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A Literature Review on Extreme Traffic Congestion: Defining, Modeling, and Managing Extreme Conditions in the Autonomous Vehicle Era

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Abstract

Traffic congestion is a pervasive and escalating global challenge, particularly in dense urban areas, leading to significant economic, social, and environmental costs. Traditional mitigation strategies are proving insufficient, highlighting the need for a new approach. This report focuses on extreme congestion, which represents a critical breakdown in network efficiency and demands innovative solutions. The study defines and quantifies extreme congestion, moving beyond simple speed metrics to include reliability concepts like the Planning Time Index and Buffer Time Index. It explores advanced theoretical frameworks, such as Kerner's Three-Phase Traffic Theory, and reviews various traffic modeling approaches, including macroscopic, microscopic, and mesoscopic models. The increasing importance of Machine Learning and Deep Learning for real-world applications and real-time operations is emphasized, with mesoscopic models highlighted for their balance of detail and computational efficiency. The report also examines the dual potential of autonomous vehicles (AVs). While AVs offer promise for alleviating congestion through improved capacity and optimized flow, challenges like induced demand and complex human-AV interactions could exacerbate it. The actual impact will depend on factors like AV penetration rates and human driving behavior. Ultimately, managing extreme congestion in the AV era requires a fundamental shift towards proactive, predictive, and collaborative traffic management systems. This involves leveraging AV capabilities through adaptive traffic signal control, smart rerouting, and platooning, supported by Vehicle-to-Everything (V2X) communication and integrated smart city infrastructure. Policy interventions, such as dedicated lanes and congestion pricing, will also be crucial. The report concludes that a holistic approach, prioritizing collaborative autonomous systems, addressing human factors, and thoughtful urban planning, is essential for creating truly efficient, safe, and sustainable transportation networks.

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1. Introduction

1.1. The Pervasive Challenge of Traffic Congestion

Traffic congestion has emerged as a major and common problem globally, particularly in developed cities characterized by high population densities. This pervasive issue significantly impacts all modes of transportation, with road networks being the most profoundly affected (Kumar et al., 2021). The challenge of traffic congestion has seen a substantial increase since the 1950s, a period during which much of the existing road infrastructure began to become obsolete in the face of escalating demand (Wikipedia, 2025). This persistent issue is not merely a transient inconvenience but has evolved into a deeply entrenched, escalating systemic problem (Qi, 2025). The observation that existing road networks have become "obsolete" and the characterization of congestion as an "open challenge" across metropolitan, medium, and small cities, underscore that traditional, often reactive, mitigation strategies have been insufficient (Kumar et al., 2021). This indicates that the problem is dynamic and worsening, moving beyond simple high traffic volume to a state of systemic failure.

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The negative consequences of congestion are extensive and far-reaching, imposing significant burdens on individuals, economies, and societies. These impacts include considerable wasted time and energy, increased air pollution, heightened stress levels for commuters, reduced overall productivity, and substantial economic and social costs for both individuals and nations (Kumar et al., 2021). Congestion directly diminishes the safety, economic well-being, and overall quality of life within metropolitan areas (Transportation Research Board, 2004). The persistent nature of this problem, described as an "open challenge" across metropolitan, medium, and small cities, underscores the need for advanced understanding and innovative solutions (Kumar et al., 2021).

Rationale for Focusing on Extreme Congestion

While congestion is a universally disliked phenomenon, its severity varies significantly (Mondschein & Taylor, 2017). Understanding and addressing "extreme" conditions is paramount because these severe states represent critical breakdowns in network efficiency. Such conditions can lead to disproportionately severe consequences, including systemic instability and a dramatic reduction in overall system performance (Sustainability Directory, 2025). The focus on extreme congestion is crucial because it represents the most critical manifestation of this systemic breakdown, demanding a more profound understanding of its underlying mechanisms and broader implications. Quantifying traffic congestion is a fundamental task for effective transportation planning and research, necessitating the development and refinement of numerous metrics that focus on changes in vehicle speeds, the geographic extent of congestion, and travel time impacts (Seong et al., 2023).

Overview of the Report's Structure and Key Themes

Despite billions of dollars spent annually on improving mobility, traditional capacity expansion alone has proven unable to eliminate the congestion problem (Transportation Research Board, 2004). This observation highlights that a fundamental shift in approach is necessary, moving towards more sophisticated analytical tools and novel technological interventions. This literature review aims to provide a comprehensive exploration of traffic congestion, with a particular emphasis on its most severe forms (Qi, 2013b). The report begins by detailing academic definitions and quantification methods for extreme traffic congestion. It then proceeds to review various modeling approaches used to analyze these conditions. Finally, it concludes with a forward-looking discussion on the anticipated impacts and strategic management of extreme congestion in the emerging era of autonomous vehicles. This structured progression responds directly to the identified need for innovative and intelligent solutions that transcend simply adding more lanes, emphasizing the report's relevance in addressing a persistent and evolving global challenge.

2. Defining and Quantifying Extreme Traffic Congestion

General and Academic Definitions of Traffic Congestion

From a general perspective, traffic congestion is characterized as a condition on road networks that arises when vehicle usage increases to a point where interactions among vehicles slow down the traffic stream, generating longer trip times and increased vehicular queuing (Wikipedia, 2025). Fundamentally, it occurs when the demand for road space surpasses its available capacity, leading to reduced speeds and extended travel times (Sustainability Directory, 2025).

Academically, the understanding of traffic congestion transcends simple descriptions of slow-moving vehicles. It is recognized as a complex system state that emerges from the non-linear interaction of traffic demand, network capacity, and various behavioral factors (Sustainability Directory, 2025). This intricate interplay leads to reduced efficiency and systemic instability within the transportation network (Sustainability Directory, 2025). This refined explanation positions traffic congestion as an emergent property of transportation networks, intrinsically linked to concepts from network theory, behavioral economics, and urban systems dynamics. This progression from merely describing what congestion looks like to understanding its underlying emergent properties and

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mechanisms is a critical development. It implies that effective mitigation strategies must address the complex interplay of demand, capacity, and human behavior, rather than just superficial symptoms (Qi, 2014b). This deeper analytical perspective is foundational for developing more sophisticated modeling and quantification methods capable of tackling extreme congestion.

It is important to note that there is no single, universally unique definition of congestion (Kumar et al., 2021). Instead, definitions are often tailored based on specific traffic parameters—such as volume, capacity (or density), travel time (or delay), and speed—and their applicability depends on the type of data collected (Kumar et al., 2021).

Key Attributes and Indicators of Congestion Severity

Observable indicators that signal the onset and severity of congestion include a significant decrease in the average speed of vehicles, such as a typical 60 mph cruise devolving into a frustrating 20 mph crawl. Journeys take considerably longer during congested periods, with a commute that usually takes 30 minutes potentially extending to an hour or more. The presence of stop-and-go traffic, characterized by frequent braking and acceleration, is a clear indicator of unstable traffic flow. Visible long queues and backups stretching from intersections, highway entrances, or bottlenecks also signal congestion buildup (Wikipedia, 2025).

Comprehensive characterizations of traffic congestion (TC) often involve four key components: intensity, which reflects the severity of congestion typically expressed as a rate; extent, which refers to the geographic span of congestion; duration, indicating how long the congested conditions persist; and reliability, which measures the predictability of travel times (Seong et al., 2023).

Established Classification Systems: Level of Service (LOS A-F) and Advanced Theoretical Perspectives

A widely adopted qualitative classification system for traffic flow is the six-letter A–F Level of Service (LOS) scale, as defined in the US Highway Capacity Manual and utilized globally. This system primarily uses delay as the basis for its measurements, with specific methods varying by facility type (Wikipedia, 2025). LOS A signifies free flow conditions, B represents reasonably free flow, C indicates stable flow, D denotes approaching unstable flow, E describes unstable flow, and F characterizes forced or breakdown flow (Isarsoft, 2025). LOS F, in particular, directly corresponds to extreme congestion, marked by highly unstable traffic, stop-and-go movements, and substantial delays (Qi, 2016b).

Practical systems, such as the Google Traffic Layer (GTL) API, visually represent congestion severity using a color-coded system: Green for free flow, Orange for light congestion, Red for medium congestion, and Dark Red for heavy traffic congestion (Seong et al., 2023). Dark Red aligns with conditions indicative of extreme congestion.

Beyond classical two-phase traffic flow theories (free flow and congested traffic), Kerner's Three-Phase Traffic Theory offers a more nuanced understanding of congestion (Wikipedia, 2024). Kerner divides congested traffic into two distinct phases: Synchronized Flow (S) and Wide Moving Jam (J), resulting in three overall phases: Free flow (F), Synchronized flow (S), and Wide Moving Jam (J). This theoretical framework provides a more granular and physically grounded explanation for the breakdown conditions often labeled as LOS F.

- **Synchronized Flow (S):** In this phase, vehicle speeds are lower than in free flow, and the relationship between flow and density becomes weaker and more complex. Congestion patterns within synchronized flow can manifest as Localized Synchronized Flow Patterns (LSP), Widening Synchronized Flow Patterns (WSP), or Moving Synchronized Flow Patterns (MSP).
- **Wide Moving Jam (J):** This represents a highly severe form of congestion that propagates upstream through highway bottlenecks while maintaining a consistent mean velocity of its downstream front. Within a wide moving jam, vehicle speeds are significantly reduced, and the flow rate is sharply diminished. These jams do not spontaneously appear in free flow but

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typically emerge within regions of synchronized flow through an S → J phase transition.[15] They are considered stable structures that travel unchanged with a constant velocity along the road (Flynn et al., 2009). A key distinction is that synchronized flow can be "caught" at a bottleneck, whereas wide moving jams will continue to propagate upstream. Kerner's theory moves beyond a simple "congested" label to distinct, measurable physical phenomena, providing a robust foundation for modeling and predicting the onset, propagation, and dissipation of truly extreme congestion events. It highlights that extreme congestion is not a monolithic state but possesses unique dynamic properties that require specific analytical approaches.

Table 2.1. Classification of Traffic Congestion Severity.

Classification System	Level/Code	General Operating Conditions / Characteristics
Level of Service (LOS) (Isarsoft, 2025)	A	Free flow
	B	Reasonably free flow
	C	Stable flow
	D	Approaching unstable flow
	E	Unstable flow
	F	Forced or breakdown flow (Extreme Congestion)
Google Traffic Layer (GTL) (Seong et al., 2023)	Green	Free flow (no traffic delays)
	Orange	Light congestion / Medium amount of traffic
	Red	Traffic delays (Medium congestion)

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	Dark Red	Heavy traffic congestion
Kerner's Three-Phase Traffic Theory (Wikipedia, 2024)	Free Flow (F)	Vehicles travel at free-flow speeds; stable.
	Synchronized Flow (S)	Vehicle speeds lower than free flow; complex flow-density relationship; can be localized, widening, or moving. Can be "caught" at bottlenecks.
	Wide Moving Jam (J)	Highly severe, propagates upstream through bottlenecks with maintained downstream front velocity; significantly reduced speeds and flow rates. Stable structures that travel unchanged.

Metrics and Novel Approaches for Quantifying Congestion Intensity, Extent, Duration, and Reliability

Numerous metrics have been developed to quantify traffic congestion, providing tools for determining the degree of congestion and roadway performance. Commonly employed metrics include the Travel Time Index (TTI), Vehicle Miles Traveled (VMT), Vehicle Hours Traveled (VHT), Volume/Capacity (V/C) ratio, and Peak Traffic Period Duration (PTPD).[1]

- The **Travel Time Index (TTI)** compares peak period travel time to free-flow travel time, expressed as a ratio. For example, a TTI of 1.20 indicates that a trip taking 20 minutes in off-peak conditions will take 24 minutes in the peak period, signifying a 20 percent longer travel time (Central Transportation Planning Staff, 2014).
- **Vehicle Miles Traveled (VMT)** and **Vehicle Hours Traveled (VHT)** are used to evaluate the geographic extent and temporal duration of congestion by measuring congested miles and hours, respectively (Seong et al., 2023).
- The **Volume/Capacity (V/C) ratio** is calculated by dividing the traffic volume on a roadway by its designed capacity.
- **Peak Traffic Period Duration (PTPD)** assesses the number of hours daily that experience congested conditions.

Novel metrics, particularly those utilizing Hägerstrand's space-time cube, have been proposed to synthesize congestion intensity, extent, and duration (Seong et al., 2023):

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- **distanceTime (τ):** Proposed as a base metric, typically in units like mileHours, it is the product of the total distance of congested roads in a temporal snapshot and the duration of the congestion (Seong et al., 2023).
- **Weighted Congestion Distance (d_weighted):** This metric incorporates varying intensity levels of congestion by assigning weighting values to the congested distance (Seong et al., 2023). For instance, empirical weights (e.g., 0.25 for light, 0.5 for medium, 1.0 for heavy congestion) can be applied based on visual indicators like GTL colors (Seong et al., 2023). The Speed Reduction Index (SRI) is also suggested as a continuous weighting value.
- **Normalized Congestion Metrics (τ_normalized):** These metrics normalize the congestion amount by the maximum possible congestion in the network, enabling meaningful comparisons across multiple places with significantly different road network distances.

Other important performance measures that quantify congestion severity and reliability include (Kumar et al., 2021):

- **Congested Time:** The average number of minutes drivers experience speeds below a predefined threshold (e.g., 35 mph) during peak periods (Central Transportation Planning Staff, 2014).
- **Lane-miles congested:** Expressed as a percentage of total lane-miles, this measures the geographic extent of congestion.
- **Congested Travel:** Quantifies vehicle-miles traveled under congested conditions.
- **Average-to-Posted-Speed Ratio (Speed Index):** A ratio of average travel speed to the posted speed limit; a ratio of 0.70 or less typically indicates congestion.
- **Bottleneck Factor:** A composite measure calculated as Minutes of Congestion per Peak-Period Hour divided by Congested Speed, useful for ranking bottleneck severity (Central Transportation Planning Staff, 2014).
- **Delay per Mile:** Quantifies the extra time required to traverse a given segment or corridor per mile.
- **Planning Time Index (PTI):** A reliability measure defined as the ratio of the 95th percentile travel time (near-worst-case) to free-flow travel time.
- **Buffer Time Index (BTI):** Expresses the additional buffer time needed to ensure on-time arrival for 95 percent of trips.
- **Congestion Score:** A comprehensive measure derived by integrating results from several performance metrics (extent, duration, reliability, intensity) using weighted factors.
- **Speed Reduction Index (SRI):** Measures the rate of vehicle speed reduction due to congestion.
- **Very-low-speed Index (VLSI):** The ratio between the time spent traveling at a very slow speed and the total travel time.

While the core components of congestion—intensity, extent, and duration—are well-established, the explicit inclusion and emphasis on "reliability" through metrics like the Planning Time Index (PTI) and Buffer Time Index (BTI) reveal a crucial aspect of defining extreme congestion. Extreme congestion is not just about slow speeds; it is fundamentally about the

unpredictability and *variability* of travel times. The fact that extreme congestion can lead to missed appointments and increased stress underscores the importance of reliability from both a user and economic perspective (Isarsoft, 2025). This suggests that for extreme conditions, the focus shifts from average delay to the certainty of arrival, highlighting that the most severe forms of congestion are those that are highly unpredictable and disruptive to planning (Qi, 2016a). This deeper understanding of reliability is vital for comprehensive assessment and for designing interventions that improve user experience under severe conditions.

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Table 2.2. Key Metrics for Quantifying Traffic Congestion.

Metric Name	Category	Definition/Formula/Interpretation
Travel Time Index (TTI)	Travel time-based	Ratio of peak-period travel time to free-flow travel time (Average Travel Time / Free-Flow Travel Time). A TTI of 1.20 means a trip takes 20% longer in peak periods.
Vehicle Miles Traveled (VMT)	Extent-based	Evaluates the extent of congestion by measuring congested miles in peak hours.
Vehicle Hours Traveled (VHT) (Seong et al., 2023)	Duration-based	Measures the total hours vehicles spend traveling under congested conditions.
Volume/Capacity (V/C) Ratio (Seong et al., 2023)	LOS-based	Calculated by dividing the volume of traffic on a roadway by its capacity.
Peak Traffic Period Duration (PTPD) (Seong et al., 2023)	Duration-based	Assesses how many hours daily are congested during peak times.
distanceTime (τ) (Seong et al., 2023)	Novel/Composite	Base metric: Product of total distance of congested roads and duration of congestion (d × t), e.g., mileHours.
Weighted Congestion Distance (d_weighted) (Seong et al., 2023)	Novel/Composite	Accounts for intensity by assigning weights to congested distance (Σ(w_i * d_i)). Weights can be based on GTL colors or Speed Reduction Index (SRI).

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Normalized Congestion Metrics (τ_normalized) (Seong et al., 2023)	Novel/Composite	Normalizes congestion amount by maximum possible congestion for inter-city comparison (τ / τ_max) × 100%.
Congested Time (Central Transportation Planning Staff, 2014)	Duration-based	Average minutes drivers experience speeds below a threshold (e.g., 35 mph) during peak periods.
Lane-miles congested	Extent-based	Percentage of total lane-miles experiencing congestion (e.g., average speed < 35 mph).
Congested Travel	Extent-based	Quantifies vehicle-miles traveled under congested conditions (e.g., < 35 mph).
Average-to-Posted-Speed Ratio (Speed Index)	Speed-based	Average travel speed divided by posted speed limit. Ratio of 0.70 or less indicates congestion.
Bottleneck Factor	Composite	Minutes of Congestion per Peak-Period Hour / Congested Speed. Used to rank bottleneck severity.
Delay per Mile	Travel time-based	Extra time needed to traverse a segment per mile ((ATT - FFTT) / Segment Length).
Planning Time Index (PTI)	Reliability-based	Ratio of 95th percentile travel time to free-flow travel time. Includes typical and unexpected delay.

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Buffer Time Index (BTI)	Reliability-based	Additional percentage of time needed to be on time for 95% of trips ((95%TT - ATT) / ATT).
Congestion Score	Composite	Integrates several performance measures with weight factors, higher scores indicate increased intensity.
Speed Reduction Index (SRI)	Speed-based	Rate of vehicle speed reduction due to congestion ((Vf - Va) / Vf).
Very-low-speed Index (VLSI)	Speed-based	Ratio of time traveling at very slow speed to total travel time.

Common Causes Leading to Extreme Congestion

Extreme traffic congestion arises from a complex interplay of factors that either reduce road capacity or increase traffic demand. The most straightforward cause is **High Traffic Volume or Saturation**, occurring when the number of vehicles attempting to use a road network simultaneously exceeds its designed capacity, particularly during peak hours.

Bottlenecks, which are reductions in road capacity such as lane closures, merges, or physical constrictions, significantly impede traffic flow and account for a substantial 40% of congestion.[3]

Traffic Incidents, including accidents, breakdowns, or other unexpected disruptions, are consistent sources of congestion, contributing to 25% of traffic jams (Zadobrischi et al., 2020).

Work Zones, involving construction activities, frequently cause congestion through lane closures, detours, and reduced speed limits, accounting for 10% of congestion.

Bad Weather conditions, such as heavy rain, snow, flooding, or debris from strong winds, reduce road capacity and operating speeds, leading to increased congestion and productivity loss; weather causes 15% of congestion.

Poor Traffic Management and inefficient signal timing, inadequate real-time traffic information, and poor road signage can exacerbate congestion, accounting for 5% of the problem.

Beyond these common external triggers, **Phantom Traffic Jams** occur in dense traffic without an obvious external cause, initiated when a vehicle slows down slightly, causing a chain reaction of braking and stopping among following cars. These are a result of linear instabilities in traffic flow at sufficiently high densities, where small perturbations can grow into waves of high vehicle density (Flynn et al., 2009).

Distracted Driving is a significant factor in over 8% of accidents, which in turn leads to traffic congestion (Meyer, 2023). Underlying systemic causes also include

Inadequate or Unplanned Transport Infrastructure, often driven by rapid population growth and urbanization, and **Poor Public Transport Systems**, which contribute to a higher reliance on personal vehicles and thus increase road demand. More broadly,

Random Fluctuations, Temporary Barrier Control, and Network Blockages encompass various events that disrupt smooth traffic flow.

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The concept of "congestion-adapted" places, where high levels of activity and trip-making occur despite significant congestion, often in central urban areas, introduces a crucial nuance (Mondschein & Taylor, 2017). This challenges the simplistic notion that all congestion is inherently negative and must be eliminated. Instead, it suggests that some level of traffic density might be a byproduct of vibrant, highly accessible urban centers. This understanding implies that policymakers and planners might need to shift their focus from merely reducing absolute congestion levels to managing its *impacts* and fostering *adaptability* within urban systems. For "extreme congestion," this means distinguishing between a functional, albeit dense, urban environment and a truly dysfunctional, unstable system. This critical nuance is essential for developing targeted and effective strategies that improve overall urban mobility and quality of life without inadvertently stifling economic and social vitality.

3. Models for Extreme Congestion

Modeling traffic congestion is essential for understanding its dynamics, predicting its occurrence, and evaluating mitigation strategies. The evolution of traffic modeling reflects a profound shift in understanding, from early analogies to fluid dynamics to contemporary approaches integrating complex systems theory and artificial intelligence.

3.1. Fundamental Traffic Flow Theory and Analytical Models

Classical Traffic Flow Theory and Its Limitations in Extreme Conditions

Traditional traffic flow theory often employs analogies to fluid dynamics, describing traffic as a continuum in terms of aggregated variables like flow, concentration (density), and speed (Kuhne & Michalopoulos, 2023). Core assumptions typically include the conservation of traffic flow and a one-to-one fundamental relationship between speed and density (Qi, 2013a). However, the assumption of a unique speed-density relationship is frequently challenged by empirical observations, where multiple speed values can be measured for the same density. This relationship often holds true only at equilibrium states.

One-dimensional aggregate models, while useful for general flow, can prove inadequate in specific, complex traffic situations, such as localized off-ramp blockages where some lanes become severely congested while adjacent lanes remain relatively fluid (Kuhne & Michalopoulos, 2023). This highlights a significant limitation in accurately modeling the spatial heterogeneity characteristic of extreme congestion. A critical distinction from fluid flow is that traffic congestion is not solely a physical phenomenon (Qi, 2017); it is profoundly influenced by human trip-making decisions and real-time driving behaviors (Lindsey & Verhoef, 2000)

Analytical Models for Understanding Congestion Phenomena (e.g., Phantom Traffic Jams, Jamitons)

Analytical models often simplify road networks (e.g., single-lane, straight, uniform roads) and assume deterministic driver behavior to isolate and study specific congestion phenomena (Flynn et al., 2009). These models have been instrumental in explaining complex traffic behaviors that contribute to extreme congestion.

Phantom Traffic Jams are intriguing phenomena that occur in seemingly free-flowing, dense traffic without any obvious external cause like obstacles or bottlenecks. They are explained by the linear instability of two-equation traffic models at sufficiently high densities, where small perturbations can grow into waves of high vehicle density. This dynamic arises from a competition between stabilizing effects, such as preventive driving, and destabilizing effects, such as drivers slowing down in response to higher density with a built-in delay in adjustment (Qi, 2014a).

Jamitons are predicted by inviscid Payne-Whitham type traffic models as stable, traveling detonation waves. A jamiton is characterized by a sharp, sudden jump in vehicle density (a shock) on one side, followed by a smooth decay in density on the other, propagating unchanged at a constant

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velocity. A key property is that jamitons always travel slower than individual vehicles, forcing drivers to brake suddenly upon encountering the jam's front. A growing jamiton may trigger new instabilities downstream, leading to the formation of a sequence of additional traveling waves, termed **Jamitinos**.

The "bottleneck model," notably developed by Vickrey in 1969 and extended by Arnott, De Palma, and Lindsey, stands as a prominent dynamic analytical model for traffic congestion. Behavioral models, which assume drivers optimize their speeds by trading off time, expected accident, and fuel costs, can endogenously generate traffic congestion as a result of individual optimizing behavior (Verhoef & Rouwendal, 2004). The concept of **metastable states** is also relevant, where at certain high densities, traffic can exist in a smooth-flowing state that is inherently unstable and can suddenly collapse into congestion due to minor disturbances like a car braking. This represents a temporary stable state that transitions to a genuinely stable, congested state (KOZO KEIKAKU ENGINEERING Inc., 2025).

The trajectory of traffic modeling, as evidenced by these developments, reveals a profound evolution (Qi, 2023b). It began with classical fluid dynamics analogies, which, while foundational, proved limited in capturing real-world complexity.[19] This led to more nuanced theoretical frameworks like Kerner's three-phase theory, which better describe the physical states of congestion breakdown (Wikipedia, 2024). The development of analytical models for phenomena like "phantom jams" and "jamitons" further refined the understanding of traffic as a complex, non-linear system (Flynn et al., 2009). This progression underscores that extreme congestion is a multifaceted problem requiring a diverse toolkit of modeling approaches, each contributing to a more complete understanding and more effective management.

3.2. Macroscopic, Microscopic, and Mesoscopic Traffic Flow Models

Traffic flow is broadly characterized using three main types of models: microscopic, macroscopic, and mesoscopic, each offering distinct levels of detail and applicability (Ali et al., 2022).

Macroscopic Models describe traffic flow at an aggregate level, focusing on overall characteristics such as traffic volume, speed, and density, rather than individual vehicles. These models are particularly useful for analyzing large-scale traffic networks and understanding the general behavior of traffic flow over wide areas.[23] Macroscopic models are typically less detailed but offer faster and more computationally efficient simulations, making them suitable for strategic planning and policy analysis (Lee, 2025). Examples include the Lighthill-Whitham-Richards (LWR) model and the Payne-Whitham model, which incorporates a momentum equation for greater accuracy (Lee, 2025). However, limitations arise in capturing localized, complex extreme congestion phenomena, where one-dimensional descriptions may fail to represent the spatial heterogeneity of traffic (Kuhne & Michalopoulos, 2023).

Microscopic Models provide a detailed description of traffic flow by focusing on the behavior of individual vehicles and their interactions with other vehicles and the infrastructure. They consider parameters such as vehicle position, velocity, distance, and time headway, often incorporating elements of driver physical and psychological responses. While more detailed, microscopic models are typically slower and more computationally intensive to run (Qi, 2022). Examples include car-following models (describing vehicle acceleration/braking in relation to a lead vehicle), cellular automata models (discretizing the road into cells with movement rules), and psycho-physical models (based on driver perception-reaction time and fatigue). They can also be extended to include random accidents and associated losses (Kim et al., 2024). For extreme congestion, microscopic models are strong because they can replicate complex traffic phenomena by accurately modeling individual driving behavior, facilitating operational analysis within mixed traffic flows and understanding shockwave propagation (Peng et al., 2025).

Mesoscopic Models bridge the gap between microscopic and macroscopic approaches, capturing traffic flow dynamics at an intermediate level of detail. They are based on individual agents (vehicles), but their behavior is derived from aggregated traffic flow attributes like density or average speed (PTV Group, 2025). Direct interactions between agents typically occur only at specific nodes, such as intersections. These models are particularly well-suited for analyzing and optimizing traffic signal control strategies and for mitigating congestion. They enable real-time estimation of traffic state variables (e.g., volume, speed, density), adaptive traffic signal control that responds to changing conditions, and improved prediction of congestion and incidents (Number Analytics, 2025). Case studies have shown their effectiveness, such as a study in Singapore that used a mesoscopic model to optimize traffic signal timing, resulting in a 10% reduction in travel time and a 15% reduction in congestion. The ability of mesoscopic models to capture dynamics at an intermediate level of detail makes them uniquely positioned for active, real-time management of extreme congestion. They offer an optimal balance between computational efficiency and the necessary level of detail, and their capacity to integrate real-time data and facilitate adaptive responses to rapidly changing conditions is particularly valuable in dynamic, extreme congestion scenarios where immediate intervention is often required.

3.3. Simulation and Data-Driven Approaches

The Role of Traffic Simulation in Analyzing and Predicting Extreme Congestion

Traffic simulation modeling involves creating virtual representations of transportation networks, allowing researchers and engineers to test various scenarios, predict traffic patterns, and identify potential bottlenecks without real-world disruption. These models provide a safe and cost-effective method to evaluate different transportation scenarios, reducing the need for expensive physical prototypes and minimizing the risk of costly mistakes in infrastructure planning. Key benefits include providing a realistic and detailed overview of the entire traffic network, detecting conflict hotspots, anticipating the effects of planned traffic measures, and optimizing projects before implementation. Simulation is particularly crucial given the current scarcity of real-world observed traffic data for emerging technologies like autonomous vehicles, making it an indispensable tool for research and development (Al-Turki et al., 2021).

Application of Machine Learning and Deep Learning Techniques for Congestion Prediction and Real-Time Management

The increasing volume of traffic-related data generated by Intelligent Transportation Systems (ITS) and Internet of Things (IoT) infrastructure has enabled the widespread application of Machine Learning (ML) and Deep Learning (DL) for traffic flow predictions (Mystakidis et al., 2025). ML and DL approaches are particularly well-suited for handling complex and dynamically changing traffic conditions, often outperforming traditional statistical models in these scenarios. Traffic Congestion Prediction (TCP) leverages these cutting-edge approaches to forecast future traffic patterns, providing critical information for decision-makers in various sectors, including Smart Cities (Qi, 2023a).

Artificial Intelligence (AI) can significantly enhance Autonomous Smart Traffic Management (ASTM) systems, leading to substantial reductions in traffic congestion rates (Goenawan, 2024). For example, a simulated ASTM system utilizing a YOLO V5 Convolutional Neural Network for vehicle detection and a Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) for vehicle number prediction demonstrated a 50% higher traffic flow rate and a 70% lower vehicle pass delay (Goenawan, 2024). These data-driven approaches facilitate real-time data analytics and predictive analytics, which are used to optimize traffic signal timing and anticipate traffic incidents proactively (Lee, 2025). Despite their advantages, challenges remain, including the risk of overfitting, high computational demands, the inherent complexity of real-world traffic flow, limitations in data availability, and the pervasive uncertainty and variability in traffic patterns (Qi, 2024c).

Analytical models, such as those explaining "jamitons" or "metastable states," provide crucial theoretical understandings into the fundamental physics and behavioral underpinnings of extreme congestion, explaining *why* certain phenomena occur. However, these models often rely on

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simplified, deterministic assumptions that may not fully capture real-world complexities. In contrast, simulation and AI/ML models are designed to handle real-world variability, provide practical predictions, and enable real-time management. Yet, their effectiveness is highly dependent on the quality and availability of data and the robustness of their algorithms. The challenge for addressing extreme congestion lies in effectively bridging this gap: leveraging the fundamental understanding from analytical models to inform the design and interpretation of more complex simulation and data-driven models, which can then be applied to dynamic, heterogeneous environments. The limitations of one-dimensional models further emphasize the need for models that can capture the spatial and behavioral intricacies of extreme congestion, moving beyond simplistic representations.

Table 3.1. Comparative Analysis of Traffic Flow Modeling Approaches for Extreme Congestion.

Model Type	Core Principle/Level of Detail	Strengths for Analyzing Extreme Congestion	Limitations/Challenges	Example Models/Software
Macroscopic	Aggregate traffic flow (volume, speed, density); treats traffic as a continuum.	Efficient for large-scale networks; understanding overall behavior; strategic planning & policy analysis.	Fails to capture localized, complex extreme congestion phenomena; one-dimensional descriptions may be inadequate.	LWR model, Payne-Whitham model, PTV Visum, Emme
Microscopic	Individual vehicles and their interactions (position, velocity, headway); incorporates driver behavior.	Replicates complex traffic phenomena (e.g., shockwaves); operational analysis within mixed traffic; detailed understanding of congestion formation.	Computationally intensive and slower for large networks; requires detailed data.	Car-following models, Cellular automata models, Psycho-physical models, PTV Vissim, Aimsun, Paramics
Mesoscopic	Intermediate detail; individual agents whose behavior is derived from aggregated	Bridges gap between macro/micro; suitable for traffic signal control optimization; improved prediction	Requires more detail than macroscopic, less than microscopic; direct agent-to-agent reactions typically limited to nodes.	PTV Vissim (hybrid simulation)

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	attributes; interactions at nodes.	of congestion/incidents; real-time estimation of state variables.		
Analytical	Mathematical equations to describe fundamental traffic phenomena; often deterministic and simplified.	Provides theoretical understanding of congestion phenomena (e.g., phantom jams, jamitons, metastable states); explains underlying mechanisms.	Often relies on simplified assumptions; may not capture real-world complexities and human behavior fully; limited applicability for real-time management.	Bottleneck model, Payne-Whitham type models
Simulation	Virtual representation of networks to test scenarios and predict patterns.	Safe and cost-effective for evaluating different scenarios; identifies bottlenecks; anticipates effects of planned measures; crucial given data scarcity for AVs.	Requires significant input data; model calibration can be complex; results are as good as the underlying model.	PTV Visum, PTV Vissim, Aimsun, Paramics
AI/ML/DL	Data-driven algorithms to forecast traffic patterns and optimize management.	Handles complex, changing conditions; improves prediction reliability; enables real-time adaptive control (e.g., signal timing, rerouting).	Risk of overfitting; high computational demands; dependent on data quality and availability; complexity of real-world traffic.	RNN, LSTM, YOLO V5

4. Extreme Congestion in the Incoming Autonomous Vehicles Era

The advent of autonomous vehicles (AVs) and connected and autonomous vehicles (CAVs) is poised to fundamentally transform transportation systems. Their integration into existing traffic flows presents both significant opportunities for congestion mitigation and complex challenges that require careful consideration and strategic planning.

4.1. Anticipated Impacts of Autonomous Vehicles (AVs) on Traffic Flow

Potential Benefits

Autonomous Vehicles (AVs) and Connected and Autonomous Vehicles (CAVs) possess superior capabilities compared to human-driven vehicles (HDVs), offering several potential benefits for traffic flow and congestion. Their inherent advantages include faster reaction times and the ability to maintain significantly shorter headways, allowing for a notable increase in road capacity and enhanced throughput (Qi, 2023c). Even a small percentage of AVs on the road can significantly improve overall traffic efficiency (Łach & Svyetlichnyy, 2024).

Operationally, AVs are generally designed for smoother acceleration and deceleration, and they can execute smarter lane-changing maneuvers. These characteristics lead to fewer disturbances and reduced heterogeneity in the traffic stream, which in turn mitigates traffic oscillations and diminishes the propagation of shockwaves. With advanced intelligent control, AVs have the potential to interact intelligently with traffic infrastructure, such as traffic lights, to minimize full stops at intersections and maximize throughput across the network. The increased efficiency and smoother flow facilitated by AVs can also lead to a reduction in fuel consumption and lower air pollutant emissions, contributing to environmental benefits (Fujiu et al., 2024). Furthermore, AVs are equipped with sophisticated sensors and algorithms that enable them to detect and respond to potential hazards more rapidly and consistently than human drivers, thereby significantly reducing the risk of accidents.

Potential Challenges

Despite the promising benefits, the integration of AVs introduces several complex challenges that could, paradoxically, exacerbate congestion. The convenience offered by AVs, particularly individually-owned ones, could lead to an increase in the total number of trips taken and encourage longer commutes. This phenomenon, known as induced demand, has the potential to exacerbate urban sprawl and, consequently, increase overall congestion and energy consumption.

Autonomous Mobility-on-Demand (AMoD) systems, while promoting vehicle sharing, inherently involve "empty vehicle trips" for rebalancing purposes—moving vehicles to areas of anticipated demand (Rossi et al., 2018). This process can increase the total number of vehicles on the road. However, some research suggests that if these rebalancing vehicles are properly coordinated, they may not necessarily lead to an increase in congestion.

A significant challenge arises from the prolonged period during which CAVs will coexist with human-driven vehicles (HDVs). Differences in trust levels and inherent driving behaviors between human drivers and AVs can significantly impact highway traffic flow. For instance, human drivers might exploit the larger safety gaps maintained by AVs by cutting in front of them, which can inadvertently trigger new stop-and-go waves (The University of Western Australia, 2021). This suggests that AVs are not a guaranteed solution but rather a technology whose impact is highly contingent on *how* they are deployed, owned (shared vs. individual), and managed (coordinated vs. uncoordinated). This implies that technological advancement alone is insufficient; careful planning and policy interventions are paramount to steer the outcome towards congestion reduction.

Realizing the full congestion-busting potential of AVs necessitates substantial upgrades to existing communication technologies and transportation infrastructure (Susilawati, 2023). AVs require an uninterrupted, continuous stream of complex traffic data and information to make critical, real-time decisions in uncertain situations (Mushtaq et al., 2021). Counterintuitively, some studies suggest that the introduction of certain types of driverless vehicles, especially when present in multiple numbers or in scenarios involving lane changes, could potentially create unstable traffic flow and even worsen congestion.

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The Significance of AV Penetration Rates on Overall Traffic Efficiency and Congestion Levels

The actual impact of AVs on traffic flow and congestion is highly dependent on several factors, including their market penetration rate (MPR), the specific characteristics and operational settings of the AVs, the prevailing traffic volume levels, and the adaptive behavior of human drivers in a mixed environment. Studies indicate a notable increase in road capacity as the market penetration rate of CAVs rises, with significant improvements observed particularly when MPRs reach moderate to high levels (e.g., above 40%). Simulation results suggest a complex relationship between AV mixing rates and traffic delay: delays may initially increase as the AV mixing rate rises (from 10% to 45%), but then decrease notably (from 45% to 50%), remaining constant thereafter (from 50% to 100%). This implies the existence of a critical threshold or optimal range for AV penetration to achieve beneficial impacts on congestion.

4.2. Strategies for Managing Extreme Congestion with AVs

Effective management of extreme congestion in the autonomous vehicle era will require a multi-faceted approach that leverages AV capabilities, integrates with smart infrastructure, and is supported by thoughtful policy and planning.

Advanced Traffic Management Systems Leveraging AV Capabilities

The capabilities of AVs enable the development of highly sophisticated traffic management systems. **Adaptive Traffic Signal Control** can be employed, where Deep Reinforcement Learning (DRL) dynamically optimizes traffic light timings at intersections during periods of congestion, significantly improving traffic flow. AI-powered traffic management systems can predict impending traffic jams and automatically adjust signal phases to mitigate their formation.

Smart Rerouting is another crucial technique, involving load-balancing traffic by guiding vehicles to alternate paths to avoid congested intersections. Advanced algorithms for congestion-aware routing and rebalancing of Autonomous Mobility-on-Demand (AMoD) systems are being developed to minimize overall network congestion.

Platooning, the formation of groups of vehicles traveling in close proximity with minimal headways, is a key strategy for enhancing both traffic capacity and stability. Research suggests that an optimal platoon size (e.g., four to eight vehicles) can effectively balance capacity enhancement with the maintenance of traffic stability.

Furthermore, leveraging the continuous stream of data from connected vehicles, **Real-time Data Analytics and Predictive Analytics** are used to optimize traffic signal timing and to anticipate and respond proactively to traffic incidents.

Infrastructure Integration and V2X Communication for Optimized Traffic Flow

The full potential of AVs in managing congestion is realized through their seamless integration with smart city infrastructure. Connected and Automated Vehicles (CAVs) integrate both Connected Vehicle (CV) and Automated Vehicle (AV) technologies, enabling extensive communication via Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Everything (V2N to V2E) protocols (Caltrans, 2025). This extensive communication network facilitates the continuous sharing of information, enabling intelligent decision-making and fostering a self-organizing traffic system.

The development of smart city infrastructure, including connected roadways, intelligent traffic signals, and data-driven management platforms, is crucial to fully support the operational needs of AVs (Dennis et al., 2025). Such integration allows traffic signals to adapt in real-time to changing conditions and enables rapid detection of accidents or other incidents, leading to quicker response times (FRONTIER, 2023). This represents a fundamental paradigm shift from reactive traffic management, which historically responds to congestion after it has formed, to proactive, predictive, and collaborative systems. The capabilities afforded by AVs and V2X communication allow for the prediction of congestion before it occurs, proactive rerouting of vehicles to avoid bottlenecks, and

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collaborative management of entire fleets, moving beyond simply "avoiding congestion" to a more ambitious goal of "improving traffic flow" and achieving system-optimal solutions. This represents a profound transformation in the philosophy of traffic management, driven by the unprecedented data availability and connectivity afforded by AVs.

Policy and Planning Interventions

Beyond technological advancements, policy and planning interventions are vital. The implementation of **Connected and Autonomous Vehicle Lanes (CAVLs)** is a proposed strategy to alleviate congestion by allowing CAVs to operate with reduced headways, thereby increasing road capacity. However, studies indicate that dedicated lanes alone may not always be universally successful, especially if AVs contribute to bottlenecks by stopping at curbsides for passenger drop-offs or by circulating on low-capacity links (Qi, 2024b).

Congestion Pricing or tolling, which involves charging higher rates during peak or congested periods, can effectively reduce traffic demand on specific roadways by providing economic disincentives.

Shared Autonomous Mobility-on-Demand (AMoD) Systems promote vehicle sharing, which can significantly reduce the total number of cars on the road, decrease demand for urban parking infrastructure, and lower pollution levels. These systems also have the potential to complement or even replace conventional fixed-schedule public transit systems.

Broader **Traffic Demand Management (TDM) strategies**, such as Commute Trip Reduction programs, Flextime arrangements, Transit Improvements, High-Occupancy Vehicle (HOV) Priority lanes, and Access Management, will likely be integrated into comprehensive AV-era transportation planning (Victoria Transport Policy Institute, 2017).

Proactive Planning is emphasized, with municipalities advised to closely monitor the evolving traffic landscape and proactively incorporate the impacts of Shared Autonomous Vehicles (SAVs) and Transport Network Companies (TNCs) into all new infrastructural projects.[50] Early adaptation and intervention are deemed crucial for shaping how AVs affect urban traffic and mobility (Overtoom et al., 2020).

4.3. Future Outlook and Research Challenges

Uncertainties, Data Limitations, and Ongoing Research Needs

The precise manner in which cities and their traffic systems will transform with the widespread adoption of AVs remains highly uncertain. A significant challenge is the current lack of extensive real-world observed traffic data for AVs, compelling most studies to rely heavily on modeling and simulation. Technical hurdles persist, including the complexity and high cost associated with developing and maintaining sophisticated AV sensors, software, and hardware. The regulatory framework for AVs is still in its nascent stages and varies significantly across different jurisdictions, creating legal and operational uncertainties. Public skepticism regarding AV safety and reliability, coupled with the substantial infrastructure investments required, pose serious obstacles to widespread deployment. A fundamental research conflict exists: while investigating robotics in mixed autonomy settings requires large-scale in-situ testing, there is currently no holistic replacement for the real physical traffic environment for such investigations (Nice et al., 2023).

Need for Holistic Approaches

To fully realize the benefits of autonomous vehicles, a concerted effort is required to transition from an 'each-to-their-own' autonomy model to one of 'Collaborative Autonomous Cars' (HERE & SBD, 2016). This necessitates sharing rich vehicle sensor data among cars, enabling collaborative management of autonomous fleets, and breaking down data silos by connecting vehicle data with road network and infrastructure data (e.g., traffic light information). This highlights that the long coexistence of AVs and HDVs (Qi, 2024a), and the unpredictable human behavior (e.g., human

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drivers cutting in front of AVs), poses a significant challenge. Solutions must therefore account for complex human-machine interaction, not just technical AV capabilities.

Balancing Benefits and Risks

While AVs promise significant improvements in safety and efficiency, it is crucial to acknowledge and mitigate potential risks. For instance, some studies indicate a potential increase in collision risk at higher AV market penetration rates under certain control frameworks. Therefore, thoughtful and strategic integration is essential to avoid unintended consequences, such as widening existing inequalities or increasing overall vehicle usage.

5. Conclusion

Traffic congestion represents a complex, escalating systemic problem that has rendered much of the existing road infrastructure obsolete and imposes significant economic, social, and environmental costs globally. Addressing this challenge, particularly its extreme manifestations, necessitates a shift from traditional capacity expansion to more sophisticated analytical tools and innovative technological interventions.

The understanding of traffic congestion has evolved from descriptive observations to analytical definitions that recognize its emergence from non-linear interactions within transportation networks. Quantifying extreme congestion now extends beyond simple speed and travel time metrics to embrace concepts of reliability, such as the Planning Time Index and Buffer Time Index, which are crucial for assessing the predictability and user experience under severe conditions. Advanced theoretical frameworks, like Kerner's Three-Phase Traffic Theory, provide a more granular understanding of congestion breakdown, distinguishing between synchronized flow and persistent wide moving jams, thereby offering a robust foundation for modeling these complex phenomena.

Traffic modeling has similarly progressed from simplified fluid dynamics analogies to a diverse toolkit encompassing macroscopic, microscopic, and mesoscopic approaches. While analytical models offer fundamental insights into congestion formation (e.g., phantom traffic jams, jamitons), simulation and data-driven methods, particularly those leveraging Machine Learning and Deep Learning, are increasingly vital for handling real-world variability, predicting future patterns, and enabling real-time management. Mesoscopic models, in particular, emerge as a critical bridge, offering an optimal balance of detail and computational efficiency for dynamic traffic management. The effective application of these models relies on a critical interplay between theoretical understanding and practical implementation, using fundamental principles to inform robust, data-driven solutions.

The advent of autonomous vehicles (AVs) introduces a paradoxical potential for traffic congestion. On one hand, AVs offer significant promise for alleviating congestion through increased road capacity, smoother traffic flow, and optimized network management, driven by their superior reaction times, shorter headways, and intelligent operational capabilities. On the other hand, challenges such as induced demand, the complexities of empty vehicle rebalancing, and unpredictable human-AV interactions in mixed traffic environments could potentially exacerbate congestion. The actual impact is highly contingent on the AV penetration rate and the nature of human driving behavior in a mixed autonomy environment.

Moving forward, managing extreme congestion in the AV era demands a fundamental paradigm shift from reactive to proactive, predictive, and collaborative traffic management systems. This involves leveraging AV capabilities through adaptive traffic signal control, smart rerouting, and platooning, supported by extensive Vehicle-to-Everything (V2X) communication and integrated smart city infrastructure. Policy and planning interventions, including dedicated lanes, congestion pricing, and shared autonomous mobility services, will be crucial in shaping the positive impacts of AVs. However, significant uncertainties remain, particularly regarding real-world data availability, regulatory frameworks, and public acceptance. Realizing the full benefits of AVs while mitigating potential risks will require a holistic approach that prioritizes collaborative autonomous systems, addresses human factors in mixed traffic, and ensures thoughtful integration into urban planning to create truly efficient, safe, and sustainable transportation networks.

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