Microscopic Traffic Flow Models: a survey for mixed autonomous vehicles flow

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Abstract: Traffic flow modeling is a critical tool for understanding, forecasting, and evaluating transportation systems. This literature review provides a comprehensive analysis of microscopic traffic flow models, which simulate individual vehicle movements to provide detailed insights into complex traffic dynamics. The review traces the evolution of major model categories, including car-following models (e.g., GM, IDM, OVM) and lateral movement models, highlighting their progression from simple stimulus-response mechanisms to more sophisticated behavioral approaches. A central finding is the indispensable role of robust calibration and validation for ensuring model reliability. Despite their maturity and utility in diverse applications, the review identifies persistent challenges. These include the significant demand for extensive, high-quality empirical data, the substantial computational intensity required for large-scale network simulations, and the inherent difficulty in accurately representing the complexity of human driving behavior. The review concludes by highlighting a transformative era for the field, driven by the rise of Connected and Autonomous Vehicles (CAVs) and advancements in Artificial Intelligence (AI) and Machine Learning (ML). These emerging technologies present both opportunities to overcome current limitations and new challenges related to modeling the intricate interactions between human and autonomous vehicles. Future research is expected to focus on developing hybrid modeling approaches that integrate traditional behavioral models with data-driven algorithms, aiming to enhance traffic efficiency and safety through smart infrastructure integration.

Key words: microscopic flow, autonomous vehicles, safety, efficiency

1. Introduction to Microscopic Traffic Flow Models

Traffic flow modeling serves as a cornerstone in modern transportation research and practice (Abdelgawad et al., 2014; Aghabayk et al., 2011), providing essential tools for comprehending intricate traffic phenomena, forecasting system performance, and evaluating the ramifications of infrastructure modifications and policy interventions (Garavello et al., 2020; Ghanim & Abu-Lebdeh, 2022). Within this domain, microscopic traffic flow models stand out for their unique approach to simulating vehicular movement (Gong et al., 2025; Gu et al., 2023).

1.1 Context and Importance of Traffic Flow Modeling

The increasing complexity of urban and interurban transportation networks necessitates sophisticated analytical tools (Jayson et al., 2024; Jerath et al., 2015; Jia et al., 2019; Jia & Ngoduy, 2016). Traffic flow modeling offers a structured framework to analyze current conditions, predict future scenarios, and test the efficacy of proposed solutions before costly real-world implementation. These models are fundamental for optimizing traffic signal timings (Knospe et al., 2002; Kotagi et al., 2020), designing efficient road networks, evaluating intelligent transportation systems (ITS), and understanding the dynamics of congestion formation and dissipation.

1.2 Defining Microscopic Models and Their Unique Characteristics

Microscopic traffic flow models distinguish themselves by simulating the behavior of individual vehicles and drivers (L. Li & Chen, 2017; M. Li et al., 2020; P. Li & Shrivastava, 2002), capturing their interactions with a high degree of fidelity. Unlike macroscopic models, which treat traffic as a continuous fluid and focus on aggregate variables such as flow, density, and average speed, or mesoscopic models that consider platoons or groups of vehicles (Chen, Sun, Qi, 2017; Qi, 2025; Qi, 2017), microscopic models delve into the discrete actions of each entity.

The defining characteristics of these models include their ability to represent individual vehicle dynamics (Qi, Chen and Ying, 2022; QI, Dai, Tang et al, 2020a;), such as acceleration, deceleration, and desired speed, alongside driver-specific attributes like reaction times and preferred following distances. This granular level of detail enables a nuanced understanding of localized traffic phenomena (F. Ali et al., 2023, 2025; Y. Ali, 2025; QI and Chen, 2023;), including the formation and propagation of shockwaves, lane-changing maneuvers, and the precise impact of specific infrastructure elements like merge points or intersections.

The inherent detail of microscopic models, while offering unparalleled fidelity in representing traffic dynamics, carries a direct consequence for their computational demands and data requirements (Xu, Shang, Yu et al, 2016; Zhang and Qi, 2023; Coifman & Li, 2017; Coppola et al., 2023;). Simulating millions of individual vehicles over extensive networks for prolonged periods is computationally intensive, as each entity necessitates its own set of calculations at every time step (Cui & Levinson, 2020; da Rocha et al., 2015; Qi, Wang, Chen et al, 2013b; Qi, Wang, Chen et al, 2014a;). Furthermore, to accurately capture the diverse behaviors of individual drivers and vehicles, these models demand extensive real-world data for calibration and validation. This often involves collecting disaggregate data on vehicle trajectories, driver characteristics, and specific event observations (QI and Zhang, 2019; Hamdar & Mahmassani, 2008; Han et al., 2021; Han & Ahn, 2018;). The selection of a modeling approach—be it microscopic, mesoscopic, or macroscopic—therefore becomes a strategic decision, contingent upon the specific research question, available computational resources, and the accessibility of relevant data. Microscopic models provide high fidelity but at a significant cost in terms of scalability and data acquisition. This inherent trade-off underscores a continuous research effort aimed at striking a balance between behavioral realism and computational efficiency.

1.3 Scope and Objectives of the Literature Review

This literature review aims to systematically explore the theoretical foundations, major categories of microscopic models (including car-following, lane-changing, and gap-acceptance), and the critical processes of calibration and validation. It will also examine the diverse applications of these models in transportation engineering and planning, identify their inherent challenges and limitations, and highlight emerging trends and future research directions, particularly in the context of connected and autonomous vehicles.

2. Fundamentals of Microscopic Traffic Flow Theory

This section delves into the core concepts that form the bedrock of microscopic models and provides a brief comparative context with other traffic modeling paradigms.

2.1 Key Concepts in Microscopic Modeling

Microscopic models are constructed upon fundamental concepts that describe individual driver-vehicle behavior. These include:

- **Desired Speed:** This refers to the speed a driver attempts to maintain under free-flow conditions, unhindered by other vehicles or traffic controls. It reflects a driver's preference and the vehicle's capabilities (S. Chen et al., 2023; Chow et al., 2021; Coifman, 2015).
- **Desired Spacing/Headway:** This is the preferred distance or time gap a driver seeks to maintain to the vehicle immediately ahead. This parameter is crucial for ensuring safety and influencing road capacity (Xiong et al., 2025).
- **Reaction Time:** This represents the delay between a driver perceiving a stimulus (e.g., the leading vehicle braking) and initiating a response. Driver reaction time significantly influences traffic stability, safety, and the propagation of disturbances (Qi and Zhang, 2022; Zhang, Qi, Wang et al, 2017).
- **Acceleration/Deceleration Logic:** These are the rules governing how vehicles accelerate to reach desired speeds or decelerate to avoid collisions. These rules often incorporate maximum and comfortable rates of acceleration and deceleration, reflecting both vehicle performance limits and driver comfort preferences (Akhtar et al., 2015; Alahmadi & Alzahrani, 2025; Qi, 2024e; Qi, 2025a;).

These parameters are often heterogeneous, meaning they can vary significantly from one driver to another, and may also be influenced by prevailing road conditions, traffic density, and specific driver characteristics.

2.2 Brief Comparison with Macroscopic and Mesoscopic Approaches

Microscopic models offer the highest level of detail by simulating individual vehicles and their interactions. This contrasts sharply with other modeling paradigms:

- **Macroscopic models** conceptualize traffic as a continuous fluid, focusing on aggregate variables such as flow rate (vehicles per unit time), traffic density (vehicles per unit length), and average speed. These models are well-suited for large-scale network analysis and strategic planning, but they inherently sacrifice the nuances of individual behavioral responses (An et al., 2022; Arkatkar & Arasan, 2010; Qi and He, 2020;).
- **Mesoscopic models** occupy an intermediate position, bridging the gap between microscopic and macroscopic approaches. They often simulate platoons or groups of vehicles, offering a balance between capturing some behavioral detail and maintaining computational efficiency.

The choice between these modeling paradigms is not merely a matter of selecting the most detailed option, but rather a strategic decision based on the specific type of question being asked and the particular phenomena one wishes to observe. While more detail might intuitively seem superior for accuracy (Wang and Chen, 2013; Farid et al., 2021; Fei et al., 2025;), the significant computational cost associated with microscopic models means that employing such a model for a problem better suited for a macroscopic approach (e.g., regional traffic assignment) would be inefficient and unnecessary. Conversely, a macroscopic model, by its very nature, cannot capture localized bottleneck formation resulting from a specific lane-changing maneuver or the precise impact of an adaptive cruise control system (B. Kerner et al., 2006; Qi, Liu, Zhang et al, 2016; B. Kerner & Klenov, 2004). The research question therefore dictates the appropriate modeling paradigm. If the inquiry pertains to individual driver responses to a specific intelligent transportation system (ITS) intervention, or the impact of a single merge point, microscopic models are indispensable. However, if the focus is on overall network performance, regional emissions, or large-scale congestion patterns, macroscopic models may suffice or even be more appropriate (Asaithambi et al., 2018; QI, Dai, Tang et al, 2020b; Qi and Hu, 2018; Awal et al., 2022;). This underscores the fundamental importance of methodological fit in scientific research, where investigators must carefully consider the scale and granularity required to answer their specific questions, rather than simply defaulting to the most detailed model available. This also suggests that integrated, multi-scale modeling approaches, where different paradigms are combined, could represent a valuable future direction for comprehensive traffic analyses.

3. Detailed Review of Car-Following Models

Car-following models constitute the foundational element of microscopic traffic simulations, describing how a driver adjusts their speed and position in response to the vehicle immediately ahead.

3.1 Historical Development and Evolution

The genesis of car-following models dates back to the mid-20th century, with early efforts focusing on simplistic stimulus-response relationships (Bakibillah et al., 2021; Wang Qi and Xu, 2010; Xu, Shang, Qi, et al, 2016; Baumann et al., 2024;). Over subsequent decades, these models have undergone significant evolution, progressively incorporating more complex psychological and physical aspects of driving behavior. Broadly, these models can be categorized based on their underlying principles:

- **Stimulus-Response Models:** These models are predicated on the idea that a driver's acceleration or deceleration is a direct reaction to the relative speed and distance to the leading vehicle. Early General Motors (GM) models are prime examples of this category.
- **Desired Behavior Models:** In these models, drivers are assumed to actively strive to maintain a desired speed and a safe following distance, adjusting their acceleration or deceleration to achieve these targets. The Intelligent Driver Model (IDM) and Optimal Velocity Model (OVM) fall into this category.
- **Psycho-Physical Models:** These models incorporate human perception thresholds and reaction times, acknowledging that drivers do not react instantaneously or to infinitesimally small changes. Gipps' model and the Wiedemann model are notable examples.

3.2 Analysis of Prominent Models

A closer examination of some prominent car-following models reveals their distinct characteristics:

- **General Motors (GM) Models:** A series of pioneering stimulus-response models developed in the 1950s and 60s. Their underlying equations generally relate a vehicle's acceleration to a power function of its current speed and the relative speed to the leading vehicle, often inversely proportional to the spacing. For instance, a common formulation is the "follow-the-leader" model. These models assume that a driver's acceleration is directly proportional to the relative speed difference and inversely proportional to the distance to the lead vehicle (Hidas, 2005; Qi and Hu, 2019b; Hou et al., 2024;). While conceptually simple and foundational, GM models often struggle to reproduce realistic traffic phenomena such as stop-and-go waves or traffic oscillations observed in congested conditions. They typically lack explicit consideration of desired speeds or comfortable deceleration rates.
- **Intelligent Driver Model (IDM):** A widely adopted desired behavior model known for its robustness and ability to reproduce realistic traffic dynamics. The IDM defines acceleration based on several parameters: desired speed, current speed, a desired minimum gap, a desired time headway, maximum acceleration, and comfortable deceleration. Its core objective is to allow a vehicle to accelerate to its desired speed under free-flow conditions while smoothly transitioning to maintaining a safe following distance when approaching a leading vehicle. The model assumes drivers aim for a desired speed and maintain a safe following distance, incorporating a smooth transition between free-flow and congested conditions. Its strengths include its robustness, capability to reproduce realistic traffic oscillations, and relatively few parameters, making it widely used in simulation software. However, it can sometimes produce overly smooth behavior, potentially not fully capturing aggressive driving styles (Karbasi et al., 2024; Qi, Liu, Wang et al, 2016; Kardous et al., 2022;).
- **Optimal Velocity Model (OVM):** Another desired behavior model that gained prominence

for its simplicity and ability to generate traffic oscillations. In the OVM, acceleration is a function of the difference between the current speed and an "optimal velocity," which itself depends on the spacing to the leading vehicle (Schönhof et al., 2006; Qi, Chen, Hu, 2024; Shang et al., 2022, 2024; Sheu, 2007). The model assumes drivers attempt to reach an optimal speed that is a direct function of the distance to the vehicle ahead. Its simplicity allows it to reproduce traffic oscillations and phantom jams. A limitation is that it can sometimes lead to unrealistic accelerations or decelerations, particularly during rapid changes in spacing (Bekiaris-Liberis et al., 2016, 2017; QI, Chen, Wang, 2019;).

- **Gipps' Model:** A safety-distance-based model characterized by explicit constraints to ensure collision avoidance. The model calculates the maximum safe speed a driver can maintain based on their current speed, the leading vehicle's speed, the driver's reaction time, and the maximum deceleration rates for both vehicles. It assumes drivers select a speed that guarantees they can stop safely if the leading vehicle suddenly brakes, considering their own maximum comfortable deceleration and the leading vehicle's maximum braking capabilities. Its primary strength lies in its explicit guarantee of collision avoidance, making it suitable for safety-critical applications. Its parameters are also intuitive (Nejadasl et al., 2006;). However, it can sometimes be overly conservative, potentially leading to lower capacities than those observed in real traffic.
- **Wiedemann Model:** A sophisticated psycho-physical model, notably implemented in the VISSIM simulation software. This model is based on detailed perception thresholds and distinct driver behavior zones (e.g., free driving, approaching, following, and braking). It assumes that drivers have specific thresholds for perceiving changes in speed and distance, which trigger different behavioral responses. Its strengths include its high level of detail and its ability to capture realistic driver behavior nuances. However, its numerous parameters make it complex and challenging to calibrate accurately.

The selection of an appropriate car-following model is contingent upon the specific application and the desired level of behavioral realism. Simpler models offer computational efficiency but may lack fidelity in capturing complex dynamics, whereas more intricate models provide greater realism at the expense of higher computational cost and increased calibration effort (Pueboobpaphan et al., 2013; S. Qi & Zheng, 2025;). The evolution of car-following models illustrates a clear progression from purely mechanistic (stimulus-response) representations to more behaviorally realistic (desired behavior, psycho-physical) approaches. This trajectory has been driven by the persistent need to accurately capture complex traffic phenomena, such as the formation and propagation of oscillations and phantom jams (Qi, Wang, Chen et al, 2013a;). Early GM models, for instance, were relatively simple in their stimulus-response formulation. However, their limitations, particularly their struggle to reproduce realistic traffic phenomena, spurred the development of more nuanced models like IDM, OVM, Gipps', and Wiedemann, which incorporate desired states, safety constraints, and perception thresholds (Qu et al., 2022; Rad et al., 2020; Qi and Ying, 2023; Rahman et al., 2018;). Researchers recognized that simple reactive behaviors were insufficient to explain the emergent, often counter-intuitive, patterns observed in real traffic. This progression reflects a general trend in scientific modeling: as understanding of a system deepens and computational capabilities advance, models become increasingly complex to better mimic reality (B. S. Kerner et al., 2013; Qi, Ying, Lin et al, 2021; Khondaker & Kattan, 2015;). The shift from purely physical to psycho-physical models further emphasizes the growing recognition of the human element's critical role in traffic flow, moving beyond purely deterministic physics to integrate aspects of behavioral psychology. This suggests that future models will continue to incorporate more cognitive and behavioral dimensions, especially with the advent of human-AI interaction in shared control scenarios (Durrani et al., 2016; J. Zhou & Peng, 2005; Beigi et al., 2025; Bento et al., 2019;).

Table 1: Comparison of Prominent Car-Following Models

Model Type	Core Equation/Logic	Key Parameters	Underlying Assumptions	Strengths	Weaknesses
General Motors (GM)	Acceleration ∝ (Spacing)n(Relative Speed)m	Sensitivity coefficients, desired time headway	Driver's acceleration is a direct reaction to leader's speed and spacing.	Pioneering, conceptually simple.	Struggles to reproduce realistic oscillations, lacks explicit desired states.
Intelligent Driver Model (IDM)	Acceleration based on desired speed, current speed, desired gap, time headway, max acceleration, comfortable deceleration.	v0 (desired speed), s0 (min gap), T (time headway), a (max accel), b (comfortable decel).	Drivers aim for desired speed while maintaining safe following distance; smooth transition between free-flow and congestion.	Robust, reproduces realistic oscillations, widely used, relatively few parameters.	Can produce overly smooth behavior, may not fully capture aggressive driving.
Optimal Velocity Model (OVM)	Acceleration is a function of (Optimal Velocity - Current Speed), where Optimal Velocity is a	Sensitivity coefficient, optimal velocity function parameters.	Drivers try to reach an optimal speed that depends on the distance to the vehicle ahead.	Simple structure, can reproduce traffic oscillations and phantom jams.	Can lead to unrealistic accelerations/decelerations, especially during rapid spacing

	function of spacing.				changes.
Gipps' Model	Calculates max safe speed based on current speed, leader's speed, reaction time, max deceleration rates.	Desired speed, reaction time, max acceleration, max comfortable deceleration, min desired spacing.	Drivers ensure collision avoidance by stopping safely if leader brakes suddenly.	Ensures collision avoidance, good for safety-critical applications, intuitive parameters.	Can be overly conservative, potentially leading to lower capacities.
Wiedemann Model	Based on psycho-physical perception thresholds and driver behavior zones (e.g., free driving, approaching, following, braking).	Numerous parameters defining thresholds and desired behaviors.	Drivers react based on perception thresholds for speed and distance changes.	Highly detailed, captures realistic driver behavior nuances, widely used in VISSIM.	Complex to calibrate due to many parameters.

4. Lane-Changing and Gap-Acceptance Models

Beyond the longitudinal dynamics captured by car-following models, microscopic simulations must also account for lateral movements and complex interactions at junctions. This section explores models governing lane-changing and gap-acceptance behaviors (X. Li, Cheng, et al., 2024; Qi and Yu, 2025;).

4.1 Principles of Lane-Changing Behavior

Lane-changing maneuvers are fundamental to traffic flow, particularly in multi-lane environments, and significantly influence network capacity and efficiency. These maneuvers are typically classified into two main categories:

- **Mandatory Lane Changes:** These are required due to road geometry, such as a lane drop, or regulatory signs indicating a turn-only lane. Drivers are compelled to change lanes to continue on their desired route.

- **Discretionary Lane Changes:** These are performed voluntarily by drivers to improve their travel conditions. Motivations include achieving a higher desired speed, avoiding perceived congestion in the current lane, or positioning the vehicle for an upcoming exit.

The decision-making process for a lane change is complex, involving multiple stages: the initial desire to change lanes, the identification of a suitable gap in the target lane, and the subsequent execution of the maneuver. Safety and efficiency criteria often guide these intricate decisions.

4.2 Review of Key Lane-Changing Models

Lane-changing models typically involve a multi-step decision process:

1. **Desire:** Is there a motivation to change lanes (e.g., current lane too slow, need to exit)?
2. **Feasibility:** Is there a suitable gap available in the target lane, both ahead and behind the potential merging point?
3. **Acceptance:** Is the identified gap large enough and safe to enter, considering the speeds of surrounding vehicles?
4. **Execution:** The actual maneuver, which often involves a coordinated acceleration/deceleration and lateral movement, typically coupled with car-following logic in both the current and target lanes.

Examples of lane-changing models range from simple rule-based approaches, which dictate maneuvers based on predefined speed differences or gap sizes, to more advanced models such as the Social Forces Model. The Social Forces Model, for instance, conceptualizes vehicles as particles influenced by attractive and repulsive forces, mimicking the social dynamics of human interaction in traffic (Al-Kaisy et al., 2005;).

4.3 Principles of Gap-Acceptance and Its Application

Gap-acceptance refers to a driver's decision to accept or reject a gap in a conflicting traffic stream. This behavior is fundamental at various conflict points within a road network, including unsignalized intersections, merging sections where ramp traffic joins a mainline, and weaving areas where vehicles cross paths (Bonneson, 1998; Zou et al., 2023).

Key parameters within gap-acceptance models include:

- **Critical Gap:** This is defined as the minimum time gap in the conflicting traffic stream that a driver is willing to accept to perform a maneuver (e.g., turning, merging). This is a crucial parameter, and its value often varies significantly based on individual driver characteristics, vehicle type, and specific traffic conditions.
- **Follow-up Headway:** This represents the time interval between successive vehicles from a minor stream using the same gap in the major traffic flow. It accounts for the time it takes for a second vehicle to enter the same gap after the first (Zhu et al., 2024; Zong et al.,

2022;).

Models for gap-acceptance can be empirical, derived directly from observed field data, or theoretical, based on probabilistic or utility maximization approaches.

4.4 Analysis of Prominent Gap-Acceptance Models

Prominent gap-acceptance models frequently employ probabilistic functions, such as logit or probit models, to determine the likelihood of a driver accepting a given gap. These models consider a range of factors, including the size of the available gap, the type of vehicle, specific driver characteristics, and prevailing traffic conditions (Mahmood & Kianfar, 2019; Chen, Liu, Qi, H., et al, 2014; Makantasis et al., 2020;).

The accuracy of lane-changing and gap-acceptance models is particularly sensitive to driver heterogeneity and contextual factors (Coifman et al., 2016; Y. Zhou et al., 2012;), making their calibration and transferability exceptionally challenging. Observations indicate that lane-changing involves complex decision processes, and critical gap parameters in gap-acceptance models vary significantly among drivers. This inherent variability means that a single set of model parameters may not adequately represent the diverse driving population (Chai et al., 2023; Qi, Lin and Ying, 2022; Qi, Wang and Bie, 2015; Q. Chang & Chen, 2024;). Consequently, calibrating these models demands extensive, granular data that captures individual driver choices under a wide array of varying conditions. The ability to transfer models, meaning their applicability from one geographic area or driver population to another, becomes a substantial issue (Beojone et al., 2024; Chen, Sun, Qi, 2017; Beza et al., 2022;). A model calibrated for a specific city or cultural driving norm might not perform accurately in a different context due to variations in driver behavior or infrastructure design. The fundamental variability in human decision-making and risk perception directly contributes to increased complexity in modeling and calibration, and subsequently reduces the generalizability of these models (Cen et al., 2025; Cetin, 2012; X. Chang et al., 2022; A. Y. Chen et al., 2020). This highlights a need for future research to concentrate on more adaptive and personalized modeling approaches, potentially leveraging machine learning techniques to capture and predict individual driver profiles, or developing robust methods for transfer learning in traffic models (Qi, Wang, Chen et al, 2014c;). It also underscores the necessity for extensive and diverse real-world data collection efforts to adequately account for these behavioral variations.

5. Model Calibration, Validation, and Parameter Estimation

This crucial section addresses how microscopic models are made to accurately reflect real-world conditions, emphasizing the indispensable processes of calibration and validation.

5.1 Importance of Calibration and Validation

For any microscopic traffic model to be considered reliable and useful for decision-making, rigorous calibration and validation are paramount.

- **Calibration:** This is the process of systematically adjusting the model's internal parameters (e.g., desired speed, reaction time, desired headway) to ensure that the model's outputs closely match observed real-world traffic data (Hu et al., 2021; Qi and Hu, 2023;). It is essential for ensuring that the model accurately represents the specific traffic conditions and driver population it aims to simulate (Shi et al., 2023; Shin et al., 2024; D. Song et al., 2019; H. Song et al., 2023, 2024;).
- **Validation:** Following calibration, validation involves verifying that the calibrated model accurately predicts traffic behavior for independent datasets that were not used during the calibration phase. This step assesses the model's predictive power and its generalizability to new, unseen conditions (L. Jin et al., 2021; P. J. Jin et al., 2013;).

Without these rigorous processes, a microscopic model, regardless of its theoretical sophistication, cannot be considered a credible tool for transportation analysis or planning.

5.2 Common Methodologies for Parameter Estimation

Parameter estimation involves identifying the optimal values for model inputs that best reproduce observed traffic phenomena. Various methodologies are employed:

- **Trial-and-Error:** This involves manual adjustment of parameters and iterative comparison with observed data. While simple, it is often used for initial tuning and can be time-consuming for complex models.
- **Optimization Algorithms:** These are automated search techniques designed to minimize the difference between simulated and observed data. Common examples include genetic algorithms, simulated annealing, and particle swarm optimization (L. Li et al., 2024; Qi and Hu, 2024; Qi, Song, Huang et al, 2024; X. Li et al., 2018;). These algorithms efficiently explore the parameter space to find near-optimal solutions.
- **Statistical Methods:** Approaches such as regression analysis or maximum likelihood estimation can be used to statistically derive parameter values from empirical data.
- **Sensitivity Analysis:** This technique is employed to understand how changes in individual input parameters affect the model's outputs. It guides the calibration process by identifying parameters to which the model is most sensitive, allowing for more focused tuning efforts (Campana et al., 2021; Campi et al., 2024; Cao et al., 2013; Carboni et al., 2024).

5.3 Challenges in Real-World Application

Despite the advancements in calibration methodologies, several challenges persist in the real-world application of microscopic models:

- **Data Requirements:** Microscopic models demand high-resolution, disaggregate data, such as individual vehicle trajectories, speeds, and headways. Such data is often expensive and technically challenging to collect (Kamal et al., 2010, 2016, 2018; Qi, Wang, Chen et al, 2014b; Qi, Ye, Xu et al, 2016;). Moreover, the quality of the collected data significantly impacts the accuracy and reliability of the calibration process.

- **Computational Intensity:** The calibration process itself, particularly when employing optimization algorithms with large datasets, can be computationally demanding, requiring substantial processing power and time (J. Zhao, Malenje, et al., 2020; Zhao-Cheng et al., 2013; J. Zhou & Zhu, 2021;).
- **Uniqueness of Parameters:** Given the inherent complexity of driver behavior and the numerous interactions, it can be challenging to find a unique set of parameters that perfectly fit all observed conditions (Dongmo et al., 2025; Qi, Ying and Zhang, 2022; Du et al., 2013, 2023; Fang & Elefteriadou, 2010;). This is exacerbated by driver heterogeneity, where individual drivers exhibit varying behaviors.
- **Model Transferability:** A model calibrated for a specific geographic area or driver population may not be directly applicable to another without extensive re-calibration. Cultural driving norms, local infrastructure, and regional driver characteristics can all influence behavior, necessitating localized calibration.
- **Validation Methods:** Validation typically involves comparing simulated outputs—such as traffic flow rates, average speeds, densities, and queue lengths—with independent field data. Common statistical metrics used for this comparison include Mean Absolute Percentage Error (MAPE) or Root Mean Square Error (RMSE) (B. Zhao et al., 2022; J. Zhao et al., 2024; J. Zhao, Kigen, et al., 2020;).

The effectiveness of microscopic models is fundamentally constrained by the quality and quantity of real-world data available for calibration and validation. This creates a bottleneck that can undermine even the most theoretically sound models. Observations confirm that calibration and validation are essential for reliable results, and these processes heavily rely on real-world data (Heshami & Kattan, 2024; Qi, 2024b; K. Huang et al., 2020;). However, data collection is often expensive and difficult, and the quality of this data can significantly impact accuracy. This means that poor data quality or insufficient data volume directly leads to inaccurate parameter estimation, which in turn results in a poorly calibrated model. A model that is inadequately calibrated, even if its theoretical framework is robust, will produce unreliable simulation results, rendering it unsuitable for practical applications or accurate predictions. This establishes a feedback loop where the model's ultimate utility is limited by the practical constraints of data acquisition (S. Huang et al., 2024; Hyun et al., 2021). This situation highlights a critical bottleneck in the advancement and practical application of microscopic models. While theoretical model development continues to progress, their real-world utility remains heavily dependent on overcoming these data collection challenges (Qi, Yu, Tang et al, 2022; Tang, Hu and Qi, 2020;). This implies a pressing need for continued research into advanced data collection techniques, such as the use of drone footage, ubiquitous sensor networks, or anonymized vehicle data. Furthermore, it underscores the importance of developing robust calibration methodologies that can effectively handle noisy or sparse data, alongside fostering data-sharing initiatives within the transportation research community (K. Zhang et al., 2022; L. Zhang et al., 2021; P. Zhang et al., 2020; T. Zhang et al., 2025;).

Table 2: Typical Parameters and Ranges for Microscopic Models

Parameter	Description	Typical Unit	Typical Range/Value	Relevant Model Types
Desired Speed (v0)	The speed a driver aims to maintain in free-flow conditions.	km/h or mph	90-120 km/h (55-75 mph)	Car-following (IDM, Gipps')
Desired Time Headway (T)	The preferred time gap a driver maintains to the vehicle ahead.	seconds	0.8 - 1.8 s	Car-following (IDM, GM, Gipps')
Desired Minimum Gap (s0)	The minimum bumper-to-bumper distance a driver maintains at standstill.	meters or feet	0.5 - 2.0 m (1.6 - 6.6 ft)	Car-following (IDM, Gipps')
Maximum Acceleration (a)	The maximum acceleration rate a vehicle can achieve.	m/s^2 or ft/s^2	2.0 - 4.0 m/s^2 (6.5 - 13.0 ft/s^2)	Car-following (IDM, Gipps')
Comfortable Deceleration (b)	The comfortable deceleration rate a driver typically uses.	m/s^2 or ft/s^2	1.5 - 3.0 m/s^2 (5.0 - 10.0 ft/s^2)	Car-following (IDM, Gipps')
Reaction Time	The delay between stimulus and driver response.	seconds	0.5 - 1.5 s	Car-following (Gipps'), Lane-changing, Gap-acceptance
Critical Gap	Minimum time gap a driver accepts in a conflicting stream.	seconds	3.0 - 6.0 s (varies by maneuver/location)	Gap-acceptance

Follow-up Headway	Time interval between successive vehicles using the same gap.	seconds	2.0 - 4.0 s	Gap-acceptance

Note: Ranges are approximate and can vary significantly based on vehicle type, driver population, road conditions, and specific model calibration.

6. Applications of Microscopic Traffic Flow Models

This section illustrates the diverse utility of microscopic models across various transportation engineering and planning contexts, demonstrating their practical significance.

6.1 Traffic Simulation and Its Role in Transportation Planning

Microscopic simulation represents a primary and indispensable application of these models. It enables the creation of virtual traffic environments, allowing researchers and planners to test various scenarios that would be impractical, excessively costly, or even dangerous to implement and evaluate in the real world (Feng et al., 2014; Qi, 2024d; Fountoulakis et al., 2017;). This capability makes microscopic simulation a vital tool in several areas of transportation planning:

- **Capacity Analysis:** Microscopic models are used to accurately assess the maximum throughput of individual road segments, intersections, or complex merge/diverge areas under various conditions (QI, Chen, Hu et al, 2024; Mahdi et al., 2019; Malecki et al., 2022;).
- **Bottleneck Identification and Mitigation:** They are highly effective in pinpointing specific locations within a network where congestion frequently forms and persists (C. H. P. Nguyen et al., 2022; T.-H. Nguyen & Jung, 2021; Niels et al., 2024; Nygren et al., 2023;), enabling the evaluation of targeted solutions to alleviate these bottlenecks.
- **Network Performance Evaluation:** By simulating individual vehicle movements, these models can analyze the system-wide impacts of proposed changes, such as new road links or traffic management schemes (Y. Zhang, Chen, et al., 2022; Y. Zhang, Huang, et al., 2022; Y.-T. Zhang et al., 2023;), on overall network performance metrics like travel time, delays, and emissions.

6.2 Case Studies Demonstrating Model Utility

Microscopic models are particularly invaluable for analyzing localized and complex traffic phenomena, providing detailed insights that aggregate models cannot offer:

- **Impact Assessment of Infrastructure Changes:** These models are routinely used to evaluate the effects of proposed infrastructure modifications, such as the addition of new lanes, redesigns of complex intersections (e.g., conversion to roundabouts), or the implementation of ramp metering systems (Hernandez-Moreno et al., 2022; Qi and Hu, 2019a; Jafaripournimchahi et al., 2022;), on traffic flow, safety, and operational efficiency.
- **Intelligent Transportation Systems (ITS) Evaluation:** Microscopic models form the analytical foundation for assessing the performance of various ITS strategies. This includes evaluating adaptive signal control systems that dynamically adjust timings based on real-time demand (Lederer et al., 2005; Lee et al., 2018; K. Li & Ioannou, 2004;), variable speed limits, incident management systems, and even specific applications like emergency vehicle preemption at intersections (Luo et al., 2025; K. Ma & Wang, 2021; X. Ma et al., 2019, 2021b, 2021a) .
- **Traffic Management Strategies:** Beyond ITS, these models are critical for optimizing signal timing plans for individual intersections or corridors, evaluating different lane assignment strategies (e.g., dedicated turn lanes), and designing reversible lanes (Kashyap et al., 2020; J. Kim et al., 2023; S. Kim et al., 2024;) for peak hour management.
- **Pedestrian and Bicycle Interaction:** In urban environments, microscopic models are increasingly used to simulate the complex interactions between vehicles, pedestrians, and cyclists, which is crucial for designing safer and more efficient shared spaces.

6.3 Impact Assessment of Infrastructure and Policy Changes

Beyond specific ITS applications, microscopic models are extensively employed to forecast the impact of broader infrastructure and policy changes:

- They can predict the effects of new developments, such as shopping malls or large residential areas, on the surrounding road networks, helping planners anticipate and mitigate potential congestion (Dimitriou et al., 2018; Q. Ye et al., 2023; Yi & Horowitz, 2006; Yi-Zhou et al., 2019;).
- They are used to analyze the behavioral responses to policy changes, such as congestion pricing schemes or the introduction of High-Occupancy Vehicle (HOV) lanes, and their subsequent impact on driver route choice and overall network performance (Prasanth et al., 2010; Pribyl et al., 2020; W. Qi et al., 2023; Qiao et al., 2023;).
- Furthermore, their detailed output allows for sophisticated safety analyses, by simulating near-misses or evaluating the impact of different road designs on collision risk factors.

The detailed nature of microscopic models, while computationally demanding, allows for the evaluation of causal relationships between specific design interventions or policy changes and their localized, emergent effects on traffic flow, which aggregate models cannot capture (Pooladsanj et al., 2023; Qin & Wang, 2019; Qiu & Du, 2023; Rahmati et al., 2019;). Observations confirm that microscopic models are utilized for specific, localized interventions such as bottleneck analysis, signal timing optimization, ITS evaluation, and infrastructure impact assessment. The ability to simulate individual vehicle behavior means that a microscopic model can explicitly demonstrate precisely how a specific change—for example, a new merge lane, a modified signal phase, or the introduction of an adaptive cruise control system—alters individual driver decisions, such as lane choice, acceleration, or deceleration (Malekzadeh et al., 2024; Mattas et al., 2023; Qi and Hu, 2020; Zhang and Qi, 2025; Mohammadi et al., 2024;). Crucially, it can then illustrate how these individual alterations aggregate to affect localized phenomena like queue lengths, the propagation of shockwaves, or the capacity at a specific intersection. In contrast, macroscopic models might only show a general change in overall flow or density, without elucidating the underlying behavioral mechanisms that led to that change (Y. Kim et al., 2023; X. Li, Pang, et al., 2024; Y. Li, 2023; Lin et al., 2024; H. Liu et al., 2017;). This capacity makes microscopic models indispensable for design-level decisions and for understanding the micro-level dynamics that ultimately lead to macro-level outcomes. It underscores their unique value in performing "what-if" analyses for specific, targeted interventions, moving beyond mere prediction to provide profound explanations for why certain outcomes occur (Z. Liu et al., 2025; Lombard et al., 2023; Qi, 2025;).

7. Challenges, Limitations, and Future Directions

This section critically assesses the current limitations inherent in microscopic traffic flow models and explores the exciting avenues for future research and development, particularly in light of emerging transportation technologies (Q. Liu et al., 2021; Qi, 2017; X. Liu et al., 2022; Y. Liu et al., 2006; Maglic et al., 2021; Mahajan et al., 2023;).

7.1 Computational Demands and Data Requirements

Despite their analytical power, microscopic models face significant practical constraints:

- **Computational Cost:** Simulating large-scale networks or extended periods with microscopic models is inherently computationally intensive, demanding substantial processing power and time. This limitation often restricts their applicability for very large-scale urban or regional analyses, and particularly for real-time traffic management applications where rapid simulation is required (Varga et al., 2023; Chen, Qi, Sun, 2014; Vigos et al., 2008; Wan et al., 2013; H. Wang et al., 2025; K. Wang et al., 2024;).
- **Data Intensity:** Accurate calibration and validation of these models necessitate extensive, high-resolution field data, which can be expensive and challenging to collect and process. The quality of this data is of paramount importance (Mohebifard & Hajbabaie, 2022;

Molzahn et al., 2017; Monteiro & Ioannou, 2023;), as errors or incompleteness can significantly compromise model accuracy and reliability.

7.2 Limitations in Capturing Complex Human Driving Behavior

Even with significant advancements, microscopic models continue to struggle in fully capturing the intricate nuances of human driving behavior:

- **Aggressive vs. Conservative Driving:** The inherent heterogeneity among drivers—where some drivers are aggressive, others conservative, and many exhibit context-dependent behaviors—is difficult to model comprehensively and consistently across diverse populations (Moridpour et al., 2015; Moridpour, Mazloumi, et al., 2012; Moridpour, Rose, et al., 2012;).
- **Cognitive Aspects:** Factors such as driver distraction, fatigue, emotional states, or risk perception are rarely explicitly or robustly modeled, yet they significantly influence real-world driving decisions.
- **Learning and Adaptation:** Human drivers learn from experience and adapt their behavior over time, for instance, by finding optimal routes or adjusting to new traffic regulations (Jian & Lun, 2012; Jiang et al., 2007; Jo & Oh, 2024; Qi, 2020b; Kamal et al., 2010, 2016, 2018;). Current microscopic models often do not account for this dynamic learning and adaptation process.
- **Behavioral Realism vs. Computational Efficiency:** There exists an inherent trade-off between increasing the behavioral realism of models and maintaining their computational feasibility (Yu et al., 2022; F. Zhang et al., 2023; G. Zhang & Wang, 2014; J. Zhang et al., 2021, 2023;). More detailed behavioral rules often lead to higher computational costs.
- **Model Transferability:** Models calibrated for one geographic region or cultural context may not accurately reflect driving behavior in another without extensive re-calibration (M. Dai et al., 2025; Y. Dai et al., 2023; Deng et al., 2023; Di et al., 2024;). This limits their generalizability and requires significant effort for deployment in new areas.

7.3 Integration with Emerging Technologies (Connected and Autonomous Vehicles - CAVs)

The advent of Connected and Autonomous Vehicles (CAVs) represents both a profound challenge and an unprecedented opportunity for microscopic modeling.

- **Challenges:** Existing microscopic models are primarily designed to simulate human-driven vehicles (HDVs) and may not accurately represent the deterministic, highly predictable, or cooperatively optimized behavior of CAVs. The interaction dynamics in mixed traffic environments, where HDVs and CAVs coexist and interact, are particularly complex and pose significant modeling challenges (Qi, 2024a; Qi, 2024c).
- **Opportunities:** CAVs are equipped with numerous sensors and communication capabilities, generating vast amounts of real-time, high-resolution data (Saberi et al., 2014;

Saedi et al., 2020; Sarvi & Kuwahara, 2008; Qi, 2018;Scarinci et al., 2017;). This data holds the potential to overcome current data limitations for model calibration and validation, offering unprecedented insights into vehicle behavior.

Future Directions: The field of microscopic traffic flow modeling is poised for a transformative period, driven by the rise of CAVs and advanced artificial intelligence (AI) and machine learning (ML) techniques.

- **CAV-Specific Models:** A critical area of future research involves developing entirely new car-following, lane-changing, and gap-acceptance models specifically tailored for autonomous driving algorithms, which may operate on different principles than human drivers (Do et al., 2019; Dolfin, 2012; Dong et al., 2022; Xie et al., 2018; F. Ye & Zhang, 2009;).
- **Mixed Traffic Modeling:** Simulating the complex and novel interactions in environments with both human-driven vehicles and CAVs is crucial. This requires understanding how human drivers react to autonomous vehicles and vice-versa (Olstam et al., 2008; Oskarbski & Biszko, 2023; Perraki et al., 2018; Philip et al., 2019;).
- **Machine Learning and AI:** Leveraging deep learning, reinforcement learning, and inverse reinforcement learning offers promising avenues for developing more adaptive and data-driven microscopic models (Tao et al., 2023; Tosin & Zanella, 2019; Tu et al., 2024; Vaqar & Basir, 2009;). These techniques could enable models to learn complex driving policies directly from observed data, potentially capturing more realistic and diverse behaviors than traditional rule-based models.
- **V2X Communication Integration:** Incorporating vehicle-to-everything (V2X) communication capabilities into models is essential to simulate cooperative driving maneuvers, platooning, and intelligent traffic management strategies that rely on real-time data exchange between vehicles and infrastructure (S. Wang et al., 2024; W. Wang et al., 2024; X. Wang et al., 2018, 2022;).
- **Human-AI Interaction:** Research into shared control scenarios and how human drivers interact with AI systems, particularly in situations where control transitions between human and autonomous modes, is becoming increasingly important.

The rise of Connected and Autonomous Vehicles (CAVs) represents a fundamental shift for microscopic modeling, transitioning the field from primarily descriptive models of human behavior to prescriptive models of automated behavior, and, most critically, to complex hybrid models of human-machine interaction (Y. Wang et al., 2024; Y. Wang, Tu, et al., 2022; Y. Wang, Wang, et al., 2022;). Current microscopic models are built for human drivers, implicitly assuming human-like characteristics. The emergence of CAVs means that the core assumptions of human driver models—such as variable reaction times, desired speeds, and inherent heterogeneity—may no longer apply uniformly. CAVs operate based on algorithms, potentially leading to more deterministic, cooperative, or even optimized behaviors. This implies that the very nature of the "driver" being modeled is changing from a complex, often irrational human to a programmable (Chen, Liu, Qi, H., et al, 2013), potentially rational agent. This fundamental alteration necessitates a re-evaluation of the entire modeling framework. Instead of solely calibrating against human observations, future models might need to be validated against CAV control algorithms. Furthermore, the interaction between human drivers and CAVs in mixed traffic environments introduces a new layer of complexity, where human unpredictability encounters algorithmic precision, potentially leading to novel emergent traffic behaviors. This also creates a feedback loop where the vast data generated by CAVs can inform and refine human behavior models (Ngoduy, 2012; Ranaweera et al., 2021; Qi, 2020a; Rim et al., 2011; Roncoli et al., 2016;), and conversely, human behavior models can inform the development of safer and more efficient CAV control algorithms. This represents the most significant future challenge and opportunity for the field. It implies a move towards integrating principles from control theory, artificial intelligence, and even behavioral economics into microscopic traffic flow modeling. The field is poised for a fundamental transformation, where models will not only describe but also prescribe and optimize traffic flow through automated driving, leading to potentially unprecedented levels of efficiency and safety (He et al., 2022, 2024; Moridpour, Sarvi, et al., 2012; Morrison et al., 2014;). However, this transformation will also necessitate entirely new validation paradigms and a deeper understanding of human-AI interaction, especially with the integration of V2X communication enabling cooperative behaviors currently impossible to model with traditional independent driver assumptions.

8. Conclusion

8.1 Summary of Key Findings

This literature review has underscored the critical role of microscopic traffic flow models in providing detailed insights into complex traffic dynamics. The review traced the evolution and characteristics of major model categories, including car-following models (such as GM, IDM, OVM, Gipps', and Wiedemann), and models for lateral movements like lane-changing and gap-acceptance (Y. Wang, Xu, et al., 2022; Z. Wang et al., 2023; Wegerle et al., 2020; Wei et al., 2013;). It highlighted that these models have progressed from simple stimulus-response mechanisms to more sophisticated psycho-physical and desired-behavior approaches, driven by the need to capture realistic traffic phenomena like oscillations. A central theme emphasized throughout the review is the indispensable nature of robust calibration and validation processes, which are crucial for ensuring model reliability and predictive power. However, persistent challenges remain, particularly concerning the high demand for extensive, high-quality disaggregate data and the significant computational intensity associated with simulating large-scale networks (Harsono & Arai, 2024; Hayat et al., 2023; Roy & Saha, 2020; Sreekumar & Mathew, 2020;). Despite these limitations, the review showcased the diverse and impactful applications of microscopic models across various domains of transportation planning, including infrastructure design, intelligent transportation systems (ITS) evaluation, and traffic management strategy optimization.

8.2 Overall Assessment of the State-of-the-Art

Microscopic traffic flow models have achieved a remarkable level of maturity, evolving into powerful analytical tools capable of unraveling complex traffic dynamics at a granular level. Their ability to simulate individual vehicle interactions provides unique insights into localized phenomena that are often obscured in aggregate models (L. Yan & Cai, 2024; X. Yan et al., 2025; Yang & Sun, 2015; Yao et al., 2023;).

Nevertheless, the field continues to grapple with inherent constraints. The profound complexity and heterogeneity of human driving behavior remain a formidable challenge to fully capture and represent in mathematical models (Gharibi et al., 2021; L. Sun et al., 2020; Y. Sun et al., 2023; Tan et al., 2022;). Furthermore, the practical utility of these models is often limited by the substantial need for extensive, high-quality empirical data for accurate calibration and validation, coupled with the computational demands for large-scale or real-time applications.

The landscape of microscopic traffic flow modeling is currently on the cusp of a transformative era, largely propelled by the rapid emergence of Connected and Autonomous Vehicles (CAVs) and the accelerating advancements in Artificial Intelligence (AI) and Machine Learning (ML) techniques (Ahmad et al., 2024;). This paradigm shift promises to address some of the current limitations, particularly in data availability and the potential for more adaptive modeling. However, it simultaneously introduces new and complex modeling challenges, notably concerning the intricate interactions between human-driven vehicles and autonomous systems, and the implications of cooperative driving behaviors enabled by Vehicle-to-Everything (V2X) communication. Future research will likely converge on developing hybrid modeling approaches that seamlessly integrate traditional behavioral models with data-driven learning algorithms, along with a focus on integrating these models with smart infrastructure to realize unprecedented levels of traffic efficiency and safety.

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