCVE and RVEL) along with forecasting strategies.

- **Chapter 4: Study Design and Data Collection** Describes the experimental protocols adopted across four primary studies. It outlines sensor placement, traffic composition, geometric configurations and vehicle category variations under which vibration data were collected.

- **Chapter 5: Empirical Characterization and VMD-Based Analysis of Speed Hump-Induced Vibrations** Presents a detailed empirical study on vehicle vibrations across Fiber, Bitumen and Rumble Strip profiles. VMD is employed to extract multi-modal frequency features and the results inform the optimization of hump design based on vehicle type and road use context.

- **Chapter 6: Standardization of Vibration Metrics Using PCVE and RVEL** Introduces two novel metrics: Reference Vibration Emission Level (RVEL) and Passenger Car Vibration Equivalence (PCVE), for quantifying different vehicles' absolute and relative vibrational impacts. Statistical models and a software tool were developed for real-time evaluation.
- **Chapter 7: Vibration-Based Vehicle Classification Using Machine Learning Techniques** Proposes and validates a high-accuracy vehicle classification system using statistical, spectral and energy-based features extracted from tri-axial ground vibration signals. The system achieves 99.78% accuracy through stacked ensemble classifiers.
- **Chapter 8: Traffic Forecasting and Route Optimization Using Classified Vehicle Data and GPS Augmentation** Presents a hybrid machine learning framework that integrates classified vehicle counts with GPS trajectory inputs and forecasting models (ARIMA, SVM, XGBoost) to develop congestion-aware, vibration-sensitive routing solutions. Results from real-world trials validate its effectiveness.
- **Chapter 9: Conclusions** Summarizes the core findings, practical implications and scientific contributions of the thesis. It also outlines limitations and proposes future work toward intelligent, vibration-aware transportation systems.

The next chapter presents a comprehensive literature review on traffic-induced vibrations, vehicle classification techniques and signal-based forecasting models to identify critical gaps and position the current research within the broader academic context.

Chapter 2

Literature Review

2.1 Preface

Building upon the research objectives defined in Chapter 1, this chapter critically reviews the theoretical and empirical developments relevant to traffic-induced vibrations and their management frameworks. The phenomenon of *Traffic-Induced Vibrations* (TIV) holds profound implications for urban infrastructure systems. As outlined in the preceding chapter, TIV significantly affects structural integrity, occupant comfort and the performance of vibration-sensitive equipment. Its early recognition as an engineering concern dates back to foundational observations, such as those by Chapman (1929) [36], who associated increased urban motorization with pavement distress and noticeable ground vibrations. Since then, the scope of TIV research has broadened considerably from empirical observations and vibration thresholds to advanced, multidisciplinary analyses encompassing vehicle-road-soil interaction, signal processing techniques and intelligent traffic system frameworks.

This convergence of disciplines is crucial to understanding and mitigating the complex vibratory phenomena induced by urban traffic systems. Given modern traffic's increasing complexity and variability, particularly in developing countries, a dedicated literature review is necessary and timely. This chapter aims to fulfill three key objectives.

First, it synthesizes the contributions of classical studies that established the foundational understanding of TIV mechanisms. Second, it identifies persistent limitations in conventional approaches, particularly in contexts characterized by heterogeneous vehicle compositions, high traffic density and infrastructure irregularities factors that exacerbate vibration levels, especially around traffic-calming devices such as speed humps and rumble strips. Third, it reviews recent advancements in signal decomposition, vibration-based vehicle classification and GPS-augmented traffic forecasting, enabling more accurate and context-sensitive modeling of TIV.

Overall, this literature review supports a multidisciplinary perspective essential for advancing TIV research in mixed-traffic environments, such as those prevalent in Indian cities. It further lays the groundwork for the research contributions presented in subsequent chapters by highlighting the need for integrated, vibration-informed traffic management and infrastructure resilience strategies.

2.2 Foundations of Traffic-Induced Vibrations (TIV)

2.2.1 Historical Evolution of Traffic-Induced Vibration Studies

The scientific exploration of Traffic-Induced Vibrations (TIV) has evolved significantly, commencing from early observational insights and advancing toward comprehensive modeling frameworks. The pioneering efforts in vibration investigations trace back to Sir George Humphreys (1896–1902) [37], who evaluated the impact of dynamite excavation on nearby urban structures. Captain H. Riall Sankey (1910) [37] further highlighted the importance of precise vibration measurements with the onset of electric railway systems.

Systematic research on TIV began in the late 1920s, with Chapman (1929) [36] and Hyde (1929) [37] identifying vehicle speed as a predominant factor influencing ground vibrations over static loads. The advent of early mitigation approaches such as tar macadam resurfacing in 1917 [37] showcased an initial understanding of surface enhancement for vibration control.

Subsequent investigations by Hyde (1929) [38] and the human perception threshold formulation by Reiher and Meister (1931) [39] structured the dual research focus on structural responses and human sensitivity to TIV.

A transition towards experimental quantification emerged in the mid-20th century. Studies by Bernhard (1939, 1941) [40, 41], Ferguson (1940) [42] and Sutherland (1951) [43] systematically analyzed noise and vibration phenomena induced by motor vehicle operations. Further contributions by Dieckmann (1958) [44] and Bonde (1981) [45] assessed dynamic responses of masonry structures to surface-level disturbances.

By the 1970s, research efforts pivoted to frequency content characterization and dynamic load behavior. Harmelink (1970) [46] investigated differentiating vibration sources from ambient noise. The pioneering large-scale survey by Whiffin and Leonard (1971) [27] correlated particle velocity measurements (5–25 Hz) with specific vehicle classes and pavement irregularities. Investigations by Reiter et al. (1972, 1973) [47, 48] revealed the contribution of truck tire dynamics to low-frequency excitation.

Dynamic load modeling advanced through the works of Leonard (1974) [49] and Rudder (1978) [50, 51], who introduced probabilistic frameworks for assessing both maximum and cumulative traffic-induced loads. Field evaluations by Bean (1976) [52] and Baughan (1981) [53] further demonstrated the diverse structural impacts of traffic loads.

Environmental surveys by Chilton et al. (1975) [54] and Sando (1974) [18] highlighted human discomfort due to TIV, with approximately 8% of the surveyed population reporting significant annoyance.

The late 1970s and early 1980s studies, including Martin (1978) [55, 56], formed the empirical basis for internationally accepted thresholds such as BS 6472 [16], BS 7385-2 [57] and ISO 2631-1 [15]. However, subsequent investigations by Watts and colleagues (1984–1992) [24, 58–62] identified critical limitations in these standards, particularly under complex urban conditions where nonlinear amplification effects were prevalent due to surface roughness and suspension dynamics.

Continuing the evolutionary trajectory of TIV research, the focus in the 1990s and beyond shifted towards advanced modeling techniques and real-world field validations. Cebon (1993) [63] developed integrated multi-body vehicle dynamics with pavement interaction models to predict dynamic wheel loads more accurately. This modeling advancement was further substantiated by Hunaidi (1994) [64], who utilized field instrumentation to correlate surface condition, tire impact force and subgrade characteristics with vibration propagation patterns.

Efforts to simulate soil-structure interaction (SSI) were spearheaded by Al-Hunaidi and Tremblay (1995, 1996) [65, 66], leveraging frequency-domain FEM-BEM hybrid models. Concurrently, Krylov (1995–1998) [67–70] investigated Rayleigh wave generation under moving loads, identifying significant amplification near critical velocities, particularly in soft soil environments. These insights were further validated through field investigations by Domenichini et al. (1998) [71]. Recent analytical models [72–74] have emphasized vehicle-induced dynamic loading impacts on heritage structures and proposed structure-specific vibration thresholds.

Entering the 2000s, field studies gained prominence, emphasizing the inadequacy of linear wave propagation models in soils exhibiting high damping or nonlinearity. Experimental validations by Lombaert et al. (2003) [75], Ju (2006) [76], Lombaert and Degrande (2001) [77], Degrande et al. (2000) [78], Lak et al. (2011) [79] and Mhanna et al. (2012) [80] reinforced the significance of nonlinear soil behavior modeling for accurate TIV predictions.

Further contributions by Hunaidi and Nicks (2000) [81] examined the influence of bus suspension systems on vibration transmission to adjacent structures, while Klaeboe (2003) [82] established statistical models linking vibration exposure to human annoyance levels.

Advanced modeling efforts continued with Shimura et al. (2014) [83], Aliyu and Yusuf (2016) [84] and Czech (2016) [85], who analyzed road surface conditions, vehicle dynamics and mitigation strategies, respectively. Field assessments by Coquel and Fillol (2017) [86], Quagliata (2018) [87] and Arana and Grino (2018) [88] further enriched practical knowledge of TIV effects and control mechanisms.

Recent studies by Erkal (2020) [89], Testa (2020) [90], Zhang and Zhang (2019) [91] and Costanzo et al. (2022) [92] have provided comprehensive insights into vibration impacts on heritage structures, demonstrating the importance of monitoring campaigns and anti-vibration designs.

Mitigation strategies evolved with Al-Hunaidi and Rainer (1991) [93, 94], Persson et al. (2014, 2016) [95, 96] and Ducarne et al. (2017, 2018) [97, 98], who incorporated vehicle axle configurations, local road profiles and dynamic hump-vehicle interactions in their models.

Field evaluations by Fozi et al. (2019) [99], Lozancic et al. (2019) [100] and Shiferaw et al. (2021) [101] highlighted the complexity of TIV scenarios under mixed-traffic and heterogeneous soil conditions. Additionally, Crispino and D'Apuzzo (2001) [102] emphasized the vulnerability of heritage buildings, necessitating site-specific predictive modeling and tailored mitigation measures.

In conclusion, the research evolution of TIV demonstrates a methodological progression from basic field observations to advanced, multi-domain modeling approaches, underscoring the need for context-specific analysis to address the multifaceted challenges of traffic-induced vibrations in modern urban environments.

2.2.2 Frequency Content and Dynamic Loading Characteristics

Understanding the frequency content of Traffic-Induced Vibrations (TIV) and the dynamic loading characteristics has been pivotal in predicting the response of structures, pavements and human perception to vehicular excitations. Early empirical investigations by Whiffin and Leonard (1971) [27] identified that heavy vehicles traversing uneven pavements generate dominant vibration energy within the 5-25 Hz range, which coincides with the fundamental frequencies of low- to mid-rise buildings. Martin (1978) [56] validated this through extensive field studies, correlating these frequencies with increased discomfort and potential structural resonance.

Leonard (1974) [49] significantly advanced dynamic load characterization, highlighting that vehicular suspension systems exhibit frequency-dependent responses to pavement unevenness. Rudder (1978) [51] further demonstrated that transient vehicular loads can excite structural resonances, particularly when excitation frequencies overlap with natural structural modes.

In addition, field experiments by Hunaidi (1994) [64] and Watts et al. [24, 62] established that road surface discontinuities elevate spectral energy concentration, shifting peak frequencies depending on surface geometry and wheel impact dynamics.

Analytical models progressed through Cebon (1993) [63], who incorporated multi-body vehicle-pavement interaction in the frequency domain. Complementary work by Krylov (1995–1998) [67–70] explored wave propagation mechanisms, showing critical velocity-induced amplification of Rayleigh waves in soft soils. Localized spectral decomposition techniques were advanced to capture transient high-frequency components induced by speed humps and irregularities [103–105].

Studies by Sun (2002) [106] and Melcer (2006) [107] provided stochastic models quantifying the power spectral density (PSD) of pavement loads, correlating low-frequency energy with heavy vehicles and high-frequency transients with surface roughness.

Experimental validations by Lombaert and Degrande (2001) [77], Ju (2006) [76] and Al-Hunaidi and Tremblay (1995, 1996) [65, 66] underscored the significance of soil damping and stratification in modifying frequency propagation characteristics.

Further developments by Persson et al. (2014, 2016) [95, 96] and Ducarne et al. (2017, 2018) [97, 98] illustrated that speed control devices and short-wavelength defects introduce high-frequency transients, often exceeding 25 Hz.

Recent field studies by Fozi et al. (2019) [99], Lozancic et al. (2019) [100] and Shiferaw et al. (2021) [101] performed detailed spectral decomposition of real-world TIV data, affirming the prevalence of low- to mid-frequency components across vehicle classes.

Advanced spectral analysis and classification techniques were emphasized by Stocker (2014) [108], who demonstrated the applicability of situational vibration data for vehicle classification using hybrid spectral-temporal methods. In parallel, recent studies such as Liu et al. (2022) [109] and Jakubczyk (2016, 2017, 2018) [110–112] explored frequency-domain features primarily for structural health monitoring and building response prediction under traffic-induced vibrations.

Additional studies from Astrauskas (2017) [31], Agostinacchio (2014) [23] and Lu (2015, 2018) [113, 114] highlighted the role of stochastic road profiles and multilayered pavement modeling in capturing realistic dynamic loading scenarios. Parametric investigations revealed that axle configuration and gross vehicle weight substantially influence vibration profiles [115, 116].

Thus, frequency content analysis combined with advanced vehicle-road-soil interaction modeling remains indispensable for accurately predicting vibration propagation, structural resonance risks and vibration-based vehicle classification under mixed-traffic conditions.

2.2.3 Soil-Structure Interaction and Wave Transmission Behavior

The propagation of Traffic-Induced Vibrations (TIV) through soils and structures is predominantly governed by Soil-Structure Interaction (SSI) mechanisms and wave transmission behavior. Early studies by Ferguson (1940) [42] and Sutherland (1951) [43] highlighted the critical role of soil properties in amplifying or attenuating ground vibrations, reporting severe fatigue and cracking in structures adjacent to traffic corridors.

Comprehensive field investigations by Hunaidi (1994) [64] and controlled experiments by Al-Hunaidi and Tremblay (1995, 1996, 1997) [65, 66, 117] demonstrated that soft subgrades substantially amplify vertical vibrations, while stiff soils with higher damping capacity attenuate energy transmission. Their findings emphasized the influence of shallow foundations, seasonal variations in soil stiffness and pavement condition on vibration propagation.

Numerical advancements by Lombaert and Degrande (2001) [77], Ju (2006) [76] and Maeda (1998) [118] integrated frequency-dependent soil damping and stratified profiles into SSI models, accounting for site-specific response characteristics. Experimental validation by Taniguchi (1979, 1981) [119, 120] and Hao and Shen (2001) [121] confirmed the critical dependence of wave attenuation on water saturation and impedance contrasts across layered soils.

Studies by Hanson et al. (2006) [122], Shen et al. (2008) [123], Divett and Dravitzki (2008) [124] and Li and Omenzetter (2009) [125] explored transit-induced building vibrations and traffic-induced floor responses under varying vehicle loads and surface profiles. Site-specific vibration limits for residential areas were proposed by Talja and Tornqvist (2010) [126], emphasizing the necessity of customized SSI analysis.

Further contributions by Watts and Stait (2009) [127] and Ertugrul and Ulgen (2010) [128] addressed the role of vehicle-specific conditions and soil type variations in altering vibration amplitudes, Garg and Sharma (2010) [129] measured the vibration level for railway vehicles at Delhi, while Levenberg (2012) [130] introduced embedded sensors for real-time pavement monitoring.

Wave propagation theories developed by Krylov (1995–1998) [67, 68, 70] identified Rayleigh waves as dominant energy carriers, with amplification zones forming when vehicle speeds approach critical wave velocities in soft soils. Field validations by Fozi et al. (2019) [99], Lozancic et al. (2019) [100] and Shiferaw et al. (2021) [101] correlated vibration recordings with geotechnical profiles, highlighting resonance effects in stratified and water-saturated soils.

Investigations by Watts and King (2004) [131], Gerritsen et al. (1999) [132] and Persson et al. (2016) [96] examined complex wave paths involving reflection, refraction and scattering at subsurface boundaries. Koga (2000) [133] detailed frequency amplification in areas with shallow groundwater, while Jakubczyk et al. (2016, 2017) [110, 111] emphasized the influence of underground utilities on wave propagation patterns. Recent developments in vibration mitigation include anti-vibration pavements, reinforced subgrades and damping materials to attenuate dominant frequency bands [134–136].

In conclusion, accurate modeling of TIV impacts requires integrating site-specific geotechnical data, detailed SSI models, advanced wave propagation theories and empirical validations. The evolving urban landscape necessitates hybrid numerical-experimental approaches to mitigate vibration transmission, particularly in infrastructure-dense environments with heterogeneous subsurface conditions.

2.2.4 Modeling Frameworks for Traffic-Induced Vibrations

Accurate modeling of traffic-induced vibrations (TIV) is essential for predicting ground motion, evaluating structural vulnerabilities and formulating effective mitigation strategies. Over the decades, modeling approaches have evolved from empirical formulations to comprehensive multi-physics frameworks integrating vehicle dynamics, pavement irregularities, soil layering and soil-structure coupling.

Leonard (1974) [49] introduced an early empirical formulation that related dynamic tire forces to road unevenness and subgrade stiffness. Rudder (1978) [50] introduced probabilistic models to evaluate both instantaneous and cumulative structural vibration effects, establishing serviceability thresholds. Stochastic approaches were pioneered by H.E.M. Hunt (1991) [137], modeling vehicles as mass-spring-damper systems moving over rough profiles. Chiostrini (1995) [138] validated numerical models incorporating frequency-dependent damping using field measurements.

Advanced FEM-BEM formulations by Al-Hunaidi and Tremblay (1995, 1996) [65, 66] simulated wave transmission through layered soils, integrating stiffness and damping properties. Koga (2000) [133] demonstrated wave trapping in soft subgrades prolonging vibration durations. Cebon (1993) [63] developed vehicle-pavement interaction models using multi-body simulations to predict axle load fluctuations.

Coupled modeling integrating wave propagation was advanced by Lombaert and Degrande (2001) [77] and Ju (2006) [76], highlighting the influence of soil stratification on vibration amplitudes. Krylov (1995–1998) [67, 69, 70] proposed semi-analytical wave models identifying resonance amplification zones near Rayleigh wave velocity. Kogut and Kawecki (1999) [139] applied ANN techniques combined with response spectrum analysis for improved vibration prediction.

Boundary element methods (BEM) were extended by Schevenels et al. (2004) [140] and Clouteau (2001) [141], emphasizing wave scattering and soil impedance characterization. Stochastic modeling frameworks were enriched by Xu (2008) [142], Papadopoulos (2016, 2018) [143–145] and Sun (2013) [146], who analyzed traffic-induced building vibrations considering random vehicle distributions and subsoil uncertainties.

Lombaert et al. (2003) [75] conducted field validation of simulation models, confirming the role of suspension dynamics and soil damping in waveform evolution. Mhanna et al. (2011–2014) [80, 147, 148] incorporated soil saturation effects and absorbing boundary conditions in finite-difference modeling frameworks.

Advanced numerical modeling frameworks have significantly improved TIV predictions, considering dynamic vehicle-road-soil interactions [26, 149, 150]. Boundary element methods (BEM) and finite element methods (FEM) further refined wave propagation modeling for complex layered soils [151–155]. Optimized barrier geometries and foundation design strategies were introduced to minimize vibration transmission pathways [156, 157].

Recent studies, including Zhang et al. (2017, 2019) [91, 158], utilized meshless particle techniques for adaptive modeling in irregular subsoil profiles. Astrauskas (2017) [31] adapted train-induced vibration models to road traffic scenarios across varied soil types. Lu et al. (2009–2018) [113, 114, 159] analyzed wave scattering from underground structures, while Ducarne et al. (2017, 2018) [97, 98] modeled dynamic-structural coupling across various speed hump profiles.

Hybrid physics-based and data-driven models were explored by Jakubczyk et al. (2016–2018) [110–112], integrating vibration measurements with machine learning techniques, such as artificial neural networks (ANN) and support vector machines (SVM), to predict traffic-induced vibration impacts on buildings under varying soil, road and vehicle conditions. Despite recent advocacy for standardized equivalence models [160–163], efforts to integrate vibration metrics into transport planning frameworks remain limited.

In summary, TIV modeling has transitioned from empirical approximations to multi-domain integrated frameworks leveraging FEM, BEM, stochastic methods and AI-driven models. These frameworks are critical for site-specific vibration prediction, impact assessment and strategic mitigation planning in complex traffic and urban environments.

2.3 Vehicle Classification Studies

With the increasing complexity of urban transportation systems, the development of automated frameworks for vehicle detection, monitoring and classification has become imperative, particularly in heterogeneous and vibration-sensitive corridors. Among these, vehicle classification based on size, axle configuration and gross weight emerges as a foundational component for traffic management, regulation enforcement and infrastructure resilience [164]. Efficient classification enables authorities to detect oversized or overweight vehicles violating speed or access restrictions, monitor compliance in heavy-vehicle-prohibited corridors and dynamically regulate traffic in sensitive zones. From a broader systems perspective, accurate vehicle classification underpins congestion mitigation, fuel consumption control, emissions reduction and resource optimization at critical transport interfaces such as toll plazas, intersections and freight terminals [165–167].

The advent of machine learning (ML) and real-time signal processing techniques has transformed traditional classification paradigms. By enabling rapid, robust and scalable inference on heterogeneous traffic streams, these innovations have become instrumental in intelligent transportation systems (ITS) [29, 168]. Despite such advances, conventional classification frameworks, especially those reliant on image-based or sensor-intensive systems, continue to suffer from intrinsic limitations such as high deployment costs, operational vulnerability to environmental factors and unresolved ethical concerns around surveillance and privacy [33].

A comprehensive review of vehicle classification modalities by Won (2020) [17], Gholamhosseinian et al. (2021) [169] and Wang (2022) [170] elucidates the broad spectrum of available sensing technologies and computational models. The performance and applicability of each modality are strongly context-dependent and constrained by factors such as installation overhead, lighting, weather, signal fidelity and ambient noise. Historically relying on manual observation or fixed infrastructure, traditional vehicle classification schemes have given way to hybrid approaches incorporating machine vision [171, 172] and acoustic features [173]. However, these methods still face performance degradation in poor visibility, adverse weather and occlusion-rich settings [174]. Vehicle classification technologies are broadly categorized as intrusive and non-intrusive based on their installation method, data acquisition modality and interaction with vehicular flow. GPS-based trajectory data has also been explored for vehicle classification using acceleration and deceleration patterns. However, these methods often suffer from decreased accuracy when distinguishing between vehicles of similar types [175]. Further, Gaussian Mixture Models have been employed with loop detector data to enhance vehicle length and type estimation, providing probabilistic interpretations in constrained sensor setups [176].

2.3.1 Intrusive Techniques

Intrusive vehicle classification systems are characterized by their integration within or beneath the road surface. Loop detectors and magnetic sensors exemplify this approach. While these technologies exhibit commendable reliability under standard operating conditions, their installation mandates temporary road closures, increasing costs and causing traffic disruption [177]. Machine learning algorithms have been integrated to improve accuracy, particularly in resolving complex axle configurations and temporal vehicle signatures [178, 179]. The recent trend involves replacing energy-intensive loop detectors with low-power magnetic sensors deployed in or beside the roadway [180]. Moreover, single-loop detectors, while simplistic in design, have been extended using Gaussian models to infer vehicle lengths and categories, offering a cost-effective alternative for basic classification in budget-constrained applications [176]. When coupled with time-series waveform analysis and ML models, these newer systems have demonstrated high classification accuracy even under reduced sensor counts [181]. Such approaches are particularly effective when complemented by statistical time-series analysis and can reduce dependency on multi-sensor arrays, improving system scalability in real-world deployments.

Other intrusive modalities include weigh-in-motion systems, piezoelectric sensors, geophones and accelerometers. Weigh-in-motion platforms effectively detect gross vehicle weight and axle loads, particularly valuable in freight monitoring [182]. Piezoelectric sensors offer fine-grained axle count and spacing resolution, enabling multilayered vehicle profiling [183]. Seismic sensors such as geophones extend classification to include vehicle-induced ground vibrations and studies like Stocker (2014) [108] and Jin (2018) [184] underscore their utility in recognizing vehicle category and motion signatures. Notably, accelerometer-based systems, such as those described by Liu et al. (2022) [109] and Stocker (2014) [108], provide high-resolution vibration measurements that can be mapped to distinct vehicle classes with accuracies of up to 95%. These systems are robust to lighting, cost-effective and particularly promising for integration with vibration-focused traffic research.

Despite their effectiveness, intrusive systems remain susceptible to environmental perturbations. Environmental factors such as temperature variation, precipitation and surface contamination (e.g., oil spills) can degrade sensor performance, necessitating frequent calibration and maintenance. Sensor degradation is also influenced by thermal cycles and contamination and systems often require recalibration or protective housing to maintain long-term signal fidelity, especially in mixed-weather environments. Moreover, calibration requirements, signal drift and the need for precision alignment elevate operational complexity and maintenance overhead. Thus, their utility in large-scale deployments must be weighed against these logistical burdens.

2.3.2 Non-Intrusive Techniques

Non-intrusive vehicle classification frameworks rely on externally mounted sensors, obviating the need for road excavation or structural modifications. Vision-based systems, comprising cameras and associated image processing pipelines, are among the most widely adopted non-intrusive solutions. These systems operate through sequential tasks of feature extraction, object detection and classification, often powered by deep learning [185–189]. However, their dependency on optimal lighting, visibility and high computational demands constrains their performance in real-world traffic conditions [190]. Advanced convolutional neural networks have been applied to mitigate visibility and occlusion-related issues; however, they remain computationally intensive and sensitive to training data imbalance [174].

Alternative modalities such as infrared sensors, laser scanners and LIDAR systems have gained traction to address privacy and lighting-related limitations. These systems can generate 3D spatial point clouds and vehicle silhouettes under diverse environmental conditions [187, 191, 192]. As shown in Asborno et al. (2019) [193], LIDAR-based models offer high fidelity in shape-based classification, although at high equipment and processing expenses. Radar-based classifiers use Doppler shifts and time-of-flight measurements to infer vehicle type [194]. Meanwhile, RF and Wi-Fi transceivers employ ambient signal distortion to detect and classify vehicles, offering scalability without direct line-of-sight constraints [195, 196].

Beyond optical and RF-based systems, acoustic sensors offer an additional modality for non-intrusive classification by leveraging vehicular noise and vibration characteristics. Acoustic classifiers, as shown by Guo et al. (2012) [173], improve robustness against occlusion by relying on spectral and temporal sound patterns invariant to lighting and line-of-sight conditions. These devices capture vehicle audio signatures and apply time-frequency analysis for classification. Ntalampiras (2018) [197] reported an accuracy of

96.3% using such systems to differentiate military vehicle classes. As Zhao (2018) [198] described, optical distributed sensor fibers have also been explored for vibration capture, allowing indirect vehicle classification without direct contact.

The literature demonstrates that non-intrusive systems avoid road damage and offer rapid deployment. However, they, too, face trade-offs: vision-based systems struggle with occlusion and privacy concerns; LIDAR and radar systems require specialized hardware; and acoustic and RF-based systems may suffer from interference. Therefore, sensor fusion and multi-modal learning are promising strategies to combine the strengths of various sensors while mitigating individual limitations.

In summary, the choice between intrusive and non-intrusive classification methods involves trade-offs among cost, accuracy, scalability, environmental resilience and privacy constraints. While traditionally considered intrusive, accelerometer-based methods are increasingly deployed in semi-intrusive or surface-mounted configurations. Their high signal fidelity, robustness against environmental fluctuations and compatibility with vibration-based analytics position them as practical and scalable solutions for mixed-traffic environments. These systems balance low installation overhead and high classification accuracy, making them suitable for widespread deployment in modern intelligent transportation networks. In this regard, D'Apuzzo and Nicolosi (2003) [199] demonstrated the efficacy of optimized pavement-oriented countermeasures, where specific surface treatments substantially reduced vibration transmission, ensuring improved comfort and structural safety in urban environments. The table (2.1) comprehensively summarizes comparative sensor performance across diverse classification tasks and vehicle categories. The following table compares vehicle classification studies using various sensing modalities, highlighting their sensor types, classification accuracy and the vehicle categories addressed.

Table 2.1 Comparative review of sensor modalities used in vehicle classification across different environments and vehicle categories.

Paper	Sensors	Accuracy	Classes
[197]	Acoustic Sensor	96.3%	Dragon Wagon and Assault Amphibian Vehicle
[200]	Fiber Bragg Grating Sensors	98.5%	Small Vehicles, medium and large Trucks, Single Unit and Combinations of Truck
[201]	Camera sensor module	96.5%	Car, Bus, Light and Heavy trailers
[186]	Camera sensor module	96.5%	Motorcycle, Car, Van
[187]	Camera sensor module	97%	Small Car, Truck, Van, Bus
[202]	Camera sensor module	99%	Motorbike, Light, Intermediate, Heavy more than 2-Axles
[203]	Camera sensor module	99.78%	Acura, Audi, Bentley, BMW, Chevrolet, Dodge, Hyundai and Tesla
[204]	Camera sensor module	91%	Different Car Models
[205]	Camera sensor module	95.14%	Emergency Vehicles
[206]	Camera sensor module	92.6%	Two-Wheelers, Light Vehicles and Heavy Vehicles
[207]	Camera sensor module	89.4%	Truck, Mini-van, Passenger Car, Sedan, Bus
[208]	Camera sensor module	88%	Motorbike, Rickshaw, Auto, Car, Jeep, Covered Vehicle and Bus
[209]	Camera sensor module	97.6%	Bicycle, Bus, Car, Motorcycle, Pedestrian, Pickup Truck, Non-Motorized Vehicle, Single unit Truck and Work Van
[210]	Camera sensor module	99.01%	Car, Bicycle, Single unit truck, Pickup truck, Bus, Articulated truck, Non-motorized vehicle, Work van, Motorcycle, Background
[211]	Aerial sensor	80.3%	Van, Sedan, Pick-up, Truck
[192]	Aerial sensor	98%	Car and Truck
[193]	Lidar sensor	96%	Van & Container, Platform, Trailer, Tank, Hopper & End Dump

Continued on next page

Table 2.1 – continued from previous page

Paper	Sensors	Accuracy	Classes
[212]	Lidar sensor	99.5%	Motorcycle, Passenger Vehicle, Passenger Vehicle pulling a trailer, Single unit truck, Single unit truck pulling a trailer and multiunit Truck
[194]	Radar sensor	99%	Compact, saloon and SUV
[213]	Infrared & Ultrasonic	99%	Two-Wheeler, Bus, SUV, Pick-up Truck and Sedan
[109]	7 Accelerometers	95%	Motorcycle, hatchback, sedan, SUV, mini VAN, VAN, pickup truck, mini truck, truck and a big truck
[108]	Accelerometer	83%	Light and heavy Vehicles
[214]	Magnetometer and Accelerometer	99%	2,3,4,5,6 Axle Vehicles
[184]	Geophone	92%	Dragon Wagon and Assault Amphibian Vehicle
[182]	Weigh-In-Motion with Loop Sensor	85%	Trucks only
[215]	Loop Detectors	99%	Vehicle lengths classes: below 28 ft, 28 to 46 ft and above 46 ft
[216]	Loop Detectors	94.4%	Regular Cars and Long Vehicles
[217]	Pneumatic Tubes	73%	Bi-Cycles
[183]	Single Element, Piezoelectric Sensor, Vehicle	97%	Motorcycle, Passenger Vehicle, Two axles four tire single unit, 3-axles six tire single unit, 3-axles single unit, 4-axle single trailer, 5-axles single trailer and 7-axles single trailer
[181]	Magnetic Sensor	92.4%	Buses and Cars
[218]	Magnetic Sensor	80.5%	Sedans, Vans, Light and Medium Trucks, Heavy Trucks
[219]	Magnetic Sensor	96%	Car, SUV, Bus and Vans
[220]	Magnetic Sensor	93.6%	Motorcycle, Two-Box, Saloon, Bus and SUV
[221]	Magnetic Sensor	93%	Bicycle (Motor and EV), Car (Car/Taxi/SUV) and Mini-Bus

Continued on next page

Table 2.1 – continued from previous page

Paper	Sensors	Accuracy	Classes
[196]	Radio Frequency Transceiver	89.1%	Car, Car with Trailer, SUV, Mini-Van, Van, Truck, Truck with Trailer, Bus and Transporter
[222]	Radio Frequency Transceiver	99%	Passenger Car and Truck
[223]	Laser Scanner	86.8%	Passenger Vehicle, Passenger Vehicle with one trailer, Truck, Truck with one trailer, Truck with two trailers and motorcycles
[195]	Wi-Fi Transceivers	96%	Passenger Vehicle and Truck
[198]	Optical Distributed Sensor Fibre	89%	Car, Buses, 2-6 Axle Trucks
[188]	Vision-based (YOLOv4_AF)	83.45% and 77.08%	Cars, Trucks, Buses and general vehicle types
[189]	Vision-based Lightweight CNN (LWCNN-FO)	85.86% AP, 85.04% AR	159 fine-grained vehicle types (brands/models)
[224]	LiDAR Sensor	85-98%	20ft/40ft Intermodal, Reefer Container, Dry Van, Reefer Van, Platform, Tanker, Automobile Transporter, Open-Top Dump, Livestock/Logging
[175]	GPS Data	75%	Passenger Cars, Single-Unit Trucks, Multi-Trailer Trucks
[176]	Single-Loop Detector	97.6%	Short (<22 ft), Medium (22-40 ft) and Long Vehicles (40 ft) based on vehicle length estimation

2.4 Forecasting and Optimization in GPS-Augmented Mixed Traffic Scenarios

Accurate traffic congestion forecasting and optimal route selection are pivotal components of intelligent transportation systems, especially in developing nations characterized by high vehicular heterogeneity. With rapid urbanization placing increased stress on road networks, traditional GPS-based monitoring systems, though foundational, exhibit key limitations, including the inability to capture traffic composition, temporal dynamics and behavioral heterogeneity. Recent studies highlight the shift toward integrating machine learning (ML) techniques, vehicle classification data and auxiliary context variables such as weather, land use and semantic road features. This section reviews critical developments in GPS-augmented forecasting, outlines limitations of legacy systems and presents emerging approaches based on spatio-temporal modeling and context-aware data fusion.

2.4.1 Limitations of Traditional GPS-Based Traffic Forecasting

GPS-based traffic monitoring and prediction systems typically utilize mobile phone location signals to determine road occupancy levels and infer congestion states [225–227]. These systems effectively estimate real-time density but fail to capture traffic's composition and functional diversity, particularly in regions like India, where vehicles vary from two-wheelers to heavy commercial trucks. As Liu et al. (2023) [228] and Luperto et al. (2023) [229] highlight, reliance solely on GPS density data may result in erroneous inferences; for instance, a bus carrying 100 passengers and a car with two may contribute equally to GPS-based congestion signals, though their real-world impact differs dramatically.

Google Maps estimates congestion through color-coded lines derived from the density of GPS-enabled mobile devices [228, 229]. However, this approach lacks granularity in vehicle type, occupancy and spatial footprint, creating paradoxes in route suggestion and potentially inefficient traffic routing [230, 231]. Such systems are inherently reactive and incapable of forecasting traffic behavior under changing vehicular dynamics.

2.4.2 Machine Learning-Based Traffic Forecasting Models

Machine learning methods offer a significant advantage over traditional models in learning nonlinear patterns and adapting to temporal variations. Moses et al. (2020) [232] processed historical U.S. traffic datasets using various ML algorithms to model vehicular flow patterns. Their study demonstrated comparative model accuracies but was limited by excluding mixed-traffic contexts, a crucial factor in regions with unstructured road usage.

Alvarez et al. (2010) [233] applied a Hidden Markov Model (HMM) to predict trip destinations using portable GPS devices. Compressing trajectory data into critical support points significantly reduced data complexity. While promising, their approach lacked robustness in handling abrupt behavioral changes or unforeseen route deviations. Meneroux et al. (2020) [234] used GPS-derived speed profiles to detect traffic signal intersections, integrating image recognition and functional data analysis. Despite achieving high detection accuracy, the method demonstrated reduced efficacy in highly dynamic urban contexts.

Elfar et al. (2018) [235] used NGSIM trajectory data for congestion forecasting and achieved up to 97% accuracy through a multi-feature ML pipeline. Their model relied on vehicle kinematics (speed, acceleration, headways), but its generalizability to non-structured traffic remains uncertain. Hughes et al. (2019) [34] predicted delivery stop times from GPS traces using ML models. Though innovative, their results hinged on localized datasets and specific use cases (delivery logistics), limiting broader applicability. Similarly, Sun et al. (2019) [225] employed deep learning on GPS trajectory data for congestion detection. However, their reliance on fixed sensor infrastructure introduces logistical challenges for large-scale deployments.

Woodard et al. (2017) [227] developed the TRIP method to estimate travel time distributions using mobile GPS data. While it effectively modeled stochastic travel time variations, the methodology faced representational bias from user-specific GPS data and lacked traffic composition differentiation.

Table 2.2 provides a consolidated overview of existing traffic forecasting studies, highlighting the presence or absence of critical parameters such as GPS usage, classified vehicle volume count (CVVC), Passenger Car Units (PCU) and other contextual add-ons essential for robust traffic prediction in mixed urban environments.

Table 2.2 Summary and comparative analysis of existing work and proposed techniques. CVVC: Classified Vehicle Volume Count; HI: Human Intervention.

Work	**Technique**	**GPS**	**CVVC**	**PCU**	**Device Software**	**HI**	**Trip Based**	**Add-On to GPS**
[232]	ML modeling for traffic volume prediction	No	No	No	No	No	No	No
[233]	Device-based selected passenger route tracking	Yes	No	No	Yes	Yes	Yes	No
[234]	Intersection detection using GPS signals and speed patterns	Yes	No	No	No	No	No	No
[235]	GPS (location, acceleration, etc.) data for congestion study	Yes	No	No	No	No	No	No
[34]	Delivery time prediction using GPS record of delivery person	Yes	No	No	No	No	Yes	No
[225]	Congestion prediction with GPS trajectory data	Yes	No	No	No	No	No	No
[227]	Predicting travel time reliability using GPS data	Yes	No	No	No	No	No	No

Continued on next page

Table 2.2 – continued from previous page

Work	Technique	GPS	CVVC	PCU	Device Software	HI	Trip Based	Add-On to GPS
[30]	GPS-based route tracking with multiple vehicles	Yes	No	No	No	No	Yes	Yes
[236]	GPS and software-based route prediction	Yes	No	No	Yes	Yes	Yes	Yes
[237]	GPS with DeepSense deep learning for road traffic prediction	Yes	No	No	No	No	No	Yes
[226]	Integrated GPS with weather forecasting data	Yes	No	No	No	No	No	Yes

2.4.3 Augmentation of GPS Data with Auxiliary Inputs

Recent research has shifted toward enriching GPS data streams with contextual inputs for improved prediction. Krause et al. (2019) [30] integrated land use and point-of-interest (POI) data to infer trip purposes, using GPS records from over 260 participants across 70 days. Their model improved destination prediction but was limited by its reliance on temporal constraints and omitted transient behavioral variables.

Kamble et al. (2019) [236] implemented software-based destination prediction by tracking driver GPS activity over 2-9 weeks. ML models trained on historical routes elevated accuracy from 72% to 96% when software metadata were included. However, this approach remained vulnerable to sudden driver route deviations, limiting real-time applicability.

Niu et al. (2014) [237] proposed the DeepSense framework, leveraging spatial-temporal deep networks trained on 30,000 taxi trajectories in Wuhan. Their model achieved a 5% accuracy gain in congestion prediction but demonstrated sensitivity to GPS noise and route variability. Chou et al. (2019) [226] addressed long-term prediction by integrating weather data into GPS-based traffic models. Their study confirmed the relevance of climatic conditions in traffic trends but acknowledged challenges in accounting for unpredictable weather fluctuations.

Recent advancements also incorporate geospatial context and urban semantics into GPS-augmented traffic forecasting. Medina-Salgado et al. (2022) [238] presented a comprehensive review of traffic flow prediction techniques, highlighting the growing relevance of contextual augmentation using spatio-temporal models and sustainable computing frameworks. Guo et al. (2024) [239] further demonstrated the integration of visual and semantic features extracted from multisource geospatial data to infer updated urban land-use patterns. These studies emphasize that enriching GPS data with dynamic land use and semantic mobility patterns significantly improves prediction accuracy, particularly in complex urban environments with mixed traffic behavior.

2.4.4 Toward Hybrid and Context-Aware Models

While reviewed works show substantial progress in trajectory compression, route prediction and congestion classification, the absence of vehicle classification and volume-based metrics is evident [228]. No existing model among those reviewed incorporated the notion of classified vehicle volume count (CVVC) or Passenger Car Units (PCU) to contextualize GPS signals by vehicle type [240]. As traffic composition plays a critical role in road occupancy and delay patterns, its exclusion limits the representational power of these forecasting systems. Future forecasting frameworks must adopt hybrid architectures that integrate historical traffic trends with real-time GPS, vehicle classification metrics (CVVC, PCU) and spatial semantics derived from land use and road network topology [236]. To overcome the representational limitations of conventional and hybrid models, recent studies have increasingly turned to deep learning frameworks that can simultaneously capture spatial and temporal dependencies [241, 242].

2.4.5 Spatio-Temporal Deep Learning Models in Forecasting

Recent advances in deep learning have introduced models capable of learning both spatial and temporal dynamics of traffic flow. Yu et al. (2018) [241] proposed a Spatio-Temporal Graph Convolutional Network (ST-GCN) that captures road network topology and traffic fluctuations using graph structures and gated recurrent units. Likewise, Li et al. (2018) [242] developed the Diffusion Convolutional Recurrent Neural Network (DCRNN), which models traffic evolution as a diffusion process over a directed graph, effectively capturing long-range temporal dependencies.

These models, while achieving state-of-the-art accuracy on structured datasets like METR-LA and PEMS-BAY, are limited by their reliance on homogeneous traffic and sensor-based networks. Their scalability to unstructured, mixed traffic environments, common in developing countries, remains restricted unless augmented with vehicle classification metrics such as CVVC and PCU. Therefore, integrating these deep models with semantic features and real-time GPS-enhanced data remains critical for improving predictive performance in heterogeneous urban scenarios.

Recent advancements have also introduced transformer-based and self-supervised learning paradigms to address the limitations of traditional spatio-temporal models. Shi et al. (2024) [243] developed a transformer-based heterogeneous spatiotemporal graph learning framework that effectively captures dynamic spatial dependencies and multi-scale temporal relationships for traffic forecasting. Unlike prior graph convolutional methods, this model leverages attention mechanisms to represent spatial heterogeneity across urban regions better. Complementarily, Ji et al. (2023) [244] proposed a self-supervised learning approach that pre-trains spatio-temporal representations without requiring labeled data, enhancing model generalizability across diverse traffic scenarios.

In summary, the reviewed literature demonstrates an evolution from density-based GPS methods to multisource, ML-augmented systems. Yet, challenges remain in scaling these models to complex, unstructured traffic conditions without incorporating vehicle type differentiation and contextual dynamics. Integrating deep spatio-temporal learning models with real-time classification data and environmental semantics offers a promising pathway for future traffic prediction systems. Additionally, adopting transformer-based and self-supervised learning frameworks may enhance adaptability and scalability in real-world applications.

2.5 Speed-Hump–Induced Vibrations

2.5.1 Experimental Investigations

Experimental investigations into speed-hump–induced vibrations have revealed significant sensitivity to hump geometry, vehicle characteristics and operational speeds. Watts and Cox (1996) [245] demonstrated that round-top and short trapezoidal humps induce elevated peak particle velocities (PPVs), particularly for rigidly suspended vehicles. This was corroborated by Harris and Watts (1999) [246], highlighting increased vibration amplitudes for unladen heavy vehicles. Zarei et al. (2022) [28] quantified a 20% increase in PPV with speed increments from 20 to 60 km/h. Kojima and Yoshida (2011) [247] experimentally validated the role of closely spaced sinusoidal humps in vibration reduction by minimizing re-acceleration patterns. Lak et al. (2011, 2015) [79, 248] provided detailed analysis across vehicle categories, confirming the critical role of hump height and vehicle speed. Baraccani et al. (2020) [249] emphasized long-term subgrade degradation due to dynamic load cycles imposed by speed-control devices.

2.5.2 Soil-Structure Interaction and Wave Propagation

Wave transmission and amplification mechanisms associated with speed humps have been investigated within SSI frameworks. Watts and King (2004) [131] and Gerritsen et al.

(1999) [132] demonstrated that layered soils alter wave intensity and spectral composition. Persson et al. (2016) [96] and Xu et al. (2022) [163] confirmed that soil stiffness and damping dictate amplitude decay and wave dispersion. Hamdan et al. (2015) [250] and Maeda (1998) [118] established that elastic modulus variations control wave propagation paths. Ju (2006) [76] and Cao et al. (2023) [251] highlighted the impact of nonlinear soil damping and vertical stiffness gradients.

2.5.3 Numerical and Analytical Modeling

Advanced modeling frameworks have been developed to capture vehicle–hump–soil dynamic interactions. Ducarne et al. (2017, 2018) [97, 98] employed coupled vehicle-soil models integrating FEM and multi-body dynamics. Kouroussis et al. (2017) [149] demonstrated distinct frequency signatures across sinusoidal, trapezoidal and rectangular hump profiles. Krylov (1998, 2015) [67, 252] identified resonance amplification of Rayleigh waves in soft soils. Watts and Krylov (2000) [253] proposed bell-shaped humps to mitigate peak vibration levels. Shimura et al. (2014) [83] extended modeling to 3D vehicle-hump-soil interactions considering urban boundary effects.

2.5.4 Material-Based Mitigation Approaches

Recent research has focused on material-based mitigation. Hegde and Venkateswarlu (2019) [134] demonstrated vibration attenuation using geocell-reinforced subgrades. Huang et al. (2021) [135] integrated energy-dissipative pavement layers, achieving 20% vibration reduction. Bordon et al. (2018) [156] introduced composite pavements with elastomeric interfaces, reducing peak accelerations.

2.5.5 Advanced Signal Analysis and Multidirectional Monitoring

Advanced signal processing has enhanced TIV characterization. Lak et al. (2011) [79] and Ducarne et al. (2018) [98] utilized wavelet transforms and STFT for transient analysis. Ye et al. (2020) [254] developed adaptive mobile sensing frameworks. Multi-axial vibration measurements were validated by Persson et al. (2017) [157] and Zarei et al. (2022) [28]. Emerging DFOS technology was advanced by Zeng et al. (2022) [255]. Machine learning integrations were demonstrated by Jakubczyk et al. (2018) [112] and Xu et al. (2008) [142]. Fozi et al. (2019) [99] and Astrauskas and Grubliauskas (2020) [256] confirmed higher PPVs for heavier vehicles over humps.

In summary, recent advances have bridged experimental research, SSI modeling, signal processing and material innovation, offering holistic mitigation strategies for speed-hump–induced vibrations. Future work must integrate multi-domain simulations with real-time multi-axial sensing for robust urban vibration management.

2.6 Research Gaps

Despite notable progress in understanding traffic-induced vibrations (TIV), critical research gaps continue to constrain the effectiveness and applicability of existing methods, especially in heterogeneous and dynamic urban traffic environments. Based on the literature synthesis and methodological limitations discussed earlier in this chapter, the following key gaps have been identified and directly inform the research objectives of this thesis:

- **Incomplete Characterization of Multidirectional Vibrations and Speed Hump Design Effects:** Prior studies have predominantly focused on vertical (Z-axis) vibrations, often neglecting the lateral (X-axis) and longitudinal (Y-axis) directions, which are equally critical for assessing structural fatigue, vibration-sensitive zone risks and human discomfort. Moreover, most existing investigations rely on simplified or laboratory-based traffic simulations, failing to capture the complexity of heterogeneous, real-world traffic flows. A significant gap exists in the empirical, in-situ characterization of tri-axial vibrations induced by diverse vehicle types traversing over speed-regulating structures. Specifically, the comparative influence of hump material (bitumen, fiber, rumble) and geometry on vibration profiles remains underexplored. This limits the ability to design context-sensitive, vibration-mitigating speed-control structures in urban environments.

- **Lack of Standardized Vibration Quantification Indices for Vehicle Impact Assessment:** Existing metrics such as peak particle velocity (PPV) and root mean square (RMS) acceleration do not adequately capture vehicle-specific vibrational profiles or support comparative evaluation across different categories and speeds. There is a clear need for the development of standardized indices, namely Passenger Car Vibration Equivalence (PCVE) and Reference Vibration Emission Level (RVEL), which provide meaningful, scalable measures for quantifying and comparing vehicle-induced vibrations for regulatory, planning and design applications.

- **Need for Non-Intrusive, Vibration-Based Vehicle Classification Systems:** Current classification approaches depend on axle sensors, embedded devices, or video surveillance systems, which are costly, intrusive, or sensitive to environmental factors. A gap exists in designing a robust, vibration-based vehicle classification framework capable of real-time, high-accuracy identification under field conditions. A system based on features extracted from tri-axial ground vibration signals using a single sensor and processed via ensemble machine learning algorithms would offer a practical, scalable solution for dense urban corridors.

- **Limited Integration of Classified Vehicle Data in Forecasting and Route Optimization:** Existing traffic forecasting models primarily rely on aggregated GPS data and lack integration of vehicle type-specific information critical to dynamic traffic flow modeling. A research gap exists in designing predictive frameworks incorporating classified vehicle counts and GPS trajectory data using models such as ARIMA, SVM and XGBoost. Such frameworks can improve the accuracy of congestion forecasting and support travel-time-optimized route planning, which also indirectly helps reduce vibration levels through smoother vehicular movement.

- **Absence of Vibration-Aware Route Optimization Frameworks:** While traditional route optimization tools consider congestion or travel time, they do not incorporate vibration-related impacts in decision-making. There is a critical gap in developing a routing framework that dynamically evaluates multiple route alternatives based on predicted vibration levels, using standardized indices such as PCVE and RVEL. Such a framework is essential for proactively protecting vibration-sensitive zones and ensuring smoother, low-impact vehicle flow through targeted corridor management.

Addressing these research gaps through an integrated, multidisciplinary framework is essential for enabling vibration-sensitive infrastructure design, vehicle classification and policy-driven urban traffic management in complex urban systems.

2.7 Conclusion

This chapter provided a detailed synthesis of the historical development, methodological advancements and domain-specific research trends in the study of traffic-induced vibrations (TIV). The literature was critically reviewed across foundational mechanisms of vibration generation, dynamic loading behavior, soil-structure interaction, signal decomposition techniques and intrusive and non-intrusive vehicle classification approaches. It also covered recent advances in GPS-augmented traffic forecasting and vibration responses induced by speed-control devices.

Key insights emerged regarding the limitations of conventional metrics, the underrepresentation of multidirectional vibrations in empirical studies and the need for context-sensitive modeling frameworks tailored to mixed-traffic urban conditions. The review emphasized that laboratory-based scenarios, limited vehicle diversity and inadequate integration of vibration data with traffic classification and route optimization systems constrain most existing studies.

The chapter further highlighted the growing relevance of machine learning, spectral signal analysis and real-time sensing in advancing TIV research. However, substantial gaps remain in vibration metric standardization, high-accuracy vibration-based classification and integration of vehicle-type information in predictive mobility models.

These identified gaps directly motivate the objectives and scope of the present research. The next chapter details the proposed methodology, designed to overcome these limitations through a unified, multidisciplinary framework combining field-deployed sensing, signal decomposition, machine learning and traffic modeling under real-world conditions.

The limitations and research gaps identified in this review underscore the need for an integrated framework that combines empirical vibration characterization, vehicle classification and traffic forecasting. In response to these challenges, the following chapter details the multi-stage methodology adopted in this research, including field data acquisition, signal decomposition and machine learning-based modeling.