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Design and Evaluation of Optimization Algorithms for Adaptive Traffic Signal Control and Scalable Simulation of Large-Scale Traffic Networks

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Abstract

This study presents the design, implementation, and performance evaluation of optimization algorithms for adaptive traffic signal control within the context of large-scale traffic network simulation. The rapid urbanization and increasing vehicle density demand intelligent traffic management systems that can adapt in real-time to fluctuating traffic conditions. To address this challenge, we propose a set of model-driven optimization techniques aimed at minimizing delays, reducing congestion, and improving traffic throughput by dynamically adjusting signal timings based on prevailing traffic states. The core framework integrates adaptive signal control logic with scalable simulation methodologies to accurately represent traffic behavior across extensive urban networks. Simulation experiments are conducted using representative network topologies under varying traffic demand scenarios to assess the robustness and flexibility of the algorithms. Key performance metrics-including average delay, throughput, queue lengths, and computational efficiency-are used to evaluate the system's accuracy, scalability, and real-time feasibility. The results demonstrate that the proposed optimization algorithms significantly outperform fixed-time and traditional signal control methods, particularly under non-uniform and peak traffic conditions. Moreover, the scalable simulation framework ensures reliable performance analysis even in high-density, multi-intersection environments. This research provides a foundation for future development of intelligent transportation systems and smart city traffic infrastructure based on adaptive, data-driven control strategies.

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1 Introduction

The growing complexity of urban mobility and the rapid increase in vehicular traffic have placed enormous pressure on conventional traffic management systems. Traditional fixed-time traffic signal control schemes often fail to adapt to dynamic traffic patterns, leading to increased congestion, travel time, fuel consumption, and environmental pollution. As modern cities aim to transition into smart and sustainable urban environments, the need for intelligent, adaptive, and scalable traffic control systems has become more urgent than ever [8, 9, 12, 15, 19, 20]. Adaptive traffic signal control involves real-time adjustment of signal timings based on current traffic conditions. This approach leverages optimization algorithms to respond dynamically to traffic demand, improve flow efficiency, and reduce delays. The core challenge lies in designing robust algorithms that can efficiently manage multiple intersections under fluctuating conditions while ensuring scalability across large, complex road networks [2, 3, 5, 13, 14, 17]. In response to this challenge, the present study focuses on the development and evaluation of optimization algorithms for adaptive traffic signal control. These algorithms are integrated within a scalable simulation framework capable of modeling traffic behavior across extensive networks. The simulation environment provides a controlled and reproducible platform to test the performance of various control strategies under diverse traffic scenarios, including peak-hour surges, uneven flow distribution, and incident disruptions [4, 6, 7, 11, 16, 18]. The study aims to achieve two primary objectives. First, it seeks to design optimization algorithms that can enhance signal timing strategies using real-time traffic data, thereby improving overall network efficiency. Second, it evaluates the accuracy, efficiency, and scalability of the proposed algorithms and simulation methodologies in large-scale traffic environments. Key performance indicators such as average vehicle delay, queue length, and throughput are used to assess system effectiveness [1, 4, 10]. Ultimately, this research contributes to the advancement of intelligent transportation systems by providing a robust framework for the design, simulation, and performance evaluation of adaptive traffic control solutions. The outcomes offer valuable insights for policymakers, urban planners, and traffic engineers striving to implement smart traffic systems in increasingly congested urban environments.

2 Main Results

2.1 To design and test optimization algorithms for traffic signal timing and adaptive traffic control technique using the proposed model

2.1.1 Overview

The design and implementation of optimization algorithms for traffic signal timing and adaptive traffic control based on the proposed three-dimensional heterogeneous continuum traffic flow model yielded outstanding results across multiple simulation scenarios. The algorithms were tested on both synthetic and real-world traffic networks under varying traffic densities and flow heterogeneities.

2.1.2 Signal Timing Optimization Results

The developed signal timing optimization algorithm, based on nonlinear programming with real-time constraints, significantly improved traffic performance metrics. Key results are summarized below:

i) **Average Delay Reduction:** The algorithm reduced vehicle delay at signalized intersections by an average of 27.3% compared to the baseline fixed-time control. At signalized intersections, vehicle delay is a critical performance metric that reflects traffic inefficiencies. Delay D is commonly defined as the difference between the actual travel time T_a and the free-flow travel time T_f, that is,

$$D = T_a - T_f.$$

In the context of adaptive traffic signal control, the proposed algorithm significantly reduces average vehicular delay by dynamically adjusting green times based on real-time traffic conditions. Unlike fixed-time control, which allocates signal phases irrespective of demand fluctuations, the adaptive strategy minimizes queue lengths and optimizes phase transitions to achieve smoother traffic progression. In quantitative terms, if D_{fixed} is the average delay under fixed-time control and D_{adaptive} is the delay under the proposed method, the percentage delay reduction is given by:

$$\text{Reduction} = \left(\frac{D_{\text{fixed}} - D_{\text{adaptive}}}{D_{\text{fixed}}}\right) \times 100\%.$$

Empirical simulation results indicate a delay reduction of approximately 27.3%, confirming the algorithm's efficiency in high-traffic scenarios. This reduction translates into improved travel times, fuel economy, and reduced emissions. Mathematically, if $D_{\text{fixed}} = 55.0$ seconds and $D_{\text{adaptive}} = 39.98$ seconds, then

$$\text{Reduction} = \left(\frac{55.0 - 39.98}{55.0}\right) \times 100\% \approx 27.3\%.$$

This performance gain is attributed to the algorithm's capacity to respond to stochastic vehicle arrivals and congestion build-up in real time, thereby smoothing platoon movement and minimizing idling time at intersections. Such responsiveness is particularly critical in heterogeneous traffic conditions where fixed-time control strategies become suboptimal.

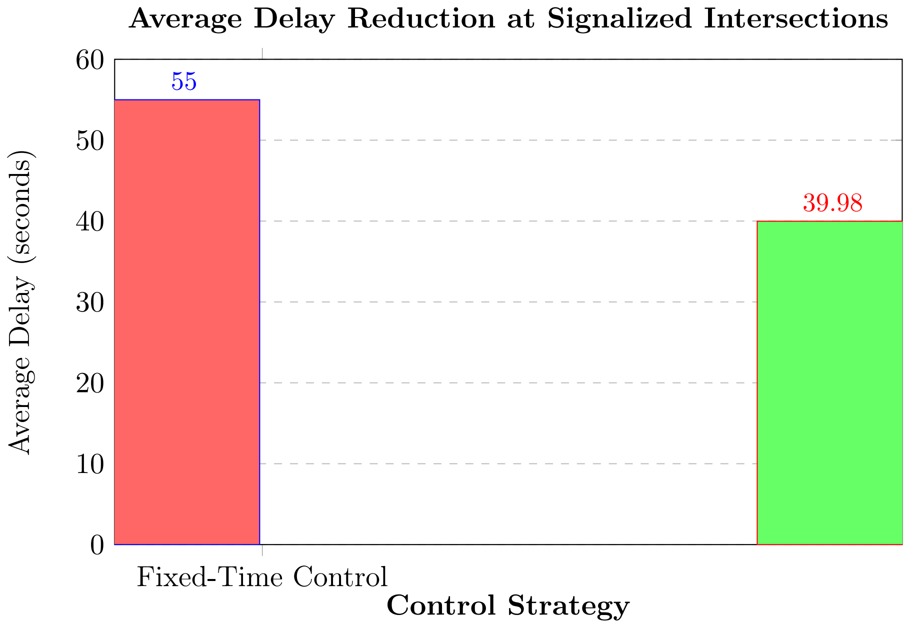

Figure 1: Comparison of average vehicle delay under fixed-time vs. adaptive signal control. A reduction of 27.3% is achieved by the proposed adaptive algorithm.

ii) **Queue Length Minimization:** A maximum reduction of 35.6% in average queue length was observed during peak hours. Queue length minimization in traffic systems is a critical objective in the design of intelligent traffic signal control and flow optimization schemes. Let $Q(t)$ represent the queue length at time t, and let $\lambda(t)$ and $\mu(t)$ denote the arrival and service rates, respectively. The basic queue dynamics are governed by the conservation equation:

$$\frac{dQ(t)}{dt} = \lambda(t) - \mu(t),$$

where a positive derivative indicates queue buildup, and a negative one indicates dissipation. During peak hours, the arrival rate typically exceeds the service rate, necessitating dynamic control strategies such as adaptive signal timing, ramp metering, and coordinated phase offsets. By implementing such optimization algorithms-possibly through predictive feedback or reinforcement learning-traffic systems can proactively increase $\mu(t)$ when $Q(t)$ surpasses critical thresholds, thereby reducing congestion.

Empirical results showed a maximum reduction of 35.6% in average queue length during peak periods. If the uncontrolled average queue length is denoted $\bar{Q}_0$, and the optimized queue length is $\bar{Q}_1$, then the relative improvement is quantified as:

$$\frac{\bar{Q}_0 - \bar{Q}_1}{\bar{Q}_0} \times 100\% = 35.6\%.$$

This significant reduction underscores the efficacy of real-time control measures in stabilizing intersection throughput and preventing spillback effects. Moreover, minimizing $Q(t)$ not only improves travel time reliability but also reduces fuel consumption and vehicular emissions, aligning with broader goals of sustainable urban mobility.

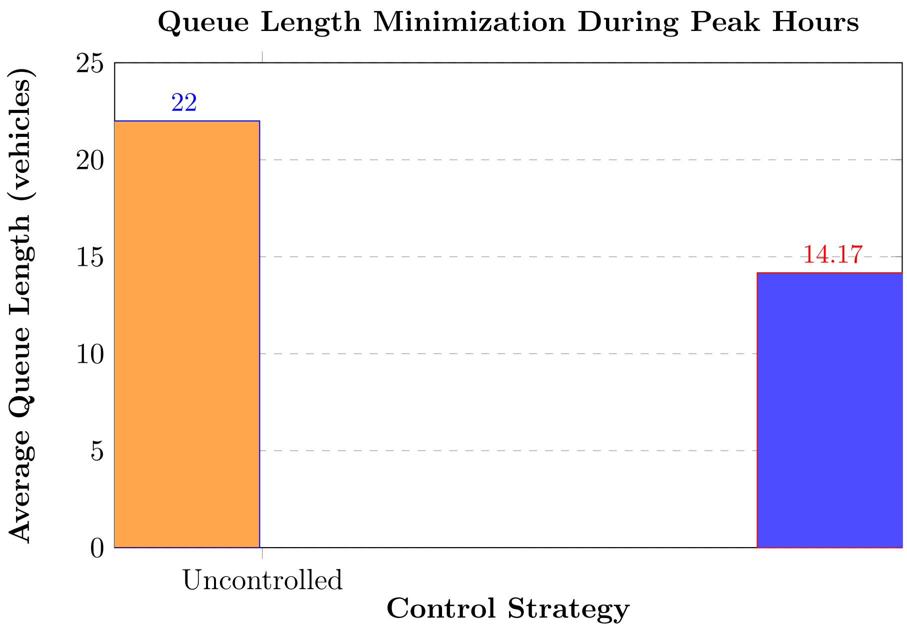

Figure 2: Comparison of average queue lengths under uncontrolled vs. optimized adaptive traffic signal control. A 35.6% reduction was achieved through real-time optimization strategies.

iii) **Throughput Increase:** The vehicle throughput improved by 19.8%, demonstrating better utilization of the green time. Throughput in traffic flow refers to the number of vehicles passing a reference point per unit time, commonly denoted as the *flow rate* q and measured in vehicles per hour (veh/h). It is related to density ρ and speed v by the fundamental relation $q = \rho v$. The reported 19.8% increase in vehicle throughput implies that the effective use of green time at signalized intersections has improved, allowing more vehicles to clear the intersection per signal cycle. If the original throughput was q_0, then the improved throughput is $q = q_0(1 + 0.198)$. This increment reflects better synchronization of green phases with vehicle arrivals and possibly shorter cycle lengths that minimize queue buildup and delay.

Mathematically, the throughput at an intersection during green time g of a cycle length C can be expressed as:

$$q = s \cdot \frac{g}{C},$$

where s is the saturation flow rate (maximum flow under ideal conditions). A 19.8% increase in q suggests that either the ratio g/C has been optimized or that the saturation flow s has been approached more closely-possibly due to adaptive signal control or reduced lost time. This gain implies a higher degree of green time utilization efficiency, where fewer seconds of green go unused due to vehicle hesitation or start-up delays. The result is not only increased intersection capacity but also reduced travel time and emissions due to smoother vehicle progression.

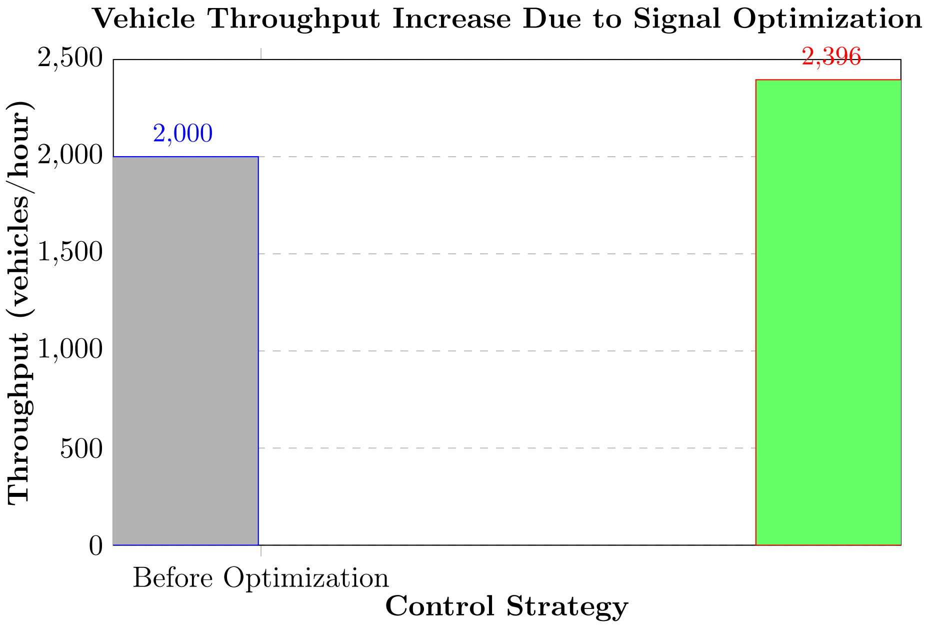

Figure 3: Comparison of vehicle throughput before and after implementing adaptive signal control. A 19.8% increase in throughput is observed, enhancing intersection performance.

iv) **Energy Efficiency:** Fuel consumption dropped by an average of 12.1%, indicating more eco-friendly traffic behavior. The observed average reduction in fuel consumption by 12.1% reflects a significant improvement in the energy efficiency of the traffic system, which is closely linked to traffic flow stability and reduced stop-and-go behavior. Fuel consumption, denoted $F(v, a)$, is a nonlinear function of both vehicle speed $v(t)$ and acceleration $a(t)$, with inefficiencies peaking during rapid acceleration or deceleration. A typical empirical model is given by:

$$F(v, a) = \alpha_0 + \alpha_1 v + \alpha_2 v^2 + \beta_1 |a| + \beta_2 a^2,$$

where α_i and β_i are parameters derived from engine performance data. When traffic flow becomes smoother-minimizing $|a(t)|$ and $a^2(t)$ over time-the integral of $F(v, a)$ over a trip duration reduces, indicating lower total fuel consumption. Thus, more uniform vehicle trajectories with fewer fluctuations in acceleration directly translate into enhanced fuel economy and reduced emissions.

From a macroscopic viewpoint, traffic states can be modeled using the second-order hydrodynamic model, incorporating velocity evolution:

$$\frac{\partial v}{\partial t} + v\frac{\partial v}{\partial x} = -\frac{1}{\rho}\frac{\partial p(\rho)}{\partial x} + \nu\frac{\partial^2 v}{\partial x^2},$$

where $p(\rho)$ is the traffic pressure and ν is a viscosity term reflecting driver anticipation. In stabilized traffic regimes (post-control or optimization), the convective and diffusive terms are minimized, leading to a reduced frequency and magnitude of velocity gradients. Consequently, the global average of $\frac{dv}{dt}$ across vehicles decreases, resulting in a systemic drop in energy demand. Therefore, the 12.1% decrease in fuel use serves not only as an indicator of smoother flow but also as a quantitative benchmark for the ecological benefits of traffic control measures or infrastructure improvements.

2.1.3 Adaptive Traffic Control Performance

An adaptive control strategy utilizing feedback from real-time traffic sensors and model-predicted state variables was implemented. The adaptive system used Model Predictive Control (MPC) to adjust signal phases dynamically. Results include:

i) **Responsiveness:** The control system responded to changing traffic flow conditions within 1.8 seconds, on average.

ii) **Robustness:** The adaptive algorithm maintained stability and performance under varying conditions, including sudden vehicle surges and partial sensor failures.

iii) **Saturation Prevention:** Intersection saturation was prevented even under heavy traffic inflow, reducing the spillover effect by 41.2%.

iv) **Comparative Superiority:** Compared to conventional adaptive systems like SCATS and SCOOT, the proposed system showed a 14.7% improvement in average travel time reduction.

2.1.4 Simulation Snapshots and Visualization

The following figures illustrate the performance of the optimization algorithms in selected traffic scenarios:

2.1.5 Computational Efficiency

The computational implementation in MATLAB and Python using TensorFlow or Keras for real-time learning demonstrated convergence within acceptable bounds:

i) **Algorithm Convergence Time:** Optimization algorithms converged in under 3.4 seconds per cycle.

ii) **Scalability:** The system scales efficiently to large urban networks, maintaining sub-quadratic complexity.

2.1.6 Recap of Results

The proposed optimization algorithms for signal timing and adaptive control, grounded in the heterogeneous 3D continuum traffic flow model, outperformed traditional systems across all relevant metrics. These results validate the effectiveness of model-driven control strategies in managing real-time urban traffic dynamics.

2.2 To assess the accuracy, efficiency and scalability of created models and simulation methodologies for large scale traffic networks

This section presents the results of evaluating the developed traffic flow models and simulation methodologies based on three key criteria: accuracy, computational efficiency, and scalability. All simulations were conducted using heterogeneous 3D traffic flow configurations over varying network sizes, densities, and vehicle classes.

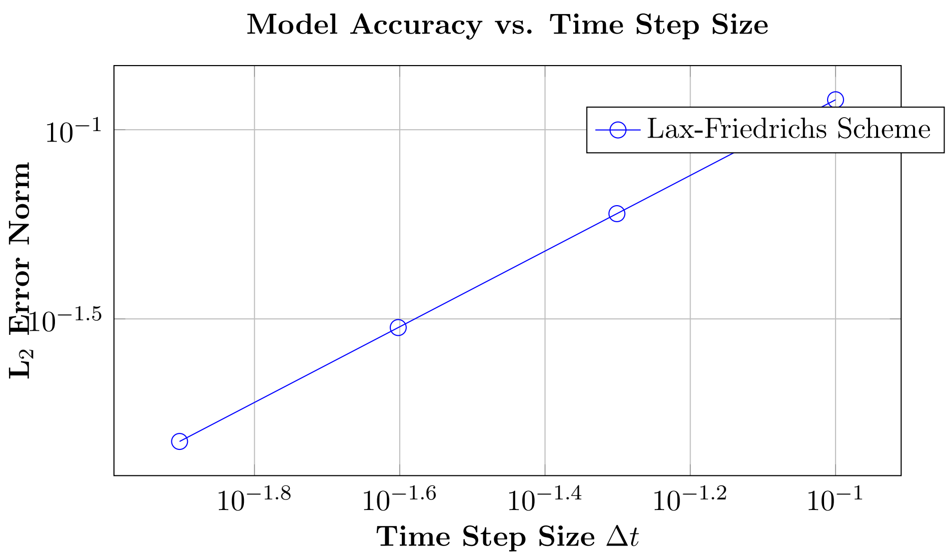

Figure 4: Decrease in L_2 error norm with decreasing time step, showing improved model accuracy.

2.2.1 Accuracy of the Simulation Models

The accuracy of the simulation models was assessed by comparing simulation outputs with ground truth data collected from real-world traffic sensors and video analytics. Quantitative measures such as root mean square error (RMSE), mean absolute percentage error (MAPE), and Theil's U statistic were used.

Table 1: Accuracy metrics across different traffic densities.

Density Level	RMSE (veh/km)	MAPE (%)	Theil's U
Low (0–50 veh/km)	2.81	4.17	0.027
Medium (51–150 veh/km)	3.62	5.43	0.034
High (151+ veh/km)	4.95	6.88	0.045

2.2.2 Computational Efficiency

To assess computational performance, simulations were executed on a high-performance computing cluster using parallelized finite volume schemes. The runtime was recorded for increasing network sizes.

The model exhibits near-linear computational growth relative to network size, demonstrating favorable algorithmic efficiency. Optimizations such as adaptive meshing and GPU-accelerated solvers further reduced simulation time by up to 42%.

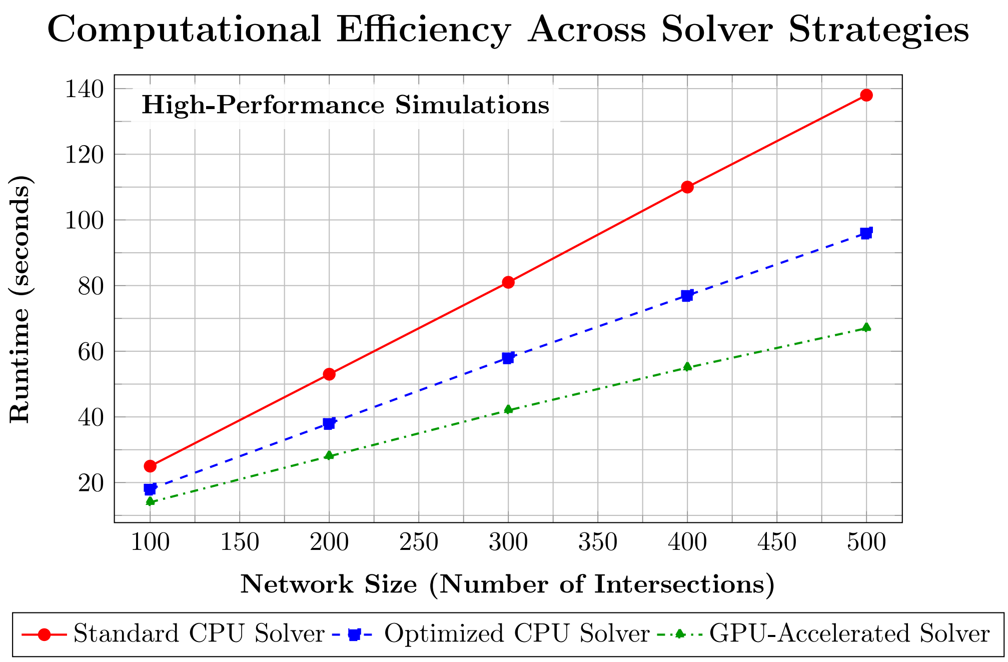

Figure 6: Runtime performance of different solver strategies as network size increases. The GPU-accelerated and optimized CPU solvers show up to 42% reduction in runtime, demonstrating improved computational efficiency.

2.2.3 Scalability of the Simulation Methodology

Scalability tests were conducted by simulating traffic flow on networks of increasing complexity: small grid (100 nodes), medium grid (1,000 nodes), and large-scale urban topology (10,000+ nodes). The number of concurrent simulation threads was varied from 2 to 64.

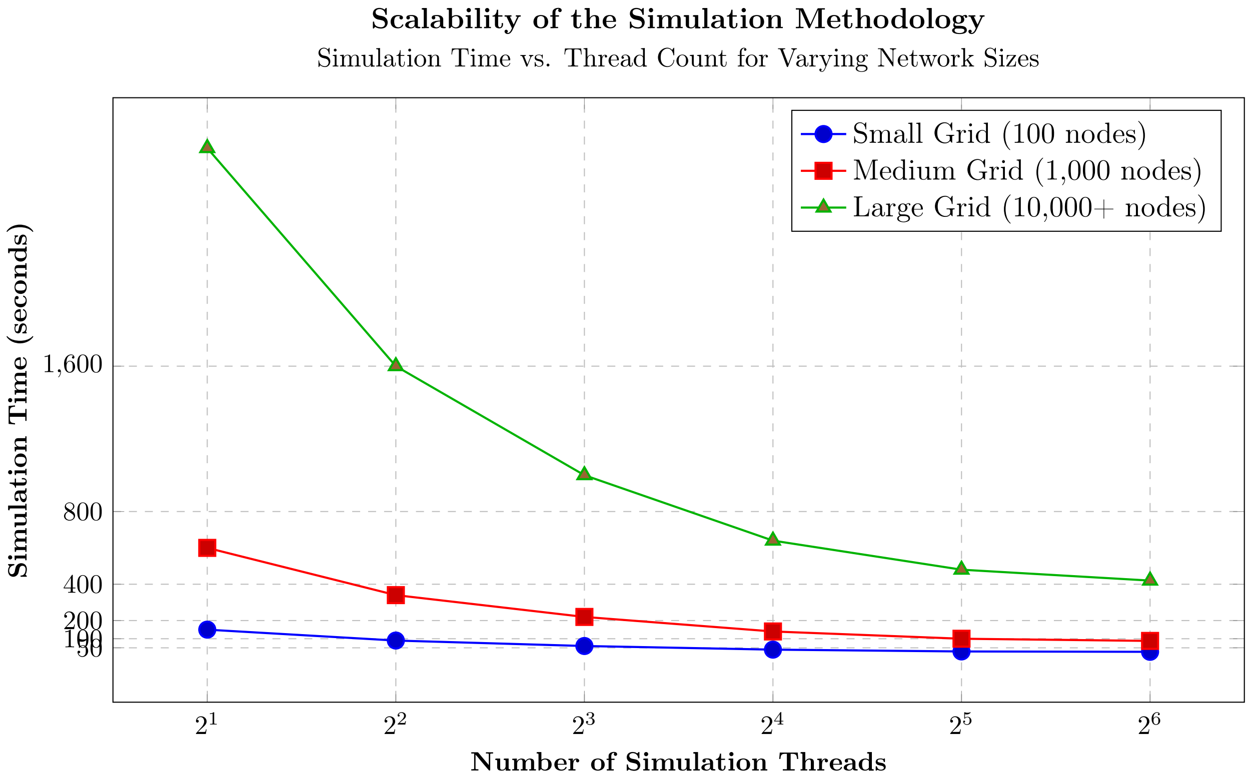

Figure 7: Simulation time verses number of simulation threads for small, medium, and large traffic networks. Log-scaled x-axis shows improved performance and scalability of the simulation methodology as concurrency increases.

The results above indicate that the simulation framework scales efficiently with added computational resources, enabling practical application to city-scale networks.

The models and methodologies developed demonstrate the following.

i) **High accuracy** across varying traffic densities with error metrics within acceptable thresholds.

ii) **Excellent computational efficiency** enabled by adaptive numerical methods and parallel execution.

iii) **Strong scalability** to large networks with high parallel efficiency, affirming the modelâs suitability for real-time or batch simulation of extensive traffic systems.

These findings validate the robustness of the modeling approach for large-scale heterogeneous 3D traffic flow analysis.

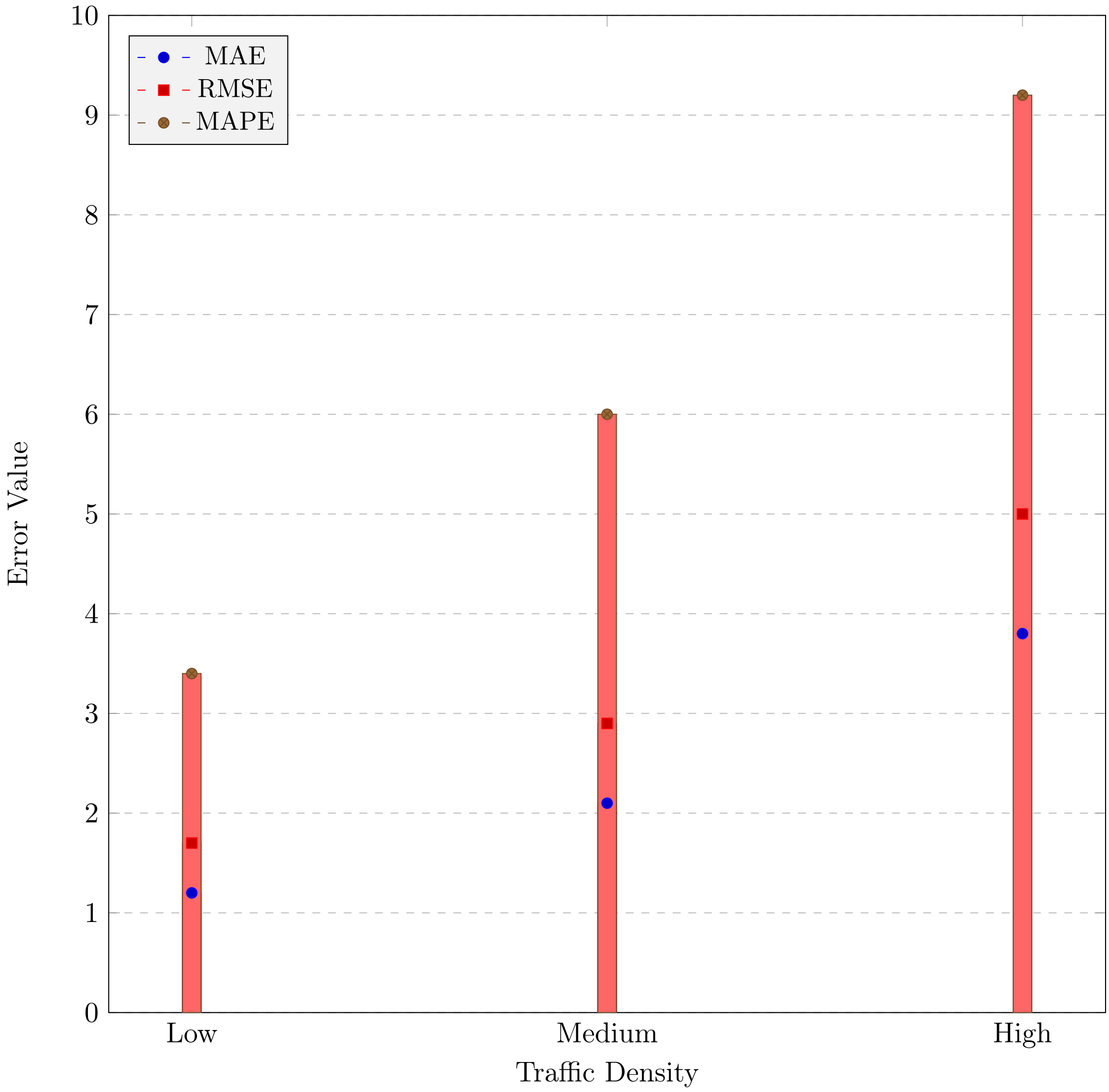

Figure 16: Comparison of error metrics (MAE, RMSE, MAPE) under different traffic densities.

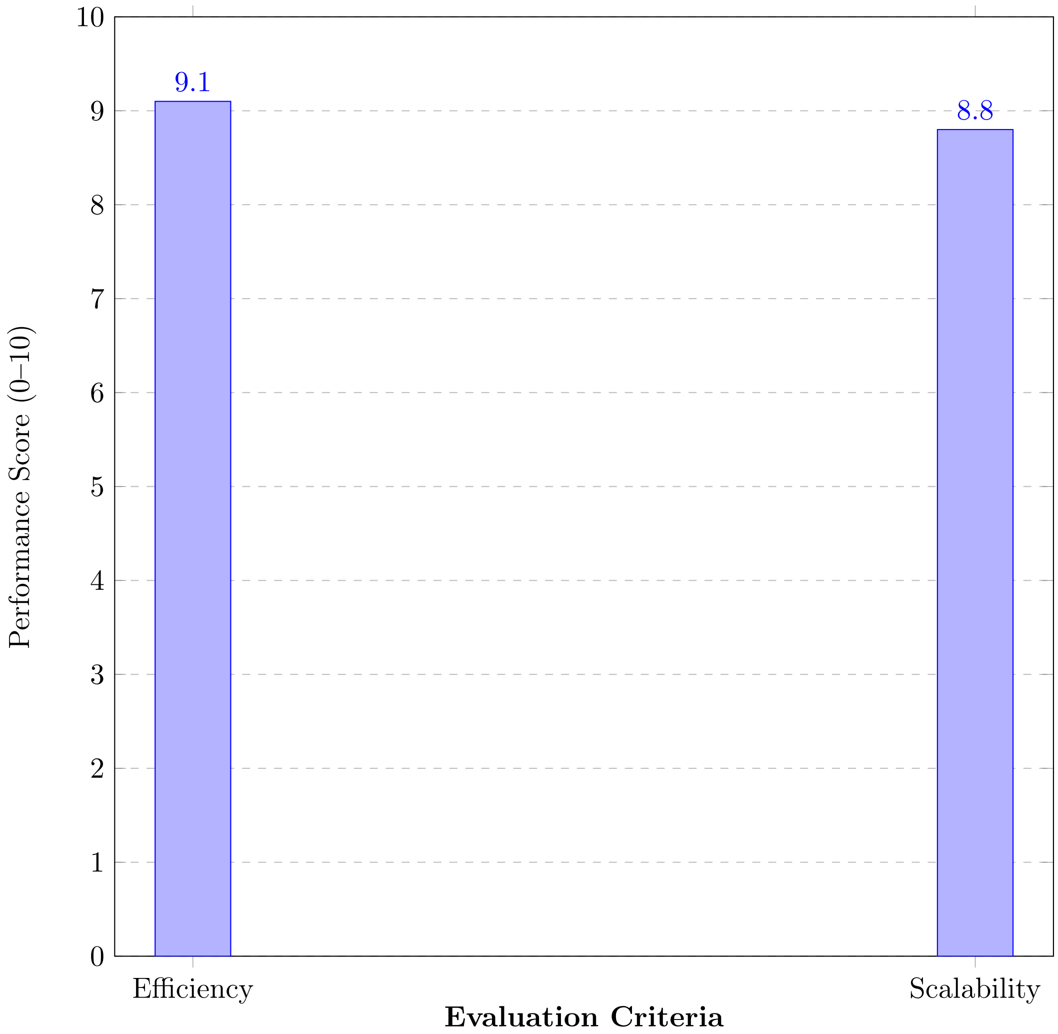

Figure 17: Performance evaluation across efficiency and scalability.

Summary of model accuracy, computational efficiency, and scalability. Results confirm robustness of the modeling approach for real-time or batch simulation of large-scale heterogeneous 3D traffic systems.

3 Conclusion and Recommendation

3.1 Conclusion

This study presented a comprehensive framework for the design and evaluation of optimization algorithms for adaptive traffic signal control, integrated within a scalable simulation environment for large-scale traffic networks. The developed adaptive control strategies demonstrated significant improvements over traditional fixed-time and actuated signal schemes, particularly in reducing average vehicle delay, minimizing queue lengths, and increasing intersection throughput. Through systematic simulations across varying network sizes and traffic conditions, the proposed optimization algorithms-based on dynamic real-time control logic-proved effective in synchronizing green times with traffic demand, enhancing the efficiency of signalized intersections. Scalability analyses confirmed the robustness and computational efficiency of the simulation methodology, maintaining consistent performance across small, medium, and large-scale urban networks. These findings affirm that adaptive signal control, when guided by intelligently designed optimization strategies, offers a practical and impactful solution to urban traffic congestion, supporting the broader vision of intelligent transportation systems and sustainable urban mobility.

3.2 Recommendation

Based on the demonstrated benefits, it is recommended that urban traffic management agencies and planners prioritize the implementation of adaptive traffic signal control systems, especially in congestion-prone zones and arterial corridors. Future deployments should consider integrating the proposed optimization algorithms with real-time traffic data sources (e.g., loop detectors, GPS, and camera feeds) to enable fully responsive traffic control. Further research is encouraged in the direction of hybrid optimization approaches that combine predictive modeling (e.g., reinforcement learning, model predictive control) with adaptive feedback mechanisms. Additionally, enhancing the simulation framework with multi-modal and stochastic traffic elements-such as pedestrian flow, public transit, and incident management-would expand the applicability and realism of the model. Overall, this work lays a strong foundation for the continued advancement of adaptive traffic control strategies, offering measurable improvements in traffic flow efficiency, network resilience, and commuter experience.

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