Network-Level Traffic Signal Coordination Using Field-Calibrated Simulation and Optimisation: A Case Study of Gandhinagar City

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Abstract
Urban traffic networks with mixed vehicle types are often afflicted by poor signal coordination, leading to long delays and longer travel times. In this study, we developed and tested a traffic signal coordination framework at six closely spaced intersections in Gandhinagar, India. We used Passenger Car Unit (PCU)-based demand to model mixed traffic and treated some left-turn movements as free-flow based on field observations. We built a detailed traffic simulation using the SUMO platform and calibrated it against peak-hour data, including traffic volumes, speeds, signal timings, and travel times. We then used a Genetic Algorithm to optimise signal coordination by adjusting cycle lengths, green splits, and offsets across the network. The model matched observed travel times, with average RMSE values of 12 seconds in the morning and 11 seconds in the evening. The optimised strategy cut total network travel time by 33,943 seconds and total control delay by 7,180 seconds, improving performance by 5.42% in the morning and 2.91% in the evening. These results show that combining field-calibrated simulation with evolutionary optimisation can help improve traffic flow in complex urban networks.

Keywords: Traffic signal coordination; Network-level optimisation; Mixed traffic conditions; Genetic

Introduction
The swift pace of urbanisation and ongoing rise in vehicle traffic have exerted considerable strain on the road infrastructure of Indian cities. Signalised intersections, which are a key for managing urban traffic flow, often function with either fixed or inadequately coordinated timings. As a result, vehicles encounter frequent halts, extended delays, and prolonged travel times, especially on corridors characterised by closed-sited intersections. These issues are exacerbated, where vehicles of varying physical and operational traits utilise the same roadway. Historically, traffic signal optimisation has been conducted at the level of individual intersections. Although these methods can enhance local efficiency, they do not account for the interactions among neighbouring intersections, leading to inefficiencies at the broader network. In urban corridors and grid networks, poor coordinated results in platoon dispersion, queue spillback, and heightened controls delays.

Coordinating signals at the network level is essential for improving traffic flow and optimizing the utilization of existing roadway capacity.

In recent years, microscopic traffic simulation has been widely adopted to analyse signal performance under realistic operating conditions. These platforms offer a detailed representation of traffic behaviour, signal operations, and driver responses, enabling robust network-level assessments. However, the reliability of simulation-based studies depends significantly on precise field calibration, particularly given the diverse traffic conditions characteristic of Indian urban areas.

Optimisation methods, especially evolutionary algorithms, have demonstrated significant effectiveness in addressing complex signal coordination challenges involving multiple decision variables. Simultaneous optimisation of cycle length, green splits, and offsets produces coordinated solutions that are typically unattainable through conventional trial-and-error approaches.

While isolated intersection optimisation and corridor-based coordination have been extensively studied, field-validated, network-level signal coordination in Indian cities with heterogeneous traffic conditions has received limited attention. Existing studies often rely on homogeneous traffic assumptions, simulation-only frameworks, or models lacking rigorous empirical validation. This research develops and validates a practical framework for network-level traffic signal coordination by integrating field-calibrated microscopic simulation with evolutionary optimisation. The methodology explicitly incorporates mixed traffic representation through PUC-based demand modelling and utilises observed travel times for both calibration and validation.

The specific contributions of this research are as follows:

- Development of a SUMO-based microscopic traffic model calibrated with field data for a multi-intersection urban network operating under mixed traffic conditions.
- Integration of Genetic Algorithm optimisation to facilitate simultaneous adjustment of cycle length, green splits, and offsets at the network level.
- Validation of simulated travel times using CCTV-derived field observations, with performance evaluated

using root mean square error (RMSE).

- Assessed network-wide improvements in travel time and control delay after optimising signal coordination.
- Demonstrated a methodology that can be applied to other urban traffic networks with mixed traffic conditions.

2. Relevant Previous Work

The estimation of traffic delays has been the focus of research for several decades, employing both field-based and analytical methodologies.

Early empirical studies utilized photographic surveys and vehicle identification techniques to measure travel speed and delays on roadway segments [1]. These methods established the foundation for travel time measurement. Theoretical modelling of delay at signalized intersections began with Wardrop, who developed analytical expressions based on deterministic and uniform vehicle arrivals [2]. Building on this work, Newell introduced queue-based delay models that incorporated stochastic arrivals [3].

Webster subsequently proposed an analytical delay model that included cycle length and effective green time [4]. Miller further improved delay estimation by considering stochastic queue characteristics in signalized intersection analysis [5].

Comparative evaluations of these foundational models assessed their applicability across varying traffic conditions. Hutchison critically analysed uniform delay components and proposed enhancements for practical implementation [6]. Cronje investigated delay under probabilistic and indeterminate traffic conditions, recommending improvements to standard models [7]. Sosin conducted a detailed analysis of model robustness under diverse demand scenarios [8]. Extending this research, Cronje introduced a Markov chain-based delay model capable of representing both under-saturated and oversaturated traffic conditions [9]. Brilon and Wu further advanced delay modelling by accommodating both Poisson and non-Poisson arrival distributions [10].

Subsequent refinements to classical models focused on improving predictive accuracy. Van assessed modifications to Webster's formulation and demonstrated superior performance of alternative analytical approaches [11]. Tarko analysed overflow delay arising from upstream signal coordination effects [12]. Heidemann introduced queue-length probability distributions to achieve more realistic delay estimation [13], and Olszewski integrated stochastic queue modelling techniques into intersection delay analysis [14].

Most analytical models decompose total delay into uniform delay, random overflow delay, and continuous overflow delay components. Hurdle refined the uniform delay component originally introduced by Webster [15]. Akçelik enhanced the representation of overflow delay by incorporating residual-queue effects into analytical models [16]. Kimber developed deterministic, time-dependent delay models suitable for variable-demand conditions [17], and Hollis further advanced time-dependent modelling [18]. Akçelik subsequently developed the Australian delay model, which integrates overflow and time-dependent components [19]. The Highway Capacity Manual later established standardised procedures for applying these delay estimation principles to coordinated intersections [20].

In response to growing traffic in urban networks, the focus of research transitioned from isolated intersections to coordinated arterial systems. In this context, Benekohal proposed analytical models addressing uniform delay in coordinated signal systems [21]. Akgungor accounted for stochastic fluctuations within traffic conditions within arterial coordination models [22]. The advancement of computational capabilities facilitated the integration of artificial intelligences methods into signal timing optimisation. Gene expression programming was subsequently applied to delay prediction and optimisation problems [23]. Subsequently, machine learning approaches, including Support Vector Regression, Random Forest, k-Nearest Neighbour, and Extreme Gradient Boosting, were introduced for traffic delay estimation and signal parameter refinement [24]. Patel emphasised the role of adaptive coordination strategies leveraging real-time traffic data for strengthening network efficiency [25]. In the context of India, the heterogeneous traffic composition and non-base movement patterns create major challenges for traditional delay models. Kadiya and Varia proposed two-way arterial coordination strategies via optimising cycle length, green splits, phase sequence, and offsets under mixed traffic conditions [26]. Shah examined the limitations of pre-timed coordination systems in Indian cities and introduced soft-computing-based adaptive structures [27]. Shah subsequently extended this approach by incorporating geometrical properties and traffic demand variability into optimisation-based coordination models [28]. More recently, reinforcement learning techniques have attracted interest for responsive signal control. Wei proposed a deep reinforcement learning model capable of large-scale coordinated signal control in response to oscillating demand [29]. Lian proposed a multi-agent deep reinforcement learning architecture for decentralised optimisation at the network level [30]. Sophisticated policy-gradient methods, such as Proximal Policy Optimisation, have been utilised for adaptive signal timing, displaying greater convergence stability and extensibility [31]. Further research has confirmed the effectiveness of reinforcement learning frameworks inside dynamic traffic settings through simulation-based experiments [32]. Hybrid frameworks combining field-calibrated microscopic simulation with evolutionary optimisation have been explored in mixed traffic conditions characteristic of Indian cities [33]. Genetic algorithms have been combined with traffic

simulation in several studies to enhance arterial coordination performance [34]. Varia has underscored the significance of field-based delay estimation and calibration strategies, particularly designed for heterogeneous traffic conditions [35]. Further studies by Varia and his team have confirmed the need for validation based on travel time in actual urban traffic contexts [36]. Recent research in India has also integrated low-cost sensing techniques and PCU-based calibration methods to enhance offsets in non-lane-based traffic flows [37]. Additional optimisation methods have tackled network-level coordination in shifting traffic demand conditions [38]. Notwithstanding these developments, the majority of current research relies on uniform traffic assumptions, simulation-based environments, or costly sensing infrastructure. Analytical delay models frequently exhibit diminished reliability in oversaturated mixed traffic scenarios, whereas numerous machine learning techniques are significantly reliant on artificial datasets that lack thorough field validation. As a result, there exists a distinct research gap for a practical, economically viable, and field-oriented methodology for network-level signal coordination that is appropriate for heterogeneous urban networks.

Consequently, this study seeks to fill the existing gap by introducing a travel time estimation framework based on field data, which incorporates evolutionary optimisation for coordinating signals at a four-way network level. This approach sidesteps reliance on proprietary simulation software and costly sensing technologies, takes into consideration the different characteristics of mixed traffic, and offers a feasible implementation framework intended at advancing urban traffic operations in Gandhinagar.

Study Area and Data Collection

Study Area

The geographical position of Gandhinagar city, along with the six chosen signalised intersections, is illustrated in Figure 1. A critical urban road network in Gandhinagar, Gujarat, India, was selected as the study area for this research. The city of Gandhinagar is designed with a grid-based road network comprising arterial and sub-arterial roads, where the traffic flow is managed through closely spaced signalised intersections. However, rising vehicular demand and fixed-time signal control led to recurrent congestion at multiple intersections during peak periods.

In the current research, six closely situated signalised intersections, specifically G2, G3, GH2, GH3, CH2, and CH3, were chosen to constitute the study network. These intersections are close enough to be linked by short distances, rendering them suitable for assessing the effects of signal coordination at the network level. The chosen network exemplifies standard urban traffic conditions in Indian cities, characterised by mixed traffic flows, diverse turning movements, and interactions between adjacent intersections.

Data Collection

Traffic volume data, classified by vehicle type, were derived from CCTV footage collected at each intersection.The recorded footage was analysed to obtain an approach-wise traffic volumes, turning movement proportions, and vehicle composition. To represent mixed traffic conditions, a vehicle counts were converted into Passenger Car Units (PCU) using standard equivalency factors suitable for Indian traffic conditions. Approach speeds and spot speeds were also. estimated from video data to support model calibration. Geometrical characteristics, including the number of approaches, lane configurations, approach widths, intersection widths, and distances between junctions, were collected through field surveys and confirmed against existing layout drawings. In addition, information on existing traffic signal control—such as signal phasing, cycle length, green time allocation, amber time, and pedestrian crossing duration—was obtained directly from signal controllers and municipal records.

Travel time data for multiple origin–destination (OD) paths were derived by tracking vehicle movements across successive intersections using CCTV footage. These data were subsequently used to validate simulation outputs using RMSE-based comparison. Table 1 provides a summary of the selected intersections, including existing green time allocations for six signalised intersections within the Gandhinagar network. The table outlines approach-wise green time distributions throughout different time periods, including weekday and Sunday peak hours. Variations in green time across approaches and intersections reflect differences in traffic demand, geometric traits, and speed limits. These existing signal timings were used as the baseline input for simulation, validation, and subsequent optimisation in the study.

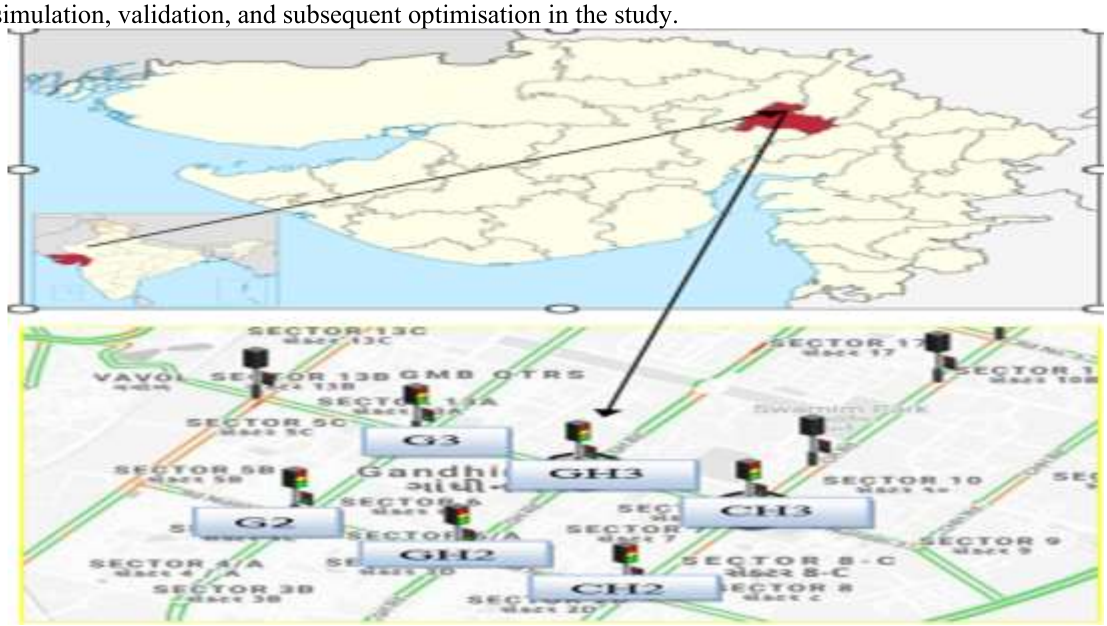

Figure 1: Study area location of Gandhinagar city and selected signalized intersections.

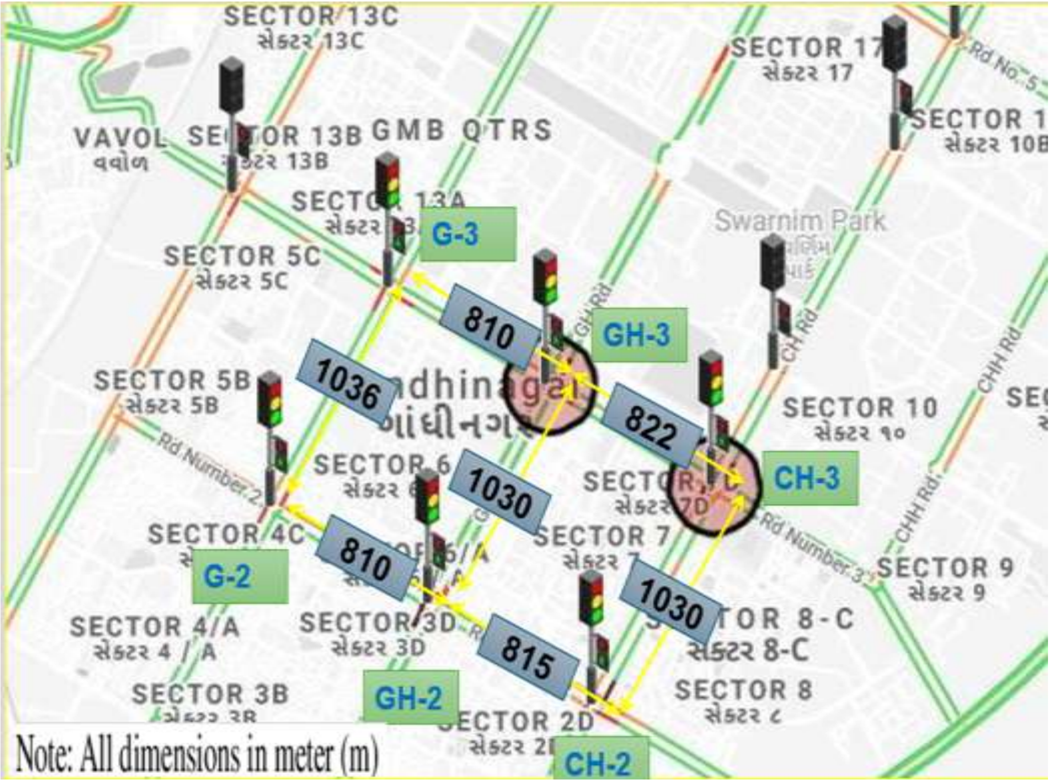

Figure 2: Layout of the selected six signalized intersections (G2, G3, GH2, GH3, CH2, and CH3)

Table 1 Characteristics of selected signalized intersections

Intersection	No. of Approaches	Cycle Length (s)	Typical Green Time Range (s)	Peak Period Considered	Speed Limit (km/h)
G2	4	90	20–25	Morning & Evening	40–60
G3	4	80	20	Morning & Evening	60
GH2	4	90	15–25	Morning & Evening	40–60
GH3	4	80	20–40	Morning & Evening	40–60
CH2	4	125	15–60	Morning & Evening	40–60
CH3	4	125	15–70	Morning & Evening	40–60

Existing Traffic Signal Cycle Timing

Sr. No.	Junction Name	Way Name	Monday to Saturday Morning Time	Monday to Saturday Evening Time	Sunday Morning Timing	Sunday Evening Timing	Speed limit
Green Time slots			09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	
1	GH-2	W1	15	15	15	15	60
	GH-2	W2	25	25	25	25	40
	GH-2	W3	15	15	15	15	60
	GH-2	W4	25	25	25	25	40
Green Time slots			09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	
2	GH-3	W1	20	20	20	20	60
	GH-3	W2	40	30	40	30	40
	GH-3	W3	25	25	20	20	40
	GH-3	W4	30	40	30	40	40
Green Time slots			09:30 to 10:30 / 10:30 to 12:00	05:00 PM to 07:30 PM	09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	
3	CH-2	W1	20	20	20	20	60
	CH-2	W2	80	30	30	30	40
	CH-2	W3	15	15	15	15	60
	CH-2	W4	30	60	20	20	40
Green Time slots			09:30 to 11:00	05:00 PM to 07:30 PM	09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	
4	CH-3	W1	25	25	20	20	40
	CH-3	W2	70	40	50	30- 30	40
	CH-3	W3	15- 20	15- 20	15	15- 20	60
	CH-3	W4	40	70	30	30- 50	40
Green Time slots			09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	
5	G-2	W1	20	20	20	20	60
	G-2	W2	25	25	25	25	40
	G-2	W3	20	20	20	20	60
	G-2	W4	25	25	25	25	40
Green Time slots			09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	09:30 AM to 12:00 PM	05:00 PM to 07:30 PM	
6	G-3	W1	20	20	20	20	60
	G-3	W2	20	20	20	20	60
	G-3	W3	20	20	20	20	60
	G-3	W4	20	20	20	20	60

Figure 3 Existing Traffic Signal Cycle Timing

Methodology

The overall methodology followed in this study is illustrated in Figure 3. The study begins with the selection of the Gandhinagar city road network comprising six signalized intersections (G2, G3, GH2, GH3, CH2, and CH3). Field data were collected using CCTV footage to obtain traffic volume, which was converted into PCU to represent mixed traffic conditions, along with speed, geometric details, and existing signal timings. Field travel times were estimated using time–space diagrams developed in AutoCAD. A SUMO-based simulation model was then developed by incorporating the road network, traffic routes, mixed traffic characteristics, and existing signal control. The model was simulated for morning and evening peak hours and validated by comparing simulated and field travel times using RMSE. Sensitivity analysis was carried out to assess the robustness of signal parameters, followed by genetic algorithm–based network-level signal optimisation of cycle length, green splits, and offsets. Finally, the performance of the optimized system was evaluated in terms of travel time and delay reduction for both peak periods, as shown in Figure 3. The overall methodology followed in this study is illustrated in Figure 4. The methodology adopted integrates field-calibrated microscopic traffic simulation with optimisation techniques to develop an effective network-level traffic signal coordination framework. The comprehensive methodology comprises three primary phases: (i) the creation of a SUMO-based traffic simulation model, (ii) the calibration and validation process utilizing field data, and (iii) the optimisation of signal control parameters through the application of a Genetic Algorithm (GA).

Study Area Selection • Gandhinagar city road network • Six signalized intersections (G2, G3, GH2, GH3, CH2, CH3)
↓
Field Data Collection • CCTV-based traffic volume • PCU conversion, speed, geometry • Existing signal timings
↓
Field Travel Time Estimation • Time–space diagram (AutoCAD) • Mixed traffic (PCU-based)
↓
SUMO Model Development • Network and route modelling • Existing signal control • Mixed traffic (PCU-based)
↓
Simulation & Validation • Morning and evening peak simulation • Field vs simulated travel time • RMSE computation
↓
Sensitivity Analysis • Variation of signal parameters • Robustness assessment • Stable parameter ranges
↓
GA-Based Signal Optimisation • Cycle length, green split, offset • Network-level optimisation
↓
Performance Evaluation • Travel time and delay reduction • Morning vs evening comparison

Figure 4 Methodology flow diagram

Development of SUMO-Based Traffic Simulation Model

The selected urban road network was modelled using the Stimulation of Urban Mobility (SUMO) platform, chosen for its flexibility, open-source nature, and effectiveness in network-level signal analysis under mixed traffic conditions. The model incorporated detailed geometric layout, lane configurations, turning movements, and inter-junctions' distances for six selected intersections, based on field surveys and official records.

Left turn movements were managed as free-flow whenever field conditions allowed, in line with observed traffic patterns. The current signal control parameters, such as cycle length, phase sequence, green time distribution, amber duration, and pedestrian clearance intervals, were utilized to mimic actual operating conditions. The preliminary simulation runs employing the existing signal timings acted as the baseline scenario for further optimisation.

Model Calibration and Validation

The simulation model was calibrated to ensure reliability by utilizing observed approach speeds, queue-formation characteristics, and travel-time data collected during peak periods. Multiple origin-destination (OD) paths were identified, and simulated travel times were compared with field-observed values obtained from CCTV-based vehicle tracking.

Root Mean Square Error (RMSE) served as the primary metric for model validation. RMSE values were calculated across various OD paths and peak periods to assess the agreement between simulated and observed travel times. The validation results demonstrate that the model reliably represents real-world traffic conditions, thereby supporting its application in optimisation analysis.

Genetic Algorithm–Based Signal Optimisation

After establishing a validated baseline model, a Genetic Algorithm (GA) was implemented to enhance network-level traffic signal coordination. The selection of GA was justified by its ability to address non-linear, multi-variable optimisation challenges without requiring explicit mathematical formulations. The decision variables in this study included cycle length, green split, and signal offsets at each intersection. An initial population of candidate signal timing strategies was generated within feasible bounds defined by field conditions and operational constraints. Each candidate solution was evaluated using the SUMO simulation, and network-level performance indicators were extracted. The objective function sought to minimise total network travel time and control delay. Standard genetic algorithm operators, including selection, crossover, and mutation, were applied iteratively to refine signal timing solutions over successive generations. The process continued until convergence criteria were met, resulting in an optimised set of coordinated signal timings for the network.

Performance Evaluation

The effectiveness of enhanced signal coordination was assessed by contrasting network-level metrics, including total travel time, total delay, and average travel time, with those derived from current signal control conditions. Improvements were assessed independently for morning and evening peak periods to reflect temporal variations in traffic demand. The methodology thus provides a systematic and transferable framework for improving network-level traffic signal coordination under heterogeneous urban traffic conditions.

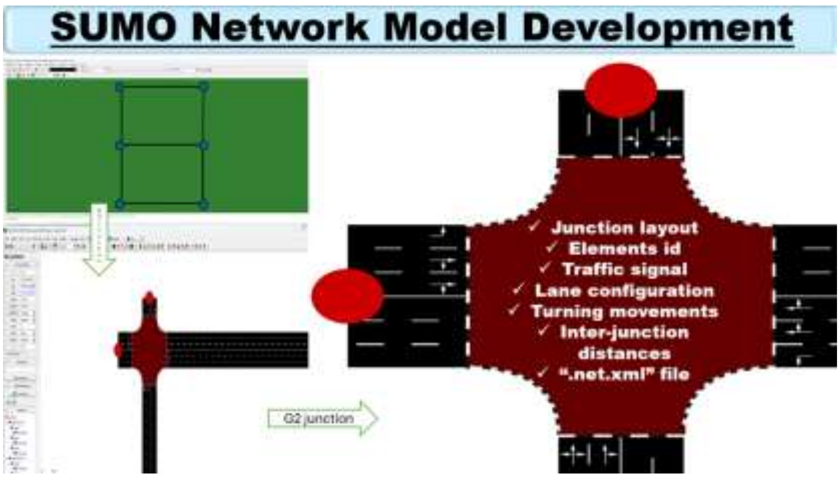

Figure 5 Development of the SUMO network model showing junction geometry, lane configuration, signal control, and turning movements

Results and Discussion

The validated simulation model was employed to evaluate the effectiveness of GA-based signal coordination across the selected network. Under existing signal operations, the network experienced frequent vehicle stoppages and noticeable queue formation, particularly along multi-intersection routes during peak periods.

Following optimisation, coordinated signal timings significantly enhanced platoon progression and reduced unnecessary stops at successive intersections. Network-level performance indicators showed substantial improvements compared to baseline conditions. Specifically, total travel time decreased by 33,943 s, while total control delay was reduced by 7,180 s. Corresponding performance improvements of approximately 5.42% during the morning peak and 2.91% during the evening peak were observed.

RMSE-based validation confirmed strong agreement between simulated and observed travel times across multiple origin–destination paths, indicating that the calibrated model reliably captures real-world traffic behaviour. Sensitivity analysis further demonstrated that moderate variations in signal parameters did not significantly alter overall network performance, highlighting the robustness of the proposed framework.

Model Validation Results

The baseline SUMO simulation model was first validated using field-observed travel time data collected through CCTV-based vehicle tracking. The agreement between simulated and observed travel times was evaluated using Root Mean Square Error (RMSE).

The RMSE values obtained across different OD paths were found to be low for both morning and evening peak periods (Network Average RMSE: 12 s and 11 s, respectively), indicating good consistency between simulated and field-measured travel times.

Network Performance under Existing Signal Control

Under existing signal control conditions, the study network experienced frequent vehicle stops and noticeable delays, particularly along routes involving multiple closely spaced intersections. The lack of coordination between adjacent signals resulted in platoon dispersion and queue formation during peak periods. The baseline simulation results served as a reference scenario against which the effectiveness of the optimized signal coordination strategy was assessed.

optimisation was applied to determine coordinated signal timings by simultaneously optimizing cycle length, green split, and offsets across the network.

The optimized signal timings resulted in improved progression of traffic platoons and reduced unnecessary stopping at successive intersections.

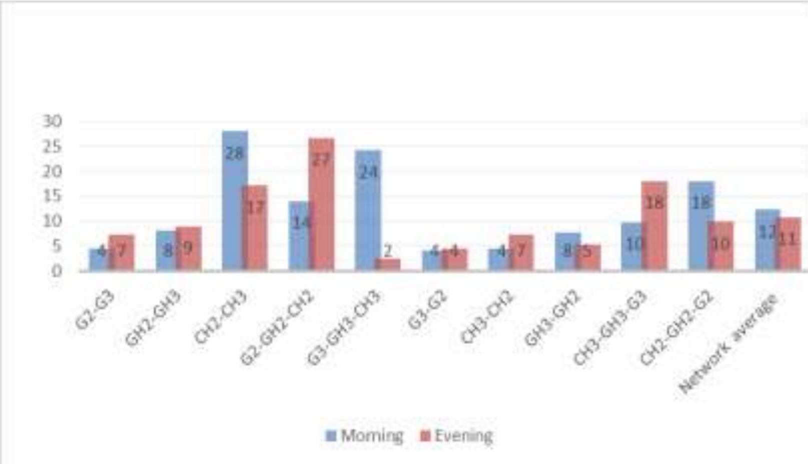

Figure 6 Comparison of RMSE values for morning and evening peak periods across different OD pairs

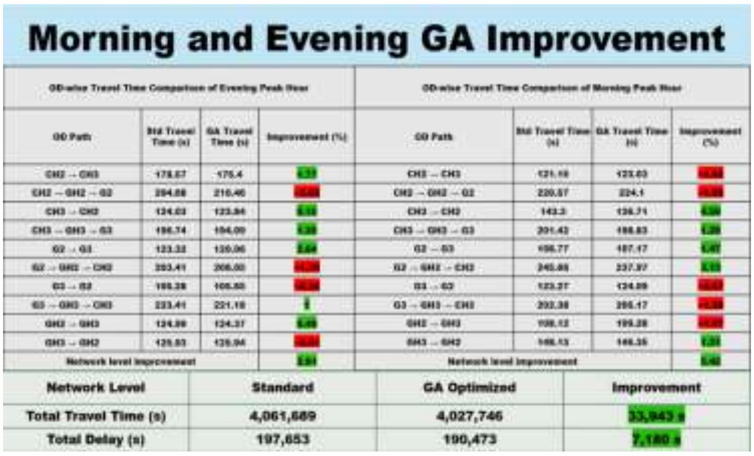

Figure 7 Genetic Algorithm (GA)–based signal coordination and optimisation framework at the network level

Table 2 Comparison of network performance under existing and GA-optimized signal control

Performance Measure	Existing Condition	GA-Optimized Condition	Improvement
Total Travel Time (s)	4,061,689	4,027,746	33,943 s
Total Delay (s)	197,653	190,473	7,180 s
Average Travel Time (s/veh)	Higher	Lower	Reduced

Morning Peak Improvement (%)	–	–	5.42%
Evening Peak Improvement (%)	–	–	2.91%

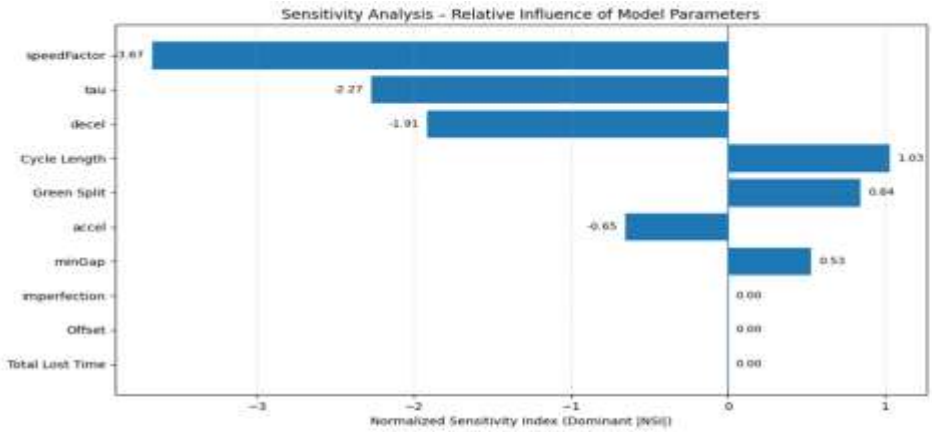

Figure 8 Results of sensitivity analysis showing relative influence of signal control and driver behaviour parameters

Effects of GA-Based Signal Optimisation

After validation, Genetic Algorithm–based As shown in Table 3, the percentage improvement was observed to be approximately 5.42% during the morning peak and 2.91% during the evening peak. The higher improvement during the morning peak can be attributed to more uniform traffic demand patterns.

5.4. Sensitivity Analysis Discussion

Sensitivity analysis was conducted to examine the robustness of the calibrated model and the stability of optimisation results.

The results show that moderate changes in signal parameters had no significant impact on overall network performance, indicating that the model is robust to minor input variations.

5.5. Discussion

The findings unequivocally indicate that coordinated signal control at the network level can significantly enhance traffic performance in urban road networks functioning under mixed traffic conditions. The combination of field-calibrated microscopic simulation with evolutionary optimisation has been shown to effectively replicate real-world traffic behaviour and to identify superior signal timing solutions. In summary, the results affirm that the suggested methodology offers a practical, scalable, and data-driven approach for network-level traffic signal coordination within Indian urban environments.

Conclusions

This research established and confirmed a framework driven by field data for coordinating traffic signals at the network level under mixed traffic scenarios, utilising microscopic stimulation and optimisation through Genetic Algorithms. The model based on SUMO, which was calibrated and validated with travel time data obtained from CCTV, showed a high level of concordance with the actual field conditions. The optimisation of cycle lengths, a green splits, and offsets led to decrease of 33,943 seconds in total network travel time and 7,180 seconds in total control delay, with enhancement during peak periods reaching 5.42%.

The finding validates that synchronised signal management at the network level provides distinct benefits compared to individual intersection optimisation, especially in urban settings characterised by closely situated intersections. The suggested approach is feasible, scalable, and transferrable, necessitating merely commonly accessible traffic data and open-source simulation software. Subsequently research could expand the framework by integrating adaptive control techniques and reinforcement learning to further improve performance in response to fluctuating traffic demands.

Ethics Approval: No human participants or animals were involved in this study. All data were collected from field observations of traffic flow and from publicly available or officially provided records; therefore, ethical approval was not necessary.

Conflict of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper.

Bhargav Jaiswal: Conceptualization, data collection, model development, simulation, optimisation, analysis, and manuscript preparation.

H. R. Varia: Methodology guidance, technical supervision, result interpretation, and manuscript review.

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