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Dynamic Signal Timing Control Algorithm for Urban Traffic Evaluation at Complex Signalized Intersections

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Abstract At present, although some metropolitan areas have implemented density-based signal timing, the majority of traffic management systems still rely on static cycles or basic adaptive techniques. These methods are inadequate for managing complex urban traffic conditions, inter-signal coordination, and real-time traffic dynamics. This underscores the urgent need for intelligent, flexible traffic controllers that leverage real-time data and hybrid optimization methods to enhance traffic efficiency. To address the above challenge, this paper proposes a dynamic signal distribution method to replace traditional, unpredictable signal timing with optimized durations. Intersections are modeled as autonomous agents within a multi-agent system, enabling decentralized and adaptive traffic control. The proposed algorithms dynamically optimize phase sequences and signal durations to reduce congestion. Simulations were conducted for up to 300 iterations, and the performance was evaluated against traditional traffic models. The results demonstrated improved traffic efficiency, with average queue lengths and vehicle waiting times reduced to 89, 114, and 83 seconds, respectively, in the simulated scenario.

Keywords Data Collection; Network Optimization; Single Agent; Multi Agent; SUMO optimizer; Statistical Inference

AMS 2010 subject classifications 99B20; 90B99

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1. Introduction

At present, optimizing traffic signal timings has become progressively more essential due to exponential population growth, the rising preference for private vehicles over public transportation, the gap between theoretical planning and real-world traffic scenarios, and the growing need for practical, cost-effective solutions to manage traffic congestion. Many researchers have studied this issue and proposed various methods to improve existing traffic signal optimization techniques using queuing theory, which considers queues with a maximum length and assumes stochastic arrival times and finite service times. [1]-[2] developed a semi-Markovian queuing model and used a steady-state-dependent methodology to study the relationship between traffic flow density and speed. Their findings showed a notable decrease in average travel times, even with minor adjustments to peak-period signal timings. [3] proposed a signal distribution model to reduce vehicle waiting times by approximately 10–15 percent under heavy traffic conditions. The proposed model was validated using the VISSIM tool on traffic networks. [4] Followed the work of [3] by optimizing urban intersection traffic flow, considering traffic parameters and average queue length, and analyzing overall traffic management efficiency. In this complex system that effectively analyzes inter-vehicle spacing and provides optimized results. This method further optimized traffic networks by selecting service rates that minimize waiting times across various routes. [5] Proposed an M/G/C/C steady-state-dependent queuing model to minimize vehicle waiting time. [6] Utilized a convolutional neural network (CNN)

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combined with a queuing model to identify efficient signal flow patterns for different categories of road users in urban networks. Additionally, deep reinforcement learning (DRL) has emerged as an effective technique for traffic light optimization, overcoming the limitations of conventional approaches by learning optimal control strategies through interaction with the traffic environment. [7]-[8] has addressed the traffic signal issues and proposed the TLO incentive mechanism algorithm for traffic flow and traffic delay to optimize signal phase durations. Using the SUMO-optimized tool, obtain the efficient green signal length in a complex traffic network.[9] Implemented modern deep reinforcement learning (DRL) techniques in combination with the SUMO micro-simulator to design a traffic light control system for heavy traffic conditions. The model used a Deep Q-Network (DQN) approach with experience replay on discredited traffic data. As a result, it significantly reduced cumulative delay by 82 percent, queue length by 66, and travel time by 20 percent compared to a hidden-layer neural network agent. [10] Implemented the modern DRL techniques along with SUMO—Micro Simulator to design the traffic light control system for the heavy traffic signal system. Using the DQN approach and experience replay on discredited traffic data. This model significantly reduced the cumulative delay by 82, the queue length by 66, and the travel time by 20 compared to a hidden layer neural network agent. The policy gradient agent directly mapped visual traffic state actions, while the value-function agent evaluated the value of all control actions, selecting the best. Simulations in SUMO demonstrated both models' superior and stable performance in predicting the optimal traffic signal control policies. Further advancing the field, [11] introduced an actor-critic model utilizing a deep neural network to interpret real-time traffic data as sequential images of intersections. This approach outperformed conventional methods and other deep reinforcement learning (DRL) techniques by optimizing queue length, average delay, and vehicle throughput. Additionally, [12] proposed a reinforcement learning-based traffic light control strategy that incorporated function approximation techniques to enhance the performance of adaptive traffic management systems. Fuel usage at multi-junction signal stations has been addressed by [13]. This led to the development of a transportation network model and the optimization of transportation networks, fuel consumption, traffic signal configurations, and vehicle speed. [14] proposed a signal distribution control algorithm, using the Deep Q-Network (DQN) method to obtain new state values and optimize traffic flow in a dynamic signal system. [19] has developed urban transportation networks by employing multi-attribute decision-making to identify dynamic critical nodes, examining network structure, trip duration, and traffic volume to enhance traffic efficiency and reliability toward intelligent and sustainable transportation systems. [16] Investigated the major issues of delayed congestion in urban traffic systems. In this context, a person-based adaptive control technique was proposed, utilizing a three-layered dynamic programming framework to integrate connected vehicle data and assign traffic signal priorities based on person-level delay. The proposed algorithm predicts vehicle discharge times and significantly reduces average person delay in complex traffic signal systems. To enhance vehicle flow and reduce vehicle delay, [17]-[18] proposed a signal timing scheme based on a two-stage fuzzy logic controller. To estimate significant vehicle delay, simulation results and accuracy under uncertainty were compared with conventional methods using a fuzzy model. In order to increase traffic signal efficiency within sensor limitations in the urban traffic network model, [19] suggested a three-phase traffic signal control system. Here, the cell transmission model is used to maximize traffic flow fairness, shorten wait times, and enhance dynamic data sharing between nearby intersections. Now, urban traffic systems still rely on static or basic adaptive control techniques, even though density-based signal timing has been adopted to some extent. These methods lack the adaptability and intelligence required to manage complex intersections, inter-signal coordination, and real-time traffic dynamics. To improve traffic flow and system responsiveness, there is a significant research gap in the development of advanced, real-time, data-driven traffic control algorithms that incorporate intelligent agents and hybrid optimization techniques.

The Linear programming optimization model is computationally efficient and interpretable for the DRL alternative. But the DRL model will require a greater number of data sets and high computational costs and clear decision variables as cycle length times and flow compatibility. DRL demonstrates adaptability in high dynamics and needs more data; it lacks interpretability and has difficulty with constraint handling. The proposed addresses the gap by enabling structured optimization in complex intersections while also laying the foundation for hybrid systems that integrate LP's efficiency and transparency with DRL's adaptive learning, ultimately contributing toward robust, real-time traffic control in dense urban networks.

The proposed algorithm effectively optimizes traffic signal timing in complex urban environments; it aims to minimize computational complexity in urban traffic network problems. This study addresses a two-level problem: (i) the upper-level network provides customized route recommendations, and (ii) the lower-level network manages traffic dynamics to determine flow ratios at crossroad intersections. The system dynamically adjusts traffic light timings based on real-time traffic parameters, thereby reducing congestion at complex intersections. The integration of state-action processing and route recommendations proves particularly beneficial for densely populated urban areas within multi-agent traffic systems. The rest of this article is organized as follows:Chapter 2 discusses the Complex Traffic Signal Control Model for Intersection Management. Chapter 3 presents the mathematical formulation of the proposed model. Chapter 4 provides a numerical example to demonstrate the model's application.

2. Methods and Methodology

The mathematical model optimizes signal timings in complex traffic systems by analyzing traffic volumes and signal weight factors. It employs queuing theory to calculate effective green times, ensuring balanced vehicle flow and minimizing delays at intersections. Designed specifically for two-flow path intersections, the model enhances throughput and reduces vehicle waiting times. It incorporates constraints related to traffic volume, signal priorities, and dynamic traffic conditions, enabling the system to adapt to real-time fluctuations in demand. By efficiently managing traffic distribution and reducing vehicle emissions, this model offers a robust, data-driven solution for addressing modern urban traffic management challenges

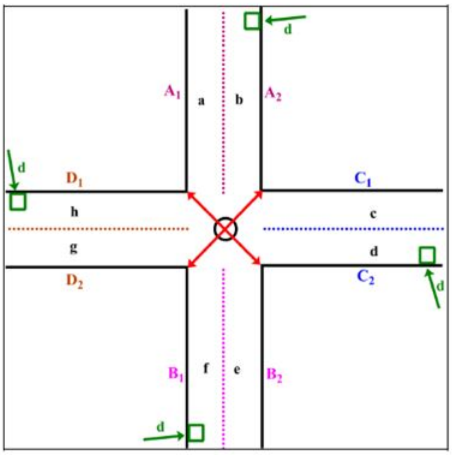

Figure 1. Single Phase Complex System

2.1. Complex Traffic Signal Control Model for Intersection Management

This model predicts and manages traffic flow at an intersection controlled by multiple traffic signals labeled a, b, c, d, e, f, g, and h. Each signal can display three colors green, yellow, and red to regulate the movement of vehicles through the intersection. Traffic flow is represented by nodes connected by edges, where each edge signifies the direction of movement between nodes. The model ensures that no two conflicting flows occur simultaneously, thereby minimizing the risk of collisions.
Intersection Flow Analysis Optimize the flow at the intersection, the model identifies the possible movement directions permitted to enter the intersection area. The main considerations are in Fig.1 are as follows: Left Turn Flow Intersections: o $A1$: The left-turn flow should intersect with the current flow $D1$ without causing conflicts. o

$D2$ and $A2$ should not intersect with the flows $B1$ and $C1$
Signal flow direction identification To effectively control traffic signals and flows, the following steps are performed: (i) Initial Flow Configuration: Establish different initial flow patterns based on the entry and exit points of vehicles. (ii) Preliminary Assumptions: o Assume initial conditions for left-turn signal flows. o Consider whether the current left-turn flow has the same end vertices as the previous one. (iii) Flow Compatibility Analysis: o Non-parallel flows: $A1$ and $D1$ are not parallel. o Parallel flows:$D2$ and $B1$, as well as $B2$ and $C1$, can run in parallel without conflict. (iv) Node and Flow Representation: o Each flow is represented with nodes on the traffic network graph. (v) Edge Association in Signal Network: o Two nodes are connected by an edge if consecutive flows match the nodes of connected intersections. o This association defines the movement from one intersection to another, optimizing the traffic management network.

2.2. Agent-Based Architecture for Advanced Traffic Time Optimization

In Fig.2 is an are effective for solving complex, distributed traffic management problems by decentralizing control and data. These systems are especially suited for scenarios like vehicle-to-infrastructure communication, route optimization, and intersection coordination. Despite growing interest in engineering, their full potential in advanced traffic management remains underexplored. To enhance agent decision-making, multi-objective Markov Decision Processes (MDPs) are employed, allowing agents to consider multiple control objectives. Reinforcement learning, coupled with function approximation and threshold ordering, is integrated to improve learning efficiency and decision quality. This intelligent control strategy supports various traffic control methods including signals, ramp metering, and speed or lane regulation—within an agent-based modeling framework. Here, each traffic control component operates as an autonomous agent, adapting to real-time conditions and external traffic dynamics.

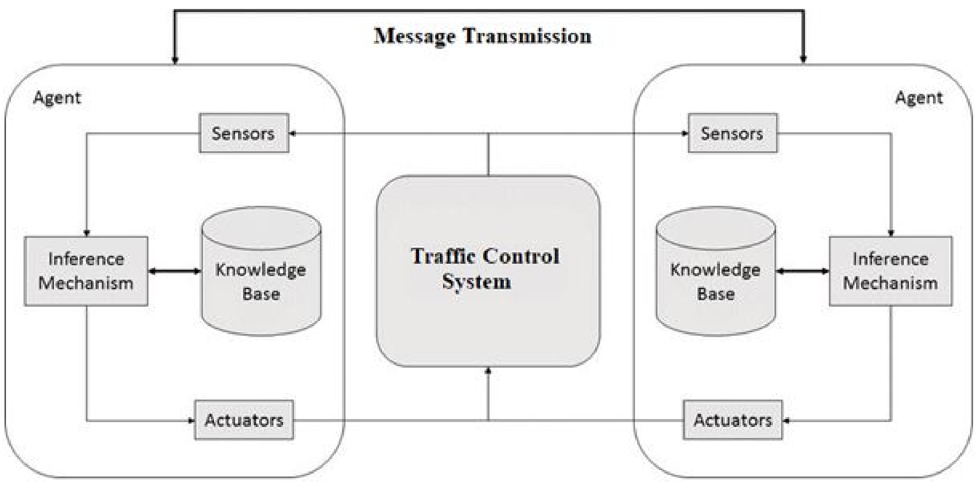

Figure 2. Multi$_{Agent_{System}}$

2.3. Methodology Flow Chart

Description Fig.3: Inputs $((\lambda_i,\mu_{i,i}(t),\phi))$.
Procedure: (i) Initialization: (a) Set initial phase duration equality (b) Communication links with neighboring agents (c) Local traffic state
(ii) Simulation Setup: (a) Observe State: (i)measure queue lengths for each incoming movement(ii) estimate

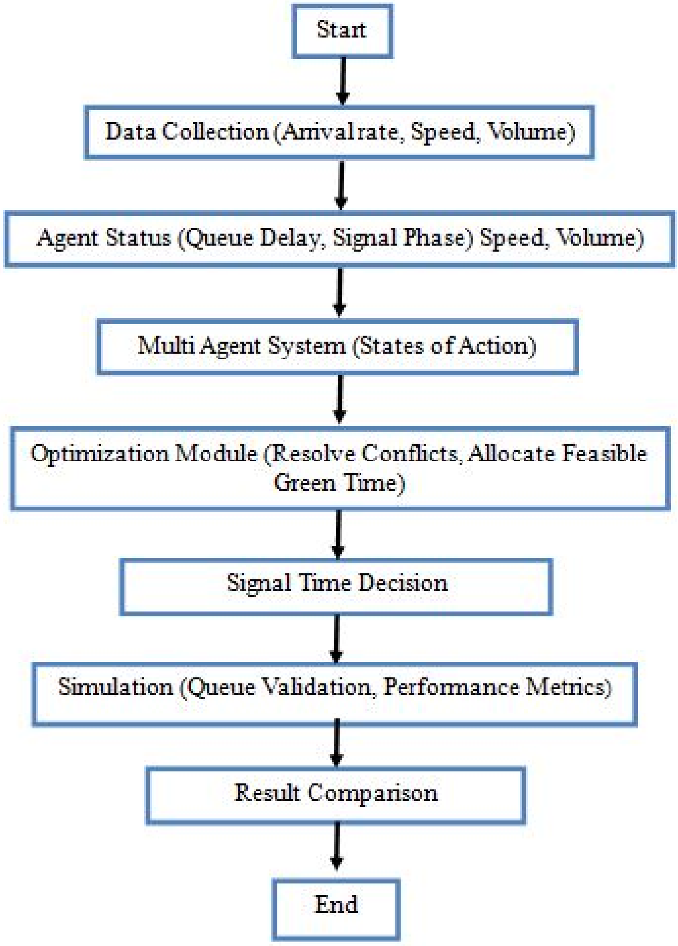

Figure 3. Methodology

arrival rate from recent arrivals (iii)compute delay. (b) Generate Actions: (i) Possible actions (ii) ensure safety constraints. (c) Conflict resolution: Check phase compatibility (if conflict exist, discard infeasible actions).
(d) Compute optimization and coordination with neighbors
(iii)Apply Selected phase timing in SUMO
(iv) Update metrics (Average queue length, waiting time)
(v) Repeat until max completed
(vi) Outputs:Optimal Signal plan and Performance Comparison

2.4. Pseudo Code

Input:
Cycle Length C
Decision Bounds[t-min,t-max]
Service rate μ
Repeat for each cycle length:
Measures arrival in current cycle to n_k.

Compute arrival rate to λ_k.
Receive green time from neighboring intersections.
Formulate Linear Program

$$Z = \sum \phi_k * x_k$$

Constraint as follows

$$s_k \le \mu_k;$$
$$s_k \ge \lambda_k * C;$$
$$\sum t_k = C;$$
$$t^{min} \le t \le t^{max};$$

Obtain LP Optimal t_k value
Implement t_k in the next cycle
Broadcast chosen t_k to neighboring intersections
End Repeat.

Flow Analysis the flow at the intersection, the model identifies the possible movement directions permitted to enter the intersection area. The main considerations are:

3. Mathematical Model Formulation

The mathematical model for optimizing traffic signal control at the intersection is defined as follows: Objective Function: N: Set of nodes (Intersection Points) E: Set of edges (Possible Vehicle movement directions) P: Set of phases in the signal cycle F: Set of possible vehicle flows (movements) T: Time horizon (discrete time steps) Decision Variables is:

$$x_{i,j} = \begin{cases} 1 & \text{flow from } i^{\text{th}} \text{ node to } j^{\text{th}} \text{ destination in phase } p \text{ at } t' \\ 0 & \text{otherwise} \end{cases}$$

Conserving Flow Consideration is:

$$\sum (y_{ij}(t) - \sum (y_{ki}(t) = D_i(t) \forall i \in N, \forall t \in T$$

Flow limit for traffic unit:

$$0 \le y_{ij}(t) \le Q_{ij}(t) \times x_{ij}(t) \forall (i,j) \in E, p \in P, t \in T$$

Avoiding Conflict: For any two opposing flows:

$$x_{ij}^t + x_{mn}^p \le 1,$$

Phase Time Allocation: The overall cycle time must be respected by each phase:

$$\sum g_p + L = C$$

Signal Phase Activation: Only during phase may a movement be active:

$$y_{ij}(t) \le Q_{ij}(t) \times x_{ij^p}$$

Flow compatibility for left turns:

$$LT_{ij} : x_{ij}^{p}(t) + x_{mn}^{p}(t) \leq 1$$

If flows (i, j) and (k, l) are parallel (non-conflicting), then parallel flow allowance:

$$x_{ij}^{p}(t) + x_{mn}^{p}(t) \leq 2$$

Derived Measures: Flow Volume over time T at node ”i”:

$$V_t = \sum_{t \varepsilon T} \sum_{j \varepsilon N} y_{ij}(t))$$

Therefore, Flow density at time t on edge (i,j) is

$$\rho_{ij}(t) = \frac{y_{ij}(t)}{Lenghtofsegment(i,j)}$$

The congestion level is

$$F_i(t) = \sum_{y \varepsilon N} y_{ij}(t))$$

Reduce overall latency and increase throughput:

$$Min(z) = \sum D_i - \sum Q_j$$

Non-Conflicting flow constraints

$$Q_i - Q_j = 0,$$

Here $'i'$ and $'j'$ are conflicting and it flows cannot occur in simultaneously. Phase Duration constraint is :

$$\sum_{k=1top} t_k = T$$

. In this model, intersections are represented as directed graphs, where nodes correspond to signal sites and edges denote permitted vehicle movements. The optimization of the objective function, subject to defined constraints, can be achieved using either dynamic programming or linear programming techniques. The model’s effectiveness in optimizing signal timings can be validated through the application of traffic simulation tools. By minimizing points of conflict between vehicle flows, reducing intersection delays, and decreasing vehicle waiting times, the model significantly enhances operational safety and efficiency. This advanced system for controlling traffic signals combines mathematical modeling, graph theory, and optimization methods to improve traffic flow management at urban intersections. It contributes to reduced conflict occurrences, increased throughput, and the overall safety of all road users. In the traffic flow timing configuration at an intersection junction, each traffic movement is initially assigned an equal length and weight. However, the allocated flow time is extended for heavily congested traffic streams relative to lighter flows, such as right or left turns at less populated bends, to accommodate varying demand levels and improve overall intersection performance. In the traffic network, four straight roads are directly connected to node , while the remaining roads are designated for left or right turning movements. The interval variable is assigned based on the following set of instructions:

$$A_2 \rightarrow x_1, D_1 \rightarrow x_3, B_2 \rightarrow (x_1 and x_2) C_3 \rightarrow x_3, A_1 \rightarrow x_1, D_2 \rightarrow (x_1, x_2, x_3)$$

The Objective function classification: Let the movement indexed by kto NS,WE,LR
t_k - green time allocated to movement ’k’
C - Cycle Length
n_k - observed number of vehicles for movement ’k’
$\lambda_k = (n_k/T)$

μ - service time during green sigbals
s_k - vehicle served from movement 'k' in the cycle (decision variable)
ϕ - weight assumed to movement'k' in the objective
The Proposed Model Mathematical formulation is:

$$Z = \sum \phi_k * x_k \tag{1}$$

Constraint as follows

$$s_k \leq \mu_k; \tag{2}$$

$$s_k \geq \lambda_k * C; \tag{3}$$

$$\sum t_k = C; \tag{4}$$

$$t^{min} \leq t \leq t^{max}; \tag{5}$$

4. Numerical Method

This study analyzes traffic waiting times at Solinganallur Junction by collecting real-time data during peak hours (7:00–8:00 a.m.) over a one-month period. Traffic flow data was segmented into 10-minute intervals, with each signal cycle set to 600 seconds. It was assumed that two vehicles are serviced per second during green phases, while continuous arrival patterns were considered for analysis. Key parameters recorded included traffic volume, time stamps, signal phases, and day-of-the-week variations. The objective was to evaluate total waiting times and assess the effectiveness of existing and proposed traffic control methods in reducing delays and improving intersection performance. For the experimental setup, SUMO software was used for simulation, considering a four-way intersection. Each road was 100 meters long, with the total intersection area measuring 200 meters by 200 meters. The road network was divided into cells of five meters each, creating a 40×40 grid, with a minimum distance of two meters between vehicles. n the simulation configuration, vehicles arrived at a rate of one every 0.1 seconds, with flow rates set at one vehicle per 0.2 seconds in each opposite direction. The maximum allowed speed was 30 km/h, with acceleration and deceleration rates set at 1.0 m/s² and 4.5 m/s², respectively. The flow rate for turning movements in all directions was maintained at one vehicle per 0.1 seconds. The simulation was run for 300 iterations, applying the agent network model and flow optimization techniques. Table.1 represent the flow level in each direction//

Marginal	Sub Flow	Waiting Time	Moving Time	Total Time
Before Divider	Total Flow	450	150	600
After Divider	(P=A1,A2,D2);(Q=D2,D1,C1,C2)	200	400	600
After Divider	(P=A1,A2,D2);R(B1,B2,C2)	250	300	600
After Divider	(P=A1,A2,D2,D1); R=(D2,D1,C1,C2)	300	300	600

Table 1. Vehicle Flow for each direction

In Table 2 represents the traffic management system efficiently arranges actual vehicle volumes at junctions by taking into account all potential path combinations, including left and right turns during each signal cycle, even though the described traffic flow is simplified to straight-line movement. Uniform time intervals are established to account for this, and depending on some presumptions, the quantity of cars passing in each interval can be disregarded. Dynamic weights are allocated with the goal of reducing the waiting time for each arriving vehicle in order to improve system performance.

Marginal	Red Light	Green Light	Total Time
(A1,A2)	145	205	300
(B2)	133	217	350
(C1)	218	132	350
(D1)	225	125	350
(D2,B1)	225	125	350
Total	946	804	

Table 2. Initial Flow Time

S.No	Flow Index	Flow for Certain Time
1	A1	112
2	A1	151
3	B1	112
4	B2	252
5	C1	196
6	C2	217
7	D1	113
8	D2	259
Total		1459

Table 3. Flow Index

Formulation of the problem as follows:

$$Z = \phi_1(2x_1 + x_2 + 2x_3) + \phi_2(2x_1 + 3x_2 + 2x_3) \tag{6}$$

Constraint as follows

$$x_1 + x_2 + x_3 = 600; x_1 \geq 150; x_1 + x_2 \geq 150; x_2 \geq 150; x_1 + x_2 + x_3 \geq 150; \tag{7}$$

The arrival rates λ_{NS}
From (1) and (2), the LP constraints produce upper bounds $s_k < n_k$
Since $\mu * C$ = 2*600 = 1200 veh /cycle, but total arrival taken from table.3, we get 263+309+748-1320 $>$ 1200
The system is demanded beyond capacity the LP will allocated green times according to weights ϕ_k and the capacity constraint.
We aggregate directions into three movement groups NS (A1 A2), WE(B1 B2) and LR(all left , right combined). For each group 'k' we estimate an arrival rate. WE solve the equation for every cycle C to obtain optimal green durations t_k and expected served vehicles s_k.
Using (3) and (4) for the LP explicitly enforces service capacity μ (veh/sec) and cycle and safety bounds. Using the data shown in table.3 as n_{NS} = 263, n_{WE} = 309, n_{LR} = 748 and T = 600 and the computed arrival rates are:λ_{NS} = 0.4383, λ_{WE} = 0.515, λ_{LR} = 1.2647, because n_k -1320 $> \mu * C$
The Demand Fractions: From table (3), p_{NS} = (263/1320) = 19.92, p_{WE} = 19.92, p_{LR} = 56.67
Therefore, $t_{NS}4 = 131.5$,t$_{WE}$ = 154.5, t_{LR} = 374.
Using (5), total required time values is 131.5 + 154.5 + 374 = 600 $>$ C-660, so the cycle cannot serve all the times. The greedy allocation that assigns time first to the highest ϕ_k until it t_k^{req} is reached yields LP in the monotone piecewise linear case.
Therefore objective function is defiend as: (0.5667)LR $\rightarrow$ (0.2341)WE $\rightarrow$ (0.1992) NS.
Alloacted cycle time C = 600
t_{LR} = 374.0s, the remaining cycle time = 600 - 374 - 220

t_{WE} = min(154.5, 226) = 154.5. The remainig time = 226-154.5-71.5s
t_{NS} = 71.5
The serviced vehicles s_k = min (μ_k, n_k)
s_{LR} = min (2*374,748) = 748, s_{WE} = min (2*154.5, 309) = 309, s_{NS} = min (2*71.5,263) = 143
Using (6) and (7), The objective value Z = 143 * p_{NS} + 309* p_{WE} + 748 * p_{LR} = 1200
The calculated traffic flow for each direction as follows:
s_{NS} = (143/1359) * 100 = 10.52, $s_W E$ = (309/1359) * 100 = 21.11, T_{LR} = (748/1359) * 100 = 55.04.
The Objective of max flow: Z = 10.52*s$_{NS}$ + 21.11*s$_{WE}$ + 55.04*s$_{LR}$
By the data, the current minimal flow is 400 second. The total flow of green light is 804 seconds. The construed new model for the above problem is as follows:

$$Z = 10.52 * S_{NS} + 21.11 S_{WE} + 55.26 T_{LR} \tag{8}$$

Subject to the constraint is:

$$S_{NS} + S_{WE} + T_{LR} = 804 \tag{9}$$

$$S_{NS} \geq 120 \tag{10}$$

$$S_{NS} + S_{WE} \geq 120 \tag{11}$$

$$S_{WE} \geq 120 \tag{12}$$

$$S_{WE} + T_{LR} \geq 120 \tag{13}$$

$$T_{LR} \geq 120$$

(14)

$$S_{NS} + S_{WE} + T_{LR} \geq 120 \tag{15}$$

Using (8) to (15), we get the optimal value of the traffic flow direction is $x_1 = 19; x_2 = 8; x_3 = 9$
The objective function value is 972.22.
Traffic scenario has discussed in various method such as sequential ideal flow traffic, continuous flow traffic on all sides, dense flow traffic on all sides, dense flow traffic on a single side, and moderate flow traffic on all sides were used to evaluate the effectiveness of the proposed model.
After applying the City Flow technique in a traffic simulation, the performance evaluation results are presented in the figure below in terms of average queue length, cumulative vehicle waiting time, and duration of red signal lights. As shown in Fig.6 and Fig.5,is shows as the flow prediction level in single and multi agent network model and these values were 83 seconds, 114 seconds, and 89 seconds, respectively.
The multi-agent environment with a modest traffic scenario is used to apply all the currently available approaches, such as City Flow, Fixed time, and queuing systems, in order to perform the performance study in Fig.4.

The proposed multi-agent queuing system demonstrates significantly lower cumulative vehicle waiting times, 368 seconds, compared to the single-agent system in real-time traffic scenarios. Performance evaluations at various intervals show that the multi-agent approach consistently outperforms the single-agent method. In Fig.4 results were indicate superior performance, confirming the model's effectiveness in reducing traffic signal waiting times. The regression plot in Fig.7 demonstrates an inverse relationship between waiting time (Wq) and queue length (Lq), with queue length accounting for 56.7 percentage of the variability in waiting time. This implies that Wq decreases as Lq increases, indicating a moderate correlation that can be useful for optimizing traffic signal timing.

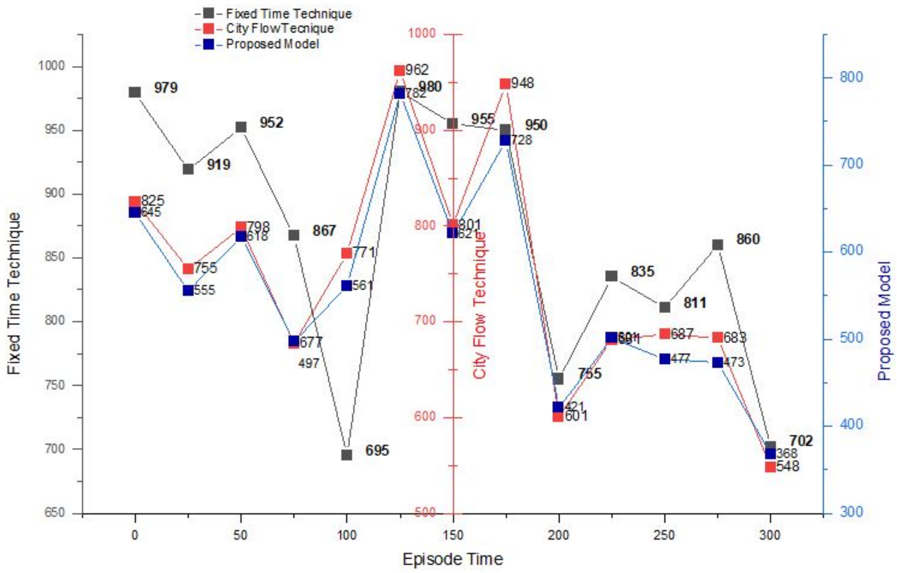

Figure 4. Result Comparison

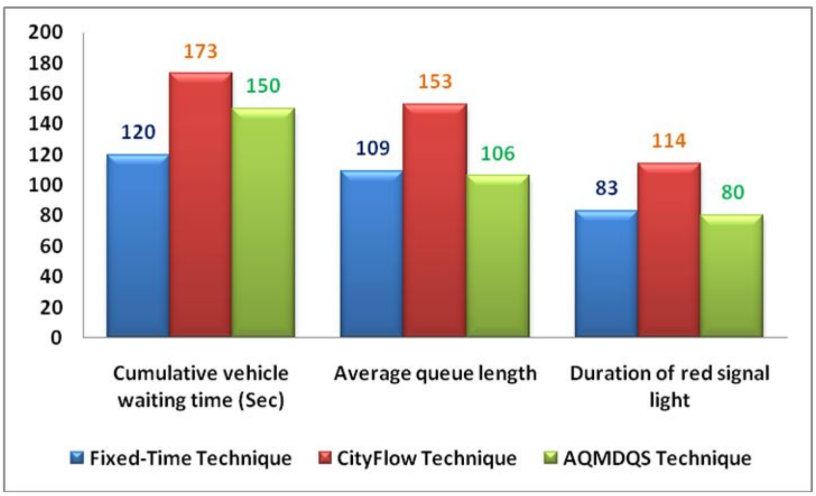

Figure 5. Average Queue Length Comparison

5. Conclusion

A sophisticated model for controlling traffic signals, based on a network flow system combined with signalized intersections at a crossroads junction, is presented in this study. To maximize overall traffic flow, the connected roadway sections are methodically divided into several segments, each representing a potential direction of vehicle movement. This segmentation enhances the model's ability to capture and manage intersection traffic dynamics by precisely mapping vehicle path flows. To evaluate its effectiveness, the proposed approach was compared with an existing traffic signal model. The results indicate a significant improvement, with the proposed model achieving a

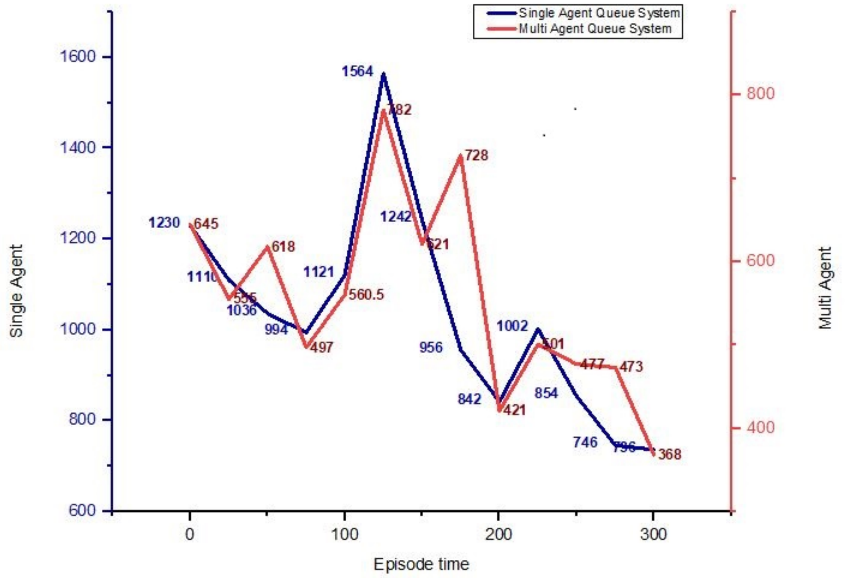

Figure 6. Single Agent vs Multi Agent

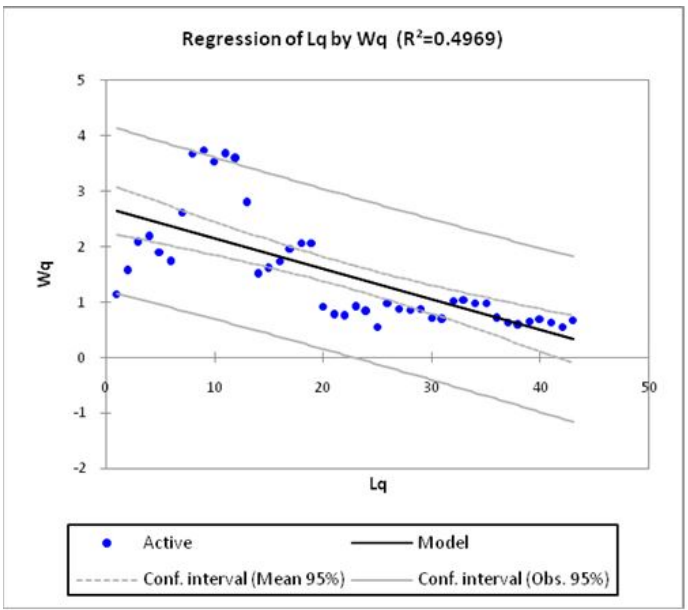

Figure 7. Relation Between Lq and Wq

vehicle flow time of 804 seconds compared to 400 seconds in the conventional model. Additionally, it produced an objective function value of 972, highlighting its potential to reduce congestion and improve traffic flow efficiency. One of the key features of this model is its adaptive signal control capability for specific traffic directions, such as North-South (NS), South-East (SE), and Left-Right (LR). This directional flexibility enables real-time adaptation to changing traffic conditions, ensuring continuous and efficient vehicle movement. The proposed model offers greater flexibility and efficiency than traditional methods for controlling traffic signals and demonstrates noticeably better performance. Its benefits include reduced delays, cost savings, and equitable signal distribution across all directions. Furthermore, the development process of this signal scheme has been statistically validated, reinforcing its reliability and robustness. Finally, the proposed model achieves average queue lengths and waiting times of 89, 114, and 83 seconds, respectively. These results demonstrate superior performance compared to the fixed-time and City Flow methods, confirming the model's effectiveness in minimizing traffic signal delays.

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