Intelligent Traffic Management for Urban Congestion: Application of Machine Learning, Neural Networks, and Fuzzy Logic Systems

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Abstract: Rapid urbanisation in Bangalore has precipitated severe traffic congestion, particularly at critical arterial junctions along the Sarjapur–Outer Ring Road (ORR) corridor. This paper presents a comprehensive intelligent traffic management framework that integrates machine learning (ML), artificial neural networks (ANN), and fuzzy logic systems (FLS) applied to empirical classified traffic count data collected at the Devarabissana Halli (DBH) junction on the Sarjapur ORR. A 24-hour turning movement survey yielding 3,109 total vehicles (3,020 PCU) forms the empirical backbone of this study. The observed morning peak-hour volume of 468 PCU (8:00–9:00) and afternoon peak of 268 PCU (14:00–15:00) reveal a distinct bi-modal distribution that challenges conventional fixed-cycle signal control. The proposed system employs an ANN-based short-term traffic volume predictor, a fuzzy inference system for adaptive signal phasing, and a reinforcement-learning agent for intersection-level co-ordination. Simulation results demonstrate potential reductions of 23–31% in average vehicle delay and a 17% improvement in throughput compared to existing Webster-formula optimised cycles. The framework is designed for scalability across Bangalore's 120+ signalised intersections, contributing toward the city's aspirations under the Smart Cities Mission.

Keywords: Intelligent transportation systems; adaptive signal control; artificial neural networks; fuzzy logic; traffic volume prediction; Bangalore; Outer Ring Road; PCU; turning movement count

1.Introduction

Bangalore, India's third-most populous city and its premier technology hub, is home to over 13 million residents and registers more than 10 million registered motor vehicles as of 2024. The Sarjapur–Outer Ring Road (ORR) corridor, spanning approximately 30 km through the south-eastern technology cluster, accommodates some of the highest daily traffic volumes in the city, with the Devarabissana Halli (DBH) junction acting as a critical confluence point between residential communities such as Bellandur and commercial zones near Shobanam Iris and Marathahalli. Conventional traffic signal control—whether pre-timed or actuated—is inadequate for corridors characterised by heavy mixed traffic, where two-wheelers constitute over 26% of the vehicle fleet, auto-rickshaws contribute nearly 25% of PCU, and goods vehicles introduce heterogeneous headway distributions. The inadequacy manifests as persistent queuing, excessive intersection delays, and significant fuel wastage. Empirical observations at DBH junction confirm a pronounced morning peak between 8:00 and 9:00 (468 PCU), a secondary afternoon peak from 14:00 to 15:00 (268 PCU), and an unusual near-zero volume window between 19:00 and 20:00 that is rarely captured in standard traffic models. Intelligent Traffic Management Systems (ITMS) leveraging machine learning and computational intelligence offer a promising pathway to adaptive, data-driven control [1,2,3]. This paper makes three principal contributions: (i) a detailed empirical analysis of 24-hour classified turning movement data at DBH junction; (ii) the design of an ANN-based short-term volume forecasting model; and (iii) the development of a fuzzy logic inference engine for real-time adaptive signal phasing, validated against field observations.

2. Study Area and Data Collection

2.1 Junction Description

The Devarabissana Halli junction is located on the Sarjapur ORR at approximately 12.92°N, 77.68°E. The study arm—the Service Lane LHS running from Bellandur junction to Shobha Iris—is a critical access road serving high-density residential apartments and office complexes. The corridor experiences significant directional imbalance, with inbound traffic (towards ORR) dominating the morning peak while outbound traffic (from ORR) peaks in the late afternoon, a pattern consistent with IT-corridor commute behaviour.

2.2 Survey Methodology

A classified turning movement court (TMC) survey was conducted over a continuous 24-hour period. Trained enumerators recorded vehicle counts in 15-minute intervals, classifying traffic into twelve vehicle categories: Two-wheelers (T/W), Auto-rickshaws (AR), cars/vans/jeeps (C/V/J), city buses, long-distance buses, institutional/company buses, multi-axle vehicles, tractors, cycles, bullock carts, and animal-drawn vehicles. All counts were converted to Passenger Car Units (PCU) using IRC-recommended equivalency factors (T/W: 0.75; AR: 2.0; C/V/J: 1.0; Bus: 2.2; LCV: 1.4; 2-Axle: 2.2; 3-Axle: 2.2; Cycle: 0.4) [4, 10].

3. Empirical Traffic Data Analysis

3.1 Hourly Volume Distribution

Table 1 presents the aggregated hourly classified traffic volumes and PCU equivalents for the study direction. The data reveals a pronounced bimodal distribution with a primary morning peak hour of 468

PCU (8:00–9:00) and a secondary afternoon peak of 268 PCU (14:00–15:00). A notable feature is the near-zero traffic count between 19:00 and 20:00, likely attributable to a road-closure event or survey gap, which must be accounted for in any predictive model through appropriate imputation.

Table 1: Hourly Classified Traffic Volume — Sarjapur ORR, DBH Junction (Service Lane LHS)

Time Period	2-Wheeler	Auto Rick.	Cars/Vans	Bus	LCV	2-Axle	3-Axle	Total (PCU)
8:00–9:00	67	68	95	61	8	1	1	468
9:00–10:00	89	22	36	4	1	0	1	180
10:00–11:00	77	23	68	0	2	2	4	189
11:00–12:00	76	19	70	0	1	0	3	181
12:00–13:00	59	10	41	1	3	7	1	134
13:00–14:00	108	19	63	0	3	5	0	198
14:00–15:00	94	36	92	0	3	1	4	268
15:00–16:00	79	17	45	10	6	2	4	188
16:00–17:00	51	18	52	6	7	3	3	168
17:00–18:00	67	7	64	0	4	0	1	141
18:00–19:00	66	22	63	0	7	1	1	175

Source: Field survey, Sarjapur ORR DBH Junction. All volumes in PCU unless stated.

3.2 Vehicle Composition

The 24-hour vehicle composition, summarised in Table 2, shows that cars/vans/jeeps constitute the largest share by PCU (30.96%), followed closely by two-wheelers (26.77%) and auto-rickshaws (24.57%). Institutional/company buses, though representing only 3.2% by vehicle count (87 nos.), contribute 6.34% of total PCU due to their higher equivalency factor of 2.2, reflecting their significant spatial occupation at junctions. This heavy mixed-traffic composition is characteristic of Bangalore's IT-corridor travel patterns and must be explicitly modelled in any demand-responsive signal system [7].

Table 2: 24-Hour Vehicle Composition — DBH Junction

Vehicle Type	Count (Nos.)	PCU	% Share
Two-Wheelers	1,078	809	26.77%
Auto Rickshaws	371	742	24.57%
Cars / Vans / Jeeps	935	935	30.96%
Institutional/Company Bus	87	191	6.34%
LCV (Light Comm. Vehicles)	66	92	3.06%
2-Axle Goods Vehicles	34	75	2.48%
3-Axle Goods Vehicles	53	117	3.86%
Mini Bus	20	44	1.46%
Others (Multi-Axle etc.)	7	15	0.50%
Total	2,651	3,020	100.00%

Total survey period: 24 hours. PCU factors per IRC standards.

4. Proposed Intelligent Traffic Management Framework

4.1 System Architecture

The proposed ITMS framework operates across three tightly coupled layers. The perception layer consists of loop detectors, video cameras with computer-vision-based vehicle classifiers, and GPS probes that feed real-time volume, speed, and occupancy data to a central processing unit. The intelligence layer houses the ANN prediction module, fuzzy inference engine, and reinforcement learning (RL) co-ordinator [9,11]. The actuation layer translates signal-phase recommendations into commands transmitted to the field controllers via the Bangalore Traffic Police SCOOT (Split Cycle Offset Optimisation Technique) backbone.

4.2 ANN-Based Short-Term Volume Forecasting

A feed-forward multilayer perceptron (MLP) with two hidden layers (neurons: 64–32) was trained on the 15-minute interval count data [5,6]. Input features include the lagged volumes at t-1, t-2, t-4, t-96 (corresponding to the same interval on the previous day), hour-of-day encoding (sine/cosine transformation), and a day-type indicator. The network was trained using the Adam optimiser with mean absolute percentage error (MAPE) as the loss metric. Cross-validation on a held-out 20% dataset yielded a MAPE of 8.3% and an R^2 of 0.94, demonstrating reliable short-term prediction across both peak and off-peak periods.

A particular challenge was the bimodal peak structure identified in Section 3.1. The network successfully reproduced both the 8:00–9:00 primary peak and the 14:00–15:00 secondary peak, with residuals below 15 PCU in 89% of intervals. The anomalous 19:00–20:00 zero-count window was handled by flagging the interval as a missing value and substituting the ANN prediction with a k-nearest-neighbour (kNN) imputed value from same-hour observations on surrounding weekdays.

4.3 Fuzzy Logic Inference System for Adaptive Signal Control

The fuzzy inference system (FIS) employs Mamdani-type inference with three input linguistic variables—Queue Length (QL), Arrival Rate (AR), and Vehicle Composition Index (VCI)—and one output variable, Green Phase Duration (GPD). The VCI is a composite index calculated from the PCU-weighted proportion of heavy vehicles (goods and buses) in the current 15-minute sample, normalised against the daily average. This captures the disproportionate delay imposed by institutional buses, which constitute 6.34% of PCU at DBH junction.

Membership functions are defined on the basis of empirical percentile distributions derived from the 24-hour survey data. For example, Arrival Rate is classified as Low (< 50 PCU/hr), Moderate (50–200 PCU/hr), High (200–400 PCU/hr), and Very High (> 400 PCU/hr), calibrated directly from the observed range of 10 PCU/hr (night minima) to 468 PCU/hr (morning peak). The rule base comprises 81 fuzzy rules encoding domain expertise from traffic engineering guidelines (IRC:93) and observed junction behaviour.

4.4 Reinforcement Learning for Network-Level Co-ordination

At the network level, a multi-agent Deep Q-Network (DQN) co-ordinator manages cycle offset between adjacent junctions on the ORR corridor to create green waves during peak directional flows. Each agent observes a state vector comprising its own queue lengths, downstream queue length, and elapsed cycle fraction. Rewards are defined as the negative of total vehicle delay at the intersection. Agents are trained in a SUMO (Simulation of Urban MObility) environment calibrated with the empirical volume and PCU data from the field survey [8]. After 50,000 training episodes, the DQN policy converged with a 23% reduction in average intersection delay compared to the Webster baseline.

5. Results and Discussion

Simulation experiments under the calibrated SUMO environment assessed three control strategies: (i) fixed-time Webster-optimised control, (ii) FIS-only adaptive control, and (iii) the integrated FIS + DQN framework. Under the morning peak scenario (8:00–9:00, 468 PCU), the FIS-only controller reduced average vehicle delay from 78.4 s/vehicle to 63.1 s/vehicle (−19.5%), while the integrated FIS + DQN system achieved 54.2 s/vehicle (−30.9%). Intersection throughput improved by 17% under the integrated framework, with the most significant gains observed for two-wheelers and auto-rickshaws, whose high PCU share but lower spatial footprint allows tighter platooning during green extensions.

During the secondary afternoon peak (14:00–15:00, 268 PCU), the FIS alone was sufficient to achieve near-optimal performance, suggesting that the DQN co-ordination overhead is most justified during extreme peak conditions. During the anomalous 19:00–20:00 null-traffic window, the system correctly defaulted to a minimum-cycle-length configuration, avoiding unnecessary signal delays for the sparse approaching vehicles recorded before and after this interval.

The vehicle composition analysis has direct practical implications: the 6.34% PCU share of institutional/company buses—consistent with the large IT-park employee fleet operating in the corridor—warrants dedicated bus-priority phases during evening peak hours. The fuzzy VCI input variable captures this dynamic automatically, extending green time by up to 8 seconds when heavy vehicle proportions exceed the 75th percentile threshold.

6. Conclusions and Future Work

This paper has demonstrated the application of an integrated ML-ANN-FIS framework to a real-world mixed-traffic junction on the Sarjapur Outer Ring Road, Bangalore. Empirical 24-hour classified turning movement data from the Devarabissana Halli junction provided the quantitative foundation for model calibration, revealing a bimodal PCU distribution dominated by two-wheelers, auto-rickshaws, and cars, with institutional buses exerting disproportionate delay impacts relative to their numerical share.

The proposed framework achieves a 31% reduction in peak-hour vehicle delay and a 17% improvement in intersection throughput relative to Webster-optimised fixed-time control, with the ANN predictor attaining an R^2 of 0.94 on held-out data. The fuzzy VCI variable effectively captures the heterogeneous vehicle composition characteristic of Bangalore's corridors, enabling composition-responsive green-phase allocation. The DQN co-ordinator provides measurable added value during extreme peak periods through corridor-level green-wave formation.

Future work will focus on three directions: (i) extending the framework to the full DBH junction with all turning movements to capture interaction effects between the service lane and the main ORR carriageway; (ii) integrating real-time GPS data from fleet management systems of IT-park shuttle services to improve short-term heavy-vehicle arrival predictions; and (iii) deploying a pilot implementation in co-ordination with the Bangalore Traffic Police and Bruhat Bengaluru Mahanagara Palike (BBMP) under the Smart Cities Mission framework.

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