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Traffic Light Green-Time Prediction Using Machine Learning: A Review Of Adaptive Signal Control From Fixed Timing To Learning-Based Intersections

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Abstract—Traffic congestion is a major urban problem, worsened by conventional traffic lights that operate on fixed time intervals without considering how many vehicles are waiting on each approach. This paper reviews approaches to adaptive traffic signal control and focuses on using machine learning to predict suitable green-light durations for each lane of an intersection based on traffic demand. It traces the field from classical signal timing formulas through adaptive systems that adjust timings from detector data, to data-driven prediction of traffic flow and reinforcement learning controllers that learn signal policies through simulation. Input parameters such as lane-wise vehicle counts from cameras, traffic density, queue length, waiting time and time of day are discussed, along with traffic simulators used for safe training and evaluation. A five-layer prototype architecture is proposed in which vehicle detection feeds feature construction, a regression model predicts green times, a safety and constraint layer enforces minimum and maximum phases and pedestrian crossing times, and a controller updates the signal. Research gaps, objectives, a comparison of control approaches and challenges such as sensor reliability, mixed Indian traffic and coordination across intersections are discussed.

Index Terms—Traffic signal control, adaptive traffic lights, machine learning, green-time prediction, vehicle detection, reinforcement learning, SUMO

I. INTRODUCTION

At many city junctions, signals switch on a fixed cycle regardless of traffic. A lane with a long queue may get the same green time as an empty lane, increasing waiting time, fuel consumption and pollution. Traffic police often override signals manually at peak hours, showing that fixed plans do not match real demand.

Adaptive signal control adjusts timings to measured traffic. Classic systems such as SCOOT [1] and SCATS [2] used loop detectors to adapt cycle lengths and splits. Machine learning now allows cameras to count vehicles accurately and models to predict the green time each approach needs. Wei *et al.* [3] surveyed traffic signal control methods from conventional to learning-based.

This paper reviews these approaches and proposes a prototype that predicts lane-wise green durations using machine learning.

II. RELATED WORK

Webster [4] proposed the classic formula for cycle length that minimizes delay under steady demand. Hunt *et al.* [1] described SCOOT, which uses upstream detectors to model queues and adjust timings in small steps, and Sims and Dobinson [2] presented SCATS, which selects plans and adjusts splits based on measured saturation.

Lv *et al.* [5] applied deep learning with stacked autoencoders to traffic flow prediction and showed improvement over shallow models, a basis for predicting future demand at intersections. Varaiya [6] proposed max-pressure control, which gives green to the phase with the largest difference between upstream and downstream queues and is provably stable.

Reinforcement learning has been widely studied. Genders and Razavi [7] used a deep RL agent with a dense state representation in simulation, Wei *et al.* [8] proposed IntelliLight and tested it with real traffic data, and PressLight [9] combined RL with max-pressure ideas to coordinate arterial signals. SUMO [10] is the most common open-source simulator for training and evaluating such controllers. Vehicle counts can be obtained from cameras using detectors such as YOLO [11]. Table I summarizes these works.

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Ref.	Method	Key Findings	Limitations
[4]	Optimum cycle formula	Classic delay-minimizing timing	Assumes steady demand
[1]	SCOOT adaptive control	Detector-based incremental adjustment	Needs dense detectors
[2]	SCATS adaptive system	Plan selection from saturation	Proprietary tuning
[5]	Deep learning flow prediction	Better than shallow models	Freeway data
[6]	Max-pressure control	Provably stable network control	Needs queue measurements
[7]	Deep RL signal agent	Learned control in simulation	Simulation only
[8]	IntelliLight RL	Tested with real traffic data	Single intersection
[10]	SUMO simulator	Open microscopic simulation	Calibration effort

TABLE I Summary of Literature Survey

III. PRELIMINARIES

3.1 Signal Timing Concepts

A signal cycle consists of phases that give right of way to different movements. Webster [4] derived formulas for optimum cycle length and green splits from traffic flows and saturation flows, which remain the basis of fixed-time planning.

3.2 Control Strategies

Fig. 1 classifies strategies: fixed-time, actuated, adaptive optimization, prediction-based machine learning and reinforcement learning.

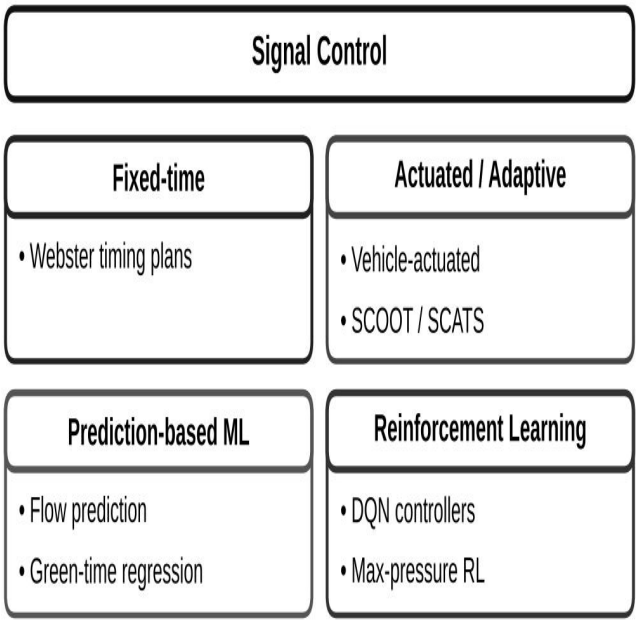


Fig. 1. Traffic signal control strategies.

IV. PROBLEM STATEMENT AND OBJECTIVES

4.1 Identified Research Gaps

1. 1) Most learning-based controllers are evaluated only in simulation.

2. 2) Lane discipline and mixed vehicles in Indian traffic challenge detection and modelling.

3. 3) Pedestrian needs and emergency vehicles are often not considered.

4. 4) Coordinating many intersections remains difficult.

5. 5) Interpretable models are needed for traffic authorities to trust automated timings.

4.2 Objectives Of The Review

- **O1:** To review traffic signal control from fixed timing to learning-based methods.
- **O2:** To identify traffic parameters useful for green-time prediction.
- **O3:** To propose a machine-learning prototype predicting lane-wise green durations.
- **O4:** To compare control approaches.
- **O5:** To discuss challenges and future improvements.

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4.3 Proposed Framework

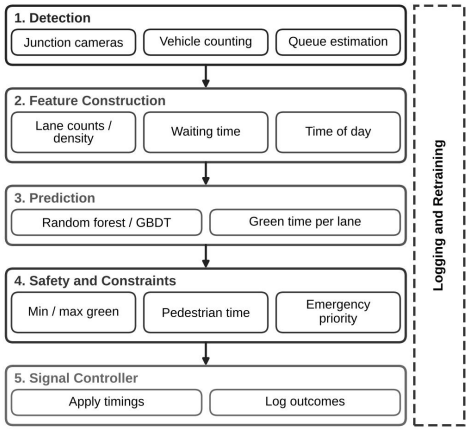


Fig. 2 shows the prototype architecture.

Fig. 2. Proposed ML-based green-time prediction prototype.

4.4 Detection Layer

Cameras at the junction detect and count vehicles per lane, estimate queue length and classify vehicle types.

B. Feature Construction Layer

Features include lane-wise counts, density, average waiting time, arrivals in the last cycle, time of day and day of week.

4.5 Prediction Layer

A regression model such as random forest [12] or gradient boosting [13] predicts the green time needed to clear each approach.

4.6 Safety And Constraint Layer

Predicted times are bounded by minimum and maximum green, pedestrian crossing time and amber and all-red intervals; emergency vehicles receive priority.

4.7 Signal Controller Layer

The controller applies the timings for the next cycle and logs outcomes for evaluation and retraining.

V. WORKING METHODOLOGY

Fig. 3 outlines the workflow. Webster's optimum cycle length, used as a baseline, is

$$C_o = (1.5L + 5) / (1 - Y) \quad (1)$$

where L is the total lost time per cycle and Y is the sum of critical flow ratios. The ML model instead predicts green time g_i for approach i directly from features x_i, $g_i = f(x_i)$, trained on simulated or historical data in which green times that minimized waiting were recorded.

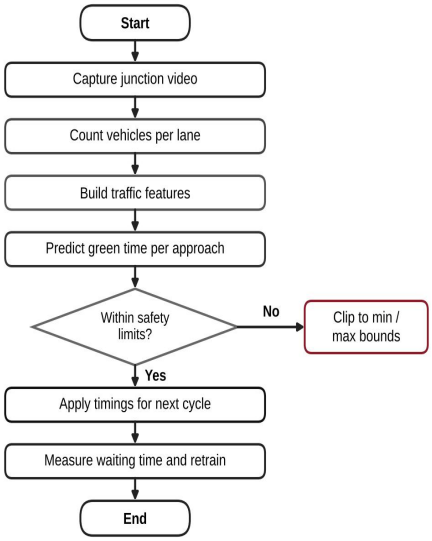


Fig. 3. Green-time prediction and control workflow.

Evaluation in SUMO compares average waiting time, queue length and throughput against fixed timing.

VI. DISCUSSION

6.1 Comparison Of Approaches

Table II compares control approaches. Fixed timing is simple, actuated control reacts to detectors, adaptive systems optimize continuously, ML prediction offers lane-specific timings and RL can learn complex policies but needs extensive simulation.

Approach	Adaptivity	Data Need	Deployment
Fixed-time	None	Low	Easy
Actuated	Low–Medium	Detectors	Easy
Adaptive (SCOOT / SCATS)	Medium–High	Detectors	Moderate
ML green-time prediction	High	Counts + history	Moderate
Reinforcement learning	Very high	Simulation	Hard

TABLE II Comparison of Signal Control Approaches

6.2 Open Challenges And Future Work

Table III summarizes challenges. Future work includes coordinated control of corridors, RL fine-tuned on real data, pedestrian and emergency detection and integration with city traffic management centres.

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Challenge	Mitigation
Detection errors	Robust detectors; sensor fusion
Mixed Indian traffic	Local training data; vehicle classes
Pedestrian safety	Minimum crossing times
Network coordination	Corridor-level models
Trust of authorities	Interpretable models; pilot trials

TABLE III Challenges and Mitigation

VII. CONCLUSION AND FUTURE WORK

Fixed-time traffic lights waste time and fuel when they ignore real demand. The reviewed literature shows how adaptive systems, traffic prediction and reinforcement learning can respond to actual conditions. A practical prototype that counts vehicles with cameras, predicts lane-wise green times with machine learning and enforces safety constraints can reduce waiting times and congestion, and provides a path toward fully learning-based signal control.

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