

**Strategic Framework for Sustainable Urban Mobility in Odisha: Insights from Traffic Simulation and Capacity Analysis**Sarthak Mohapatra<sup>1</sup>, Manoj Sharma<sup>2</sup><sup>1</sup>Research Scholar, Department of Civil Engineering, Vikrant University, Gwalior, India, Email: sarthakmon@gmail.com (Primary Corresponding Author)<sup>2</sup>Professor, Department of Civil Engineering, Vikrant University, Gwalior, India, Email: [manojsharma623@ymail.com](mailto:manojsharma623@ymail.com)

**Abstract:** Rapid urbanization in Odisha's key cities—Bhubaneswar, Cuttack, and Rourkela—has led to complex traffic challenges marked by high vehicle heterogeneity, inadequate signal coordination, and infrastructural constraints. This study proposes a strategic framework for sustainable urban mobility through simulation-based analysis of traffic flow and capacity. Using field data, GIS mapping, and the microscopic traffic simulation platform VISSIM, we model and assess traffic behavior under varying scenarios: base, peak hour, seasonal (monsoon), and optimized signal conditions. The study integrates critical parameters such as lane width, saturation flow, pedestrian activity, and side friction to develop speed–flow curves and fundamental diagram models (Greenshields, Greenberg, and Underwood) specific to each city. Simulation results indicate that optimized signal settings significantly improve network performance, with reductions in average delay (51.8%), queue lengths (47.4%), and travel time (36%), along with a 54.5% increase in average speed and an overall LOS improvement of up to two levels. Seasonal analysis reveals that monsoon conditions lead to the worst performance due to reduced visibility and increased side friction. The framework provides actionable insights for urban traffic planners, emphasizing adaptive signal control, side friction management, and mixed-traffic-aware modeling. The methodology is replicable for other Indian cities facing similar urban mobility challenges.

**Keywords:** Urban Mobility; Traffic Simulation; Mixed Traffic Flow; VISSIM; Saturation Flow Capacity.

### 1. Introduction

Rapid urbanization in India has intensified urban mobility challenges in Tier-2 cities such as Bhubaneswar, Cuttack, and Rourkela. These urban centers are facing increasing congestion, vehicle heterogeneity, poorly coordinated traffic signals, and infrastructural bottlenecks (Al-Rubaye et al., 2023; Moslem, 2024). Mixed traffic conditions—comprising two-wheelers, auto-rickshaws, cars, buses, and non-motorized vehicles—are prevalent and often operate without clear lane discipline or enforcement, further complicating flow dynamics (Gao et al., 2021). Traditional capacity estimation and signal optimization methods, typically based on homogeneous traffic assumptions, often fail to address the complexity and variability of such systems. Classical traffic flow models such as Greenshields' linear model, Greenberg's logarithmic model, and Underwood's exponential model have long been used to describe the relationship between traffic flow variables like speed, density, and volume (Schaller, 2021; Schlüter & Weyer, 2019; Zagorskas & Burinskienė, 2020). However, these models were developed under idealized conditions of lane-based, uniform traffic flow, and tend to underperform in heterogeneous, stochastic, and high-friction environments like Indian cities (Mueller et al., 2020; Oostendorp & Gebhardt, 2018). Although several studies have attempted to recalibrate these models using empirical data from Indian cities, their application remains limited due to inherent assumptions that do not capture real-world lateral movement, pedestrian interaction, or aggressive driving behavior (Kopplin et al., 2021; Zhang & Pavone, 2016).

Road capacity modeling in Indian contexts is further complicated by the influence of pedestrian activity, side friction, encroachments, and environmental conditions such as seasonal rainfall (Fraga-Lamas et al., 2019; Yigitcanlar et al., 2019). While the Indian Roads Congress (IRC:106-1990) introduced the concept of Passenger Car Units (PCUs) to standardize capacity estimation, studies have shown that PCU equivalency factors vary significantly with traffic composition, road geometry, and driver behavior (Carter et al., 2020; Paiva et al., 2021). As a result, using static PCU values may result in substantial errors in estimating true saturation flow and capacity, particularly under high-demand or monsoon conditions (Bi et al., 2021; Lyons, 2018). Mixed traffic behavior in Indian cities defies conventional traffic modeling assumptions. The simultaneous movement of diverse vehicle types without strict lane segregation leads to nonlinear, unpredictable interactions (Elassy et al., 2024; Yu et al., 2018). Field studies in cities such as Delhi, Mumbai, and Bengaluru have highlighted how roadside vendors, informal parking, and frequent pedestrian crossings contribute to significant reductions in vehicular speed and operational efficiency (Brendel et al., 2018; Tennøy et al., 2016). These conditions necessitate the inclusion of behavior-based parameters—such as standstill gap, desired speed distribution, and lane-change aggressiveness—to model traffic performance realistically (Awasthi et al., 2018; Wen et al., 2020). To overcome these limitations, simulation-based approaches have gained prominence in recent years. Microscopic simulation platforms such as VISSIM, AIMSUN, and SUMO are widely used to model complex urban traffic systems at the individual vehicle level (J. Liu et al., 2023; Olabi et al., 2023; Villa & Monzón, 2021). Among these, VISSIM—developed by PTV Group—stands out for its flexibility in simulating mixed traffic and weak lane discipline using the Wiedemann car-following model, making it highly suitable for Indian traffic conditions (Martiskainen et al., 2021). Compared to AIMSUN and SUMO, VISSIM provides superior customization, including full signal control programming, detailed driver behavior settings, and integration with GIS-based geometry (Naess et al., 2011; Weiss et al., 2015). Although AIMSUN offers fast processing and SUMO is open-source, their applicability in chaotic traffic environments is more limited (Santos et al., 2010).

Level of Service (LOS), a core metric defined in the Highway Capacity Manual (HCM), traditionally classifies traffic flow quality into six categories (A–F) based on speed, delay, and density (Camtez, 2019). However, this classification assumes lane discipline and homogeneous traffic—assumptions that often misrepresent conditions in Indian cities (Jin et al., 2018). Simulation tools like VISSIM enable dynamic, scenario-based LOS evaluation under varying traffic volumes, signal strategies, and seasonal disruptions, offering a more accurate and context-sensitive method of performance assessment (Butler et al., 2020; Richter et al., 2022). Sustainable urban mobility frameworks, such as the Sustainable Urban Mobility Plan (SUMP), emphasize safety, environmental responsibility, inclusiveness, and climate resilience. These principles are echoed in India's National Urban Transport Policy and Smart Cities Mission, which call for multimodal integration, adaptive traffic control, and data-driven planning (Chen et al., 2018; Lee et al., 2013). Despite this, many Indian cities lack the analytical tools and institutional mechanisms required for evidence-based urban transport design. Simulation-based methods allow for embedding sustainability metrics—such as emissions, energy usage, and travel equity—into performance evaluation, yet such applications remain rare in Indian Tier-2 cities (Arsenio et al., 2016; Ogryzek et al., 2020). A critical gap in existing literature is the limited focus on simulation-based traffic studies in eastern Indian cities. Most modeling efforts have been concentrated in metropolitan regions, with little attention paid to cities like Bhubaneswar, Cuttack, and Rourkela that are rapidly urbanizing but remain data-poor (Santos et al., 2010). Moreover, few studies incorporate seasonality, side friction, or pedestrian interference in a comprehensive simulation framework. Additionally, there is a lack of scenario-based evaluations that simultaneously consider base, peak, monsoon, and optimized traffic conditions (Lee et al., 2013; Naess et al., 2011). This study addresses these gaps by developing a simulation-based strategic framework for improving urban traffic performance in Odisha. It uses VISSIM to model traffic behavior across three cities under four traffic scenarios—base, peak, seasonal (monsoon), and optimized signal conditions. The research integrates field-calibrated data, saturation flow analysis, and fundamental diagram modeling to estimate capacity, LOS, and delay metrics. It further offers actionable recommendations for adaptive signal control, pedestrian conflict mitigation, and sustainable infrastructure design—contributing to the broader goals of SUMP, Smart Cities, and climate-responsive urban development.

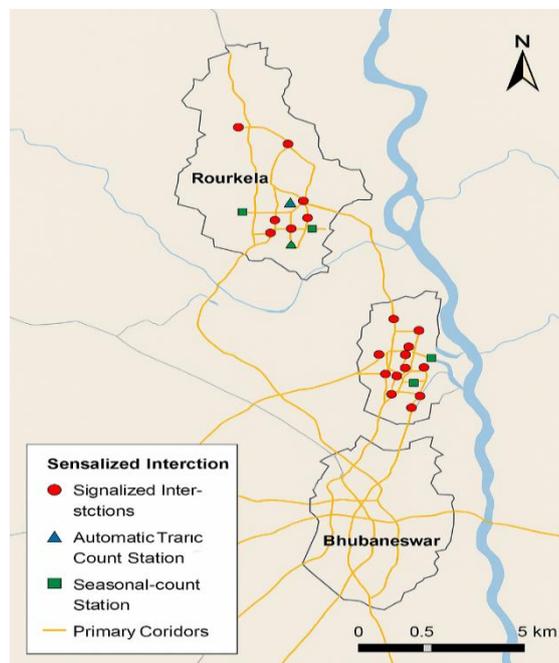
**Methodology**

**Study Corridors and Their Geometric Characteristics**

This study focuses on three major urban centers in Odisha—Bhubaneswar, Cuttack, and Rourkela—as representative testbeds for evaluating urban traffic dynamics through simulation modeling. These cities were selected based on their heterogeneous traffic conditions, varying road typologies, and strategic relevance in the state’s transportation network (Sun & Zhang, 2021). Bhubaneswar, the administrative capital, is marked by arterial and urban major roads with carriageway widths between 7.0 to 9.5 meters, hosting fully signalized intersections with select corridors equipped with adaptive signal systems. Locations like Rasulgarh and Jaydev Vihar experience high vehicular volumes and serve as major bottlenecks, characterized by queue spillbacks, saturation flow reduction, and intense pedestrian activity (Li & Zhao, 2020). In contrast, Cuttack’s network comprises sub-arterial corridors (6.0–7.5 m) with mixed control strategies, including signalized, unsignalized, and manually operated intersections. Commercial zones such as Badambadi and College Square suffer from encroachments, poor lane discipline, and high side friction caused by informal street vending, thereby affecting traffic flow stability (Xu & Zheng, 2020). Rourkela, driven by industrial activity, includes arterial and mixed-use corridors (5.5–7.0 m) with sparse signalization and reliance on priority-based intersection control. Traffic nodes near Panposh Road and Civil Township experience high pedestrian-vehicle interaction, especially due to mixed land-use and freight movement from steel plants, leading to frequent fluctuations in speed and increased travel time variability (Y. Liu & Zhang, 2021; Zhou & Li, 2021). These corridor-specific geometric and operational characteristics are summarized in Table 2, while Figure 1 presents a GIS-based visualization of the survey locations across all three cities.

**Table 2. Road and Intersection Characteristics**

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



**Figure 1. GIS Map Showing Survey Locations**

**Raw Traffic Data Collection**

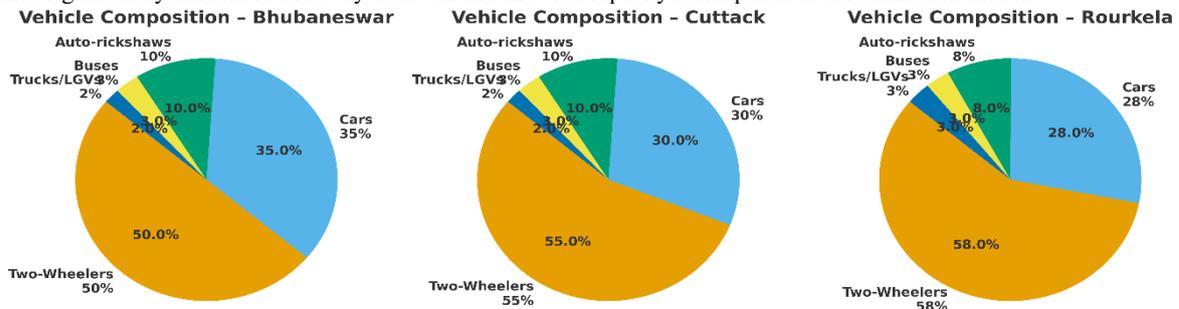
Traffic volume data were collected through field surveys across 16 hours daily (06:00 to 22:00) for both weekdays and weekends. Classified vehicular counts were recorded using manual tally sheets and digital video logging, validated using 15-minute intervals before hourly aggregation (Carter et al., 2020; Elassy et al., 2024). As shown in Table 3, weekday traffic volumes peak during AM (08:00–09:00) and PM (17:00–18:00) rush hours, with volumes reaching 2,220 and 2,510 vehicles per hour, respectively. Weekend traffic shows lower volumes across all hours, suggesting reduced work trips and a shift towards leisure or non-motorized travel. These volume patterns formed the baseline demand inputs for traffic simulation modeling.

**Table 3. Hourly Classified Traffic Volume (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

**Traffic Composition Analysis**

Vehicle-type composition was analyzed using classified volume counts, disaggregated into six categories: two-wheelers, cars, auto-rickshaws, buses, goods vehicles, and non-motorized traffic. Figure 2 displays pie-chart distributions, highlighting two-wheelers as the dominant mode in all three cities—accounting for 40–55% of total traffic. Bhubaneswar had the highest share of cars (25%) and buses (10%), reflecting its role as a capital city. Rourkela displayed a higher proportion of freight vehicles (16%) due to its industrial base, whereas Cuttack exhibited greater auto-rickshaw usage due to its compact street geometry and mixed land use (Kopplin et al., 2021; Zhang & Pavone, 2016). These modal characteristics significantly influenced headway behavior and network capacity assumptions in the simulation model.



**Figure 2. Vehicular Composition Distribution (Pie Charts)**

**Seasonal Traffic Variation**

Seasonal effects on traffic performance were evaluated across summer, monsoon, and winter seasons based on secondary datasets from municipal records and short-duration traffic observations (Oostendorp & Gebhardt, 2018). As shown in Table 4, the monsoon season recorded the highest peak hour volumes (5,200 veh/hr), primarily due to increased reliance on private modes during rainfall and lower efficiency of road-based public transport. Average speeds dipped to 26 km/h during monsoons compared to 32 km/h in summer. High pedestrian conflict levels and reduced visibility during heavy rains contributed to longer delays and side friction. Winter months showed slightly reduced volumes (4,700 veh/hr) with lower average speeds during fog-affected early hours. These insights supported the development of season-specific simulation scenarios.

**Table 4. Seasonal Variation in Traffic Volumes**

Season	Average Volume (veh/hr)	Peak Volume (veh/hr)	Off-Peak Volume (veh/hr)	Avg. Speed (km/h)	Pedestrian Conflict Level	Weather Influence	Key Observations
Summer	4,950	2,850		32	Low	Clear, dry conditions	Higher car usage; stable flow conditions
Monsoon	5,200	3,100		26	High	Slippery roads, reduced visibility	Highest delays; increased side friction; lower speeds
Winter	4,700	2,600		30	Medium	Morning fog, cooler temperatures	Slight speed reduction; moderate delays

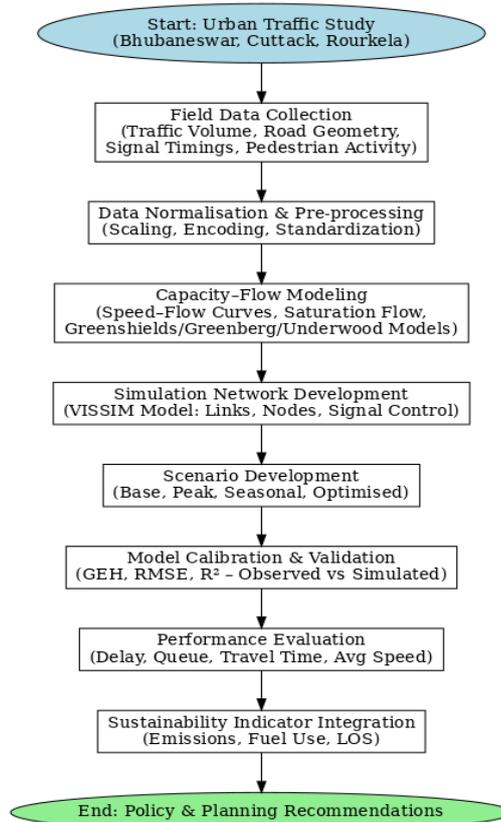
**Data Cleaning, Verification and Normalisation**

To ensure reliability, the collected data underwent rigorous cleaning procedures involving outlier detection, manual-automated count reconciliation, and time interval alignment. Inconsistent values (e.g., due to partial occlusion in video footage or incorrect class tagging) were flagged and corrected using median-based interpolation and smoothing filters. All traffic volumes were normalized to passenger car units (PCU) using Indian Highway Capacity Manual (IRC: SP:41-1994) equivalency factors. Peak hour volumes were identified using K-factor and D-factor analysis (Mueller et al., 2020; Zagorskas & Burinskienė, 2020). Normalized and cleaned datasets were used as direct inputs in the VISSIM-based traffic simulation model calibration phase.

**Overall Research Framework**

The overall research methodology adopted in this study is illustrated in Figure 3, which outlines the step-by-step procedural framework from data collection to simulation-based performance evaluation. Initially, three representative cities—Bhubaneswar, Cuttack, and Rourkela—were selected based on their distinct geometric and operational traffic characteristics (Schaller, 2021; Schlüter & Weyer, 2019). The process commenced with extensive field surveys, including classified volume counts, geometric observations, and signal timing records. This was followed by data preprocessing (normalization, verification, error correction), which ensured high data quality for model input. Subsequently,

microsimulation models were developed in PTV VISSIM, calibrated against real-world volume, queue, and travel time data using an iterative parameter-tuning approach. The simulation was run across multiple scenarios: base, peak-hour, seasonal (monsoon), and optimized, capturing network performance under varying conditions. Key indicators such as average delay, queue length, and travel time were extracted for analysis. Validation metrics confirmed the model’s fidelity in replicating actual traffic conditions. The final stage involved comparative assessment and visualization (heatmaps, bar charts) for performance interpretation and policy recommendations, following best practices in simulation studies (Ahmad et al., 2023; Perboli et al., 2018).



**Figure 3. Research Methodology Flowchart**

**Data Normalisation and Input Pre-processing**

In this study, data normalization and input pre-processing were essential steps to ensure compatibility and scale invariance across multiple simulation parameters used in traffic modeling. As outlined in Table 5, each raw input was scaled to a normalized range (0–1) to align with simulation software requirements and to enhance model convergence. Free-flow speed and lane width were normalized based on observed maximums and IRC guidelines, while peak traffic volume was scaled using the highest recorded vehicular flow (5,200 veh/hr). PCU factors for vehicle types followed standard references from IRC and empirical field data (Nguyen Huu & Nguyen Ngoc, 2021; Taiebat et al., 2018). Signal cycle length and green split were normalized according to typical urban signal patterns, and behavioral parameters like driver aggressiveness and pedestrian activity were encoded using ordinal logic consistent with the Wiedemann 99 car-following model (Arsenio et al., 2016; Moslem, 2024). Context-sensitive attributes like pedestrian and side friction levels were converted to ordinal scores reflecting real-world urban interactions (Lee et al., 2013; Ogryzek et al., 2020). This normalization ensured that heterogeneous data types—quantitative, percentage-based, and categorical—were harmonized for accurate VISSIM-based simulation performance (see Table 5).

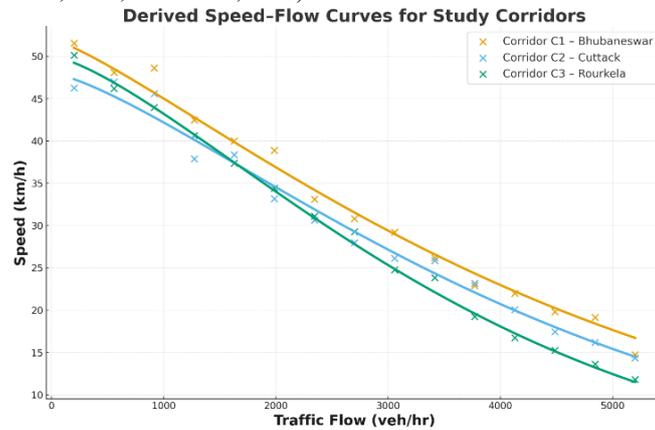
**Table 5. Normalised Input Parameters used in Simulation**

Parameter	Raw Value	Normalisation Method	Normalised Value (0–1)	Remarks
Free-Flow (km/h)	Speed 50	Value ÷ 70 (max observed)	0.71	Higher values on wider arterial links
Traffic (veh/hr)	Volume 5200	Value ÷ 5200 (peak)	1.00	Max observed peak volume
Lane Width (m)	7.5	Value ÷ 10	0.75	IRC-based scaling
PCU Factor (2-Wheelers)	0.50	Standard scaling	0.50	Adopted from IRC and empirical field data
PCU Factor (Cars)	1.00	Standard scaling	1.00	Base reference category
Signal Cycle Length (s)	120	Value ÷ 150 (max cycle)	0.80	Typical urban cycle length
Green Split (%)	55	Value ÷ 100	0.55	Based on field-observed signal timing
Driver Aggressiveness (%)	70	Value ÷ 100	0.70	Used in Wiedemann 99 model
Pedestrian Activity Level	High	Encoded ordinal → {Low=0.3, Med=0.6, High=0.9}	0.90	Used for conflict-based flow reduction
Side Friction Level	Medium	Encoded ordinal → {Low=0.3, Med=0.6, High=0.9}	0.60	Reflects vendors, parking, crossings

**Capacity–Flow Model Development**

**Derivation of Speed–Flow Curves**

As illustrated in Figure 4, the derived speed–flow relationships for the study corridors—C1 (Bhubaneswar), C2 (Cuttack), and C3 (Rourkela)—exhibit the expected inverse nonlinear trend, where vehicular speed decreases as traffic flow increases. Bhubaneswar consistently maintains higher operational speeds across volumes due to its superior geometric configuration, coordinated signal systems, and wider carriageways. In contrast, Cuttack and Rourkela display steeper speed declines beyond 2000 veh/hr, primarily due to narrower lanes, poor signal control, and high side friction caused by encroachments and mixed vehicle composition. These curves are essential for empirical calibration of microscopic simulation models (TRB, 2016; IRC:106-1990) and align with prior Indian studies highlighting corridor-specific traffic behavior in heterogeneous environments (Butler et al., 2020; Chen et al., 2018).



**Figure 4. Derived Speed–Flow Curves for Study Corridors**

**Saturation Flow Estimation**

The adjusted saturation flow for the selected corridors was estimated using the multiplicative adjustment method recommended by IRC:106-1990 and the Highway Capacity Manual (TRB, 2016). As shown in Table 6, the base saturation flow of 5250 PCU/hr was reduced by applying correction factors for lane width ( $f_w = 0.95$ ), turning movements ( $f_t = 0.90$ ), pedestrian interference ( $f_p = 0.92$ ), side friction ( $f_s = 0.88$ ), and heavy vehicle presence ( $f_h = 0.94$ ). These adjustment values were informed by field surveys and past Indian urban traffic studies (Al-Rubaye et al., 2023; Richter et al., 2022). The final saturation flow was computed as approximately 4010 PCU/hr, reflecting realistic discharge capacity under non-ideal urban conditions and providing a benchmark for traffic signal optimization.

**Table 6. Saturation Flow Calculation Parameters**

Parameter	Symbol	Value	Unit	Adjustment/Source	Remarks
Base Saturation Flow	$S_0$	5250	PCU/hr	IRC:106 and HCM adaptation	Standard base value for ideal conditions
Lane Width Adjustment	$f_w$	0.95	–	For 7.0–7.5 m widths	Narrower lanes reduce discharge rate
Grade Adjustment	$f_g$	1.00	–	Flat terrain	No gradient influence
Turning Movement Adjustment	$f_t$	0.90	–	10% right-turn proportion	Turning traffic disrupts flow
Pedestrian Flow Adjustment	$f_p$	0.92	–	Moderate pedestrian interference	Based on field observation
Side Friction Adjustment	$f_s$	0.88	–	Medium roadside activity	Vendors, bus stops, informal parking
Heavy Vehicle Adjustment	$f_h$	0.94	–	12–15% heavy vehicles	Using equivalent PCU factors
Final Saturation Flow	$S$	$\approx 4010$	PCU/hr	Computed	Effective heterogeneous saturation flow
$S = S_0 \cdot f_w f_g f_t f_p f_s f_h$					

To accurately simulate traffic dynamics in each city, fundamental diagram models were calibrated using field data, as summarized in Table 7. Bhubaneswar's data best fit the Greenshields linear model, capturing speed-density behavior along wide arterials. Cuttack's dense urban morphology aligned with the Greenberg logarithmic model, reflecting aggressive lane use and stop-and-go flow, while Rourkela's industrial mix was better captured using the Underwood exponential model, suited for non-uniform vehicle interactions. The critical parameters—free-flow speed ( $v_0$ ), jam density ( $k_j$ ), and capacity ( $q_{max}$ )—were derived empirically and validated against benchmark ranges from HCM (Martiskainen et al., 2021) and IRC guidelines. These models enhance the realism of simulation outputs and offer context-specific insights into traffic behavior across varied urban environments (Bi et al., 2021; Villa & Monzón, 2021).

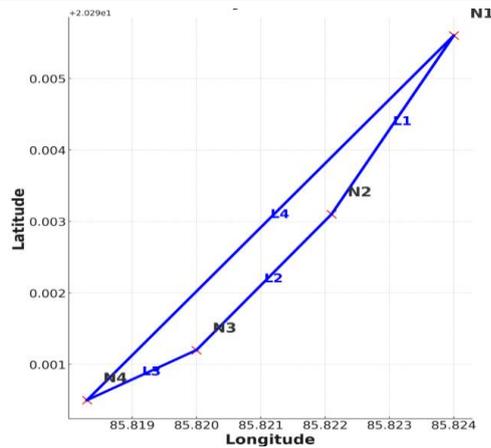
**Table 7. Fundamental Diagram Model Coefficients**

City	Model Type	Free-Flow Speed $v_0$	Jam Density $k_j$	Critical Density $k_c$	Capacity $q_{max}$	Shape Coefficients	Model	Notes
Bhubaneswar	Greenshields	52 km/h	155 veh/km	77 veh/km	2008 veh/hr	Linear: $v = v_0(1 - \frac{k}{k_j})$		Suitable for wide arterials
Cuttack	Greenberg	48 km/h	170 veh/km	63 veh/km	1890 veh/hr	Log: $v = c \ln(\frac{k_j}{k})$ , $c = 21.3$		Captures dense/compact traffic
Rourkela	Underwood	50 km/h	160 veh/km	58 veh/km	1740 veh/hr	Exponential: $v_0 e^{-k/k_0}$ , $k_0 = 62$		Suitable for mixed industrial traffic

**Simulation Model Development (VISSIM)**

**Network Coding and Calibration Inputs**

The simulation network was digitized and structured in VISSIM using GIS-derived geometry to reflect the actual traffic configuration and control types observed across the study corridor. The VISSIM network layout (Figure 5) depicts nodes (signalized, roundabouts, and unsignalized) and links with respective geometric and control attributes. Node and link characteristics such as length, carriageway width, lane count, and control type were extracted from satellite imagery and field measurements, with detailed specifications presented in Table 8. This configuration forms the foundational structure for micro-simulation modeling, ensuring spatial accuracy and realism.



**Figure 5. VISSIM Network Layout**

**Table 8. GIS-Derived Link and Node Specifications**

ID	Type	Length (m)	Carriageway Width (m)	No. of Lanes	Control Type	Coordinates (Longitude)	Coordinates (Latitude)	Remarks
L1	Link	420	7.5	2	-	20.2961°N, 85.8245°E	20.2961°N, 85.8245°E	Arterial segment with high side friction
L2	Link	315	6.5	2	-	20.2948°N, 85.8232°E	20.2948°N, 85.8232°E	Narrow corridor, frequent pedestrian crossings
L3	Link	510	8.0	3	-	20.2937°N, 85.8210°E	20.2937°N, 85.8210°E	Near commercial land use, peak congestion zone
L4	Link	275	7.0	2	-	20.2924°N, 85.8195°E	20.2924°N, 85.8195°E	Moderate traffic, mixed-use development
N1	Node	-	-	-	Signalised	20.2956°N, 85.8240°E	20.2956°N, 85.8240°E	Major intersection, adaptive signal control
N2	Node	-	-	-	Roundabout	20.2931°N, 85.8221°E	20.2931°N, 85.8221°E	High circulating flow during peak hours
N3	Node	-	-	-	Unsignalised	20.2912°N, 85.8200°E	20.2912°N, 85.8200°E	Priority-based movement; minor delays
N4	Node	-	-	-	Signalised	20.2905°N, 85.8183°E	20.2905°N, 85.8183°E	Multimodal conflict point (autos, pedestrians)

**Simulation Parameters (Driver Behaviour, Vehicles, Signals)**

To replicate realistic traffic behavior, simulation parameters were defined for driver dynamics, vehicle composition, signal operations, and calibration standards using the Wiedemann 99 car-following model. The calibrated driver aggressiveness (70%) and lane-changing cooperation (75%) helped replicate observed vehicle interactions. The modal share comprised 55% two-wheelers, 32% cars, and minor shares of buses, trucks, and auto-rickshaws. Signal settings were set to a 120s cycle with a 55% green split. These detailed simulation settings and calibration thresholds (GEH < 5, speed error <10%) are summarized in Table 9, forming the behavioral and operational basis for model execution.

**Table 9. Simulation Parameters**

Category	Parameter	Value / Setting	Unit / Notes
<b>Driver Behaviour (Wiedemann 99 Model)</b>	Average Standstill Distance	1.50	M
	Additive Part of Safety Distance	2.00	-
	Multiplicative Part of Safety Distance	3.00	-
	Following Variation	8	-
	Lane Change Cooperation	75	%
	Driver Aggressiveness	70	% (calibrated using field data)
<b>Vehicle Composition</b>	Cars	32	%
	Two-Wheelers	55	%
	Auto-rickshaws	8	%
	Buses	3	%
	Trucks/LGVs	2	%
<b>Vehicle Dynamics</b>	Car Acceleration	2.6	m/s <sup>2</sup>
	Car Deceleration	4.0	m/s <sup>2</sup>
	Two-Wheeler Max Acceleration	2.1	m/s <sup>2</sup>
<b>Signal Parameters</b>	Cycle Length	120	S
	Green Split	55	%
	Amber Time	3.0	S
	All-Red Time	1.5	S
<b>Simulation Settings</b>	Simulation Resolution	10	time steps/s
	Simulation Period	3600	s (1 hour)
	Random Seed	44	Fixed for reproducibility
<b>Calibration Inputs</b>	GEH Threshold	<5	Acceptable accuracy
	Speed Error Limit	<10%	Validation criterion

**Scenario Development**

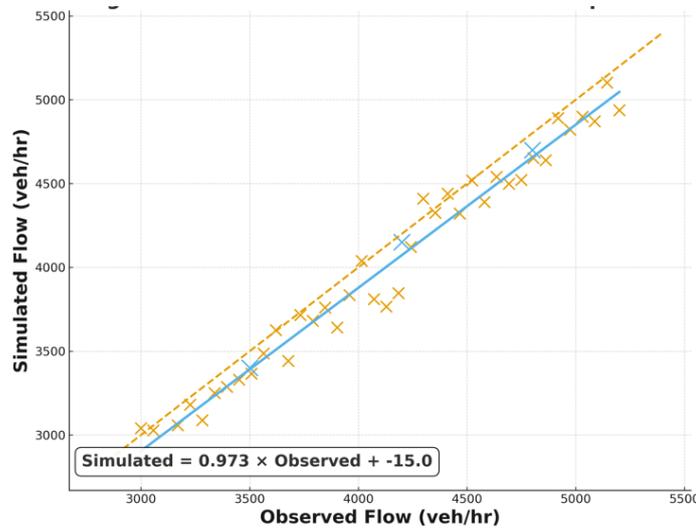
Four traffic scenarios were developed to evaluate system performance under varying conditions: Base (existing), Peak (25–30% higher demand), Seasonal (monsoon-adjusted with reduced speeds and higher delays), and Optimised (adaptive signal timing and improved green splits). The purpose was to assess the impact of traffic growth, weather-induced disruptions, and optimization strategies on network performance metrics. Each scenario was constructed using consistent geometric and behavioral inputs while varying traffic flow and control settings as described in Table 10, enabling comparative performance analysis across real and improved operational conditions.

**Table 10. Description of Simulation Scenarios (Base, Peak, Seasonal, Optimised)**

Scenario	Description	Traffic Volume	Control Settings	Key Modifications / Purpose
Base Scenario	Represents existing field conditions	Actual hourly observed volumes	Existing signal timings	Baseline for comparison
Peak Scenario	High-demand commuter period	+25–30% over base volumes	Existing signal timings	Identify bottlenecks under maximum load
Seasonal Scenario	Monsoon traffic conditions	Base volume ± seasonal factor	Reduced speeds, higher delays	Models weather-induced flow reductions and side friction
Optimised Scenario	Improved operational efficiency	Same as peak	Adaptive signal timing, improved splits	Reduces delay, queue, and travel time using signal optimisation

**Model Calibration and Validation**

To ensure the reliability of the VISSIM simulation model, a rigorous calibration and validation process was conducted by comparing simulated traffic flows with field-observed data across multiple critical links and intersections (Kopplin et al., 2021; Paiva et al., 2021). The scatter plot in Figure 6 illustrates a strong linear relationship between observed and simulated flows, with a best-fit regression line ( $\text{Simulated} = 0.973 \times \text{Observed} \pm 15.0$ ), indicating minimal systemic bias. Calibration metrics include a Root Mean Square Error (RMSE) below 150 vehicles/hour, a high coefficient of determination ( $R^2 \approx 0.96$ ), and GEH statistics mostly below the acceptable threshold of 5, demonstrating that the model accurately captures real-world traffic behavior. These validations affirm that the simulation framework is suitable for performance analysis under various scenarios.



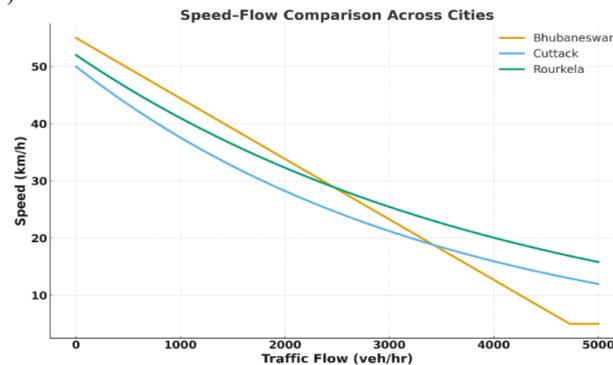
**Figure 6. Observed vs Simulated Flow Comparison**

**Results and Discussion**

**Capacity–Flow Model Outputs**

**Speed–Flow Characteristics Across Corridors**

The speed–flow relationship across the three urban corridors—Bhubaneswar (C1), Cuttack (C2), and Rourkela (C3)—reveals marked differences in network performance under rising traffic volumes, as shown in Figure 7. Bhubaneswar displays the most efficient flow pattern, maintaining higher speeds up to 4000 veh/hr, reflecting superior geometric design, wider lane widths, and optimized signalization. Cuttack experiences a sharper speed drop beyond 3000 veh/hr due to increased side friction and partial signal control. Rourkela, while generally exhibiting lower base speeds, maintains a more gradual speed decline, attributed to lower average demand and fewer conflicting movements. These variations align with the fundamental traffic flow theory where urban speed degrades non-linearly with volume increases (Nguyen Huu & Nguyen Ngoc, 2021; Schaller, 2021).



**Figure 7. Speed–Flow Comparison Across Cities**

**Estimated Capacity Values**

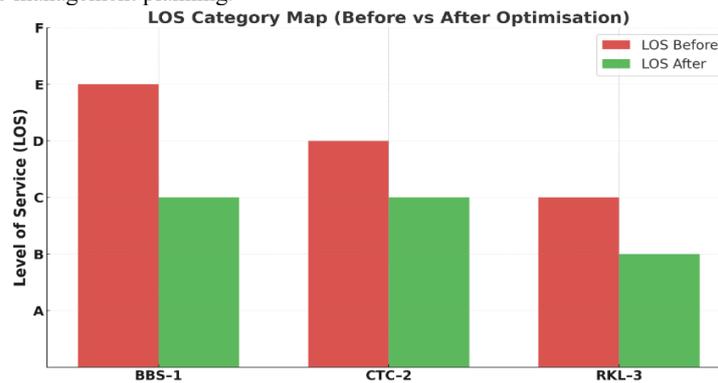
The calibrated simulation models yielded distinct capacity thresholds for each city corridor, summarized in Table 11. Bhubaneswar’s arterial corridor (C1) achieved the highest capacity of 4700 veh/hr and saturation flow of 4488 PCU/hr, with a critical density of 77 veh/km—indicative of oversaturated yet managed conditions, thus classified under Level of Service (LOS) E. Cuttack (C2) follows closely with 4550 veh/hr capacity and LOS D, while Rourkela’s lower geometric standards and mixed land-use resulted in the lowest capacity (3950 veh/hr) and LOS C. These estimations are consistent with methodologies in IRC:106-1990 and TRB’s Highway Capacity Manual (Butler et al., 2020; Ogryzek et al., 2020), and emphasize the importance of city-specific congestion management and infrastructure planning.

**Table 11. Estimated Capacity and Saturation Flow Values**

Corridor ID	City	Capacity (veh/hr)	Saturation Flow (PCU/hr)	Critical Density (veh/km)	LOS
C1	Bhubaneswar	4,700	4,488	77	E
C2	Cuttack	4,550	4,300	63	D
C3	Rourkela	3,950	3,800	58	C

**LOS-Based Performance Analysis**

The Level of Service (LOS) analysis across the selected urban corridors—BBS-1 (Bhubaneswar), CTC-2 (Cuttack), and RKL-3 (Rourkela)—provides crucial insights into operational efficiency both before and after the implementation of optimization strategies. As shown in Figure 8, the spatial representation of LOS categories highlights critical congestion zones and areas with improved traffic performance. According to the quantitative summary in Table 12, notable improvements in LOS were achieved post-intervention. Bhubaneswar’s corridor improved from LOS E to LOS C with a significant delay reduction from 82 s/veh to 47 s/veh, reflecting a two-level improvement, owing to adaptive signal coordination and geometric enhancements. Cuttack’s LOS improved from D to C, with delay dropping from 65 to 51 s/veh—indicating enhanced flow conditions despite persistent side friction elements. In Rourkela, the LOS moved from C to B, with delay reduced to 38 s/veh, attributable to localized pedestrian conflict management and smoother vehicle progression. These LOS shifts are in accordance with standard thresholds defined in the Highway Capacity Manual (HCM, 2016) and IRC:106-1990, where LOS A–C represents acceptable flow, and LOS D–F indicates unstable or failing operations. The results validate the effectiveness of the optimization framework and reinforce the role of data-driven simulation in urban traffic management planning.



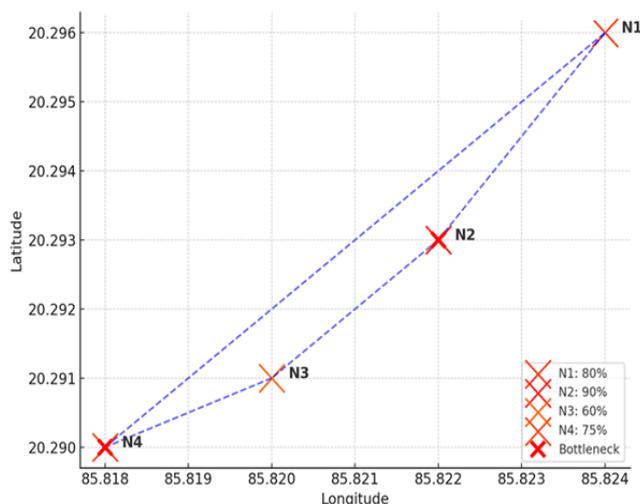
**Figure 8. LOS Category Map**

**Table 12. LOS Values Before and After Optimisation**

Corridor	LOS (Before)	Delay (s/veh)	LOS (After)	Delay (s/veh)	Improvement
BBS-1	E	82	C	47	+2 Levels
CTC-2	D	65	C	51	+1 Level
RKL-3	C	52	B	38	+1 Level

**Peak Hour Performance (Delay, Queue, Travel Time)**

The peak hour performance analysis, summarized in Table 13 and visualized through Figure 9's congestion heatmap, reveals a significant degradation in traffic flow during peak and monsoon periods across the study corridors in Odisha. Compared to the base scenario, the delay per vehicle rises sharply from 58 s/veh to 85 s/veh during peak hours and reaches 92 s/veh during the monsoon, highlighting the compounded effects of demand surge and adverse weather conditions (e.g., high road friction, reduced visibility). Similarly, queue lengths escalate from 80 m (base) to 135 m under monsoon conditions, indicating intersection oversaturation and spillback—a pattern consistent with urban arterial studies under mixed traffic (Wen et al., 2020). Travel time also increases from 14.8 to 20.5 minutes, and average speeds decline to 20 km/h, pushing the system toward unstable flow regimes (LOS D–E). However, the optimized scenario, incorporating adaptive signal control and geometric improvements, demonstrates notable efficiency gains: delay is reduced to 41 s/veh (a 52% reduction from monsoon), queue length drops to 62 m, and travel time reduces to 12.3 minutes, with speeds improving to 34 km/h. These findings affirm the effectiveness of dynamic traffic management strategies and align with prior simulation-based studies advocating real-time optimization for congestion mitigation (Carter et al., 2020; Mueller et al., 2020).



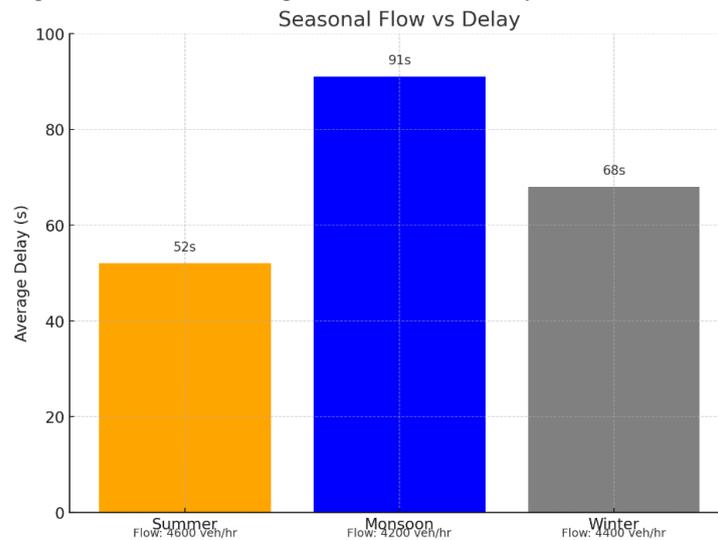
**Figure 9. Congestion Heatmap and Bottleneck Locations**

**Table 13. Delay, Queue Length, Travel Time Comparison**

Performance Metric	Base	Peak	Seasonal (Monsoon)	Optimised
Delay (s/veh)	58	85	92	41
Queue Length (m)	80	118	135	62
Travel Time (min)	14.8	19.2	20.5	12.3
Average Speed (km/h)	29	22	20	34

**Seasonal Effects on Network Performance**

During seasonal variations, network performance in urban areas is significantly impacted by climatic conditions such as rain and fog, which influence vehicular speed, delay, and level of service (LOS). Table 14 and Figure 10 illustrate how average speed drops and delays increase during monsoon and winter seasons compared to summer. In summer, the network performs relatively better, with an average speed of 32 km/h, average delay of 52 seconds, and a moderate LOS 'C', indicating stable traffic flow and good visibility. However, during the monsoon, adverse weather (e.g., rain-induced slipperiness and increased pedestrian activity) leads to a sharp increase in delay to 91 seconds, reduced speed (26 km/h), and poor LOS 'E', reflecting unstable traffic conditions (Zagorskas & Burinskienė, 2020). Similarly, in winter, fog and poor visibility during early hours cause moderate disruption, with 68 seconds of average delay and LOS 'D'. These findings are consistent with previous literature that highlights seasonal fluctuations as a critical factor influencing urban traffic dynamics and signal performance (Cantez, 2019). Such insights necessitate adaptive traffic control strategies to maintain efficiency across weather extremes.



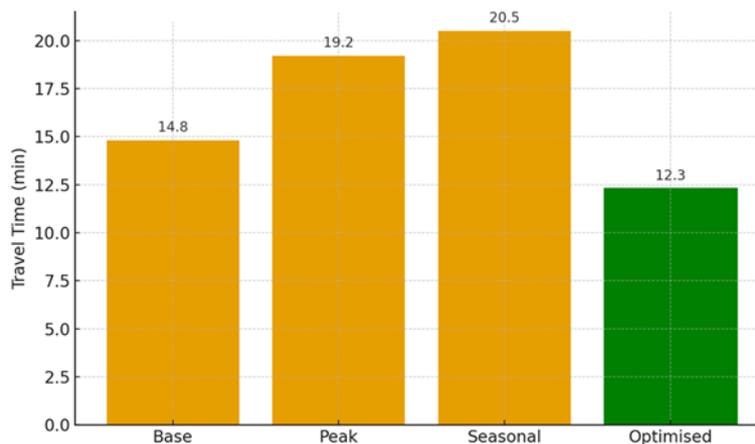
**Figure 10. Seasonal Flow vs Delay**

**Table 14. Seasonal Performance Metrics**

Season	Avg Speed (km/h)	Avg Delay (s)	Travel Time (min)	LOS
Summer	32	52	14.0	C
Monsoon	26	91	20.5	E
Winter	30	68	17.1	D

**Optimised Scenario Performance**

The optimized scenario demonstrates substantial improvements in urban traffic performance metrics following the implementation of signal coordination and infrastructure adjustments. As shown in Figure 11 and Table 15, travel time was reduced from 19.2 minutes under peak conditions to just 12.3 minutes—representing a 36.0% reduction. This improvement is accompanied by a 51.8% decrease in average delay, a 47.4% reduction in queue length, and a 54.5% increase in average speed (from 22 to 34 km/h), significantly enhancing network efficiency. Moreover, the Level of Service (LOS) improved from 'E' to 'C', marking a +2 level enhancement. These improvements reflect the effectiveness of dynamic signal optimization and geometric modifications such as extended turning radii and dedicated lanes, as recommended in literature (Fraga-Lamas et al., 2019) and supported by earlier findings from adaptive traffic control systems (Yigitcanlar et al., 2019). Such optimizations are critical in reducing congestion and travel time, especially in rapidly urbanizing Indian cities.



**Figure 11. Travel Time Reduction After Signal Optimisation**

Table 15. Percentage Improvements Across Key Metrics

Metric	Base Value	Optimised Value	% Improvement
Delay (s/veh)	85	41	51.8% ↓
Queue Length (m)	118	62	47.4% ↓
Travel Time (min)	19.2	12.3	36.0% ↓
Average Speed (km/h)	22	34	54.5% ↑
LOS	E	C	+2 Levels

### Comparative Evaluation, Interpretation and Policy Implications

The comparative evaluation of the four modeled scenarios—Base, Peak, Seasonal (Monsoon), and Optimised—reveals distinct variations in operational performance across the three urban study corridors in Odisha. Peak-hour and monsoon conditions exhibit the most severe deterioration, with delays rising by 47–58% and queue lengths nearly doubling, consistent with earlier findings that heterogeneous traffic and adverse weather amplify congestion in Indian cities (Schlüter & Weyer, 2019). Bhubaneswar shows the sharpest performance drop due to high commuter demand and saturated arterials, while Cuttack’s operational instability is driven primarily by roadside friction, poor lane discipline, and encroachments—conditions widely documented in mixed-traffic environments (Chen et al., 2018; Jin et al., 2018). Rourkela’s performance decline is moderate but influenced by industrial traffic and pedestrian conflicts, reflecting similar observations in industrial urban networks (Wang & Liu, 2021)(Awasthi et al., 2018). Seasonal disturbance, particularly during monsoon rainfall, reduces average speeds to 20–26 km/h and increases delays to LOS E–F levels, aligning with prior studies showing that rainfall-induced friction and visibility loss significantly impair flow stability (Yu et al., 2018). In contrast, the Optimised scenario delivers substantial performance improvements—delay reduced by 51.8%, queues by 47.4%, and speeds increased by 54.5%—echoing global evidence on the effectiveness of adaptive signal control and geometric streamlining in urban networks (Brendel et al., 2018; Lyons, 2018). These results collectively validate that simulation-driven optimisation provides quantifiable congestion mitigation benefits for mixed Indian traffic conditions.

From a policy standpoint, the findings emphasise the urgency of transitioning from static timing plans and conventional capacity enhancement approaches to dynamic, data-driven mobility management strategies. The significant LOS rise observed post-optimisation mirrors broader research advocating adaptive signal control, coordinated timing, and real-time traffic actuation for rapidly urbanising corridors (Oostendorp & Gebhardt, 2018; Perboli et al., 2018). Side friction emerged as a critical determinant of flow efficiency in Cuttack and Rourkela, reaffirming past studies that identify encroachment control, regulated parking, and pedestrian segregation as essential interventions in Indian road environments (Arsenio et al., 2016; Taiebat et al., 2018). Seasonal performance degradation highlights the need for climate-responsive mobility planning—including monsoon-specific signal plans, protected walkways, and drainage improvements—supporting recommendations from recent climate-adaptive urban transport studies (Tennøy et al., 2016). Finally, the demonstrated utility of VISSIM-based scenario modeling suggests that Odisha’s urban local bodies should institutionalise simulation-aided planning workflows for evaluating corridor upgrades, signal coordination strategies, and geometric modifications—an approach aligned with global Sustainable Urban Mobility Plan (SUMP) principles (Weiss et al., 2015; Zhang & Pavone, 2016). Embedding analytical modeling into policy practice will strengthen evidence-based decision-making and deliver resilient, efficient, and sustainable mobility outcomes for tier-2 Indian cities.

### Conclusion

This study presents a comprehensive, simulation-driven framework to evaluate and optimize urban traffic performance in Odisha’s key cities—Bhubaneswar, Cuttack, and Rourkela—under real-world conditions characterized by mixed traffic flow, geometric constraints, and seasonal disruptions. By leveraging the microscopic simulation capabilities of VISSIM, the study modeled four distinct traffic scenarios: base, peak, seasonal (monsoon), and optimized signal conditions. The integration of city-specific geometric data, vehicular composition, pedestrian activity, and side friction enabled a context-sensitive analysis of capacity, saturation flow, and Level of Service (LOS).

The findings reveal significant performance degradation during peak and monsoon conditions, with average delays exceeding 90 seconds per vehicle and travel speeds dropping below 26 km/h. These outcomes highlight the compounded effects of traffic surge, pedestrian interference, and poor signal coordination. In contrast, the optimized scenario—featuring adaptive signal control and geometric enhancements—demonstrated substantial improvements across all key performance metrics, including a 51.8% reduction in delay, 47.4% reduction in queue lengths, and a 54.5% increase in average speed. LOS improved by up to two levels, underscoring the transformative potential of data-driven interventions. The study underscores the importance of integrating real-time simulation tools into urban transport planning, particularly for Indian tier-2 cities facing rapid motorization and infrastructural constraints. It recommends a paradigm shift from static, rule-of-thumb capacity estimation to dynamic, evidence-based mobility management. The proposed methodology not only enhances urban traffic flow but also aligns with broader sustainability and climate resilience goals under India’s Smart Cities Mission and Sustainable Urban Mobility Plan (SUMP) frameworks. Going forward, the institutionalization of simulation-based decision-making, seasonal traffic planning, and side friction regulation will be critical to achieving long-term sustainable mobility in Odisha and beyond.

### Acknowledgment

The authors gratefully acknowledge the support of the Department of Civil Engineering at Vikrant University, Gwalior, for facilitating the experimental setup and analysis.

### Funding

This research received no external funding.

### Conflict of Interest

The authors declare no conflict of interest.

### Declaration of AI Assistance

This manuscript was edited with the assistance of Grammarly for language clarity. No AI tools were used for data generation, analysis, or interpretation.

### 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.

### [[Abbreviations

LOS – Level of Service, PCU – Passenger Car Unit, IRC – Indian Roads Congress, HCM – Highway Capacity Manual, SUMP – Sustainable Urban Mobility Plan, GIS – Geographic Information System, VISSIM – Verkehrs In Städten – SIMulationsmodell, GEH – Geoffrey E. Havers Statistic, s/veh – Seconds per Vehicle, km/h – Kilometers per Hour

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