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ORIGINAL RESEARCH

Novel system for road traffic optimisation in large cities

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Abstract

Traffic congestion and road intersection management have become a significant issue, mainly with the highly increasing number of vehicles in cities. There is a common belief from vehicle drivers that installing traffic lights with some consideration of traffic flows will be dominant in traffic movements. This article proposes a novel system for Urban Traffic Control (UTC) with a continuous dynamic environment adaptation to improve traffic flow on large cities' network roads. The proposed system introduces vehicle counting method, lane evaluation of the current status and controlling method considering the effect on the whole traffic network—not just the intersection itself—to provide an efficient traffic scheduling. The main objective of the authors' system is to reduce traffic jam, by reducing waiting time and trip time for vehicles at intersections. Some indicators and models are introduced in this work to assign traffic flow schedules with minimum traffic congestion and vehicle waiting time. These indicators and models include a traffic jam indicator, vehicle priority and lane weight. A multi-agent urban traffic control system is proposed as the simulation environment using NetLogo simulator. (A total of 150) Vehicles are generated with random behaviour distributed over 25 intersections for 9 h duration to compare the normal fixed cycle traffic light and the authors' smart traffic control. Results show a reduction in the total average waiting time of all vehicles for the simulation period by more than (29.98%). Hence, it is more suitable for the complexity of the current traffic condition with minimum changing infrastructure.

KEYWORDS

road traffic control, road traffic management, smart cities, smart traffic light, urban traffic control, UTC

1 | INTRODUCTION

In the first 20 years of the current millennium, road vehicles that had been registered in the U.S. has increased by 19% (more than 46 million extra vehicles) [1]. This rapid increase has amplified the importance of issues such as road congestion, environment pollution and traffic accidents. Intelligent Transportation Systems (ITS) and smart traffic lights are considered potential solution to some of these problems by providing less waiting time at traffic lights and more effective driving. Traffic jams and waiting time are crucial in large cities, where scheduling traffic and improving traffic flow at intersections help in reducing congestion, trip time and carbon dioxide emission [2]. Traffic optimisation is divided into the following: one—intelligent traffic lights system (ITS) including the genetic algorithm [3], fussy logic [4], neural network [5], microcontroller and programmable logic (PLC) [6], statistical methods and machine learning in both division classic and deep learning [7]. Two—Virtual Traffic light (VTL) [8, 9], presented in smart cities and IoT environment in many types (V2X) [10]: Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I) and Vehicle to Network (V2N). See Figure 1.

Traffic lights simply consist of a controller and light heads, where the controller is the brain to force lights to change through a predefined sequence. The sequence may follow a fixed time, vehicle automation, or Urban Traffic Control (UTC) techniques. The fixed time method summarised in the green light will be displayed for the same amount of every cycle regardless of the current traffic status. On the one hand, this technique may cause a waste of time where no waiting vehicles

FIGURE 1 Virtual traffic light

or in areas that are heavily congested. On the other hand, the automated method considers the vehicle demands on each intersection to coordinate the green light cycles. A detector is placed on the road side or on the traffic lights to receive vehicle demand. Vehicles require a phase changing to green in the closest possible time. The green status may be on extension, where this phase is decided on the basis of other approaching vehicles or according to the minimum and maximum cycles assigned for this intersection. The automated technique is more efficient than the fixed time technique. However, the performance of this technique is still disappointing in heavily crowded junctions, as the maximum time is difficult to determine in these cases. In UTC method, a network is used to collect data on a centralised computer to optimise traffic flows. The timing plans vary according to the current traffic status [11]. UTC systems are proposed to provide an alternative solution for the need of new infrastructure, such as bridges, tunnels, new roads and road expansion, in addition to optimising road traffic, vehicle trips and emission reduction. A road traffic control system should consider the traffic volume, vehicle priority, input and affected output traffic to maintain efficient control. In this study, a system that can adapt a dynamic environment that captures real-time differences in traffic is proposed with a multi-phase and self-adjustment from the continuously updated current status data to reduce the entire journey time and vehicle waiting time.

The rest of this paper is structured as follows: Section 2 overviews the related literature in the field of road traffic optimisation. The proposed methodology is introduced in Section 3. Section 4 presents the proposed simulation for optimising traffic lights. Then, a discussion is presented in Section 5. Finally, the work is concluded and the future work is listed in Section 6.

2 | RELATED WORK

Traffic management using traditional traffic light system is not efficient given the increased number of vehicles. The fixed waiting time at traffic lights, even if other lanes at the intersection have few or no vehicles, is a significant problem. Many researchers have proposed solutions to optimise the traffic density on all lanes of the intersection through several proposed techniques, such as genetic algorithm, neural network, virtual traffic lights, which all demand a network and hardware on the road or vehicles or both [9].

Pandey et al. used image and video processing to obtain the traffic volume of junctions. They proposed a method to decide the time division for the traffic lights. The proposed method has been proven useful for traffic management [12].

Xu et al., 2020 introduced a road traffic state prediction based on a generative adversarial network. They claimed that traffic state prediction plays an important role in intelligent transportation systems. It helps travellers to make better plans and governments to provide effective basis for transportation management. Their framework is based on three models: (1) The generator (G): to deploy the historical traffic states in a spatiotemporal matrix to produce a future traffic state, (2) the discriminator (D): to measure the difference between the real and generated data and (3) the adversarial training: to ensure the balance between (D) and (G). Their framework has provided a 5-min traffic prediction in terms of traffic flow [7].

An intelligent traffic signalling system (I-SIG) has been developed by Robust Net Research Group and Michigan Traffic Laboratory at Michigan University, under the support of the U.S Department of Transportation. This system aims to reduce traffic congestion and to avoid crashes. The system has been installed and tested in different US states including AZ, CA, NY and Tampa-Florida. The vehicles in the developed system share their real-time location and speed with the closest traffic light, to evaluate the traffic status and modify the traffic timing. Unfortunately, they claimed that the sensors underlying I-SIG system are not trustworthy since they can easily be hacked [13].

Solving traffic jam is a significant challenge. Hence, many research groups worked hard to minimise traffic jam and the loss of 'precious' time during rush hours. Avinet al. defined traffic light that causes bottlenecks in the traffic flow. Thus, they proposed a virtual traffic light and traffic light scheduling broadcasting-based location to each vehicle using wireless technologies. They developed a simulation to evaluate the capacity of the intersection and to improve the performance accuracy. The simulation results showed an increase of 5% in the fraction of vehicles and a decrease of up to 50% in the delay time. Notably, they only considered un-delayed vehicles [14].

In 2017, Saini et al. focussed on the traffic light state recognition challenge and proposed a convolutional neural network (CNN) based on the state recognition method. Their system was robust under various illumination of different weather conditions and helpful in driving assessment [15].

Meanwhile, Hagenauer et al. examined the network performance of self-organised traffic management algorithms focussing on Vehicle-to-Vehicle (V-2-V) networking. In the proposed system, Virtual Traffic Light (VTL) uses a leading vehicle at the intersection to control instead of the traditional traffic light. The researchers developed an algorithm to lead the election and traffic light computation in realistic vehicular networking scenarios. They extended an algorithm to support arbitrary intersection layouts and investigated the proposal in synthetic and realistic scenarios. They concluded that VTL efficiently employs all resources at the vehicular network and improves the driving experience in the average network load only [16].

Artificial intelligence has been proposed widely for scheduling smart traffic in multi-intersection traffic networks. Arelet et al. employed a reinforcement learning (RL) neural network framework to control traffic light cycles efficiently. They aimed to minimise the average waiting time, congestion, and likelihood of intersection cross-blocking. They experimented on five intersections at a road network, where every intersection served as an autonomous intelligent agent (either central agent or outbound agent). The proposed methodology using RL utilised the Q-Learning algorithm with a feedforward neural network for value function approximation. The experimental results proved the advantages of multi-agent RL-based control over LQF governed isolated single-intersection control [17].

Traffic synchronisation using multi-agent fuzzy logic distribution and Q learning was discussed by Iyer et al. to coordinate with traffic agents through communication. They claimed that the fuzzy system can handle the various levels of input data received from traffic lights [18].

Teo et al. studied the effect of waiting vehicle queue, green light duration and amber time in a traffic light system using simulation. They schedule the traffic light time cycling using genetic algorithm to optimise vehicle passing at the intersection. Genetic algorithm is able to find the optimised solution in its tuning process; it takes the current queue length as an input and optimises green time for the intersection. The result of genetic algorithm is further improved by employing incoming traffic flow during red time of each phase, as it requires time to process the genetic algorithm depending on the data length to find the results [3].

Wang et al. proposed an adaptive linear quadratic regulator (LQR) with incremental changes in microscopic simulation. Thirty-five intersections were presented by a multi-agent simulation. The results had shorter average traffic delay compared with normal traffic lights (an average of 29.9 s for a 20 s green cycle) [19].

Siyal and Fathy proposed a method using both edge detection and neural network algorithms to optimise traffic at the intersection. The edge detection technique is used for vehicle detection and motion estimation, while the neural network is used to measure the queue parameters. Several environments at road traffic have been considered for training the neural network to obtain more efficient results compared with traditional image processing algorithms [20].

John et al. presented a computer vision and machine learning algorithms for varying illumination conditions using the CNN to extract and detect features from visual camera images. On-board GPS sensor is used here for the recognition accuracy improvement. The GPS identifies the region-of-interest for the containing traffic light. The proposed algorithm was evaluated using datasets gathered in several environments and was compared with the traditional traffic signal. They proved the high recognition accuracy of their proposed system in various illumination conditions [21].

Zou et al. introduced an economically designed fuzzy logic based on Wireless Sensor Network (WSN) to control traffic lights for a single intersection [22]. Single-axis magneto sensors were to be placed on road sides to detect the traffic flow in the surrounding area. The fuzzy algorithm was used to adjust vehicle passing time based on the available amount of vehicles. Real-time dynamic control and vehicles' average waiting time reduction are obtained in their research study with 22.7% for 80s simulation period compared with the traditional fixed-cycle system to conclude their results.

Sanchez et al. presented a method to optimise traffic light cycles in a multi-intersection traffic network. They used genetic algorithms for optimisation with the Cellular Automata Simulator for the evaluation process. The researchers employed the Beowulf Cluster algorithm for concurrent execution. Then, they validated the proposed methods using experimental evaluation and proved its suitability for the traffic light optimisation problem [23].

Biswas et al. deployed various approaches to enhance the traffic system. A comparative study has been explored for different potential studies aiming at optimising intelligent traffic systems. They highlighted several contributions that seemed beneficial for implementing such systems in developing countries [24].

Another work of real-time algorithm for controlling traffic lights was proposed by Zaatouri and Ezzedine. They employed computer vision and machine learning to evaluate the competing traffic flows on road intersections. Object detection based on a deep CNN algorithm called You Only Look Once (YOLO) was used to optimise traffic light performance according to the rules on waiting time and safely passing vehicles [25].

Rydzewski et al. presented a systematic review on recent advance methods and algorithms for road traffic optimisation. They explored a large number of possible simulation types that can be used for this purpose, such as SUMO, NetLogo, SCOOT, VANET, VISSIM, and AIMSUM [26]. They provided a diagram representing how often each simulator is used, as in Figure 2.

Synchronising traffic lights in the surrounding area is a complex process, but it has been investigated by many researchers, such as Tomar et al., who divided the system into levels of synchronisation as in Figure 3 [27].

They designed a framework for signal synchronisation that can work with DSRC, image processing, sensors, or any other technology, which is used to observe traffic density at intersections. They claimed that the framework is scalable and can incorporate new junctions with no problem. They used SUMO simulation for their method; the result was 19% reduction of the average trip time compared with fixed time and non-synchronised traffic control.

Nesmachnow et al. suggested a traffic light synchronisation parallel algorithm for Bus Rapid Transit systems by considering real maps and mobility data. They assigned a different priority for busses and other vehicles. They claimed that this method improves the average speed of public transport up to 15.3% and other vehicles up to 24.8% [28].

Zhonghe et al. presented a traffic control strategy called URBC (Urban Traffic Balance Control), which relies on state-feedback. The technique was done by simulating Wangjing (Beijing, China) using VISSIM. The area has 19 intersections and 56 links; they noticed that delay time could be reduced by 13%–20% [29].

Burguillo et al. used NetLogo to simulate road traffic conditions in a grid network. The authors attempted a different number of self-organising intersections to illustrate the impact on average waiting times. They concluded that if the number of intelligent intersections exceeds 50%, it will decrease the waiting time, compared with regular, fixed-time traffic lights [30].

Ahmad et al. [31] experimented a 4 × 4 traffic network grid for 1, 2 and 3 h of simulation to find an 18% reduction of the average waiting time using their proposed algorithm.

Patrascu et al. focussed on vehicle waiting time. They used Java, JADE framework and SUMO for their experiment along with several types of agents. The results of the average waiting time could be reduced, which would cause a 3.06% average fuel reduction and 9% average speed increase [32].

3 | METHODOLOGY

We introduce a system with multiple techniques to be integrated on traffic lights without implementing many changes in the infrastructure. This proposed system aims to improve traffic flow and reduce vehicle average waiting time. Moreover, it has a continuous updated values of the traffic status not only for the intersection itself but also for the whole traffic network. The indicators we identified in this research study are reflected on the current traffic status of the intersection and the leading roads affected by this situation. The intersection itself will make a decision considering the traffic volume and vehicle priority of the previous and next intersections to schedule the traffic flow with the minimum vehicle waiting time and traffic congestion in the network. The proposed traffic light controlling system is divided into three phases as illustrated in Figure 4.

3.1 | Phase 1: lane identification

Intersections mostly have four traffic lights (more or less), each with multiple lanes and two directions (forward and backward) as illustrated in Figure 5. First, we introduce a method to assign

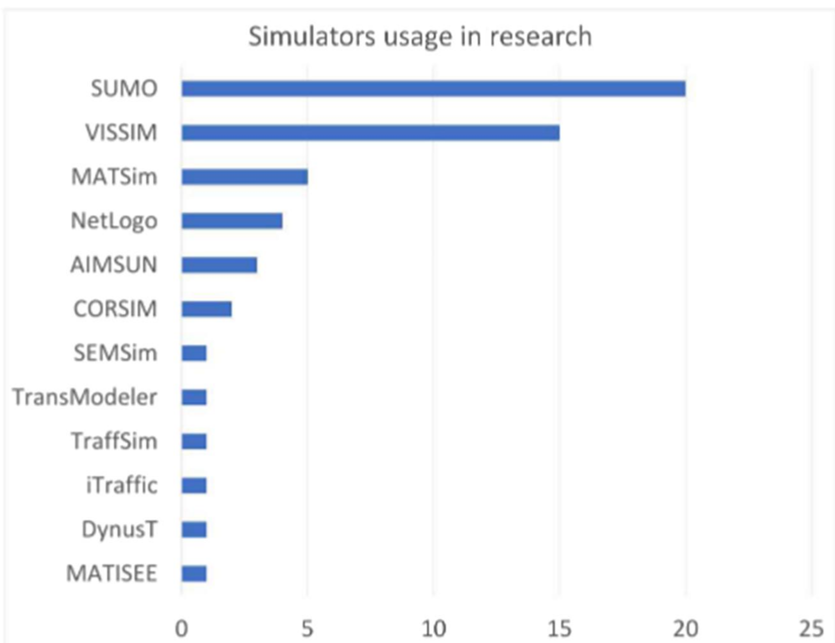

FIGURE 2 Diagram represents how often each simulator was used in analysed papers [26]

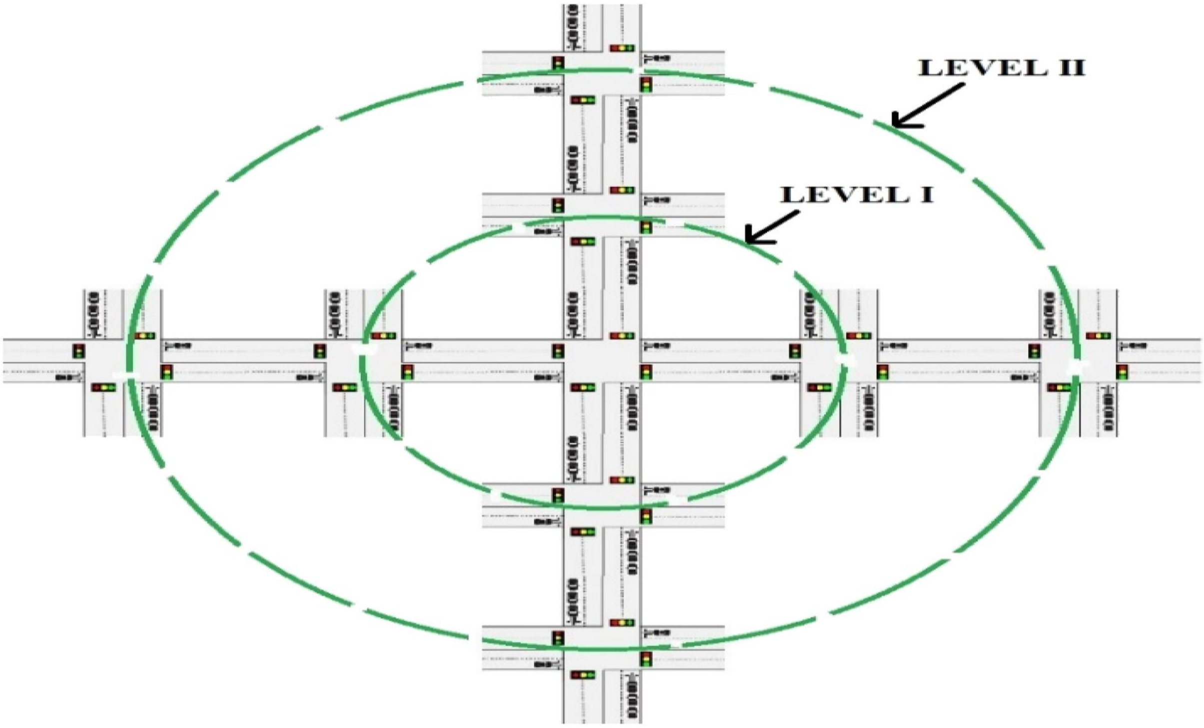

FIGURE 3 Levels of synchronisation [27]

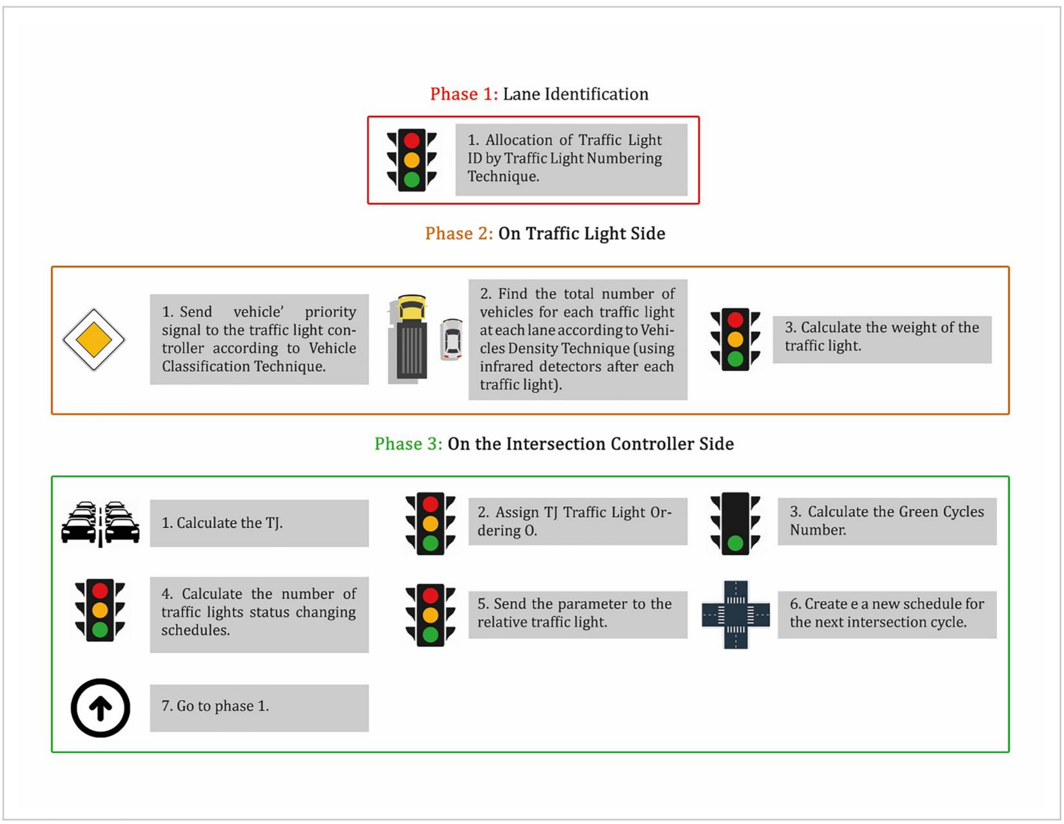

FIGURE 4 The proposed system phases

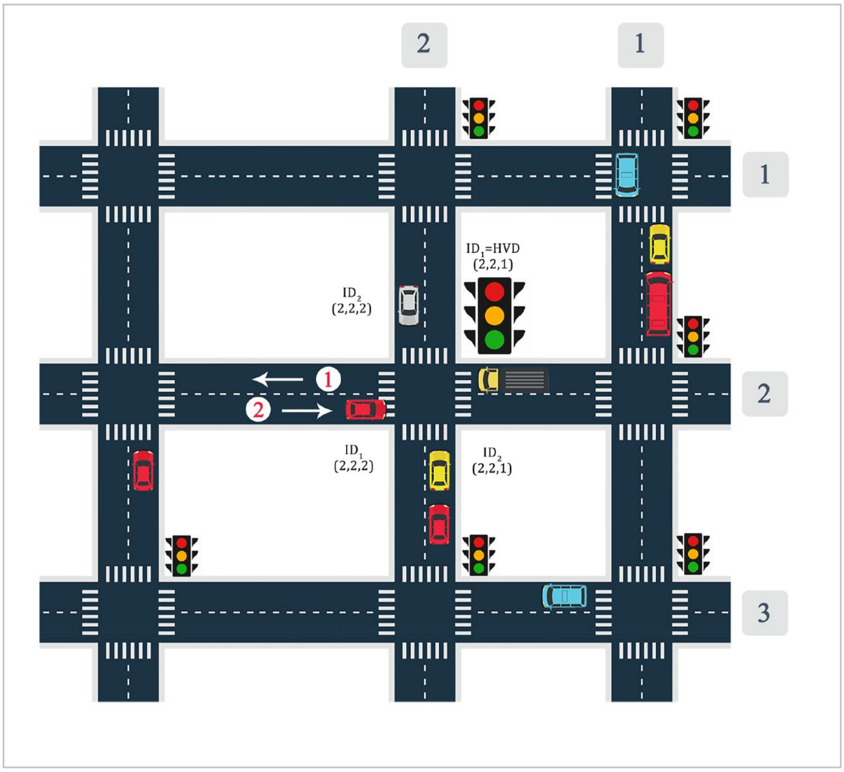

FIGURE 5 Traffic light ID assignment

an ID number for each lane on the traffic lights and an ID to distinguish the lane, direction and intersection. The ID can also define the related lanes from all directions that may be affected by the current lane traffic itself.

Traffic light ID_x consists of three numbers indicating the traffic light allocation assigning as follows:

- ID_x = HVD (horizontal, vertical, direction).
- Each path will have a number (1, 2, 3, n). Thus, each intersection will have a horizontal path and vertical path number.
- Each path has two directions (1 assigned to forward direction, 2 assigned to backward direction). For example, an HVD has an ID of (2, 2, 1). The first number indicates the second horizontal path, the second number indicates the second vertical path, and the third number indicates the direction, which is the forward direction in this case.
- x is the crossing edge and is equal to one or two or more.

Leading or affected lanes can be defined by the HVD as all intersections with the same H or V index are considered affected lanes.

3.2 | Phase 2: traffic lights side

This part will be done on each traffic light and will be concerned with collecting information. Each traffic light will calculate the number of vehicles using the previously published technique of traffic counting in Ref. [33]. The technique is based on using two infrared sensors and two timers with 1 m apart placed either at the beginning of each lane or right after the traffic light to guarantee accurate vehicle counting. See Figure 6.

The infrared transmitter is always (on) sending infrared signals to the detector on the ground in a line of sight connection. As long as the detector is receiving the infrared signal, no vehicles cross through the beam. Otherwise, the calculation of vehicle numbers crossing through will be started by determining the vehicles' speed for counting and the length for traffic volume, since long vehicles can cause more traffic jam problems than normal length vehicles. Once the vehicle interrupts the connection of the first infrared sensor, two timers will be initiated: (1) (t − 1 m) and (2) (t − of broken connection).

T − 1 m counts the time between the first connection interruption and the second connection interruption (1 m apart) to find the vehicle speed. The second timer, T − of broken connection counts the time starting at the moment of the second connection interruption until the first connection returns, to measure the car length. Based on the car length the vehicle number counter will be increased by (n) every time the t − of broken connection exceeds the time required for a normal vehicle length at the same speed.

$$\text{car speed(m/s)} = \frac{1\ \text{m}}{\text{t} - 1\ \text{meter}} \tag{1}$$

$$\text{car speed(km/h)} = \left(\frac{1\ \text{m}}{1000}\right)\left(\frac{\text{t} - 1\ \text{m}}{3600}\right) \tag{2}$$

FIGURE 6 Infrared sensors for vehicle counting

In the case of a car speed (km/h) being <5 km/h, the car is moving slowly, and the counter changes only once. If the speed >5 km/h the following equation is applicable: t − of broken connection = the time required for the car to cross the first sensor totally

$$\text{car length} = \text{car speed} * \text{t} - \text{of broken connection} \quad (3)$$

To incorporate the volume of the traffic as a part of the statistics, the counter should be increased for cars >5 m long. This can be done with the following equation:

$$k = \frac{\text{car length}}{\text{normal car length}} \quad (4)$$

$$k = \left(\text{t} - \text{of broken connection} * \frac{\text{car speed}}{5}\right) \quad (5)$$

Figure 7 illustrates the algorithm for counting the number of crossing vehicles.

$$w(\text{IDx}) = \sum_{i=1}^{n} \text{V}p(i) \quad (6)$$

We also propose a priority model to classify vehicles into three priority types to be considered in lane weight calculations as explained in Table 1. We assume that emergency vehicles, public transportation and school buses have the ability to send a signal to the traffic light identifying themselves using RFID or DSDR. After that each traffic light starts weight calculation using Equation (6). The results will be sent to the intersection controller along with the traffic light ID_x (HVD). where w is traffic light weight, n is vehicles number, and Vp is priority weight.

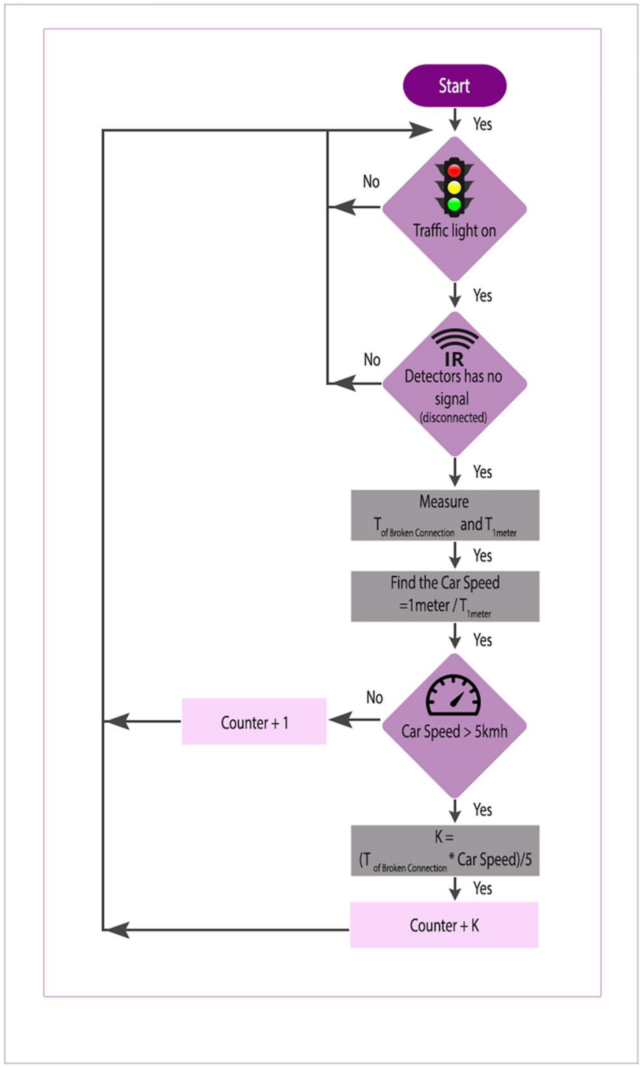

FIGURE 7 Proposed algorithm for counting the number of crossing vehicles

3.3 | Phase 3: intersection controller

Operations in this part are executed on the intersection controller side. It aims to produce a table differentiating each HVD schedule with regard to its weight, traffic jam indicator, traffic light order, number of green cycles, current status and time of next status, as seen in Table 2.

Tj (Traffic Jam Indicator) is proposed as the sum of the previous i number of HVD weights of those that will lead traffic to the path of the current HVD, and the next i number of HVDs of those that will be affected from the current HVD vehicle flow in all directions, vertical and horizontal (we select $i = 5$ in this work). This proposed indicator can reflect on the traffic status on multiple junctions. Tj can be calculated by Equation (7).

$$\mathrm{Tj} = \sum_{H-i}^{H+i} w(\mathrm{ID}x) + \sum_{V-i}^{V+i} w(\mathrm{ID}x\ ) \tag{7}$$

The traffic light with higher Tj will have higher order. Normal cycles are equal to 30 s green and 60 s red. Hence, the total time of a junction = 120 s including 30 s (10 s as a safety time between each changing in the traffic lights status). We also assume that 30 s of the green cycle is almost equal to the movement of p vehicles (almost 10 cars in average). Thus, the number of normal green cycles required for optimum number of vehicles to pass the junction is calculated according to Equation (8), and the time of next status is calculated in Equation (9).

TABLE 1 Vehicle priority weight

Vehicle	Priority weight (vp)
Emergency vehicle	1.0
School & public buses	0.5
Normal vehicle	0.1

$$\text{number of green cycles} = \frac{\text{number of car}}{p} \tag{8}$$

$$\begin{aligned}\text{Time of next status} \\ &= \sum_{1}^{N} \text{time of green cycle for traffic light with } (N) \\ &\quad + (N * 10)\end{aligned} \tag{9}$$

while $N =$ Tj order of junction lanes and 10 s as a safety for each traffic light status change.

4 | SIMULATION

We built a multi-agent urban traffic simulation model using NetLogo [34, 35]. A total of 25 linked intersections presented in a selected area with multiple lanes in all directions and 150 vehicles were deployed in a random behaviour. Two types UTC systems in particular are being tested using this simulator: Our proposed system and fixed time traffic control system.

NetLogo is a free open source software for multi-agent programmable modelling environment. It is written in Scala and Java languages and runs over Java Virtual Machines (JVM). NetLogo can model the population growth under four types of agents: Turtules, Patches, Links and Observer (more details in Ref. [34]). A multi-agent-based urban traffic system is proposed as a simulation model and presented in Table 3 to

TABLE 2 Lane scheduling

ID_x	Weight	TJ	N (TJ order)	Number of green cycles	Time of next status
-	-	-	-	-	-

TABLE 3 Agent's main attributes and methods

Agent type	Attributes	Behaviour
Vehicle agent	• Vehicle ID • Priority • Direction • Current lane • Stopping time • Waiting time • Quit time	• Set ID • Set priority • Send priority signal
Traffic light agent	• Traffic light ID • Intersection ID • Traffic light direction • Total vehicle No • total weight	• Set traffic ID • Calculate vehicle density • Calculate traffic light weight
Intersection controller agent	• Intersection ID • Traffic light ID • Travel direction • Traffic jam Indicator (TJ) • Selected traffic light • Green cycle number • Yellow cycle number • Red cycle number • Current status • Time of next status	• Calculate traffic jam indicator • Assign traffic light order • Calculate green cycles • Calculate red–yellow cycles • Determine next change

identify each agent's main attributes and methods, where each vehicle, traffic light and controller are considered a separate agent and distributed over a map of 25 intersections. The UTC agents' types are as follows:

- The Vehicle Agent.
- Traffic Light Agent.
- Intersection Controller Agent: The controlling unit for an effective diagnostic procedure as well as guidelines and modifications for traffic light units.

All the traffic lights at road junctions are managed by each agent through an observer-oriented-decided-act. However, the intersection control agent constantly perceives the current status of the traffic at the crossing. Then, it uses information gathered to decide how the agents will behave. Agent-based system components are illustrated in Figure 8. Screenshots of the simulation setups (NetLogo) are illustrated in Figure 9. A record of the average waiting time were saved for the 150 randomly behaviour vehicles with the same average trip time. The comparison between the two systems were focussed on the average vehicle waiting time for all 150 vehicles over a 9 h simulation period. Our proposed technique has been performed with the (1) controller agent: to collect data and assign schedules to HVDs, (2) traffic light agent: to record the number of vehicles and their weight for each HVD, and (3) vehicle agent: to announce their priority values. On the other hand, the fixed type is performed on the traffic light agent in the following manner: a green light displayed for 30 s, 90 s for red and 10 s as a safety time between changing in traffic light status. The controller is not used in this mode.

5 | RESULTS AND DISCUSSION

The simulation worked in a map (network) of 5 × 5 intersections for a period of 9 h for both fixed control and smart control. The average waiting time of the total trip time has been tracked for all 150 cars and the Traffic Jam Indicator (TJ) for all 25 intersections. As part of the evaluation for the proposed work we identified TJ as a parameter reflecting how much the current traffic is affected from both directions (the

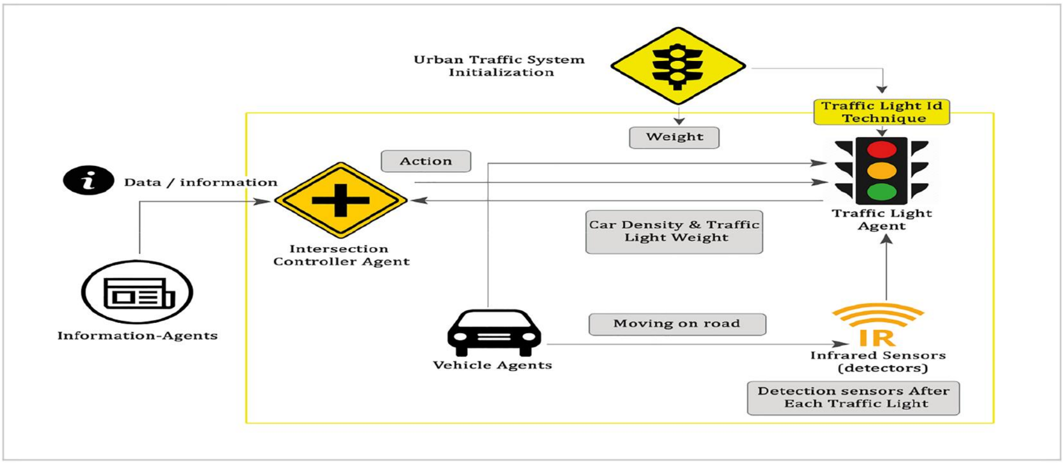

FIGURE 8 Multi-agent urban traffic system components

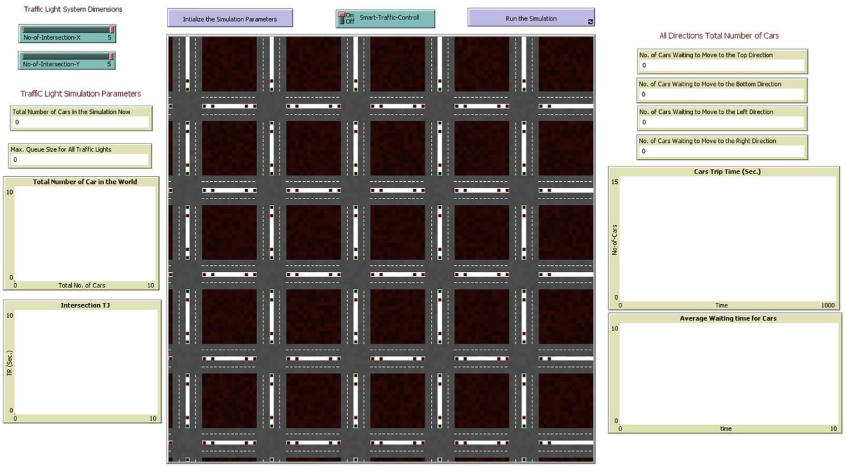

FIGURE 9 Simulation set up

paths leads to the current intersection and paths will receive the traffic from the current intersection). A record of TJ has been saved for both systems (smart and fixed) to show how this indicators will affect the traffic flow. Table 4 illustrates a sample of TJ-smart records to update the traffic light controller with the current status of the intersection and the surrounded area. Table 5 illustrated the TJ-fixed of the same intersections. The average TJ for each path ID has been calculated for both systems to compare the results not just over the intersection but all over the network (25 intersections). As illustrated in

TABLE 4 TJ-smart—sample record to update the traffic light controller with the current status of the intersection and the surrounded area

No	ID	TJ − 1	TJ − 2	TJ − 3	TJ − 4	.	.	TJ − *n*	Ave
1	111	472.79	460.67	484.92	436.43	.	.	.	472.8
2	112	517.83	504.53	531.08	477.98	.	.	.	517.8
3	121	400.81	390.53	411.08	369.73	.	.	.	400.8
4	122	517.5	504.7	531.08	477.87	.	.	.	517.8
5	131	413.43	390.5	411.08	369.96	.	.	.	403.7
6	132	406.76	390.53	411.08	369.97	.	.	.	407.9
7	141	348.27	339.34	357.2	321.48	.	.	.	348.27
8	142	408.33	397.86	418.8	376.92	.	.	.	
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
46	532	303.52	331.08	297.972	306.24	.	.	.	303.52
47	541	350.60	349.56	314.604	323.34	.	.	.	350.6
48	542	549.97	611.08	549.972	565.27	.	.	.	549.97
49	551	297.97	360.34	347.43	491.25	.	.	.	297.9
50	552	314.5	565.24	448.55	579.37	.	.	.	314.61

TABLE 5 TJ-fixed record—sample

No	ID	TJ − 1	TJ − 2	TJ − 3	TJ − 4	.	TJ − *n*	Ave
1	111	677.35	703.0	890.0	664.4	.	.	733.5
2	112	589.3	789.2	509.1	684.9	.	.	642.76
3	121	534.5	563.6	549.8	520.3	.	.	541.77
4	122	894.7	715.9	905.5	839.96	.	.	839.04
5	131	953.7	883.0	768.38	838.0	.	.	860.76
6	132	1444.1	1656.53	1932	1980.73	.	.	1650.84
7	141	1633.3	1937.75	1775.5	1548.48	.	.	1726.13
8	142	2368.4	2496.5	2432.93	2304.12	.	.	2400.54
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
46	532	9313.25	10,970.7	11,115.6	11,521.7	.	.	10,730.3
47	541	14,314.2	10,991.5	11,630.3	12,434.4	.	.	12,467.5
48	542	14,314.2	10,991.5	11,630.3	12,434.4	.	.	12,467.5
49	551	8424.56	9902.9	10,826.7	9860.3	.	.	9753.66
50	552	5454.51	7704.3	6721.3	8716	.	.	7148.87

Figure 10, the results of TJ-smart is almost steady line on the bottom of the graph for the simulation period, while the TJ-fixed has a highly variable incremental values, which means the proposed system can handle traffic jam to an acceptable range rather than the unexpected or incremental behaviour for the network as in fixed traffic control.

On the other hand, a record of the trip time and average waiting time were saved for the 150 vehicles for both systems and shown in Table 6. The reduction of the waiting time for each vehicle has been noticed using the proposed technique as in Figure 11. The results show that the calculated average waiting time of traditional fixed cycle control has an average of 40.49 s for all 150 vehicles of an average trip time of (335.44 s) and (25.97 s) for the proposed system with the same number of vehicles and average trip time.

As a result, the proposed smart system reduced the average waiting time on traffic lights by 29.98% for the entire traffic network. The results exceed other studies with similar target and environment. Reducing average waiting time means a reduction on new infrastructure needs, gas emission, time wastage etc.

6 | CONCLUSION AND FUTURE WORK

On the basis of demand and feasibility of smart traffic optimisation, this study establishes urban traffic-based intelligent techniques for traffic light scheduling to reduce vehicle waiting time with minimal changes in the current infrastructure. The proposed system introduces a few indicators and models to improve the traffic flow for the whole network and reduce the

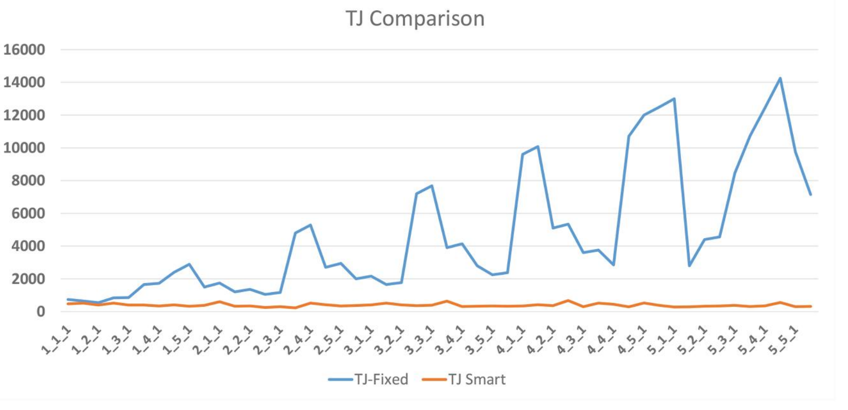

FIGURE 10 TJ fixed versus smart

TABLE 6 Vehicle trip time and average waiting time (AWT)—sample

Vehicle ID	Trip time (s)	AWT-fixed (s)	AWT-smart (s)
1	235	25.47	22.7
2	205	27.3	24.87
3	215	34.67	30.76
4	334	39.89	29.96
5	413	35.0	30.54
6	132	38.56	29.12
7	514	44.32	28.65
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
146	331	39.67	25.25
147	288	39.47	26.52
148	542	38.56	27.66
149	322	46.56	28.25
150	331	44.23	30.64

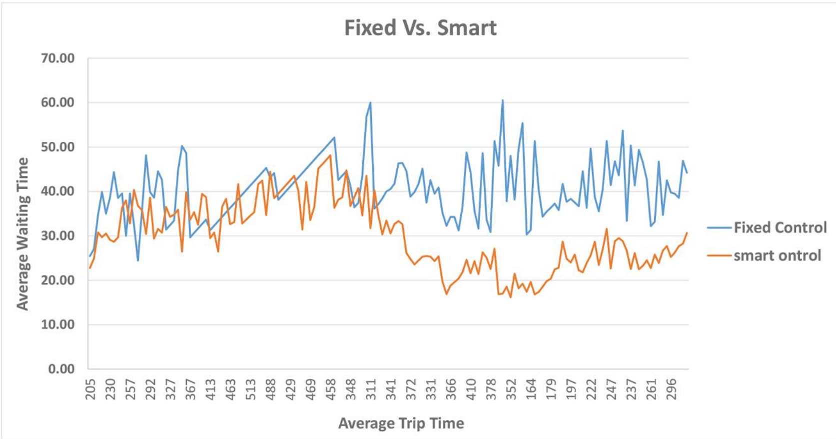

FIGURE 11 The proposed algorithm in comparison with fixed cycle control according to total waiting time

vehicle average waiting time (by 29.98%). Such system can reduce the need for new infrastructure, in addition to the fuel consumption, gas emission, driver's trip time, average waiting time and the environmental impact on fauna, flora and human health as well. Future work will be concerned in prototyping this system and applying this technique on Virtual Traffic Light Technology (VT).

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CONFLICTS OF INTEREST

The author declares that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research study reported.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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