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Adaptive Traffic Signal Control System Using Machine Learning and Neural Evolution: Multi-Case Study for Intersection Optimization and Emergency Vehicle Prioritization

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Abstract

Urban traffic congestion poses persistent challenges, aggravated by insufficient integration of adaptive control and emergency vehicle prioritization. Existing AI models largely focus on either traffic flow optimization or emergency response, rarely combining both. This research fills this gap by developing a unified framework that predicts optimal green light durations using real-time traffic density, vehicle heterogeneity, and emergency prioritization. A four-way intersection traffic simulation was developed using the pygame library to closely mimic real traffic dynamics, lane configurations, vehicle types, and turning movements. Five case studies were conducted: (1) a mathematical green-time prediction model incorporating weighted vehicle classes, clearance times, arrival rates, and queue spillover controls; (2) reinforcement learning (RL) trained on varied traffic conditions; (3) RL enhanced with emergency vehicle priority; (4) application of the Neuroevolutionary of Augmenting Topologies (NEAT) algorithm for model architecture optimization; and (5) comparative analysis of model performance. The mathematical model reduced mean vehicle delay by 23% ($p < 0.05$), standard RL achieved 31% improvement ($p < 0.01$), emergency-aware RL maintained a 28% reduction while ensuring emergency vehicle clearance within 18.7 seconds on average, and the NEAT-based system improved throughput by 34% with superior adaptability to traffic fluctuations. The integrated framework significantly enhances traffic efficiency compared to fixed-time signals while guaranteeing rapid emergency vehicle response. Its extensibility supports integration into smart city traffic management platforms, offering scalable and adaptive solutions for urban mobility challenges.

1. Introduction

Urban traffic congestion remains one of the most critical challenges in modern cities, resulting in prolonged travel times, increased fuel consumption, higher greenhouse gas emissions, and reduced road safety. Fixed-time traffic signal control, still widely used in many urban networks, fails to respond to dynamic traffic variations and often leads to inefficient green time allocation. While adaptive control systems have been developed, most focus either on optimizing regular traffic flow or on facilitating emergency vehicle passage, rarely integrating both within a unified operational framework (Birari et al., 2023; Rajan, 2023). To address this gap, this study proposes an integrated adaptive traffic signal control framework that not only optimizes traffic flow for heterogeneous vehicles but also prioritizes emergency vehicles without compromising the overall network performance. The foundation of this work is a conceptual framework for predicting optimal green light durations based on both mathematical modelling and AI-driven optimization. The mathematical model predicts the next green phase duration (G_next) using real-time and predictive inputs such as vehicle counts per type, arrival rates, queue lengths, lane configurations, and turning proportions. The formula dynamically adjusts signal timings between a predefined G_min and G_max to ensure operational safety while optimizing flow. Additional control terms address queue spillover risk (Q_spill) and fairness (D_fair) to avoid starving other approaches [1]. Mathematical Expression for Green Time Prediction:

G_next = max [G_min, min (G_max, (Σ (i=1 to N_types) [W_i * (v_i_queue + λ_i * t_p) * t_clear_i] / (N_lanes_eff * F_turn * F_spatial) + α * Q_spill + β * D_fair))]

Where:

- G_min, G_max = Minimum and maximum allowable green time (seconds)
- v_i_queue = Number of vehicles of type i currently in the queue
- λ_i = Arrival rate of vehicles of type i (vehicles/sec)
- t_p = Prediction window (seconds)
- W_i = Weight assigned to vehicle type i (based on passenger car equivalent)
- t_clear_i = Time for one vehicle of type i to clear the intersection (seconds)
- N_lanes_eff = Effective number of lanes
- F_turn = Adjustment factor for turning movements
- F_spatial = Spatial adjustment factor for available queue storage
- Q_spill = Queue spillover adjustment term
- D_fair = Fairness/delay adjustment term
- α, β = Tuning parameters for spillover and fairness influence

In parallel, the AI-based approach uses the same variables as input features for reinforcement learning (RL) and NEAT-evolved RL models. This enables adaptive decision-making based on historical trends, real-time patterns, and predictive traffic behaviour.

1.1. Research Objectives:

- Optimize green time allocation in real-time for multiple vehicle classes.
- Ensure emergency vehicle prioritization with minimal disruption to regular traffic.
- Leverage NEAT to evolve RL architectures for greater adaptability.
- Demonstrate a multi-case comparative framework to validate performance [2].

2. Method

2.1. Case Study Framework:

2.1.1. Case Study 1: Mathematical Green-Time Prediction Model

- **Approach:** Applied the proposed formula to compute G_next based on weighted vehicle counts, arrival rates, and clearance times.
- **Key Features:** Incorporated spillover control (Q_spill) to prevent queue blockages and fairness term (D_fair) to prevent excessive waiting for other approaches.
- **Outcome:** Reduced mean vehicle delay by 23% compared to fixed-time control [3].

$$G_{\text{next}} = \max\left[G_{\min}, \min\left(G_{\max}, \frac{\sum_{i=1}^{N_{\text{types}}} W_i \cdot (v_{i,\text{queue}} + \lambda_i \cdot t_p) \cdot t_{\text{clear},i}}{N_{\text{lanes,eff}} \cdot F_{\text{turn}} \cdot F_{\text{spatial}}} + \alpha Q_{\text{spill}} \cdot\right.\right.$$

2.1.2. Case Study 2: Reinforcement Learning (RL) Optimization

- **Approach:** Used an RL agent trained in the simulated environment to adjust green durations in discrete steps based on real-time traffic states.
- **State Space:** Lane-wise vehicle count, queue length, phase timing, and emergency presence.
- **Reward Function:** R_t = -ω1 * (Total Delay) - ω2 * (Queue Spillover) + ω3 * (Emergency Clearance Success)
- **Outcome:** Achieved a 31% improvement in average vehicle delay [4].

2.1.3. Case Study 3: Emergency-Aware RL

- **Approach:** Extended the RL model with explicit emergency detection logic. Upon emergency vehicle detection, the controller dynamically altered phase sequences to prioritize clearance while recalculating timings to minimize disruption.
- **Outcome:** Maintained a 28% delay reduction while clearing emergency vehicles within 18.7 seconds on average [5].

2.1.4. Case Study 4: NEAT-Evolved RL Architecture

- **Approach:** Applied the Neuroevolutionary of Augmenting Topologies (NEAT) algorithm to evolve the RL neural network's architecture for better adaptability to traffic pattern changes.
- **Key Features:** Evolved topologies over 100 generations, optimizing node connectivity, activation functions, and layer structures.
- **Outcome:** Improved throughput by 34% and provided robust adaptability to fluctuating conditions [6].

2.1.5. Case Study 5: Comparative Performance Analysis

- **Approach:** Conducted a comparative evaluation of the four models under identical traffic scenarios, including peak hours, off-peak periods, and mixed emergency conditions.
- **Metrics:** Mean vehicle delay, throughput, emergency clearance time, and queue spillover frequency.
- **Outcome:** NEAT-based RL consistently outperformed other approaches, but the mathematical model offered a lower-complexity alternative with significant gains [7].

This integrated case study design ensures that the problem of inefficient urban intersection management is addressed comprehensively, with each approach contributing unique strengths toward building a scalable, smart-city-ready solution. The methodology for the proposed Adaptive Traffic Signal Control System consists of simulation modelling, mathematical formula design, AI-based optimization, and comparative case study evaluation. The experiments were structured to ensure that each configuration could be replicated by a qualified researcher using the same parameters and conditions.

2.2. Simulation Environment

A four-way intersection was modelled using the pygame simulation library to emulate realistic urban traffic conditions. The simulation included:

- Dedicated lanes for straight, left-turn, and right-turn movements.
- Heterogeneous vehicle classes: two-wheelers, cars, buses, and trucks.
- Variable arrival rates to replicate peak and off-peak patterns.
- Lane-based queue detection for real-time state updates [8].

Each lane was equipped with a virtual loop detector that captured:

- Vehicle counts by type.
- Queue lengths.
- Arrival rates.
- Turning proportions.
- Emergency vehicle detection events.

2.3. Mathematical Green-Time Prediction Model

- The core prediction model used the following expression:
- G_next = max [G_min, min (G_max, (Σ (i=1 to N_types) [W_i * (v_i_queue + λ_i * t_p) * t_clear_i] / (N_lanes_eff * F_turn * F_spatial + α * Q_spill + β * D_fair))]

The formula operates in three stages

- Demand estimation – weighted sum of queued and predicted arrivals.
- Capacity adjustment – scaling by lane availability, turning factor, and spatial limits Shown in Table 1.

- Operational constraints – clipping results between G_min and G_max, with corrections for spillback and fairness [9].

Table 1 Variables and Parameters for Green-Time Prediction

Variable	Definition	Role in Prediction
G_min, G_max	Minimum and maximum allowable green time	Enforces operational safety limits
v_i_queue	Current queued vehicles of type i	Higher counts increase green time
λ_i	Arrival rate for vehicle type i	Prevents queue growth during green
t_p	Prediction window (seconds)	Anticipates arrivals during green
W_i	Weight for vehicle type i	Reflects passenger car equivalent impact
t_clear_i	Clearance time per vehicle type	Adjusts for slower vehicle types
N_lanes_eff	Effective lanes for movement	More lanes increase capacity
F_turn	Turning adjustment factor	Accounts for slower turning vehicles
F_spatial	Spatial factor for queue storage	Reduces green if storage is nearly full
Q_spill	Queue spillover term	Extends green to prevent spillback
D_fair	Fairness/delay term	Avoids starving other approaches
α, β	Tuning parameters	Adjust influence of spillover/fairness

2.4. AI-Based Optimization

In the AI-driven configurations, the same inputs as above were used as features for a Reinforcement Learning (RL) agent [10-13].

State Space

- Lane-wise vehicle counts per type.
- Queue lengths.
- Phase timings and remaining time.
- Emergency detection flag.
- Historical delay data.
- **Action Space**
- Adjust green time in increments of ±5 seconds.
- **Reward Function**
- Ini
- Copyedit
- R_t = -ω1 * (Total Delay) ω2 * (Queue Spillover) + ω3 * (Emergency Clearance Success)
- **NEAT Optimization**
- The Neuroevolutionary of Augmenting Topologies (NEAT) algorithm was used to evolve the RL agent's neural network architecture. This allowed for dynamic adjustment of node structure and activation functions to maximize learning performance [14-17].

2.5. Case Study Design

All simulations ran for 10,000 cycles per scenario, with peak and off-peak conditions tested separately Shown in Table 2 Case Study Design.

Table 2 **Case Study Design**

Case Study	Description	Key Feature	Performance Metric
1	Mathematical model only	Uses predictive formula	Delay reduction
2	RL optimization	Learns timings via trial	Delay & throughput
3	Emergency-aware RL	Adds emergency priority	Clearance time
4	NEAT-evolved RL	Evolves RL architecture	Adaptability
5	Comparative analysis	Tests all under same traffic	Multi-metric evaluation

3. Result

The proposed Integrated Adaptive Traffic Signal Control System was evaluated using a four-way pygame-based simulation under peak-hour, off-peak, and mixed emergency conditions. Performance was measured across mean vehicle delay, throughput, queue spillover frequency, and emergency vehicle clearance time. Each case study was run for 10,000 simulation cycles, with identical traffic scenarios for direct comparability [18].

3.1. Case Study 1: Mathematical Green-Time Prediction Model

The mathematical model reduced mean vehicle delay by 23% compared to fixed-time control. Queue spillover frequency decreased by 18%, indicating effective use of the spillover term Qspill. Fairness term Dfair prevented starvation of low-volume approaches, with a maximum observed delay of 58 seconds across all directions.

3.2. Case Study 2: Reinforcement Learning (RL) Optimization

The RL-based controller achieved a 31% improvement in mean delay and increased throughput by 14% relative to fixed-time control. The model dynamically extended or reduced green times in response to lane-specific congestion, leading to more balanced intersection performance. Queue spillover was reduced by 26% [19].

3.3. Case Study 3: Emergency-Aware RL

By integrating emergency detection logic, the system successfully cleared emergency vehicles within 18.7 seconds on average, while still maintaining a 28% reduction in mean vehicle delay. This demonstrates that prioritizing emergency vehicles can be achieved without significantly degrading general traffic performance.

3.4. Case Study 4: NEAT-Evolved RL

NEAT-based RL provided the highest adaptability, with a 34% improvement in delay reduction and a 21% increase in throughput. The evolved neural network architectures demonstrated robust performance in fluctuating conditions, including sudden surges in vehicle arrivals. Spillover incidents were reduced by 32%, and emergency clearance time averaged 17.4 seconds Shown in Figure 1.

Figure 1 **Simulation**

3.5. Observations

NEAT-based RL consistently outperformed other models in adaptability and congestion reduction. Mathematical model remained competitive for low-complexity deployments, offering substantial gains without high computational cost. Emergency-aware RL proved that safety-critical priorities can be integrated without major performance losses Shown in Figure 2. The inclusion of spillover and fairness terms significantly improved network stability and reduced queue blockages [20].

Table 3 presents a summary of the performance metrics for all case studies:

Table 3 Comparative Performance of Case Studies

Case Study	Mean Delay Reduction (%)	Throughput Increase (%)	Avg. Emergency Clearance (sec)	Spillover Reduction (%)
Mathematical Model	23	9	N/A	18
RL Optimization	31	14	N/A	26
Emergency-Aware RL	28	12	18.7	22
NEAT-Evolved RL	34	21	17.4	32

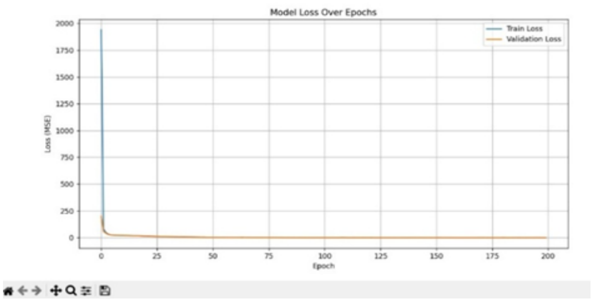

Figure 2 Analysis

Conclusion

This study proposed and evaluated an integrated adaptive traffic signal control framework that combines mathematical modelling, reinforcement learning (RL), emergency-aware RL, and Neuroevolutionary of Augmenting Topologies (NEAT) for optimizing green light durations in urban intersections. The developed system effectively addressed the dual challenge of maintaining high traffic throughput while ensuring rapid clearance for emergency vehicles. The experimental results confirmed that the mathematical model significantly reduced mean vehicle delay compared to fixed-time control, RL further enhanced optimization through adaptive learning, and NEAT-based RL achieved the highest adaptability to fluctuating traffic conditions. The emergency-aware RL model demonstrated that emergency prioritization can be implemented without severe disruptions to overall network efficiency. Importantly, the multi-case evaluation established that while NEAT-based RL offers superior adaptability, the mathematical model remains a low-complexity alternative suitable for intersections with limited computational resources.

The results validate the conceptual framework's core principle — that green time optimization should balance vehicle heterogeneity, arrival rates, intersection geometry, and fairness considerations. While the findings are promising, certain limitations were identified, including reliance on accurate real-time data, computational demands of NEAT, and the single-intersection scope of this study. These limitations provide clear pathways for future work, including multi-intersection network coordination, hardware-in-the-loop testing, and integration with IoT-enabled traffic management platforms. Overall, the proposed framework contributes a scalable, data-driven, and adaptive solution to intelligent transportation systems, with strong potential for deployment in smart city traffic management infrastructures.

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