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Research Article

Passenger-weighted Fuzzy Logic Traffic Signal Control with Congestion Risk Prediction for Urban Public Transport Efficiency

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Abstract

Signalized intersections are the main bottlenecks of urban street networks, and in medium-sized cities of Uzbekistan buses and minibuses share the same lanes with private cars and are delayed in the same queues. Conventional signal timing, including most fuzzy logic controllers, treats every vehicle equally and therefore assigns the same weight to a car with one occupant and to a bus carrying forty passengers. The objective of this study is to develop a traffic signal control model that reduces person delay at isolated signalized intersections by combining the passenger load of public transport vehicles with a short-term prediction of congestion. The method has three components. First, each signal cycle is classified as free, pre-congested or congested according to the number of cycles a queued vehicle must wait, and the sequence of cycle states is described by a three-state Markov chain whose transition matrices depend on the degree of saturation; arrival rates are forecast with Holt exponential smoothing. Second, a passenger priority index is introduced that compares the number of public transport passengers waiting on the green and on the conflicting approach. Third, a Mamdani fuzzy inference system with four inputs (forecast degree of saturation of the green and red approaches, passenger priority index and congestion-risk difference) and 81 rules corrects the Webster green time within −15 to +20 s under pedestrian and cycle-length constraints. The controller was tested in a second-by-second simulation of a two-phase intersection with input parameters representative of arterial streets in Namangan, using 20 replications for each of three demand levels. Compared with fixed-time Webster control, the proposed controller reduced mean passenger delay by 12.8% at design demand and by 17.5% under oversaturation, and reduced the share of congested cycles from 5.7% to 3.9%. A vehicle-based fuzzy controller achieved reductions of only 8.2% and 5.7%, respectively, while at low demand the differences between controllers were not statistically significant. The results indicate that weighting signal decisions by passenger load is effective when demand approaches capacity, and that the congestion-prediction input protects the conflicting approach from queue growth at the cost of a small part of the passenger benefit. The model does not require loop detectors or bus-to-signal communication and can be implemented with video detection and operator GPS data; field calibration on Namangan intersections is the next step.

Keywords

Traffic Signal Control, Fuzzy Logic, Transit Signal Priority, Person Delay, Congestion Prediction, Markov Chain, Urban Public Transport

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1. Introduction

Urban growth and rapid motorization increase traffic demand faster than the capacity of street networks can be expanded. In Uzbekistan, the number of motor vehicles owned by individuals exceeded 4.9 million in April 2026 and grew by 344.6 thousand within one year [1]. At the same time, the national reform of public transport has raised daily bus trips from 18,000 to 45,200 and daily passengers from 0.9 to 2.3 million over three years [2]. In Namangan, a city of 731.3 thousand inhabitants [3], earlier studies found that 21 of the 36 bus routes ran along A. Navoi Street, which made its intersections a major source of delay and motivated proposals for dedicated bus lanes [4]. Because buses and minibuses mostly operate in mixed traffic, every queue at a signalized intersection delays tens of public transport passengers together with private car users.

The theory of signal timing is well established. Webster derived the delay formula and the optimal cycle length for fixed-time control [5], and the Highway Capacity Manual evaluates signalized intersections by the average control delay per vehicle, with delays above 80 s classed as level of service F [6]. Adaptive systems such as SCOOT and SCATS adjust timings from detector data but require dense detection and significant investment [7, 8]. Fuzzy logic offers a lower-cost alternative because it does not need an exact mathematical model of traffic and can encode expert rules. Pappis and Mamdani built the first fuzzy controller for a traffic junction [9]; later work extended the approach to isolated intersections with uneven demand [10] and to two-stage controllers that first estimate demand and then decide on phase extension [11]. Kushchenko combined statistical prediction of pre-congestion states with a fuzzy controller whose inputs were the number of queued vehicles, its rate of change and road surface friction [12].

These controllers optimize vehicle-based measures. Transit-oriented research has shown that person-based criteria give different and often better solutions. Furth and Muller demonstrated that conditional bus priority reduces disruption to general traffic [13]. Christofa and Skabardonis optimized signals in real time by minimizing total person delay, weighting buses by occupancy [14], and later extended the method to arterials [15]. Xu et al. resolved conflicting priority requests at network level with a multi-agent fuzzy controller [16], and Handrybida and Sevastianov proposed a fuzzy controller that considers transit delay and passenger capacity [17]. Mazaheri developed conditional priority strategies based on onboard passengers and schedule adherence and showed in VISSIM that they outperform conventional priority, which grants green time even to empty buses [18]. These methods, however, rely on real-time vehicle-to-infrastructure communication and detailed detection, and they react to current conditions without predicting congestion. Recent reviews of deep-learning congestion prediction note that predicting congested states is harder than predicting free flow and that such models need large continuous datasets [19], which are not yet available in medium-sized cities of Uzbekistan.

This study addresses the gap by combining three elements in one controller: a cycle-level prediction of congestion based on a saturation-dependent Markov chain, a passenger priority index that compares public transport passengers on conflicting approaches, and a Mamdani fuzzy inference system that corrects the Webster green time. The model is designed to work with video detection and operator GPS data. Its performance is evaluated by simulation against fixed-time control and against a vehicle-based fuzzy controller. The main finding is that passenger weighting reduces mean passenger delay by 12.8–17.5% when demand approaches or exceeds capacity, and that the prediction input reduces the share of congested cycles.

2. Materials and Methods

2.1. Problem Statement and Control Framework

A two-phase isolated signalized intersection is considered: phase 1 serves the arterial approach carrying most bus routes, and phase 2 serves the cross street. At the start of each green phase the controller determines the green duration as a correction of the base timing:

$$g_k = \min(g_{\max}, \max(g_{\min}, g^0 + \Delta g_k)) \quad (1)$$

where g^0 is the base green time, Δg_k is the correction produced by the fuzzy inference system, and $g_{\min}$ and $g_{\max}$ are limits. The base timing follows Webster [5]:

$$C^0 = \frac{1.5L + 5}{1 - Y}, \; g^0{}_i = \frac{(C^0 - L)y_i}{Y} \quad (2)$$

where L is the lost time per cycle, $y_i = q_i/s_i$ is the flow ratio of phase i and $Y = \Sigma y_i$. Because the controller only corrects the base timing, it can safely revert to fixed-time operation if the input data fail. The control framework is shown in Figure 1: video detectors provide queues, arrivals and the vehicle mix; the transport operator's GPS monitoring and e-ticketing data provide the location and load of buses; a prediction block computes three inputs and a passenger block computes the fourth; a constraint block enforces safety limits.

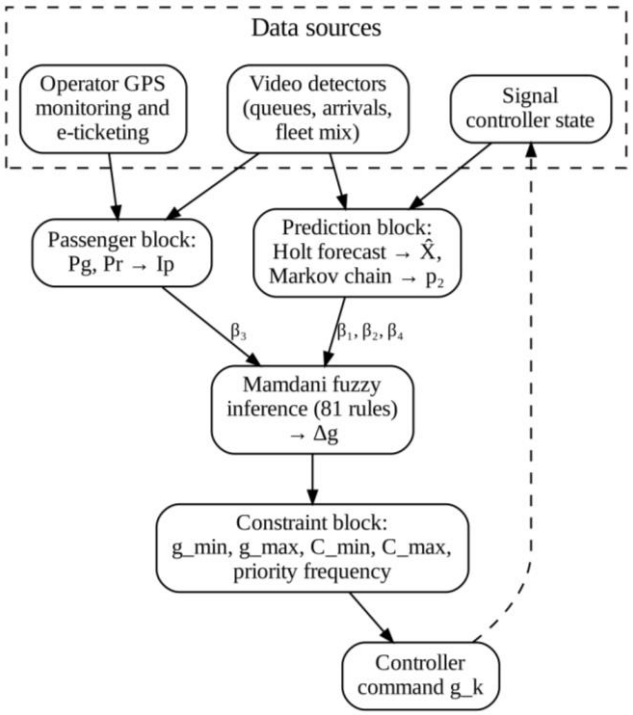


Figure 1. *Framework of the passenger-weighted fuzzy signal controller.*

The performance criterion is person delay, which weights each vehicle by its occupancy [14]:

$$D_p = \sum_i \sum_k n_{ik} \cdot o_k \cdot d_{ik} \quad (3)$$

where n_{ik} is the number of vehicles of type k on approach i, o_k their average occupancy and d_{ik} their average delay. With this measure a bus carrying 45 passengers has the same weight as about 35 cars with 1.3 occupants each.

2.2. Cycle State Classification and Congestion Prediction

2.2.1. Queue Balance and Cycle States

Queue evolution on an approach is described cycle by cycle. The residual queue at the end of green in cycle k is

$$Q_k^r = \max(0, Q_{k-1}^r + A_k - S_k) \quad (4)$$

where A_k is the number of arrivals and S_k the number of departures in passenger car units. Unlike the Webster delay formula, Equation (4) remains valid for oversaturated conditions. The number of cycles that the last queued vehicle must wait is

$$m_k = \left\lceil \frac{Q_{k-1}^r + A_k}{S_{\max}} \right\rceil \quad (5)$$

where $S_{max} = s \cdot g/3600$ is the maximum discharge in one green. Following practice in traffic engineering, where waiting through 1–3 cycles is not regarded as congestion, 3–5 cycles indicates a pre-congestion state and more than 7–8 min of waiting indicates congestion [12], each cycle is assigned one of three states: E0 (free) if $m_k \leq 2$; E1 (pre-congestion) if m_k = 3–4 and the waiting time $m_k \cdot C < 420$ s; and E2 (congestion) if $m_k \geq 5$, the waiting time exceeds 420 s or the queue spills back to the upstream intersection.

2.2.2. Saturation-dependent Markov Chain

The sequence of cycle states is modelled as a discrete-time three-state Markov chain (Figure 2). Transition probabilities are estimated from observed transitions N_{ij}:

$$p_{ij} = \frac{N_{ij}}{\sum_j N_{ij}} \quad (6)$$

Since the probability of congestion depends strongly on the degree of saturation, a single matrix underestimates the risk during peak intervals. Separate matrices $P(X)$ are therefore estimated for saturation classes (here $X < 0.90$ and $X \geq 0.90$), which makes the chain non-homogeneous. The state probabilities h cycles ahead are

$$p(k + h) = p(k) \cdot P(\hat{X})^h \quad (7)$$

where $p(k)$ is the indicator vector of the current state and $\hat{X}$ is the forecast degree of saturation. Arrival rates are forecast with Holt exponential smoothing [20] using smoothing constants $\alpha = 0.4$ and $\beta = 0.1$.

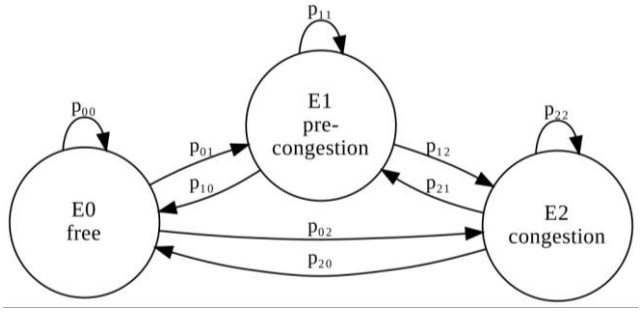


Figure 2. *Three-state Markov chain of cycle states at a signalized approach.*

2.3. Input Variables of the Fuzzy Controller

The controller uses four inputs. The first two are the forecast degrees of saturation of the green approach (g) and of the conflicting red approach (r):

$$\beta_1 = \hat{X}_g = \frac{Q_g + \hat{\lambda}_g g^0{}_g}{s_g g^0{}_g/3600} \quad (8)$$

$$\beta_2 = \hat{X}_r = \frac{Q_r + \hat{\lambda}_r C^0}{s_r g^0{}_r/3600} \quad (9)$$

where Q is the current queue and $\hat{\lambda}$ the forecast arrival rate. The third input is the passenger priority index proposed in this study:

$$\beta_3 = I_p = \frac{P_g - P_r}{P_g + P_r + P_0} \quad (10)$$

where P_g is the number of public transport passengers queued on the green approach or arriving within 20 s, P_r is the number of passengers queued on the red approach and $P_0 = 20$ is a smoothing constant. The index lies between −1 and 1 and resolves conflicting priority needs: when buses wait on both approaches, priority goes to the approach with more passengers. Occupancy is estimated from a five-level visual load scale applied to video records or from e-ticketing data. The fourth input is the difference in congestion risk predicted by Equation (7) for the horizon $h^* = 2$ cycles:

$$\beta_4 = \Delta p_2 = p_2^g(k + h^*) - p_2^r(k + h^*) \quad (11)$$

2.4. Fuzzy Inference System

A Mamdani inference system [21] was chosen because its rules can be read and checked by traffic engineers. Inputs β_1 and β_2 (range 0–1.5) have the terms Low, Medium and High; β_3 and β_4 (range −1 to 1) have the terms Negative, Neutral and Positive. The output Δg (range −15 to +20 s) has five terms: Large cut, Cut, No change, Extend and Large extension. The asymmetric range follows transit priority practice, where green extensions are usually limited to 10–20 s and red truncation is smaller than extension [18]. Trapezoidal functions are used at the range boundaries and triangular functions inside (Table 1, Figure 3).

Table 1. *Parameters of the membership functions.*

Variable	Term	Parameters
β_1, β_2	Low / Medium / High	[0, 0, 0.55, 0.75] / [0.60, 0.80, 1.00] / [0.85, 1.05, 1.5, 1.5]
β_3	Negative / Neutral / Positive	[−1, −1, −0.5, 0] / [−0.4, 0, 0.4] / [0, 0.5, 1, 1]
β_4	Negative / Neutral / Positive	[−1, −1, −0.4, −0.1] / [−0.25, 0, 0.25] / [0.1, 0.4, 1, 1]
Δg, s	Large cut / Cut	[−15, −15, −12, −6] / [−12, −6, 0]
	No change / Extend / Large extension	[−5, 0, 5] / [8, 14] / [10, 16, 20]

Four values denote a trapezoidal and three values a triangular membership function.

The rule base contains $3^4 = 81$ rules of the form "IF β_1 is A AND β_2 is B AND β_3 is C AND β_4 is D THEN Δg is E". To make the rule base consistent, each combination is assigned a priority score

$$S = \tau(\beta_1) - \tau(\beta_2) + \tau(\beta_3) + 0.75\tau(\beta_4) \quad (12)$$

where $\tau = -1, 0, +1$ for the first, second and third term. Scores $S \le -2$, $-2 < S \le -0.75$, $|S| < 0.75$, $0.75 \le S < 2$ and $S \ge 2$ map to Large cut, Cut, No change, Extend and Large extension. β_4 receives a lower weight because it is a probabilistic estimate. Two safety rules override the score: extension is forbidden when the red approach is highly saturated and its congestion risk is higher (β_2 High, β_4 Negative), which prevents spillback; and extension is forbidden when the green approach is lightly loaded without a passenger advantage, which prevents priority for empty buses. The final rule base has 9 Large cut, 22 Cut, 20 No change, 21 Extend and 9 Large extension rules. Rule strength is computed with the minimum operator, implication with minimum, aggregation with maximum, and the crisp output with the centroid method:

$$y^* = \frac{\sum_j y_j \cdot \mu(y_j)}{\sum_j \mu(y_j)} \tag{13}$$

The minimum green satisfies the pedestrian condition $g_{min} \ge t_0 + B/v_p$, where t_0 = 5–7 s, B is the crossing length to the refuge island and v_p = 1.0–1.2 m/s [6]; the cycle length is kept between 50 and 130 s, and a Large extension cannot be granted to the same approach in two consecutive cycles.

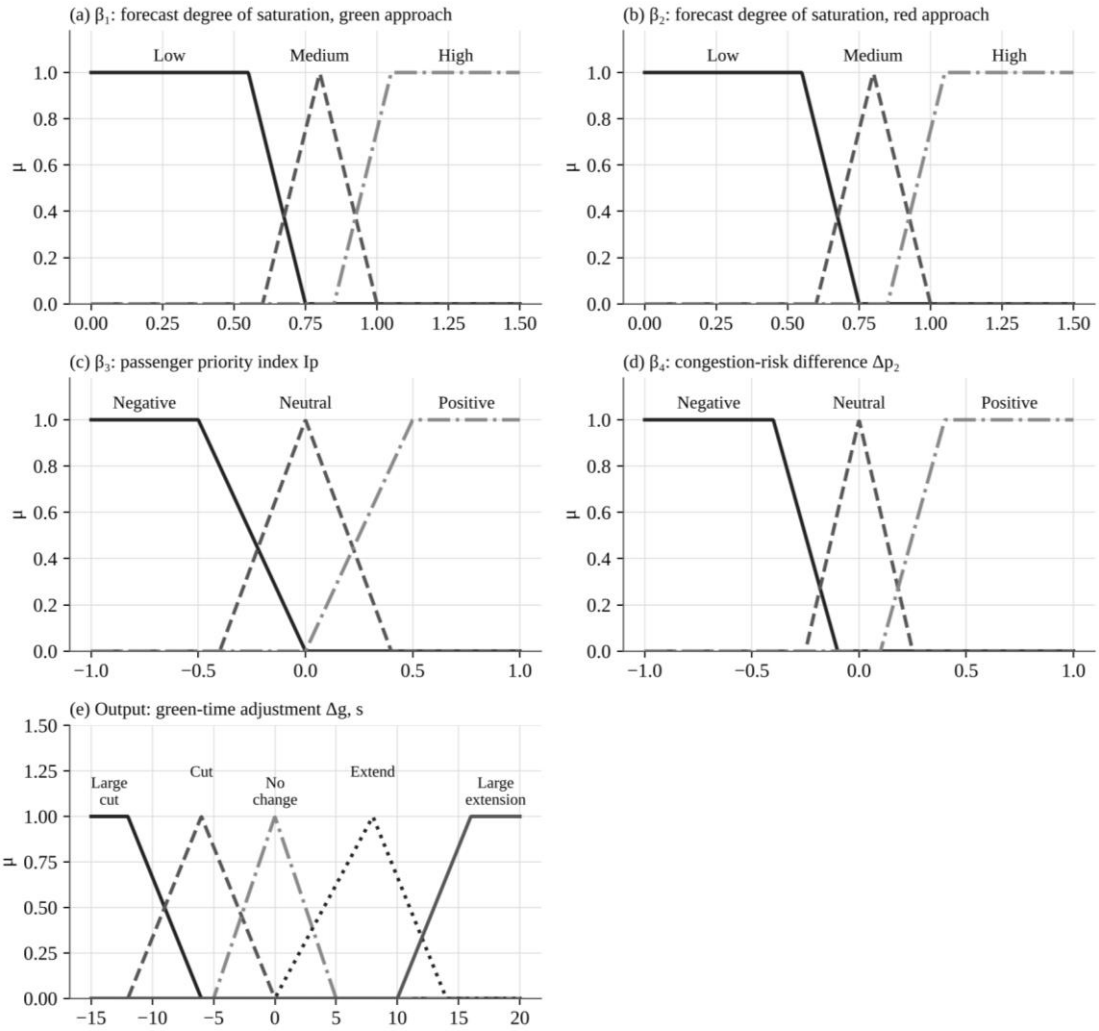


Figure 3. *Membership functions of the input variables (a–d) and of the output variable (e).*

2.5. Simulation Experiment

The controller was implemented in Python with NumPy; one inference takes about 1 ms. It was evaluated in a second-by-second discrete simulation of a two-phase intersection in which each vehicle is a separate object with arrival time, type, passenger car equivalent and occupancy. Arrivals follow Poisson processes whose rates vary over a two-hour peak period with a maximum in the middle; queues discharge first-in first-out at the saturation flow. Input values represent arterial intersections in Namangan and are listed in Table 2; they are assumptions to be replaced by field data in the calibration stage.

Table 2. Input parameters of the simulation experiment.

Parameter	Arterial	Cross street
Saturation flow, pcu/h	3600 (2 lanes)	1800 (1 lane)
Cars, veh/h (peak centre, 1.0 q)	1350	600
Minibuses, veh/h (mean load 9 pax)	70	30
Buses, veh/h (mean load 45 pax)	30	8
Car occupancy, pax	1.3	1.3
PCE: car / minibus / bus	1.0 / 1.5 / 2.5	1.0 / 1.5 / 2.5
g_min / g_max, s	15 / 70	12 / 50
Base timing: C^0 = 69 s; g^0, s	32.8	28.5

PCE: passenger car equivalent; lost time 4 s per phase.

Four controllers were compared: (1) fixed-time Webster control; (2) FLC-V, a vehicle-based fuzzy controller using only β_1 and β_2, close in content to the controller of Kushchenko [12]; (3) FLC-P, which adds the passenger priority index β_3; (4) the proposed FLC-PR with all four inputs. Three demand levels were simulated: low (0.9 q), design (1.0 q) and oversaturated (1.1 q). Each scenario was replicated 20 times with different random seeds, and the Markov transition matrices were estimated from separate training runs. Results are reported as means with 95% confidence intervals; the relative change against fixed-time control is $\delta = (D - D_{\text{fixed}})/D_{\text{fixed}} \cdot 100\%$.

3. Results

3.1. Behaviour of the Fuzzy Inference System

For the inputs $\hat{X}_g = 0.95$, $\hat{X}_r = 0.70$, $I_p = 0.45$ and $\Delta p_2 = 0.10$, fuzzification gives membership degrees Medium 0.25 and High 0.50 for β_1, Low 0.25 and Medium 0.50 for β_2, Positive 0.90 for β_3 and Neutral 0.60 for β_4. Four rules fire, three concluding Large extension and one Extend, and the centroid yields $\Delta g = +12.1$ s; the green of the approach with more passengers is extended by about 12 s. Figure 4 shows the control surface for $\beta_2 = 0.8$ and $\beta_4 = 0$. The passenger priority index affects the output as strongly as the degree of saturation: at medium saturation the green is extended if passengers are concentrated on the green approach and cut if they wait on the conflicting approach. The surface is smooth, which confirms the consistency of the rule base, and it can be stored in a controller as a look-up table.

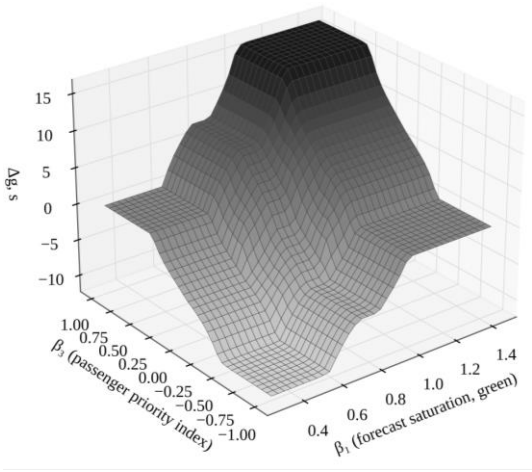


Figure 4. Control surface $\Delta g = f(\beta_1, \beta_3)$ at $\beta_2 = 0.8$ and $\beta_4 = 0$.

3.2. Simulation Results

Table 3. Simulation results (means of 20 replications).

Demand	Controller	Vehicle delay, s	Passenger delay, s (±95% CI)	Transit passenger delay, s	Arterial delay, s	Cross-street delay, s	Congested cycles,%	Passenger-hours lost
0.9 q	Fixed-time	20.2	20.9 ±0.6	21.7	17.9	25.4	0.0	47
	FLC-V	19.1	19.8 ±0.5	20.6	17.6	22.7	0.0	45

Demand	Controller	Vehicle delay, s	Passenger delay, s (±95% CI)	Transit passenger delay, s	Arterial delay, s	Cross-street delay, s	Congested cycles,%	Passenger-hours lost
1.0 q	FLC-P	20.2	20.5 ±0.5	20.8	17.9	25.4	0.0	46
	FLC-PR	20.2	20.4 ±0.5	20.8	17.9	25.3	0.0	46
	Fixed-time	30.7	31.2 ±3.5	31.8	26.6	39.7	0.2	80
	FLC-V	27.9	28.5 ±3.5	29.3	24.9	34.5	0.1	73
	FLC-P	27.2	26.7 ±2.1	26.0	21.8	39.4	0.0	68
	FLC-PR	27.2	26.6 ±2.1	26.0	21.8	39.4	0.0	68
1.1 q	Fixed-time	84.1	83.8 ±8.9	83.4	70.4	114.7	5.7	232
	FLC-V	79.3	79.2 ±8.7	79.0	66.8	107.5	5.1	219
	FLC-P	68.7	66.3 ±8.1	63.5	47.6	116.2	5.4	184
	FLC-PR	71.7	69.8 ±9.3	67.7	55.3	108.7	3.9	194

FLC-V: vehicle-based fuzzy controller; FLC-P: with passenger priority index; FLC-PR: proposed controller with passenger priority and congestion prediction.

Table 3 and Figure 5 summarize the simulation results. At low demand, all controllers performed similarly: the fuzzy controllers reduced mean passenger delay by 2–5%, and for FLC-P and FLC-PR the difference from fixed-time control was within the confidence interval (±2.7%). Queues cleared within each cycle, so there was little to gain from priority.

At design demand, FLC-V reduced passenger delay by 8.2 ±3.7% and FLC-PR by 12.8 ±4.3%. The delay of transit passengers fell from 31.8 to 26.0 s, and the passenger-hours lost in the two-hour peak decreased from 80 to 68. The cross-street delay stayed at the fixed-time level (39.4 vs 39.7 s), so the gain came mainly from reallocating green time towards the arterial, which carries most buses and minibuses. Congested cycles almost never occurred at this demand, and FLC-P and FLC-PR produced identical results, i.e., the prediction input was not activated.

Under oversaturation the differences were largest. FLC-V reduced passenger delay by 5.7%, FLC-P by 21.3% and FLC-PR by 17.5%. Although FLC-PR gave a slightly smaller passenger benefit than FLC-P, it reduced the share of congested cycles from 5.4% to 3.9% (from 5.7% under fixed-time control, a 32% reduction) and the cross-street delay from 116.2 to 108.7 s.

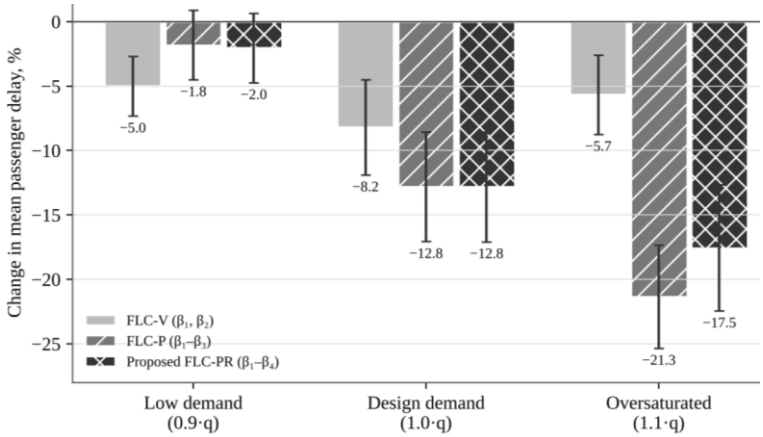


Figure 5. *Change in mean passenger delay relative to fixed-time control, with 95% confidence intervals.*

4. Discussion

The results confirm that the choice of control criterion matters more than the control technique. A fuzzy controller that counts vehicles (FLC-V) improves on fixed-time control mainly by adapting to fluctuations of demand, and its benefit decreases under oversaturation, when every approach is long-queued and vehicle counts no longer discriminate between approaches. Adding the passenger priority index changes the allocation of green time in favour of the approach that carries more people, and this effect grows with demand. This agrees with the person-based optimization of Christofa et al., who found that weighting buses by occupancy reduces total person delay compared with optimized fixed-time plans [14, 15], and with Mazaheri, whose occupancy-based conditional priority reduced per-person delay by 78% at low and 43% at high demand in a VISSIM corridor [18]. The smaller gains obtained here are expected because the proposed controller decides only once per phase, uses no bus-to-signal communication and includes safety rules that protect the conflicting approach.

The role of the congestion-prediction input is different from that of the passenger input. It does not increase passenger savings; instead, it balances them against the risk of queue growth on the cross street. In oversaturated conditions FLC-PR gave up about four percentage points of passenger delay reduction but cut the share of congested cycles by about a quarter compared with FLC-P. For a network this trade-off is important, because a queue that spills back to the upstream intersection blocks other movements and can affect public transport on other routes. The saturation-dependent Markov chain is essential for this purpose: with a single transition matrix the predicted probability of congestion two cycles ahead was about 0.2 even under high load, so the warning would rarely be issued.

The proposed approach differs from earlier fuzzy controllers in its inputs and from transit priority methods in its data requirements. Kushchenko's controller used queue length, its rate of change and road friction and did not consider passengers [12]; the multi-agent controller of Xu et al. and the conditional strategies of Mazaheri require real-time bus location and communication with the controller [16, 18]. The present model needs only video detection, which is already being installed in Uzbek cities, and the operator's GPS and e-ticketing data. The passenger priority index offers a simple way to handle conflicting requests, which both Xu et al. and Mazaheri identified as an open problem [16, 18].

The study has limitations. The simulation represents an isolated two-phase intersection and does not model turning movements, pedestrian flows, interactions between adjacent intersections or the effect of bus stops located before the stop line. Demand and occupancy values are representative assumptions rather than measurements, so the absolute delay values should be interpreted with caution; the relative comparison of controllers under identical random demand is the main result. The membership functions were set from engineering judgement and have not yet been tuned. Future work will calibrate a microscopic model of A. Navoi, Hamroh, A. Temur and I. Karimov avenues in Namangan in SUMO [22] or PTV Vissim using field video data, evaluate coordinated corridors, and estimate fuel and emission savings. The calibrated intersection model will also be integrated into the regional transport and logistics system, taking into account the state of transport and logistics services in Uzbekistan [23] and the model of the transport and logistics system of Namangan region [24].

5. Conclusions

A traffic signal control model was developed that combines cycle-level congestion prediction with the passenger load of public transport vehicles. Cycle states are classified by the number of cycles a queued vehicle waits, and their sequence is described by a Markov chain whose transition matrices depend on the degree of saturation, which allows the congestion risk to be predicted two cycles ahead. A passenger priority index compares public transport passengers on conflicting approaches and resolves conflicting priority needs. A Mamdani fuzzy inference system with four inputs, 81 rules and two safety rules corrects the Webster green time within −15 to +20 s.

In simulation with parameters representative of Namangan arterials, the proposed controller reduced mean passenger delay by 12.8% at design demand and by 17.5% under oversaturation compared with fixed-time control, while a vehicle-based fuzzy controller achieved 8.2% and 5.7%. Under oversaturation the prediction input reduced the share of congested cycles by 32% relative to fixed-time control and limited the delay increase on the cross street. At low demand the differences were not significant. Because the model works with video detection and operator data and falls back to the base timing, it is suitable for gradual deployment in medium-sized cities; field calibration and network-level testing are the next steps.

Abbreviations

FLC	Fuzzy Logic Controller
FLC-V	Vehicle-based Fuzzy Logic Controller
FLC-P	Fuzzy Logic Controller with Passenger Priority Index
FLC-PR	Fuzzy Logic Controller with Passenger Priority and Congestion Risk Prediction
TSP	Transit Signal Priority
PCE	Passenger Car Equivalent
CI	Confidence Interval
GPS	Global Positioning System
SUMO	Simulation of Urban Mobility

Author Contributions

Sidikov Otabek Abdunosir Ugli: Conceptualization, Data curation, Investigation, Methodology, Software, Writing – original draft

Tukhtabayev Mirzokhid Akhmadjanovich: Conceptualization, Formal Analysis, Methodology, Supervision, Validation, Writing – review & editing

Data Availability Statement

The data is available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Biography



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Research Field

Sidikov Otabek Abdunosir Ugli: Urban Passenger Transport, Traffic Signal Control, Fuzzy Logic Control, Public Transport Priority, Traffic Flow Modelling, Congestion Prediction

Tukhtabayev Mirzokhid Akhmadjanovich: Transport Logistics, Intelligent Transport Systems, Urban Passenger Transport, Transport Telematics, Traffic Management, Electric Vehicles