# Adaptive Traffic Control Based on the Synthesis of the Webster Model and Machine Learning

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Abstract: Urbanization processes and the increasing number of vehicles in cities have made traffic management a major challenge for urban infrastructure. Traditional traffic light control methods, including fixed-time control, do not take into account the stochastic and dynamic characteristics of real-time traffic flows, resulting in delays and congestion. This paper explores an adaptive traffic control system by synthesizing the classical Webster model with modern machine learning algorithms. The research methodology involves the use of machine learning models to collect high-frequency traffic data from sensors and predict future traffic intensity. The prediction values are integrated into Webster formulas, allowing for dynamic determination and application of green signal duration in real time. The simulation modeling results show that the efficiency of the intersection is significantly improved, and the average vehicle delay and queue length are significantly reduced compared to traditional fixed-time control methods. The theoretical significance of the presented study lies in strengthening the connections between the two methods, namely traditional optimization and data-driven machine learning methods, and in practical terms, it is based on improving the efficiency of traffic flow management at intersections. By implementing this dual-approach system, city governments can move from reactive to proactive management, thereby increasing the stability and efficiency of the transport network.

## 1 INTRODUCTION

As the pace of urbanization and economic growth accelerates worldwide, transport systems are increasingly becoming one of the most critical yet most complex components of urban infrastructure. Today, in major cities of Uzbekistan, particularly in the capital Tashkent, the population has reached nearly 3 million, while the number of vehicles in daily circulation exceeds 911,000, which has led to serious crises in traffic-flow management [1], [2].

The sharp increase in private car use, coupled with the insufficient development of public transport, has resulted in persistent congestion on urban streets, with increasingly evident socio-economic and environmental consequences. According to analytical assessments, inefficiencies and congestion within the transport and logistics system cause economic losses equivalent to 10-12% of the country's GDP [1]-[4].

In addition, the environmental and public health dimensions of the problem are highly pressing. While low-speed traffic significantly increases the share of harmful vehicle emissions in overall air pollution, excessive noise pollution contributes to a rise in nervous system and cardiovascular diseases among the population, as well as a decline in overall health and quality of life [2], [5].

To address these systemic challenges and ensure the sustainable development of the transport sector, reliance on international experience is an essential necessity. In this regard, enhancing the attractiveness of public transport, constructing toll highways that connect major cities, and widely deploying artificial intelligence technologies for intelligent traffic management are considered key solutions [4].

Accordingly, the main goal of this study is to develop and scientifically substantiate an adaptive control approach that increases the efficiency of traffic flow management in the urban road network by synthesizing the theoretical foundations of the Webster signal timing model with machine learning methods. To this end, the study involves monitoring and predicting traffic flow parameters in real time, calculating optimal cycle and phase separation using the Webster model, and proposing dynamic adaptation mechanisms that integrate traffic flows predicted based on machine learning models with the Webster model. As a result, methodological and algorithmic foundations are created to support the practical application of control solutions that reduce traffic congestion, increase road capacity, reduce fuel consumption and harmful emissions, and contribute to the sustainable development of the urban transport system.

# 2 MANUSCRIPT PREPARATION

## 2.1 Literature review and Theoretical Foundations

Traffic flow management has evolved for more than a century, beginning with early mechanical and manual signaling systems designed to ensure orderly and safe movement on roads. The first recorded manual semaphore signals appeared in London in 1868, followed by electric traffic lights in the early twentieth century. [6] As electrical engineering and manufacturing technologies advanced, these early systems were gradually standardized, enabling cities to coordinate intersection control more effectively.

Historically, urban traffic flow regulation has shifted from manual control to automated approaches. Two main traditional methods of traffic signal control can be distinguished:

- A fixed-time control method in which the duration of each phase of the traffic light cycle is predetermined and is based only on historical traffic flow data. Typically, engineers develop several static time schedules for different periods of the day, such as morning rush hour, evening rush hour, and off-peak hours. For many years, the basis for calculating such cycles has been the Webster mathematical model (1958), which allows determining the optimal cycle length to minimize vehicle delays. The main disadvantage of fixed-time control is that it cannot adapt to traffic conditions, i.e., it cannot take into account random flow fluctuations, accidents, or unexpected traffic jams [7], [8].
- Actuated control systems are the next step in control methods, using detectors (inductive loops, radar, cameras) to detect vehicles. These systems are divided into semi-actuated and fully actuated types. Using sensors, the control device can extend the green signal time if there is a demand in the traffic flow or skip the phase altogether if there is no demand. Although this method responds more effectively to road conditions, its main drawback is that traffic lights usually operate locally and it is difficult to coordinate them on a network-wide scale [7].

To overcome the problems of traffic light coordination in road networks, engineers traditionally use coordinated control methods to synchronize intersections to create a “green wave.” These methods have evolved into classic adaptive traffic light control systems such as SCOOT and SCATS, which can change phase durations in real time. However, the underlying algorithms for estimating delays and queues still rely heavily on classical queuing theory [9].

The Webster method is one of the classical approaches widely used to estimate the initial duration of a traffic light cycle based on traffic demand and lane capacity. Fixed-time control is based on a long-term statistical analysis of traffic flow on specific road sections, in which the flow rates for each direction are calculated and used to develop predetermined traffic light signals [10]. This approach predetermines the phases and their durations, and moves to the next phase when the specified time interval expires [11].

The model proposed by F. W. Webster is a fundamental basis for estimating traffic light cycle times and delays at individual intersections in transportation engineering. This approach is based on queuing theory, and its mathematical expression is usually expressed by two basic equations (1) and (2). [12]-[14].

1) Optimal cycle length (1) [15]:

$$C_0 = \frac{1.5L + 5}{1 - Y}, \tag{1}$$

where L is the total lost time per cycle (s), including start-up lost time and clearance (all-red) intervals; Y is the sum of critical flow ratios over all phases, $Y = \sum y_i$, with $y_i = q_i / s_i$, where $q_i$ is the approach flow (arrival rate) and $s_i$ is the saturation flow.

2) Average control delay (2) [8]:

$$d = \frac{C(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2q(1-x)} - 0.65\left(\frac{C}{q^2}\right)^{1/3} x^{(2+5\lambda)}. \tag{2}$$

Each term of this equation represents a separate physical process:

- The first term is the deterministic delay that occurs when arrivals and departures are assumed to be uniform, where $\lambda = \frac{g}{c}$ is the effective green share, and $x$ is the saturation level;
- The second term is the additional delay caused by stochastic arrivals and queue growth;
- The third term is an adjustment term introduced to better adapt the analytical results to practical observation (field) conditions.

These analyses show that the Webster method is a traditional basis for traffic light-controlled intersection control. However, this method is mainly designed for fixed and stable traffic flow conditions. In modern urban conditions, traffic flows are variable, requiring real-time prediction and adaptive control systems. In this context, the following sections describe the development of a single conceptual and algorithmic framework for adaptive traffic light control that integrates the analytical strengths of the Webster model with machine learning methods while retaining its main theoretical advantages.

The overall results of the analysis show that traffic flow control is evolving from traditional approaches to advanced technologies based on artificial intelligence Figure 1.

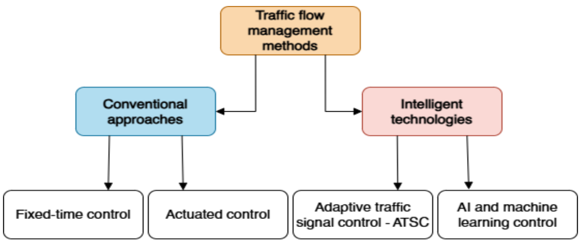


Figure 1: Traffic flow management methods.

Machine learning and artificial intelligence technologies in intelligent transportation systems enable the transition from rigid control to flexible, predictive, and optimized control systems. The application of machine learning in ITS can be broadly divided into four main areas. Including traffic flow management, safety, user comfort, and autonomous control. [16].

## 2.2 Data Collection and Model Selection

Methods for collecting and processing traffic flow data constitute an important scientific and practical basis of modern transport engineering. The main goal of this process is to reliably determine such indicators as the volume, speed and density of traffic flow, and the obtained data are used to make decisions on the design of road infrastructure, adjust the operating modes of traffic light facilities and develop traffic management strategies.

In recent decades, transport data collection technologies have developed significantly, expanding from simple methods such as manual counting to automated systems that allow for collecting data in real time across the entire transport network.

Despite the simplicity of the manual counting method, it requires the involvement of personnel to record vehicles passing at specified points at a certain time interval. Therefore, the completeness and accuracy of the data may decrease due to high labor costs and errors associated with the human factor. Passive sensors, including pneumatic tubes and rubber hoses, record the number of vehicles passing over them, providing flow data used in traditional origin-destination estimation approaches. Invasive and non-invasive technologies such as inductive loop detectors, radar sensors, infrared devices, and acoustic sensors are also widely used to measure traffic flow, speed, and occupancy [17]-[20].

Despite their reliability, these infrastructure-based conventional methods are characterized by several significant limitations, including high installation and maintenance costs, disruption of traffic flow during deployment, increased failure rates, and an inability to provide detailed information on vehicle movement trajectories [21], [22].

The emergence of intelligent transportation systems has created new opportunities for collecting traffic data using innovative approaches such as crowdsourcing, floating-car data using Bluetooth technology, unmanned aerial vehicles (UAVs), and radio-frequency identification (RFID) Real-time traffic video streaming, including roadside video surveillance and aerial photography, has become widely used for traffic monitoring. The ability to simulate video streams makes it possible to collect micro-traffic data both instantly and over the long term, providing high-resolution information in both time and space for analyzing individual and collective driver behavior [23], [24].

The review of the literature on data collection indicates that a wide range of traffic-flow detection sensors has been developed (Fig. 2), and the selection of a specific sensor type depends on the intended application. In this study, traffic data were collected using video cameras, manual counts, and synthetic datasets, as summarized in Table 1.

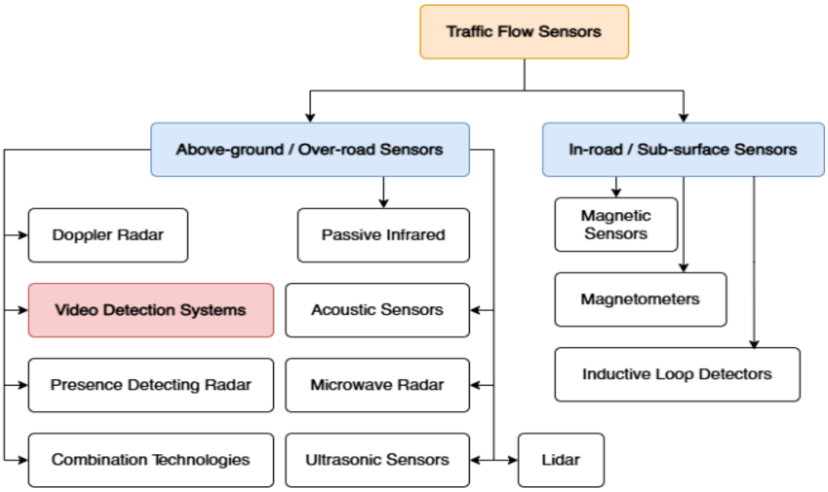


Figure 2: Traffic flow management methods.

Table 1: This caption has one line, so it is centered.

| № | datetime | vehicles | density | velocity |
|---|---|---|---|---|
| 1 | 2023-01-01 00:00:00 | 120 | 1.97 | 61 |
| 2 | 2023-01-01 01:00:00 | 140 | 2.33 | 60 |
| … | | … | … | … |
| 6343 | 2023-01-01 22:00:00 | 780 | 12.28 | 63.5 |

In the reviewed studies, a wide range of machine learning (ML) algorithms were tested to forecast traffic-flow intensity. Their results can be found in the cited literature [25], [26].

## 2.3 Webster Model and ML Synthesis Methodology

Using the developed software tool for determining the optimal cycle length and phase green times based on the Webster model, signal timing plans can be computed rapidly for a specified time interval:

Algorithm 1 represents the classical Webster-based optimization procedure, where the optimal cycle length and phase green times are determined from the estimated traffic demand and saturation flow conditions. However, since the Webster model relies on accurate traffic-flow inputs, its effectiveness depends strongly on the availability of reliable demand estimation.

In the active mode, the system continuously updates traffic-flow parameters using real-time data and recalculates the cycle length and green times at each $\Delta t$ interval. As a result, the signal plan is dynamically adjusted to the prevailing conditions at the intersection.

```
BEGIN
    INPUT n, f, q, s, g, x, lambda
    SET n = a, f = b
    FOR i = 1 TO n DO
        y_i = q_i / s
    END FOR
    y_max_f = MAX(q_i_f / s)
    Y = SUM(y_max_f)
    L = (n * l) + R
    c = (1.5 * L + 5) / (1 - Y)
    FOR j = 1 TO f DO
        g_j = (y_max_j / Y) * (c - L)
    END FOR
    FOR i = 1 TO n DO

        A = (c * (1 - lambda)^2) / (2
* (1 - lambda * x))
        B = (x^2) / (2 * q * (1 - x))
        D = -0.65 * (c / q^2)^(1/3) *
x^(2 + 5 * lambda)
        d_i = A + B - D
    END FOR
    d_mean = (1 / n) * SUM(d)
    ANALYZE results
END
```

Algorithm 1: Webster-based traffic signal timing optimization.

In the proactive mode, ML-based forecasts are used to estimate $\hat{q}_i(t+\Delta t)$ for several future time instants, and the Webster equations are then applied to pre-compute the corresponding optimal $C$ and $g_p$ values, which are planned in advance. Such "pre-

prepared" timing plans enable the controller to respond to abrupt changes in demand without delay, curb excessive queue growth, reduce delays, and ensure stable operation of the control system. Accordingly, the synthesis of the Webster model with forecasting mechanisms provides a theoretical and practical foundation for establishing efficient, adaptive, and reliable intelligent traffic-signal control at urban intersections.

As noted above, an ML model is used to obtain the approach-specific flow forecasts $\hat{q}_i(t+\Delta t)$. These forecasts are then employed to compute the critical flow ratios $\hat{y}_i = \hat{q}_i/s_i$and, for each signal phase, $\hat{y}_p = max_{\ i\in p}\, \hat{y}_i$ after which the aggregate critical ratio is calculated as $\hat{Y} = \sum_p \hat{y}_p$. To ensure stability, the condition $\hat{Y} < 1$ is enforced (in practice, $\hat{Y} \leq 1-\varepsilon$ otherwise, a safe control regime is activated for the oversaturated case.

Based on the Webster equation, the optimal cycle length is obtained as (3) and is subsequently constrained to the interval $\left[C_{\min}, C_{\max}\right]$.

$$\hat{C}_0 = \frac{(1.5L+5)}{(1-\hat{Y})}. \qquad (3)$$

Next, given the effective green time and the phase green splits are allocated according to (4) while satisfying the bounds $\left[gp, max_{p,min}\right]$ and ensuring consistency of the total via normalization.

$$G = C - L$$

$$g_p = G \cdot (\hat{y}_p/\hat{Y}). \qquad (4)$$

The integration architecture of these ML and Webster models is shown in Figure 3.

Algorithm 2 extends the conventional Webster optimization by incorporating machine-learning-based traffic prediction. Unlike the traditional Webster approach, where current traffic demand is directly used for signal timing calculation, the proposed framework uses predicted future traffic states to proactively determine cycle lengths and green-time allocation. Therefore, the controller can adapt to changing traffic conditions before congestion develops.

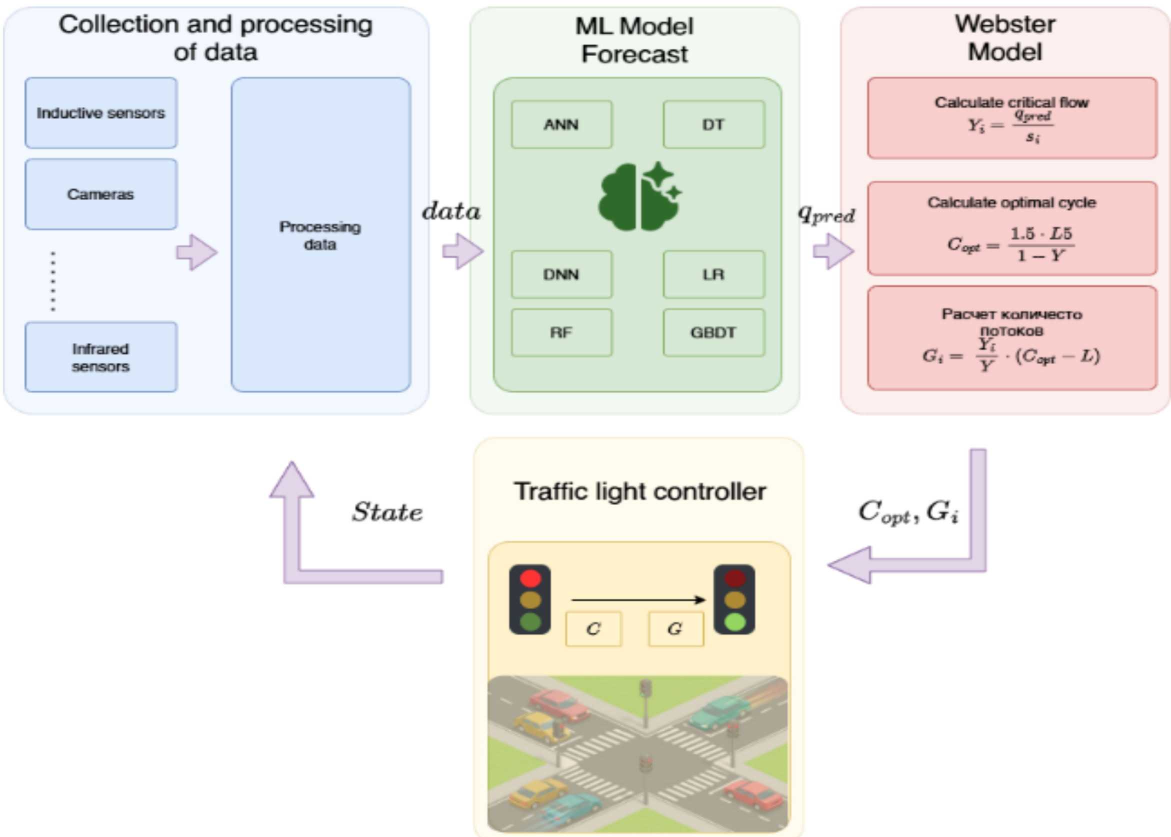


Figure 3: Integrated framework for adaptive traffic flow control using machine learning and webster method

```
BEGIN
    INPUT n, f, q, s, g, x, lambda
    SET n = a, f = b
    DEFINE green_range [g_min, g_max]
    IDENTIFY saturation_flow (s)
    PREDICT pred_flow USING ML_Model
    FOR i = 1 TO n DO
        y[i] = q_pred[i] / s
    END FOR
    y_max_f = MAX(q_pred[f] / s)
    Y = SUM(y_max_f)
    L = (n * l) + R
    c = (1.5 * L + 5) / (1 - Y)
    FOR j = 1 TO f DO
        g[j] = (y_max_f[j] / Y) * (c
- L)
    END FOR

    FOR i = 1 TO n DO
        A = (c * (1 - lambda)^2) / (2
* (1 - lambda * x))
        B = (x^2) / (2 * q_pred * (1
- x))
        D    =    -0.65    *    (c    /
q_hat^2)^(1/3) * (x^(2 + 5 * lambda))
        d[i] = A + B - D
    END FOR
    d_mean = (1 / n) * SUM(d)
    ANALYZE results
    IF  (c_min  <=  c  <=  c_max)  AND
(g_min <= g <= g_max) THEN
        PROCEED TO output_results
    ELSE
        SET c = c_max
        SET g = g_max
    END IF
END
```

Algorithm 2. ML-assisted webster adaptive signal control algorithm.

## 2.4 Experimental Part and Simulation

During the study, the AnyLogic software platform was used to model and analyze traffic flows, and an intersection located in Chirchiq city was selected as a representative case. The intersection comprises three main approaches and one minor approach. On the primary approaches, entry and exit lanes are separated, and several exit lanes are dedicated to specific turning movements. The traffic signal was operated initially under a fixed-time regime and subsequently under the ML-Webster regime. The geometric layout of the intersection is presented in Figure 4.

Within the experimental framework, the proposed ML-Webster approach (i.e., forecasting approach-specific traffic flows using ML and precomputing the optimal cycle length and phase green times via the Webster equations) was compared with the conventional fixed-time regime. Performance was evaluated using three key indicators: average travel time, average delay, and average queue length. The results are shown in Figure 5, and the following findings were recorded.

The experimental data demonstrated that the suggested ML-Webster model displayed markedly enhanced performance in comparison to the traditional fixed-time regime. The average time it takes for cars to travel went from 71 to 56 minutes. This means that traffic is now more efficient overall. The average wait time at the intersection also went down, from 37.19 to 21.6. One of the most important signs, the average queue length, went down from 3.66 to 2.02. In short, the ML-Webster model was better than the fixed-time regime in all three areas. This meant less traffic and better efficiency at the intersection.

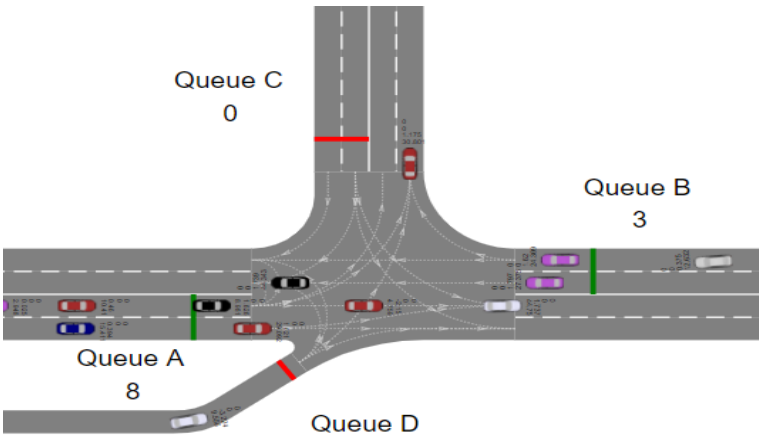


Figure 4: Simulation-based representation of the selected intersection for traffic flow analysis.

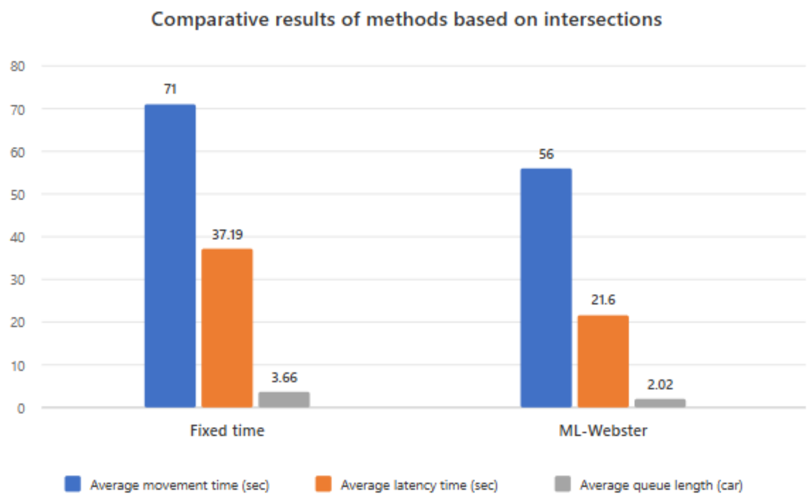


Figure 5: Comparative evaluation of traffic signal control methods based on average delay, movement time, and queue length.

# 3 CONCLUSIONS

This study utilized the practical functionalities of the Webster method and the predictive capabilities of machine learning techniques to create a unified adaptive control system designed to mitigate congestion and delays at urban intersections. The suggested ML-Webster method works in both real-time (reactive) and pre-planned (proactive) modes. This means that traffic flow parameters can be watched all the time, flow can be predicted, and the best cycle lengths and phase green times can be changed on the fly.

The experimental results derived from a simulation model created in the AnyLogic environment for a specific intersection in Chirchik city validated the efficacy of the proposed methodology. The ML-Webster mode was found to significantly reduce the average travel time, delay, and queue length compared to the traditional fixed-time control of the proposed system. So, when the Webster method is used with machine learning-based predictions, it gives a strong scientific and practical basis for making cities more adaptable to changing conditions.

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