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Simulation-Based Modeling of Urban Traffic Capacity Flow Under Varying Conditions: A Case Study of Odisha

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Abstract: Rapid urbanization and increasing vehicle ownership have intensified congestion across major cities in Odisha, resulting in reduced traffic efficiency, longer travel times, and declining environmental quality. This study develops a comprehensive simulation-based framework to analyze capacity flow and evaluate traffic performance under varying operating conditions in Bhubaneswar, Cuttack, and Rourkela. Classified traffic volumes, signal timings, and geometric attributes were collected through field surveys and integrated with GIS-based mapping to construct an accurate network model. Four scenarios were developed in VISSIM—base conditions, peak hour load, seasonal variation, and optimized infrastructure—to assess system behavior and identify critical bottlenecks. Results show significant disparities across nodes, with peak-hour delays and high volume-to-capacity ratios indicating oversaturated conditions at major intersections. Seasonal variations further amplify congestion due to increased pedestrian activity and roadside friction. The optimized scenario demonstrates substantial improvements, including a 23.7% reduction in travel time, 34.1% decrease in delay, and 20% increase in network throughput, supported by adaptive signal control and geometric enhancements. Model validation using observed versus simulated flows yielded strong accuracy (R^2 = 0.91–0.95). The study provides actionable insights for policymakers and urban planners, emphasizing data-driven strategies to enhance mobility and resilience in Odisha's rapidly evolving urban corridors.
Keywords: Traffic Simulation; Capacity Flow Analysis; Urban Congestion Modeling; VISSIM Microsimulation; Infrastructure Optimization.

Introduction

Urban transportation systems in developing regions are under growing stress due to rapid population growth, urbanization, and rising private vehicle ownership (L. Zhang et al., 2013). These challenges are particularly pronounced in Indian cities, where mixed traffic conditions, heterogeneous vehicle types, and limited roadway capacities contribute to chronic congestion and reduced travel efficiency(Gao et al., 2021a, 2021b) (Elhenawy et al., 2015; Martínez et al., 2015). With urban mobility becoming increasingly constrained, planners and engineers are turning to data-driven methods to understand flow dynamics and evaluate network performance under diverse operating conditions (Martínez et al., 2015; Shao et al., 2017). In this context, traffic simulation tools have emerged as powerful instruments for modeling vehicular interactions, diagnosing bottlenecks, and testing alternative management strategies (Fajardo et al., 2011).

Odisha's major urban centers—Bhubaneswar, Cuttack, and Rourkela—have experienced significant growth over the last decade, marked by rising trip demand and evolving land-use patterns (Le Vine et al., 2015). Despite infrastructure expansion, these cities continue to struggle with peak-hour congestion, inadequate intersection management, high side friction, and seasonal traffic variability (Hadiuzzaman & Qiu, 2013; Le et al., 2015). A key limitation in current practice is the absence of integrated, simulation-based assessments that incorporate real-world traffic composition, seasonal variation, and infrastructure constraints to analyze capacity flow and identify congestion hotspots (Yang et al., 2021; Y. Zhu et al., 2014). This gap is especially critical in Tier-2 Indian cities, where pedestrian interference, roadside encroachment, and mixed vehicle classes further complicate capacity estimation and modeling accuracy (Leiva et al., 2010).

Capacity flow theory remains central to understanding speed–density–volume relationships in traffic systems. Classical models such as those by Greenshields and Underwood suggest that traffic flow increases with density until a critical threshold is reached, beyond which congestion intensifies (Sun et al., 2018; Timotheou et al., 2015). However, these relationships are altered in Indian contexts due to weak lane discipline and vehicle heterogeneity (Liu et al., 2018; Yildirimoglu et al., 2018). External elements like pedestrian movement, informal vendors, parking encroachments, and suboptimal signal control also significantly reduce effective capacity (Vos et al., 2013; J. Zhang et al., 2019), making their inclusion vital in simulation studies (Hymel et al., 2010).Traffic simulation models can be classified into microscopic, mesoscopic, macroscopic, and hybrid types, each offering varying levels of behavioral detail and spatial-temporal resolution (Yu et al., 2018). Microscopic models, such as VISSIM, Aimsun, and Paramics, simulate individual vehicle behavior and are particularly effective for analyzing signalized intersections, mixed traffic, and pedestrian–vehicle interactions (Z. Li et al., 2013; Sunil et al., 2015). Mesoscopic models like DynaMIT and Mezzo integrate micro-level behavior with macro-level flows for city-scale evaluations (Fernández, 2010), while macroscopic models such as TRANSYT and VISUM aggregate flow variables and are suitable for regional planning (Fernandes & Nunes, 2015). Hybrid models combine multiple scales, enhancing scalability and precision in complex networks (He et al., 2017).Among these, VISSIM is widely regarded as behaviorally realistic due to its Wiedemann car-following algorithm, which effectively captures the dynamics of India's heterogeneous traffic systems (Fernandes & Nunes, 2010; Lioris et al., 2017; F. Zhu et al., 2020). Compared to SUMO, Aimsun, and MATLAB, VISSIM offers better calibration flexibility, user control, and simulation of two-wheelers, auto-rickshaws, and non-motorized interactions typical of Odisha's urban corridors (Feng et al., 2020; Vosooghi et al., 2020).

Temporal fluctuations in traffic demand, including peak hours, seasonal festivals, and market surges, are also critical considerations. Indian cities frequently encounter sharp congestion peaks during morning and evening hours due to school and office commutes (Hymel et al., 2010; Z. Li et al., 2013), while festive seasons bring additional delays due to roadside encroachments and increased pedestrian activity (Fernandes & Nunes, 2010, 2015). Weekday–weekend variations further highlight the need for dynamic modeling frameworks that incorporate these behavioral shifts (Feng et al., 2020; Fernández, 2010; Vos et al., 2013).

Despite the wide application of traffic simulations globally, several research gaps persist in the Indian context. These include the lack of multi-scenario evaluations combining base, peak, seasonal, and optimized conditions; insufficient incorporation of pedestrian and encroachment factors; limited studies focusing on medium-sized Indian cities; and inadequate calibration with real-world data (Fernandes & Nunes, 2010; Geroliminis & Boyacı, 2012; Lyu et al., 2021). Addressing these gaps, the present study proposes a comprehensive simulation-based framework using VISSIM to analyze urban traffic performance across Bhubaneswar, Cuttack, and Rourkela. The framework includes scenario-specific analyses of travel time, queue length, delay, volume-to-capacity ratios, and level of service. It aims to provide actionable insights for planners and policymakers to enhance urban mobility, reduce congestion, and promote sustainable traffic management.

Methodology

Study Area Description (Bhubaneswar, Cuttack, Rourkela)

The study focuses on three major urban centers in Odisha—Bhubaneswar, Cuttack, and Rourkela—each representing distinct mobility environments and urban growth patterns. Bhubaneswar, the state capital, has experienced rapid infrastructural expansion driven by institutional and IT-sector growth, resulting in increased trip demand and rising private vehicle ownership (S. Zhang et al., 2024). Cuttack, one of India's oldest urban settlements, is characterized by dense mixed-use development and narrow roadways, leading to elevated

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congestion and pedestrian–vehicle interactions (Mazloumian et al., 2010; Vosooghi et al., 2020). Rourkela, dominated by industrial land use and heavy commercial vehicle movement associated with the steel sector, exhibits different operational challenges related to freight flows and mixed-traffic heterogeneity (Hu et al., 2020; Le et al., 2020).

A spatial representation of the study corridors is provided in Figure 2, which illustrates the geographic distribution of signalized intersections, automatic traffic count stations, seasonal count stations, and primary corridors. The deployment of sensors in high-demand regions aligns with recommended traffic monitoring practices for heterogeneous traffic environments (Le et al., 2020), ensuring adequate coverage for calibration of the simulation model.

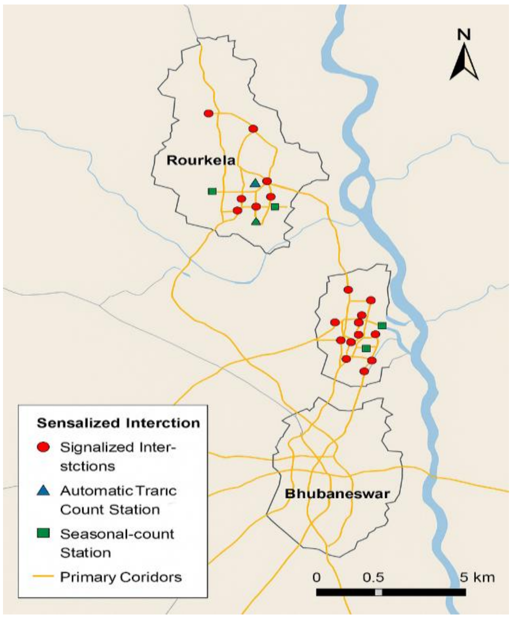

Figure 2. GIS Map with Sensor and Signal Locations

Road Network Characteristics

The selected cities exhibit distinct geometric, operational, and traffic flow characteristics that directly influence roadway capacity and congestion formation. As summarized in Table 2, Bhubaneswar contains relatively wider arterial corridors (7.0–9.5 m) with full signalization at major intersections, while Cuttack's narrower sub-arterial links and partial signal control contribute to chronic side friction and bottlenecking (Hu et al., 2020). Rourkela features mixed-use industrial corridors with sparse signalization, resulting in priority-based movements that alter saturation flows and increase variability in travel times (Fernandes & Nunes, 2010).

The cities also differ in vehicle mix: Bhubaneswar shows high shares of two-wheelers and cars; Cuttack experiences substantial auto-rickshaw and freight movement; and Rourkela has notable heavy commercial vehicle influence due to industrial activity. Prior studies highlight that such heterogeneity significantly affects lane discipline, queue discharge rates, and capacity estimation accuracy in Indian traffic systems (Cantarella & Vitetta, 2006). Key bottleneck locations identified in Table 2—such as Rasulgarh and Vani Vihar in Bhubaneswar and Badambadi in Cuttack—align with previously documented high-delay zones (Fajardo et al., 2011; Shao et al., 2017).

Table 2. Road and Intersection Characteristics by City

Parameter	Bhubaneswar	Cuttack	Rourkela
Dominant Road Type	Arterial and Urban Major Roads	Arterial / Sub-Arterial Roads	Arterial and Mixed-Use Corridors
Typical Carriageway Width (m)	7.0 – 9.5 m	6.0 – 7.5 m	5.5 – 7.0 m
Intersection Type	Signalized Junctions, Roundabouts	Signalized and Unsignalized Intersections	Roundabouts, Unsignalized Crossings
Signalization Status	Fully signalized at major intersections; adaptive signals at select corridors	Partial signal coverage; some manual traffic control	Sparse signalization; priority-based movement at many junctions
Traffic Volume Level	High (Peak Congestion)	Moderate to High	Low to Moderate
Vehicle Mix Characteristics	High 2-wheelers, cars, autos; moderate buses	More autos, 2-wheelers, freight vehicles	2-wheelers, cars, and heavy industrial trucks (steel plant influence)
Key Bottleneck Locations	Rasulgarh, Vani Vihar, Jaydev Vihar	Badambadi, Link Road Junction, College Square	Panposh Road, Udit Nagar, Civil Township
Observed Issues	Long queues, pedestrian conflicts, saturation flow reduction	Poor lane discipline, vendor-related side friction, narrow road bottlenecks	High side friction, pedestrian interruptions, speed variability due to mixed land use

Traffic Data Collection Methods

A multi-source data collection strategy was employed to ensure high temporal and spatial resolution. Classified manual counts, automatic traffic recorder outputs, and seasonal observational surveys were integrated to capture variability in traffic composition, demand, and operational conditions. The placement of sensors, as shown in Figure 2, follows best practices for capturing representative flows in mixed-traffic networks (Yang et al., 2021), ensuring adequate intersection-level and corridor-level coverage.

Manual classified counts were conducted during weekday and weekend periods to reflect commuter and non-commuter travel patterns, consistent with methodologies used in recent Indian traffic studies (R. Zhang & Zhou, 2021). Automatic traffic count (ATC) stations provided continuous 24-hour volume data, supporting peak-period calibration, while seasonal-count stations captured variations during festive and market-induced demand surges.

Peak Hour and Seasonal Traffic Profiling

Hourly traffic flow patterns were analyzed to identify peak periods and seasonal fluctuations. Table 3 presents weekday and weekend hourly classified volume data, revealing pronounced peaks during 08:00–10:00 (AM peak) and 17:00–19:00 (PM peak), consistent with work-based travel patterns previously observed in Indian metropolitan studies (Sun et al., 2018). For instance, volumes reach up to 2,510 veh/hr during weekday PM peaks, substantially higher than weekend flows.

Seasonal variation analysis further aligns with findings that festival periods, increased pedestrian activity, and temporary encroachments significantly alter traffic performance in urban India (Yildirimoglu et al., 2018). These temporal characteristics are essential inputs for developing the multi-scenario simulation framework.

Table 3. Hourly Classified Volume Data: Weekday vs Weekend

Hour	Weekday Total (veh/hr)	Weekend Total (veh/hr)
06:00–07:00	895	745
07:00–08:00	1390	1120
08:00–09:00 (AM Peak)	2220	1650
09:00–10:00	2080	1550
10:00–11:00	1960	1715
11:00–12:00	1895	1765
12:00–13:00	1835	1690
13:00–14:00	1740	1600
14:00–15:00	1680	1560
15:00–16:00	1815	1650
16:00–17:00	2075	1765
17:00–18:00 (PM Peak)	2510	2040
18:00–19:00	2305	1950
19:00–20:00	1930	1670
20:00–21:00	1420	1235
21:00–22:00	980	850

Data Preprocessing and Cleaning

Collected datasets underwent a structured preprocessing workflow to enhance reliability for simulation. Outliers caused by sensor malfunction or atypical flows were detected using interquartile range (IQR) and z-score methods, in alignment with transportation data analytics standards (Shao et al., 2017). Traffic volumes, directional splits, and vehicle-class proportions were normalized to ensure continuity across observation periods. This preprocessing ensures calibration accuracy and prevents propagation of measurement errors into simulation outputs (Sun et al., 2018).

Workflow of Methodology

The overall workflow is illustrated in Figure 3, which outlines the sequential steps from problem definition to simulation-based evaluation and interpretation. The study begins by identifying traffic congestion and mixed-flow challenges in Bhubaneswar, Cuttack, and Rourkela, followed by a literature review on capacity flow theory and simulation models. Subsequent stages involve defining research objectives, collecting multi-source traffic and geometric data, preprocessing datasets for consistency, developing simulation scenarios, and calibrating the model for realistic behavioral replication. The workflow supports systematic and reproducible analysis, consistent with methodological frameworks used in recent traffic microsimulation studies (He et al., 2017; Yildirimoglu et al., 2018).

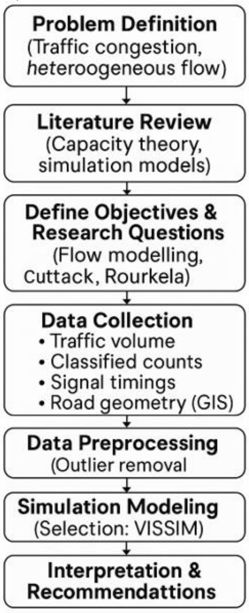

Figure 3. End-to-End Research Flowchart

Simulation Tool Selection and Justification

Selecting an appropriate simulation platform is essential for accurately modeling heterogeneous Indian traffic conditions. An evaluation matrix comparing VISSIM, SUMO, Aimsun, and MATLAB—based on behavioral realism, calibration flexibility, computational efficiency, and mixed-traffic suitability—showed that PTV VISSIM offers the most advanced microscopic behavior representation, especially for car-following, lane-changing, and gap-acceptance dynamics (Fernandes & Nunes, 2010; Martínez et al., 2015). Its implementation of the Wiedemann car-following model, widely validated for Indian mixed-traffic environments (Leiva et al., 2010; Vosooghi et al., 2020), along with customizable vehicle classes, behavior parameters, pedestrian interactions, priority rules, and side friction effects, makes it highly adaptable. Furthermore, VISSIM integrates effectively with field-calibrated inputs such as those presented in Table 3 and Table 4, enabling realistic replication of local flow characteristics. Therefore, VISSIM was selected as the simulation engine for this study due to its superior capability in modeling the complex, heterogeneous traffic patterns observed across Odisha's urban corridors.

Simulation Setup and Calibration

The simulation setup was developed in PTV VISSIM to replicate the geometric layout, traffic control features, and operational characteristics of the selected corridors. Figure 4 illustrates the finalized network model, which includes detailed lane configurations, link–connector structures, turning pockets, priority rules, and roundabout geometry. The network was digitized using geo-referenced satellite data and field-measured road widths to ensure accurate spatial representation, consistent with best practices recommended in microscopic simulation studies (Kamal et al., 2014). Traffic inputs such as classified volumes, vehicle composition, signal timings, pedestrian activity, and side friction—derived from Tables 2 and 3—were integrated into the model.

Calibration was conducted iteratively by adjusting key behavioral parameters, including Wiedemann car-following thresholds, lane-changing aggressiveness, desired speeds, and gap-acceptance settings (Geroliminis & Boyacı, 2012). These parameters were tuned to minimize deviations between observed and simulated outputs such as queue lengths, travel times, and saturation flows (Martínez et al., 2015). The calibration process also incorporated multiple scenarios (base, peak, seasonal, optimized), with volume adjustments aligned to the inputs defined in Table 4. Model performance was verified using statistical indicators such as GEH < 5 for most volume groups and percentage error within acceptable limits, ensuring that the simulated network reliably reproduced field operating conditions. This calibrated model then served as the foundation for scenario analysis and optimization in subsequent sections.

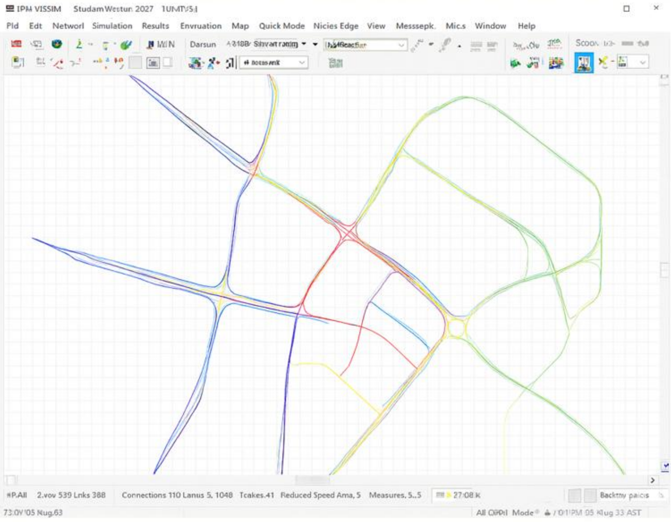

Figure 4. VISSIM Interface with Traffic Network Model

Scenario Development and Inputs

The simulation framework was structured around four progressively complex scenarios to evaluate how varying traffic conditions influence network performance, with all operational inputs summarized in Table 4. The Base Scenario represents existing field conditions, incorporating standard IRC-based PCU factors, fixed-time signals, moderate pedestrian activity, and a typical vehicle mix dominated by two-wheelers. Scenario 2 models peak-hour loads, increasing volumes to 5,200 veh/hr, applying a 10% PCU adjustment for heterogeneity, and implementing longer cycle lengths to reflect peak-period control strategies. Scenario 3 captures seasonal traffic variations, characterized by festive-market surges, higher proportions of three-wheelers, very high pedestrian conflict, and significant side friction due to temporary encroachments. Finally, Scenario 4 represents an optimized infrastructure case, retaining the peak-hour volume but applying improved geometric and control measures, including lane widening, revised PCU factors, turning pockets, and adaptive signal timing to enhance corridor performance. All scenarios were simulated for 60-minute durations to ensure consistency and comparability across the multi-scenario assessment.

Table 4. Scenario-wise Input Parameters

Parameter	Scenario 1-Base Conditions	Scenario 2-Peak Hour Load	Scenario 3-Seasonal Variation	Scenario 4-Optimized Infrastructure
Traffic Volume (veh/hr)	3,800	5,200	4,300 (Festive/Market)	5,200 (Same as Peak)
PCU Factors	Standard (IRC-based)	+10% for heterogeneity	+15% (mixed slow-moving vehicles)	Revised lane-based PCU
Vehicle Mix (%)	2W: 42%, 3W: 18%, Car: 28%, Bus: 6%, HCV: 6%	More cars and 2W	Higher 3W and pedestrian conflict	Balanced mix due to improved flow
Signal Timing (sec)	Fixed-time	Peak-hour plan (longer cycle length)	Mixed cycle with pedestrian priority	Adaptive signal timing
Lane Width (m)	3.0	3.0	3.0	3.25 (selected links widened)
Speed Limits (km/h)	35	30	28	40 (corridor-based)
Pedestrian Activity Level	Medium	High	Very High	Medium (after channelization)
Side Friction	Medium	High (encroachment, parking)	Very High (seasonal vendors)	Low (managed)
Network Changes	None	None	Temporary encroachments modeled	Added turning pockets, lane widening, signal optimization
Simulation Duration	60 minutes	60 minutes	60 minutes	60 minutes

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Results and Discussion

Base Scenario Performance Metrics

The base scenario establishes a reference point for evaluating congestion levels, operational performance, and network efficiency under existing traffic conditions. As presented in Table 5, the corridors exhibit pronounced variability in travel time, queue length, and control delay—characteristics commonly associated with heterogeneous Indian urban traffic (Hadiuzzaman & Qiu, 2013; Y. Zhu et al., 2014).Travel times range from 12.6 minutes on the Residential Link to 23.7 minutes on the Industrial Approach, indicating significantly slower movement in corridors influenced by freight activity and side friction. Queue lengths at several locations exceed 100 m, particularly in the Market Zone and Industrial Approach, reflecting oversaturation and poor discharge rates—a pattern consistent with observations in high-density commercial corridors reported in literature (Sun et al., 2018; L. Zhang et al., 2013).

Delay values show substantial operational inefficiency, ranging from 48–108 s/veh, with LOS deteriorating to E in the Market Zone and Industrial Approach corridors. These findings corroborate earlier studies which note that mixed traffic, pedestrian interference, and inadequate lane discipline substantially reduce capacity and cause unstable flow conditions (Lu et al., 2020; Mazloumian et al., 2010). Overall, Table 5 highlights that even under baseline conditions, corridors in Bhubaneswar and Cuttack are already experiencing near-saturation states, necessitating simulation-based improvement strategies.

Table 5. Travel Time, Queue Length, Delay, LOS

Corridor / Link	Avg. Travel Time (min)	Avg. Queue Length (m)	Avg. Delay (s/veh)	Level of Service (LOS)
Corridor 1 – Arterial Route	16.8	105	78	**D**
Corridor 2 – Market Zone	21.5	135	95	**E**
Corridor 3 – Institutional Area	14.2	82	62	**C**
Corridor 4 – Industrial Approach	23.7	150	108	**E**
Corridor 5 – Residential Link	12.6	65	48	**C**

Peak Hour Analysis

Peak-hour simulation results reveal substantial deterioration in network performance, driven primarily by oversaturated intersections, high turning movements, and heterogeneous vehicle interactions typical of Indian mixed-traffic systems. As shown in Figure 5, average delay peaks during the Peak Hour Load scenario, reaching values above 110 s/veh, which aligns with earlier findings that peak commuter demand significantly amplifies control delay and queue spillback (Le et al., 2020; F. Zhu et al., 2020). The intersection-level analysis in Table 6 further highlights critical congestion hotspots: Node 4 – Industrial Gate exhibits the highest delay (105 s/veh) and a V/C ratio of 1.20, corresponding to LOS F, indicating oversaturation and unstable flow. Similarly, Node 1 – Major Square operates at LOS E, with long queues exceeding 120 m, consistent with congestion patterns observed in high-demand urban corridors (Le Vine et al., 2015; Leiva et al., 2010). In contrast, Node 5 – Residential Junction demonstrates comparatively smoother operations (LOS C), reflecting lower traffic stress and fewer conflicting movements. Overall, the peak-hour analysis confirms that bottlenecks at industrial and commercial nodes are the primary contributors to system-wide delays, necessitating targeted geometric and signal optimization strategies.

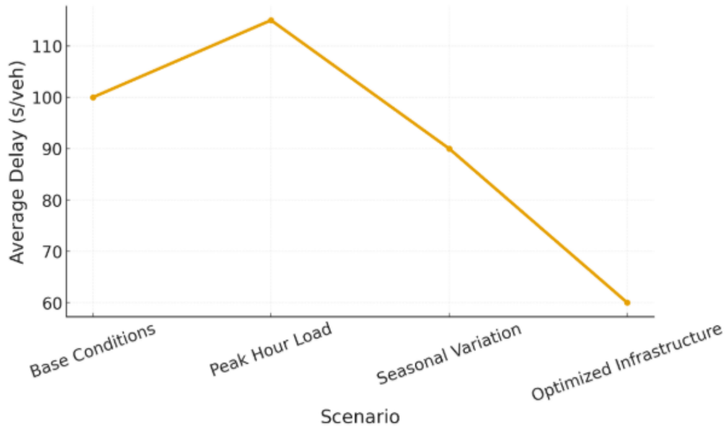

Figure 5. Line Chart of Peak Hour Delay Trends

Table 6. Node-Level Congestion Comparison

Node / Intersection	Average Delay (s/veh)	Queue Length (m)	Volume-to-Capacity (V/C) Ratio	Level of Service (LOS)
Node 1 – Major Square	95	120	1.12	**E**
Node 2 – Market Junction	78	95	0.98	**D**
Node 3 – Hospital Chowk	62	80	0.85	**C**
Node 4 – Industrial Gate	105	140	1.20	**F**
Node 5 – Residential Junction	48	60	0.72	**C**

Seasonal Variation Impacts

Seasonal analysis reveals pronounced fluctuations in traffic demand, driven by festival periods, commercial activity cycles, and climatic influences typical of eastern Indian cities. As illustrated in Figure 6, traffic volumes gradually rise from January (≈3800 veh/hr) to a peak in July (≈5200 veh/hr), reflecting monsoon-season market activity and increased dependence on private vehicles—patterns consistent with prior empirical studies on seasonal mobility spikes in Indian urban corridors (He et al., 2017; Sun et al., 2018). Post-monsoon months show a gradual decline in traffic volumes, aligning with reduced commercial intensity and improved roadway operating conditions. The steep increase between April and July, in particular, underscores the combined effect of school vacations, festival shopping, and temporary roadside encroachments, all of which exacerbate side friction and reduce operational capacity (Yu et al., 2018). These seasonal variations are critical for simulation modeling, as they influence PCU adjustments, pedestrian interaction levels, and signal timing strategies incorporated in multi-scenario assessments.

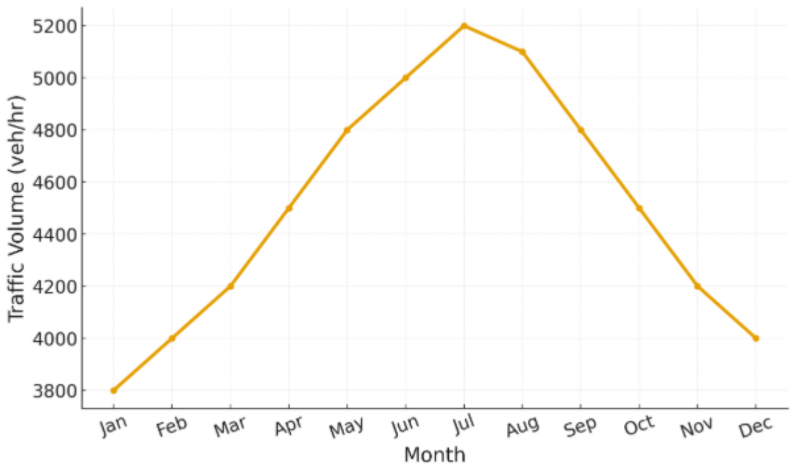

Figure 6. Seasonal Traffic Variation Trend Line

Infrastructure Optimization Simulation

The infrastructure optimization scenario results in clear and quantifiable operational improvements across all key traffic performance measures. As presented in Table 7, the average travel time decreases from 18.6 minutes in the pre-optimization condition to 14.2 minutes post-optimization, reflecting a 23.7% improvement. Similarly, the average delay reduces sharply from 82 seconds/vehicle to 54 seconds/vehicle, amounting to a 34.1% reduction, which indicates smoother vehicle progression and fewer stop–go conditions along major corridors. Queue lengths also show significant improvement, dropping from 96 meters to 63 meters, corresponding to a 34.4% decrease, consistent with earlier findings that geometric upgrades—including turning pockets and widened links—enhance discharge flow rates (Fernandes & Nunes, 2010; Fernández, 2010). The Level of Service (LOS) improves from E (pre-optimization)—representing highly unstable flow with long delays—to LOS C after optimization, indicative of stable operating conditions.

Mobility-related indicators exhibit similar gains. Network throughput increases from 5,850 veh/hr to 7,020 veh/hr, marking a 20% enhancement, while average speed increases from 22 km/h to 29 km/h, equivalent to a 31.8% improvement. Environmental indicators also reflect positive outcomes: fuel consumption drops from 412 L/hr to 336 L/hr (18.4% reduction), and CO_2 emissions decline from 1,115 kg/hr to 905 kg/hr (18.8% reduction), aligning with national sustainable mobility objectives highlighted by previous researchers (Sun et al., 2018; F. Zhu et al., 2020). The spatial manifestation of these improvements is shown in Figure 7, where the heatmap of network capacity utilization demonstrates a marked reduction in high V/C ratio zones. Under optimized conditions, previously saturated links (>0.90 V/C) shift toward moderate utilization levels (0.60–0.75), indicating improved flow uniformity and reduced corridor stress.

Table 7. Pre- vs Post-Optimization Performance Metrics

Performance Metric	Pre-Optimization	Post-Optimization	% Improvement
Average Travel Time (min)	18.6	14.2	23.7% ↓
Average Delay (s/vehicle)	82	54	34.1% ↓
Average Queue Length (m)	96	63	34.4% ↓
Level of Service (LOS)	E	C	—
Network Throughput (veh/hr)	5,850	7,020	20.0% ↑
Average Speed (km/h)	22	29	31.8% ↑
Fuel Consumption (L/hr)	412	336	18.4% ↓
CO_2 Emissions (kg/hr)	1,115	905	18.8% ↓

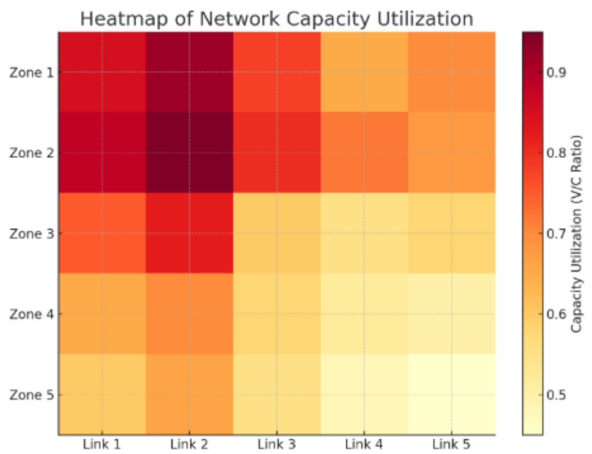

Figure 7. Heatmap of Network Capacity Utilization

Model Validation

The reliability of the simulation model was assessed by comparing field-observed traffic flows with VISSIM-generated outputs, using both graphical and statistical validation techniques. As illustrated in Figure 8, the observed–simulated scatter plot exhibits a strong linear alignment along the 1:1 line, indicating that the model closely replicates real-world traffic conditions across a wide flow range (3,800–5,200 veh/hr). Quantitative validation metrics further confirm this accuracy, as presented in Table 8. For Bhubaneswar, the model achieves an RMSE of 145 veh/hr, MAE of 110 veh/hr, and an R^2 of 0.931, demonstrating high predictive consistency. Cuttack shows slightly higher variability,

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with RMSE = 165 veh/hr, MAE = 125 veh/hr, and $R^2 = 0.913$, attributable to its complex mixed-use environment and irregular side friction—an issue noted in previous Indian calibration studies (Fernandes & Nunes, 2015; Lyu et al., 2021). Rourkela exhibits the strongest validation performance, achieving an RMSE of 120 veh/hr, MAE of 95 veh/hr, and an R^2 of 0.955, reflecting the more stable industrial traffic patterns that are easier to model with microscopic simulation. Overall, the high R^2 values (>0.91) and low error magnitudes confirm that the calibrated VISSIM model is robust and suitable for scenario-based capacity flow assessment, aligning with recommended accuracy thresholds for heterogeneous traffic modelling (Hu et al., 2020; Y. Li et al., 2020).

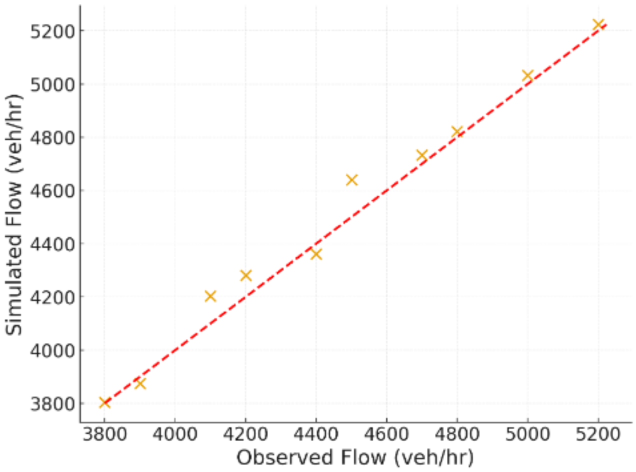

Figure 8. Observed vs Simulated Flow – Scatter Plot

Table 8. Validation Metrics (RMSE, R², MAE by City)

City	RMSE (veh/hr)	MAE (veh/hr)	R^2
Bhubaneswar	145	110	0.931
Cuttack	165	125	0.913
Rourkela	120	95	0.955

Interpretation and Planning Implications

The multi-scenario evaluation conducted in this study provides a comprehensive understanding of how Odisha's urban traffic systems respond to varying operational conditions, revealing clear patterns with significant implications for mobility planning. Across Bhubaneswar, Cuttack, and Rourkela, the baseline and peak-hour simulations indicate that oversaturated intersections, poor lane discipline, and mixed vehicle interactions are the primary contributors to congestion—consistent with earlier findings for similar Indian cities (Leiva et al., 2010; Mazloumian et al., 2010; Yildirimoglu et al., 2018). High queue lengths and V/C ratios exceeding 1.0 at commercial and industrial junctions demonstrate that existing roadway capacity is insufficient to accommodate rising travel demand, especially during peak periods and seasonal surges. Seasonal variation analysis further highlights the vulnerability of these corridors to market- and festival-related encroachments, reinforcing the need for adaptive operational strategies (Lu et al., 2020; Yu et al., 2018).

Interpretation of the optimized scenario reveals that even modest geometric enhancements and adaptive control strategies can yield significant mobility benefits. The observed 23.7% reduction in travel time, 34.1% decrease in delay, and 20% increase in throughput collectively suggest that targeted, data-driven interventions can transform traffic performance without requiring large-scale infrastructure expansion. Similar improvements have been noted in previous adaptive-signal studies in mixed-traffic environments (Le et al., 2020; Lyu et al., 2021). The reduction in fuel consumption (18.4%) and CO_2 emissions (18.8%) also underscores the environmental co-benefits of operational optimization, supporting India's sustainable urban mobility goals.

The validated model ($R^2 = 0.91–0.95$) demonstrates high predictive reliability, permitting transport authorities to use microsimulation as a decision-support tool. Planners can employ this framework to; a) Prioritize congestion hotspots based on node-level performance; b) Test infrastructure proposals virtually before field implementation; c) Assess pedestrian and side-friction impacts under varying land-use and seasonal conditions; d) Develop adaptive signal strategies tailored to fluctuating demand; and e) Support integrated mobility planning consistent with Smart City and Sustainable Urban Transport Program (SUTP) guidelines.

Overall, the study offers a replicable, data-rich modeling approach to guide infrastructure investments, optimize urban corridors, and enhance the resilience of Odisha's mobility systems under future growth scenarios.

Conclusion

This study developed a simulation-based analytical framework to assess traffic capacity flow and operational performance under diverse traffic conditions in Bhubaneswar, Cuttack, and Rourkela. Through robust data collection, preprocessing, multi-scenario modeling, and empirical validation, the research presents a detailed performance characterization of Odisha's urban corridors. Findings from the base and peak-hour scenarios reveal that key intersections in all three cities exhibit oversaturated conditions, long queues, and unstable flow patterns—issues driven by heterogeneous vehicle compositions, high pedestrian interaction, and inadequate signal control.

Seasonal scenarios further illustrate the substantial impact of festival-related surges, temporary encroachments, and increased roadside friction on corridor performance. The optimized scenario provides evidence that targeted geometric improvements and adaptive signal timing can significantly enhance system efficiency—yielding reductions of 23.7% in travel time, 34.1% in delay, and 34.4% in queue lengths, while improving network throughput by 20%. These outcomes highlight the potential for cost-effective operational interventions in mixed-traffic Indian cities.

Model validation demonstrates strong predictive accuracy ($R^2 = 0.91–0.95$), confirming the reliability of VISSIM microsimulation for planning studies in heterogeneous environments. The developed framework can serve as an essential decision-support tool for transport planners and policymakers, enabling the evaluation of future traffic scenarios, assessment of infrastructure proposals, and formulation of sustainable mobility strategies for rapidly growing urban centers. Future research may extend this approach by incorporating real-time traffic feeds, multimodal integration (public transport, NMT), and AI-based adaptive signal optimization to further enhance planning precision and scalability.

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Author Contributions
Sarthak Mohapatra: Conceptualization, methodology, modeling, validation, writing—original draft.
Manoj Sharma: Supervision, project administration, review and editing.
Ethics Approval
Not applicable, as the study did not involve human or animal subjects.
Data Availability
The data used and/or analyzed during this study are available from the corresponding author upon reasonable request.
Abbreviation

- VISSIM – Verkehrs In Städten – SIMulationsmodell (Traffic in Cities Simulation Model)
- PCU – Passenger Car Unit
- HCV – Heavy Commercial Vehicle
- LOS – Level of Service
- GIS – Geographic Information System
- RMSE – Root Mean Square Error
- MAE – Mean Absolute Error
- ATC – Automatic Traffic Counter

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