Egyptian Informatics Journal 23 (2022) 163–176

Contents lists available at ScienceDirect

Egyptian Informatics Journal

journal homepage: www.sciencedirect.com

Smart Traffic Scheduling for Crowded Cities Road Networks

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ARTICLE INFO

Article history:
Received 17 June 2021
Revised 19 September 2022
Accepted 14 October 2022
Available online 16 November 2022

Keywords:
Smart road traffic control
Smart cities
Road traffic network management
UTC
Urban traffic control

ABSTRACT

With the fast-expanding number of vehicles in smart cities, the management of road intersections and traffic congestion has grown to be major problems. Drivers often express their opinion that putting traffic lights on while taking traffic flows into account will have a significant impact on how traffic moves. This paper presents a smart Road traffic Control management system termed Urban Traffic Control (UTC) keeping real-time dynamic traffic flow in mind which helps in upgrading the level of road traffic network management. To provide an organized traffic arrangement, UTC presents methodologies such as vehicle counting, controlling process, and evaluation of lanes keeping status in mind, this whole procedure is implemented by taking the complete traffic network into an account instead of just considering intersections. The primary goal of our system is to lessen traffic jams by cutting down on the trip and waiting times vehicles spend at crossings and intersections. We need to assign a plan for traffic flow that has the least amount of traffic congestion and vehicle waiting time, for this purpose some indicators and models are introduced in this study. Lane weight, traffic jam indicator, and vehicle priority are among these models. As this work is an improvement on the current Road Network without much changing, we integrate our system on normal traffic lights which allow each lane a chance to move and we also considered the no-interference lane movement. To simulate our idea, we introduced a smart road traffic control system consisting of multi-agents, by using a NetLogo stimulator. To compare the fixed cycle traffic light, several vehicles (150 in total) with random behaviour were generated and scattered over 25 different intersections for the time duration of 9 h. This setting was used to test our smart traffic control solution on both lane flow and no interference movement flow. According to the obtained results, there was a 25.98% reduction in total average waiting time over simulation period for all vehicles and a reduction of 34.16% for no interference movement flow. These observations clearly state that suggested method is better suited for today's complex traffic conditions where change in infrastructure is minimal.

1. Introduction

Speaking of the present millennium, the rate of the number of vehicles registered in the US has risen to 19 % (i.e., approximately 46 million vehicles) in the early 20 years [1]. Due to this sudden increase, the issues of traffic accidents, road congestion, and environmental pollution have become more serious. There are some possible solutions to these issues, such as Intelligent Transportation Systems (ITS) or smart traffic lights. These methods reduce the waiting time at traffic lights and enhance the quality of driving. In major cities, waiting time and traffic jams are critical, by scheduling traffic and enhancing junction traffic flow, smart cities may lessen congestion, trip times, and carbon dioxide emissions [2]. The traffic refinement process can involve (ITS) Intelligent traffic lights system, which can include Genetic Algorithm [3], Fuzzy Logic and Neural Network [4,5], PLC [6], Machine Learning and deep learning [7], or Virtual Traffic light (VTL) [8,9]. Different forms of these technologies were introduced in smart cities and Internet of Things (IoT) schemes Vehicle to Everything (V2X) [10].

Controller and light heads are components of traffic lights, the controller act as the brain that commands the lights to change in a predetermined sequence. The sequence may adhere to a specified time interval, automated vehicles, or Urban Traffic Control (UTC)

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Peer review under responsibility of Faculty of Computers and Information, Cairo University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.eij.2022.10.002
1110-8665/

principles. Despite the current traffic situation, the fixed time technique represented in the green light will be shown for the same period during each cycle and regardless of the direction of no interference movement flow control, it is still employed on the lane flow control.

However, in highly congested locations or where there are no waiting automobiles, this approach may be ineffective. We place a detector along the side road or on the traffic signal lights to track the demands of the vehicles as the new technique takes into account the vehicle demands at each intersection in an automated manner. A vehicle needs to go through a phase-changing process where green status should be asserted as fast as possible. Depending on other incoming vehicles or the number of cycles for a particular intersection (either minimum or maximum), the phase might be detected and the green status might be extended.

Even though this automated approach is smarter than the conventional method of a fixed time, since it is not easy to calculate the maximum time limit for extremely crowded junctions, the automated method shows poor performance. In UTC, the status of current traffic flow impacts the timing measures and the network gathers data on a centralized computer to improve the flow of traffic [11].

UTC systems not only boost traffic flow, and vehicle trips and reduce emissions, it also offers a potential way as an alternative to address the demands of new infrastructure i.e., road expansion, new roads, tunnels, and bridges. An ideal traffic management system must be smart enough to manage traffic flow on roads effectively by taking input, priority of vehicles, affected output traffic, and volume of traffic into account. This research suggests a method that can practically be implemented to record incoming real-time differences in the flow of traffic. To minimize the overall time taken to travel and waiting time of vehicle, this technique inhibits multi-phase and can adjust itself with every update in status data.

The remaining paper is further divided into the following manner: Section 2 deals with the relevant literature review on the topic of road traffic optimization. The suggested technique is mentioned in section 3. Section 4 contains the suggested methods of simulation for improving traffic light system. Section 5 consist the discussion and lastly, section 6 covers the conclusion and the anticipated future work on this topic.

2. Related work

With the rapid increase in the number of vehicles, the conventional way of managing traffic by using system traffic lights is not much effective. Even if there are no vehicles in the other lanes, still the systems require moving vehicles to wait for a particular time limit, this is a genuine concern. To cope with these issues, several researchers have developed solutions that include Virtual traffic lights, a Genetic algorithm, and a neural network to improve traffic density in every lane at the junction. These techniques require instating a network and hardware either on both roads and traffic or on one of them. [9].

By applying image and video processing, Pandey et al gathered the traffic density at the intersection and put out a strategy for allocating the periods for traffic signals. The suggested approach is effective for traffic control [12].

Xu et al used a generative adversarial network to predict the state of road traffic in 202. According to them, accurate state prediction is crucial for intelligent transportation systems. Such predictions help travellers and the government to execute good plans and strategies regarding traffic management, respectively. Their proposed framework consists of three models, i.e., 1) Generator (G): Use historic traffic states to build a spatiotemporal matrix and generate future traffic states from it. (2) The Discriminator (D): Used to calculate the difference between actual and generated data. (3) The Adversarial training: Make sure that a balance exists between (D) and (G). For traffic flows, a 5-minute traffic prediction is generated by using this framework [7].

Under the supervision of the US Department of Transportation, the Robust Net Research Group and Michigan Traffic Laboratory at Michigan University have created an intelligent traffic signalling system (I-SIG). This technology seeks to prevent collisions and lessen traffic congestion. The system was set up and tested in several US states, including Tampa, Florida, AZ, CA, and NY. To assess traffic conditions and adjust traffic timing, the vehicles in I-SIG transmit their current position and speed to the nearby traffic signal. Unfortunately, they asserted that the I-SIG system's sensors are unreliable since they can easily be accessed by unauthorized sources [13].

It is a difficult task to remove traffic jams. Therefore, a lot of researchers hardly tried to reduce rush-hour traffic and the waste of "valuable" time. Traffic jams are caused by traffic lights, according to Avin et al. As a result, they suggested using wireless technology to provide a virtual traffic light and traffic light schedule broadcasting-based location of each vehicle. To assess the intersection's capacity and boost performance accuracy, they created a simulation. According to the observations, the percentage of vehicles increased by 5 %, and the wait time decreased by up to 50 %. Notably, they only took un-delayed vehicles into account [14].

For detecting traffic light states, Saini et al. introduced a convolutional neural network (CNN) in 2017, this CNN was based on the state recognition approach. Under various lighting setups and weather conditions, their technique proved reliable for driving evaluation [15].

Focusing on vehicle-to-vehicle (V-2-V) networking, Hagenauer et al studied the performance of self-organized traffic management algorithms. Instead of conventional ways of traffic light systems, this study incorporated virtual traffic light (VTL) on a leading vehicle. To carry out the election and traffic light computations in real-time vehicular networks, the researchers created an algorithm. They looked into the idea of using both synthetic and real-world cases to build an algorithm that enables arbitrary intersection arrangements. They concluded that VTL effectively uses all vehicular system resources and enhances the experience of driving only under average network load [16].

When speaking of multi-intersection networks, it is suggested to use artificial intelligence to manage smart traffic flow. Arel et al experimented to reduce average waiting time, congestion, and the possibility of intersection cross-blocking, by using reinforcement learning Neural networks (RL), they intended to control traffic light cycles effectively. They considered five intersections for this experiment, each one acted as an autonomous intelligent agent (either as a central or outbound agent). To find an approximate value function, Q-learning was implemented with a feed-forward neural network. The results of this experiment show that for an isolated single intersection control under LFQ regulation, a multi-agent reinforcement learning-based control system is beneficial [17].

To communicate with traffic agents, Iyer et al. talked about synchronizing traffic flow by employing multi-agent fuzzy logic distribution and Q learning. They stated that the fuzzy system can manage the multiple input data levels provided by traffic lights. [18].

Teo et al used a simulation on a traffic light system to observe the impact of waiting vehicle lanes, amber time, and duration of green light. To ensure effective vehicle passing at the junction, they use a genetic algorithm to arrange the traffic light time cycling. Present queue length is fed to the Genetic algorithm as input and evaluated optimal green time for intersection, in this way, the algorithm can find an optimized solution. The speed of the genetic algorithm depends on the length of data, hence to enhance the results further, the flow of incoming traffic is recorded even at times when the status is red [3].

A microscopic simulation was performed by Wang et al. They suggested an adaptive linear quadratic regulator (LQR) with incremental adjustments. A multi-agent simulation that produced 35 junction points was carried out. The observations collected from this simulation were then compared to regular traffic signals, an average of 29.9 s delay was recorded for a 20 s green cycle which was relatively less than the average traffic delay of normal lights. [19].

Siyal and Fathy applied edge detection and neural network algorithms to develop a process that improves traffic flow at the intersection. In this process, edge detection was used to identify vehicles and estimate their movement, whereas queue parameters were calculated using Neural networks. These neural networks were trained on different traffic flow records to develop a model with better accuracy as compared to conventional algorithms used for image processing [20].

Using CNN to collect and recognize features from visual camera pictures, John et al. introduced machine learning techniques based on computer vision for varying illumination environments. Here, the onboard GPS sensor is added to enhance identification accuracy. The GPS pinpoints the area of interest for the traffic signal it contains. Utilizing data sets collected from various locations, the suggested technique was assessed and contrasted with the conventional traffic signal. In various illumination environments, they demonstrated impressive identification accuracy of their suggested approach [21].

To regulate traffic lights for a single junction, Zou et al. presented an efficiently built fuzzy logic based on Wireless Sensor Network (WSN) [22]. According to this model, monitoring of traffic flow in nearby areas was done through single-axis magneto sensors that were supposed to be installed alongside roads. Based on the number of available vehicles, the fuzzy algorithm was utilized to alter the passing time for automobiles. In comparison with the traditional fixed cycle system, their research concluded that about a 22.7 % decrease in average waiting time and real-time control were obtained for the simulation period during the 80 s.

In a multi-intersection traffic network, Sanchez et al put forward an approach to improve traffic light cycles. They combined the Cellular Automata Simulator with Genetic Algorithms to carry out the improvement process and evaluated the model accordingly. For simultaneous computation, the team used the Beowulf Cluster algorithm. After that, they performed experiments to evaluate the suggested methodologies and confirmed their relevance for the traffic signal optimization task [23].

Several strategies were used by Biswas et al. to improve the traffic system. We targeted previous work done for enhancing intelligent traffic systems and carried out a detailed study to make comparisons among several different types of research on this topic. The study emphasized several contributions that appeared helpful for applying the smart traffic control system in developing countries [24].

Zaatouri and Ezzedine put out another real-time algorithm for managing traffic signals. They used computer vision and machine learning to assess the conflicting traffic flows at the road intersection. "You Only Look Once" (YOLO) named object identification algorithm was used to maximize the performance of traffic lights. This algorithm is based on a deep CNN algorithm. This method is per the guidelines for waiting time and safely passing vehicles [25].

The latest developments in the approaches and algorithms for road traffic optimisation were systematically analysed by Rydzewski et al. Various potential types of simulation that may be used in this regard were examined by the researchers, for example NetLogo, VANET, SUMO, AIMSUM and VISSIM [26].

Several researchers have examined the complicated task of synchronising traffic lights in the surrounding region. For instance, Tomar et al. analysed the system by dividing it into degrees of synchronisation [27]. A model for signal synchronisation was developed by the researchers that was capable of operating with DSRC, sensors, image processing or any other technology reviewing traffic density at intersections. It was possible to scale the framework and include new junctions without any issues. The technique used by the authors was SUMO simulation, which brought about a decrease of 19 % in the average trip time in comparison to the fixed time as well as non-synchronised traffic regulation (See Fig. 1).

Actual maps and mobility data were considered by Nesmachnow et al. when developing a traffic light synchronisation parallel algorithm for Bus Rapid Transit systems. Here, a different priority for buses and other vehicles was allocated. According to the researchers, through this approach, the average speed of public transport improves by almost 15.3 % and that of other vehicles by 24.8 % [28].

URBC (Urban Traffic Balance Control) is a traffic control strategy formulated by Zhonghe et al. on the basis of state-feedback. In this

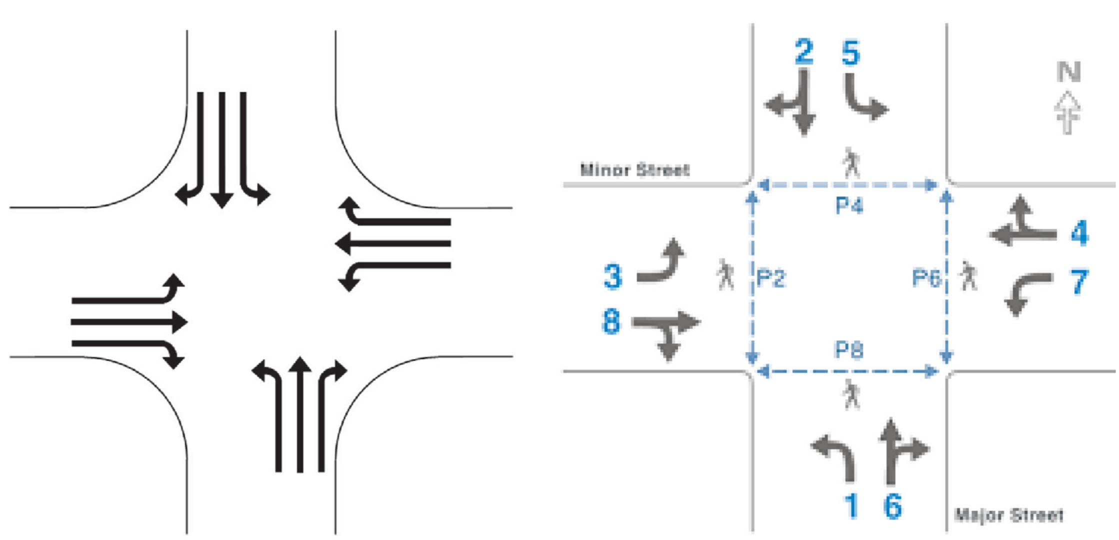


Fig. 1. Lane Flow and no Interference Movement Flow.

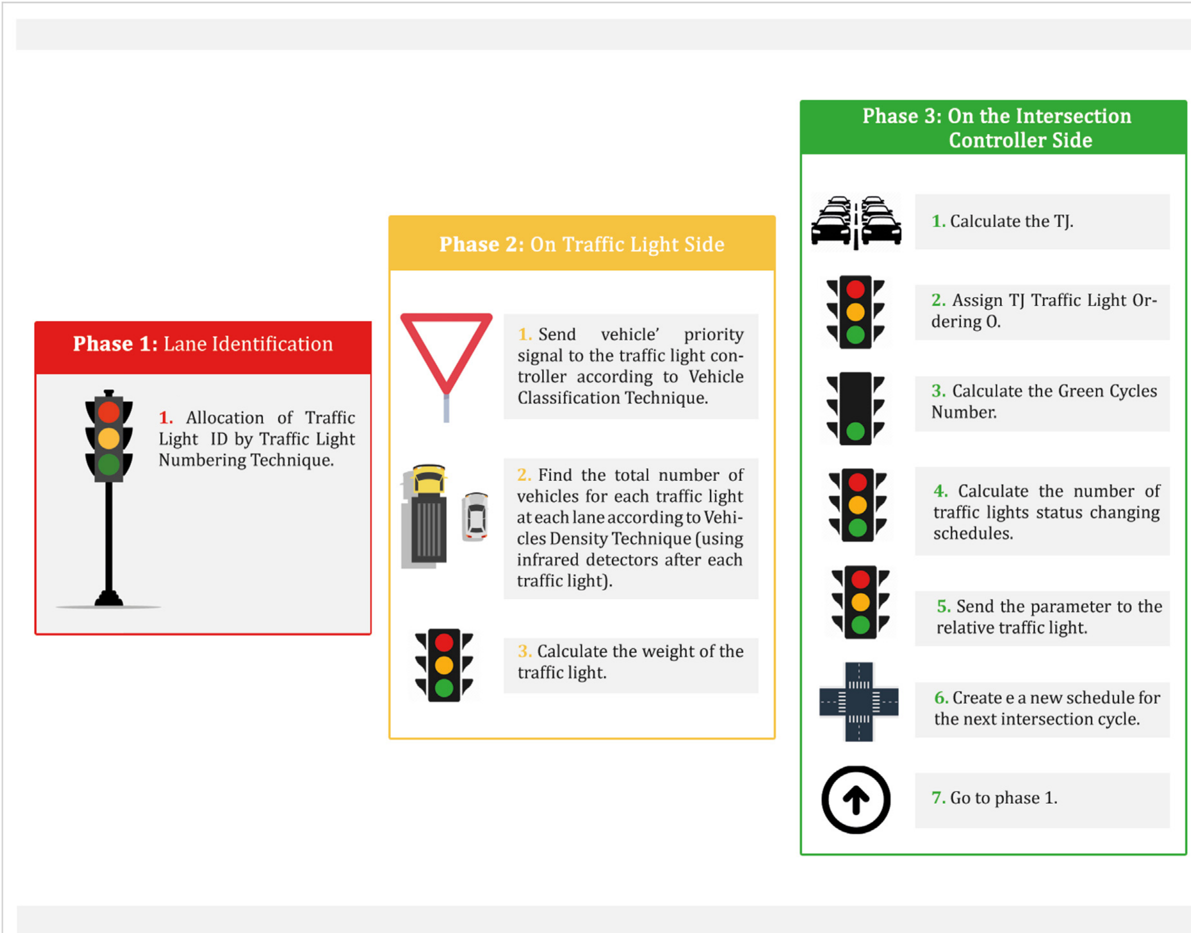


Fig. 2. The Proposed system phases.

method, VISSIM was used to simulate Wangjing (Beijing, China). There are 19 intersections and 56 links in the region, and it was observed that it was possible to decrease the delay time from 13 % to 20 % [29].

Road traffic conditions within a grid network were simulated by Burguillo et al. using NetLogo. To demonstrate how average waiting times were affected, varying numbers of self-organising intersections were used by the researchers. The findings of the study showed that the waiting time decreased in comparison to standard, fixed-time traffic lights when the number of intelligent intersections were more than 50 % [30].

Simulation was carried out on a 4x4 traffic network grid for 1, 2 and 3 h by Ahmad et al. [31]. The results showed that when the proposed method was used, the average waiting time decreased by 18 %.

Vehicle waiting time was highlighted in the study by Patrascu et al. Jade framework, Java and SUMO were employed in their study, in addition to various kinds of agents. It was possible for the average waiting time to decline, and this would lead to a fuel reduction of 3.06 % and a speed increase of 9 % on average [32].

3. Methodology

The system presented here includes various processes that would be applied to traffic lights, without significantly modifying the infrastructure. The objective of this system is to decrease vehicle average waiting time and enhance traffic flow. The system also receives consistently updated information regarding the traffic for the entire traffic network and not only the intersection. The existing traffic status of the intersection and the key roads affected due to this situation reflect the indicators determined in this study. The decision will be taken by the intersection itself, taking into account the traffic volume and the vehicle priority of the preceding and ensuing intersections, organising the traffic flow such that the vehicle waiting time and traffic jam in the network is minimized. As can be seen in Fig. 2, there are three stages of the traffic light controlling system put forward.

3.1. Phase 1: Lane identification

It can be seen in Fig. 3 that there are ty-pically-four traffic lights at intersections, each of which has multiple lanes and two directions (backwards and forwards). A technique is initially presented to allocate an IDx number for every lane on the traffic lights so that the lane, intersection and direction can be differentiated. The relevant lanes from all directions that can possibly be affected by the existing lane traffic can also be denoted by the ID.

Taking into account the lane flow technique, there are three numbers in the traffic light IDx which represent the following traffic light allocations:

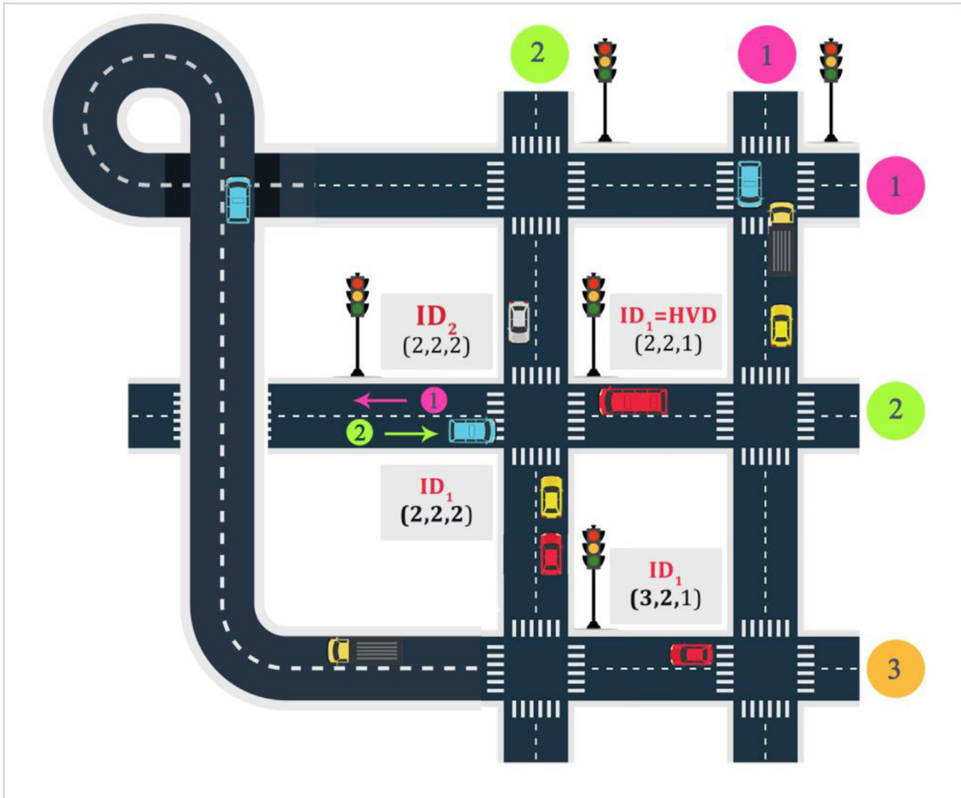


Fig. 3. Traffic light ID_x assignment-lane flow technique.

- ID_x = HVD (horizontal, vertical, direction)
- A number will be assigned to each path (1, 2, 3, n). Hence, for every intersection, there will be a horizontal as well as a vertical path number.
- There are two directions for every path (forward direction is denoted by 1 and backward direction by 2). For instance, the ID of an HVD is (2,2,1). The first number signifies the second horizontal path, the second number represents the second vertical path, while the final number is representative of the direction, which is the forward direction in this scenario.

x refers to the crossing edge, and is equivalent to 1, 2 or more.

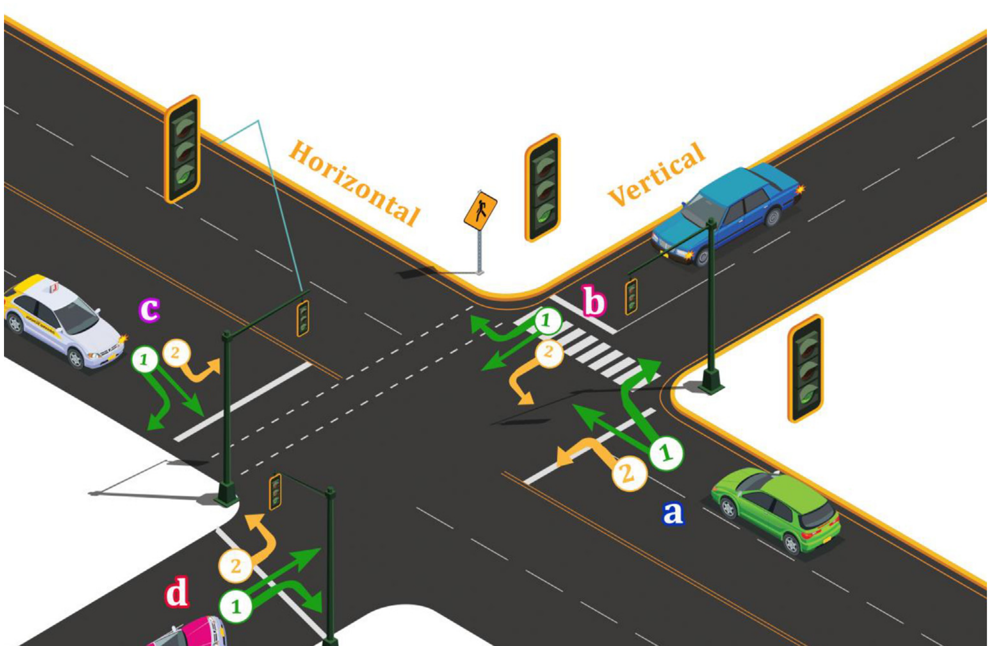


Fig. 4. No interference Movement.

The HVD can denote leading or affected lanes because all intersection that have similar H or V index are believed to be affected.

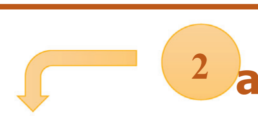
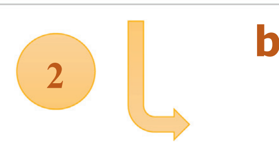
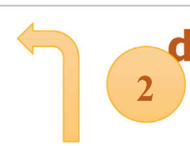
On the other hand, IDx on no-interference movement flow will include the following:

- ID_x = HVLD (horizontal, vertical, location, direction)
- A number (1, 2, 3, n) will be assigned to each path. Therefore, there will be a horizontal and a vertical path number for every intersection.
- There are four locations (a, b, c, d) in every intersection. Refer to Fig. 4 shown below.
- There are four no-interference movement in every intersection. Refer to Table 1 below.

3.2. Phase 2: Traffic lights side

In this phase, information will be gathered at every traffic light. The number of vehicles that use the method of traffic counting established earlier in [33] will be determined at every traffic light. The basis of the method is utilizing two infrared sensors and two sensors that are at a distance of 1 m from each other and are kept

Table 1
No Interference movements HVLD.

Horizontal	Vertical	L	D	
Movement (1)		a	1	
		c	1	
Movement (2)		b	1	
		d	1	
Movement (3)		a	2	
		c	2	
Movement (4)		b	2	
		d	2	

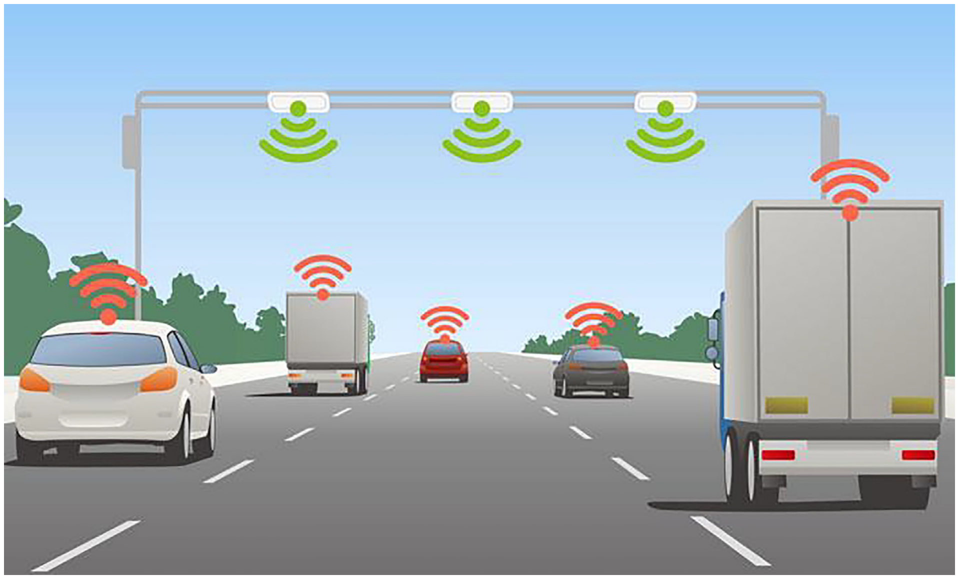


Fig. 5. Infrared Sensors for Vehicle Counting.

either at the start of every lane or right after the traffic light to ensure that vehicles are counted accurately, as shown in Fig. 5.

The perpetually (on) infrared transmitted dispatches infrared signals to the detector on the ground across a line-of-sight connection. No vehicles have moved past the beam throughout the duration the detector receives the infrared signal. In this case, the number of vehicles passing through will be determined by identifying the speed of vehicles and the length for traffic volume because longer vehicles are more likely to cause greater traffic jam issues compared to normal length vehicles. Two timers will be triggered when the connection of the initial infrared sensor is interrupted by the vehicle: (t-1 m) and (*t*-of broken connection).

To determine the vehicle speed, the time between the initial connection interruption and the subsequent connection interruption (1 m apart) is determined by the T-1 m. The car length is determined by the second timer, *T*-of broken connections, by counting the time from the point the second connection disruption occurs till the first connection reappears. On the basis of the car length, there will be an increase in the number of vehicles by (n) every time the *t*-of broken connection surpasses the time needed by a vehicle of normal length, with speed remaining constant.

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

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

When the car speed (km/h) is less than 5 km/h, the counter changes just once as the car is moving at a very low speed. When the speed becomes more than 5 km/h, the equation given subsequently is used:.$t - ofbrokenconnection = thetimeneededforthecartofully crossthefirstsensor$

$$car\ length = car\ speed * t - of\ broken\ connection \tag{3}$$

There should be an increase in the counter for cars that are more than 5 m long so that the volume of the traffic can be integrated within the statistics. The equation given below can be used for this purpose.

$$k = \frac{car\ length}{normal\ car\ length} \tag{4}$$

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

The method for determining the number of crossing vehicles is shown in Fig. 6.

A priority model is also presented in Table 2 that groups vehicles into three priority types that would be taken into account when calculating lane weights. It is assumed that emergency vehicles, school buses and public transportation can send a signal to the traffic light and can identify themselves through DSDR or RFID. Following this, Equation (6) is used at each traffic light for computing weight. The intersection controller will receive the results, in addition to the traffic light IDx (HVD).

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

Here, w refers to the Traffic light weight, n represents the number of vehicles and Vp indicates priority weight.

3.3. Phase 3: Intersection controller

In this phase, operations are carried out on the intersection controller side. The purpose of this is to create a table that distinguishes every HVD schedule with respect to its traffic jam indicator, weight, number of green cycles, traffic light order, existing status and time of subsequent status.

Tj (Traffic jam indicator) refers to the total of the previous i number of HVDs weights of those that are going to lead traffic to the path of the existing HVD, and the subsequent i number of HVDs of those that will be influenced by the existing HVD vehicle flow in all directions, horizontal as well as vertical (in this study, we choose i = 5). The suggested indicator can be indicative of the traffic status of different junctions. Equation (7) can be used to compute Tj.

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

There will be higher order of traffic light with higher Tj. In normal cycles Arelet. It is also presumed that 30 s of the green cycle is nearly equivalent to the movement of p vehicles (approximately 10 cars on average). Therefore, Equation (8) for lane flow control is used to determine the number of normal green cycles needed for

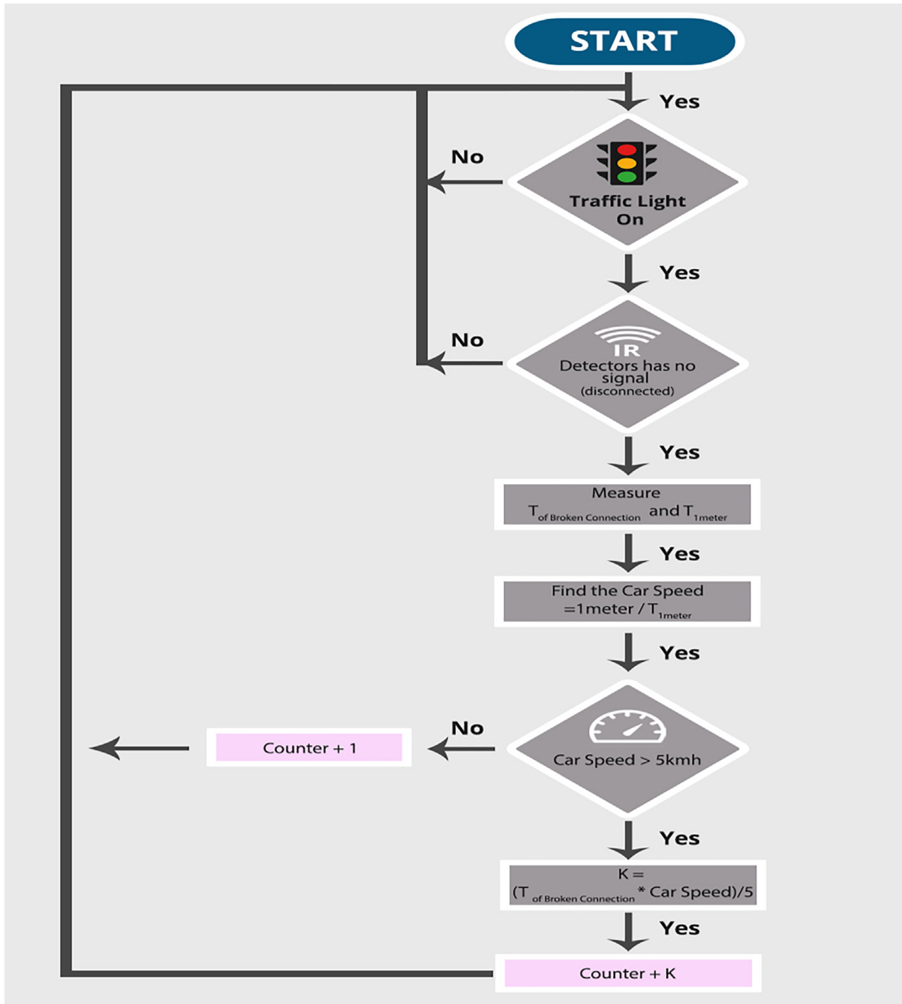


Fig. 6. Proposed algorithm for counting the number of crossing vehicles.

Table 2
Vehicle priority weight.

Vehicle	Priority weight (Vp)
Emergency Vehicle	1.0
School & public Buses	0.5
Normal Vehicle	0.1

optimum number of vehicles to move across the junction, while Equation (9) is used to determine the time of the subsequent status.

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

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

Here, N signifies Tj order of junction lanes and the 10 s as a safety for every change in traffic light status.

The computation is a little different when using the no-interference movement flow since the Traffic Jam indicator will be computed in accordance with the chosen movement:

$$\begin{aligned} &\text{Weight of Movement}(1) = \text{w}(\text{HVa1}) + \text{w}(\text{HVc1}).\\ &\text{Weight of Movement}(2) = \text{w}(\text{HVb1}) + \text{w}(\text{HVd1}).\\ &\text{Weight of Movement}(3) = \text{w}(\text{HVa2}) + \text{w}(\text{HVc2}).\\ &\text{Weight of Movement}(4) = \text{w}(\text{HVb2}) + \text{w}(\text{HVd2}). \end{aligned} \tag{10}$$

The vehicle may be involved in distinct parameters for the subsequent hop and the subsequent movement for an intersection lane of (i) cannot be predicted; therefore, we include the weight of the movement in the weight of all intersections in the given radius (i) to compute Tj as in equation (11).

$$Tj = \text{Weight of Movement (index)} + \sum_{V-i}^{V+i} \sum_{H-i}^{H+i} w(\text{IDx}), i = [1, 5] \tag{11}$$

While, Index is the movement number.

$$number\ of\ green\ cycles\ of\ movement(index) = \frac{numberofcar(L)}{p} \tag{12}$$

Table 3
Lane Scheduling.

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

$$L = \max \; number \; of \; cars$$

$$\text{Time of next status} = \sum_{1}^{N} time \; of \; green \; cycle \; for \; traffic \; light \; with(N) + (N * 10) \quad (13)$$

Lastly, Table 3 given below presents the intersection schedule:

4. Simulation

NetLogo [34,35] is used to construct a multi-agent urban traffic simulation model. We used 25 linked intersections from a given

Table 4
Agent's main attributes and methods.

Agent Type	Attributes	Behavior
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 Traffic-Light-Movement Total-Vehicles-No Total-Weight	• Set Traffic Id Calculate Vehicle Density Calculate Traffic Light Weight
Intersection Controller Agent	• Intersection-Id Traffic-Light-Id Travel-DirectionTraffic-Jam-Indicator (TJ)Traffic-Jan-index (for movement flow) Selected-Traffic-Light Green-Cycles-NumberYellow-Cycles-Number (10 s as a safety time) Red-Cycles-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

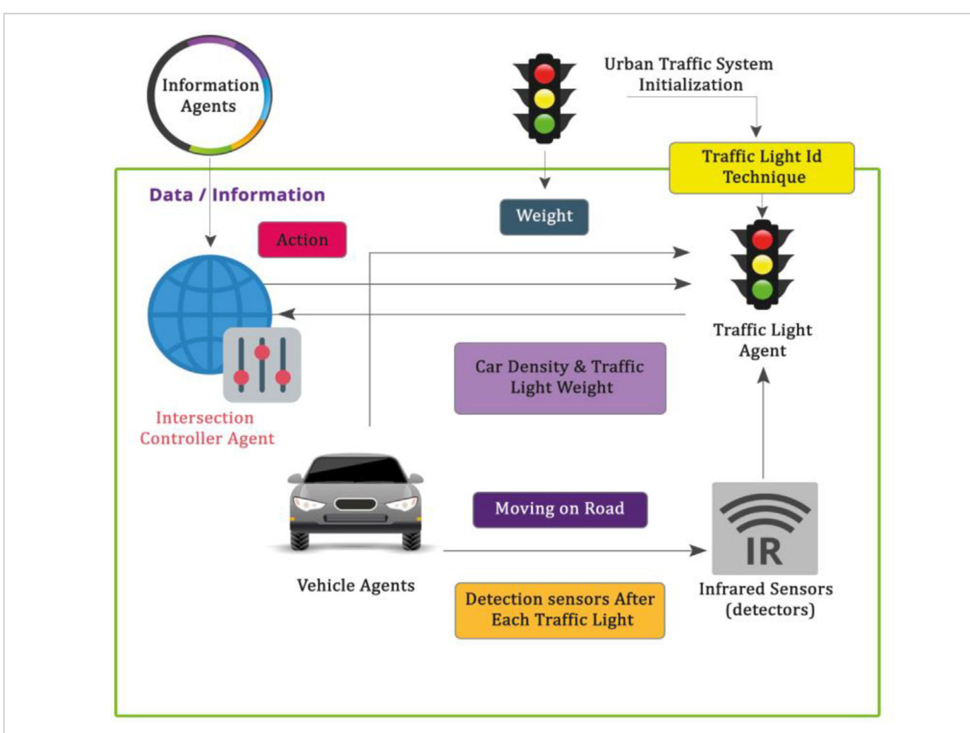


Fig. 7. Multi-Agent Urban Traffic System Components.

area with various lanes in all directions and 150 vehicles in a random behaviour. This simulator is specifically used to test three kinds of UTC systems, which are the proposed system, no interference movement and fixed time traffic control system.

Being a free open-source software, NetLogo is used for multi-agent programmable modelling environment. Scala and Java languages are used to write the programme, which operates over Java Virtual Machines (JVM). There are four kinds of agents under which NetLogo can model the population growth: Patches, Links, Turtules and Observer (further details are provided in [34]). To determine the key attributes and techniques of each agent, a multi-agent-based urban traffic mechanism is presented as a simulation model, as shown in Table 4. In this model, each traffic light, vehicle and controller are considered as a distinct agent and is spread out across a map of 25 intersections. The different types of agents of UTC are:

- Vehicle Agent:
- Traffic Light Agent.
- Intersection Controller Agent: The controlling unit to ensure that the diagnostic process is effective, which also provides directives and modifications for traffic light units.

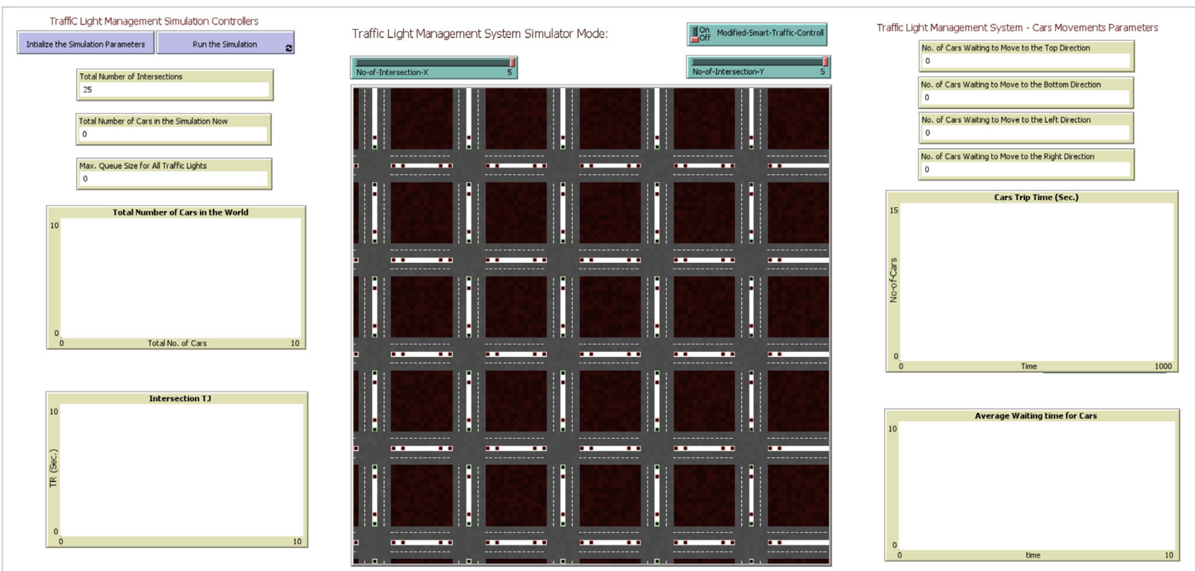


Fig. 8. Simulation Set Up.

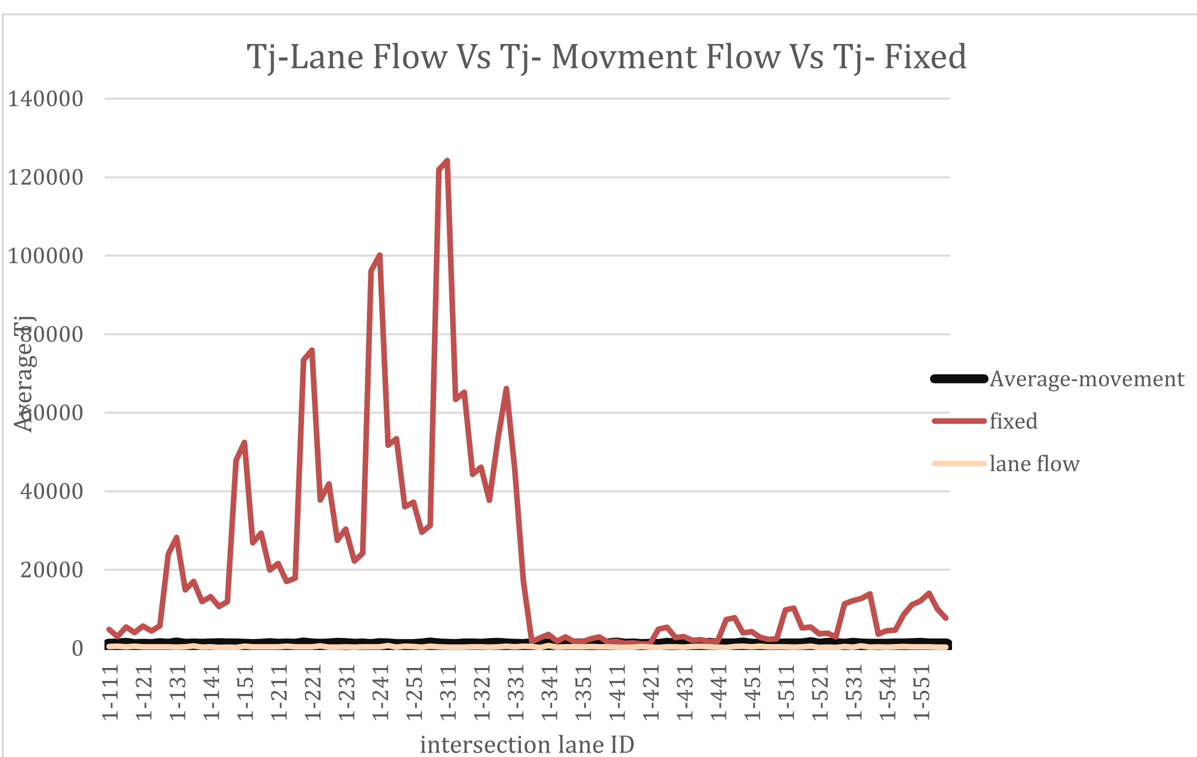


Fig. 9. Tj comparison for the three techniques.

An observer-oriented-decided-act method is used by every agent to manage all traffic lights at road junctions. Nevertheless, the existing status of the traffic at the crossing is consistently determined by the intersection control agent. The information obtained is then used to determine the behaviour of the agents. Fig. 7 shows the agent-based system components, while Fig. 8 presents the screenshots of the simulation setups (NetLogo). For 150 randomly behaving vehicles that had the same average trip time, the average wiating times were recorded. The two systems were compared by concentrating on the average vehicle waiting time for all 150 vehicles across a simulation period of 9 h. The following have been used to carry out the proposed method: (1) controller agent: to obtain data and allocate schedules to HVDs and HVLDs, (2) traffic light agent: to note down the number of vehicles and their weight for every HVD; and (3) vehicle agent: to declare their priority values in accordance with the lane flow and no-interference movement flow. In contrast, the following approach is used to carry out the fixed type on the traffic light agent: the green light shows for 30 s and red light for 90 s, and a safety time of 10 s is included to account for the change in traffic light status. In this model, the controller is not utilized.

5. Results and discussion

For fixed control as well as smart control, the simulation operated in a map (network) of 5 $\times$ 5 intersections across a time frame of 9 h. For all of the 150 cars, the average waiting time of the overall trip time and the Traffic Jam Indicator (TJ) for the 25 intersections have been monitored. It was determined in the evaluation of the suggested method that TJ was a parameter that showed the extent to which the prevailing traffic is disturbed from the two directions (the paths move towards the present intersection and will receive traffic from the existing intersection). For the two systems (smart and fixed), a TJ record has been maintained to depict how the traffic flow will be affected by this indicator. A sample of TJ-smart lane flow control records is shown in Table 5 that provides the existing status of the intersection and the adjacent region to the traffic light controller. The TJ-smart no interfer-

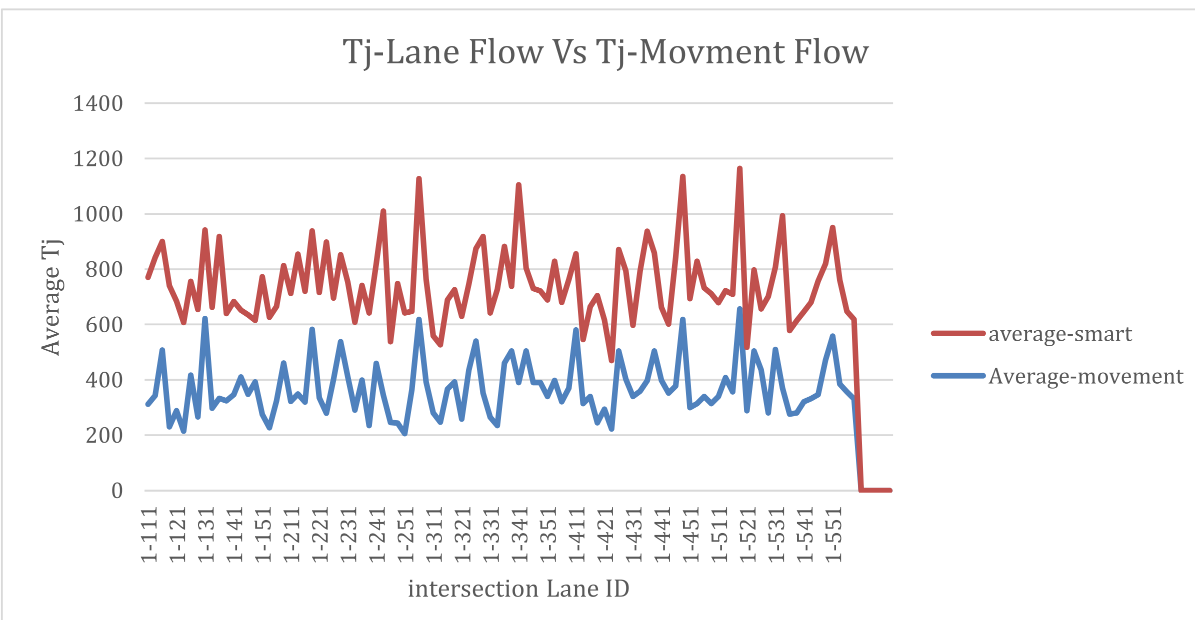


Fig. 10. Tj comparison for the lane flow and movement flow techniques.

Table 5
TJ-Smart Lane Flow Control.

No	ID	TJ-1	TJ-2	TJ-3	TJ-4	TJ-n	Ave
1	1-111	472.797	460.674	484.920	436.428	441.290	459.2218
2	1-112	517.803	504.526	531.080	477.972	467.122	499.7006
3	2-111	400.803	390.526	411.080	369.972	388.881	392.2524
4	2-112	517.803	504.526	531.080	477.972	523.904	511.057
5	1-121	400.803	390.526	411.080	369.972	406.131	395.7024
6	1-122	400.803	390.526	411.080	369.972	389.456	392.3674
7	2-121	348.270	339.340	357.200	321.480	333.598	339.9776
8	2-122	408.330	397.860	418.800	376.920	340.297	388.4414
.	.	.	.	.	.	.	.
.		.	.	.	.	.	.
96	2-542	347.509	362.037	338.569	362.037	331.822	348.3948
97	1-551	395.160	416.520	392.221	422.578	334.126	392.121
98	1-552	398.899	374.818	389.560	356.606	363.345	376.6456
99	2-551	293.805	286.578	312.100	281.975	279.221	290.7357
100	2-552	278.543	284.776	309.678	286.098	276.426	287.1042

ence movement flow records are depicted in Table 6, whereas the TJ-Fixed of the same intersections are shown in Table 7. For both the systems, the average TJ for every path ID has been determined so that the results can be compared not only across the intersection, but throughout the network (25 intersections, each of which have 4 paths).

The findings of TJ-Smart Lane flow control and no interference movement control are more or less a uniform line on the lower part of the graph for the simulation period, whereas there are extremely variable incremental values of the TJ-Fixed, as can be seen in Fig. 9. This indicates that traffic jam can be managed by the proposed method to an acceptable range instead of the unpre-

Table 6
TJ-Smart Movement Flow Control- Sample.

No	ID	TJ-1	TJ-2	TJ-3	TJ-4	TJ-5	Ave
1	1-111	300.662	316.914	320.874	312.586	306.471	311.501458
2	1-112	343.471	362.037	340.087	335.326	333.060	342.7962
3	2-111	491.471	518.037	488.822	523.058	516.554	507.5884
4	2-112	220.890	232.830	244.886	217.769	232.843	229.8436
5	1-121	278.980	294.060	277.456	290.644	301.856	288.5992
6	1-122	207.089	218.283	223.471	220.553	204.673	214.81384
7	2-121	392.089	413.283	431.438	429.341	416.773	416.5848
8	2-122	220.890	232.830	213.547	450.548	218.654	267.293824
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
96	2-542	455.972	466.166	471.808	483.231	479.667	471.3688
97	1-551	571.310	566.120	553.020	546.823	554.999	558.4544
98	1-552	414.910	398.773	384.591	359.122	363.905	384.2602
99	2-551	397.108	321.201	354.551	340.774	368.003	356.3274
100	2-552	332.968	325.065	344.411	331.389	321.442	331.055

Table 7
TJ-Fixed Control- Sample.

No	ID	TJ-1	TJ-2	TJ-3	TJ-4	TJ-5	Ave
1	1-111	4662.000	4914.221	4923.750	4931.760	4536.009	4793.55
2	1-112	2904.500	3061.500	2923.000	3191.115	2826.760	2981.38
3	2-111	5235.500	5518.500	5605.321	5521.333	5094.725	5395.08
4	2-112	3872.667	4082.000	4111.586	4103.661	3767.965	3987.58
5	1-121	5426.667	5720.000	5789.991	5891.884	5280.881	5621.88
6	1-122	4356.750	4592.250	4363.522	4427.008	4239.043	4395.71
7	2-121	5522.250	5820.750	6041.611	5762.226	5373.766	5704.12
8	2-122	23236.000	24492.876	23469.770	25886.231	22608.799	23938.74
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
96	2-542	9313.250	10970.650	11115.670	11521.760	12660.330	11116.33
97	1-551	14314.000	10991.520	11630.330	12934.000	10313.330	12036.64
98	1-552	16150.990	12550.660	15810.000	12490.530	13210.990	14042.63
99	2-551	8424.560	9902.990	10826.760	9860.350	10929.410	9988.81
100	2-552	5454.510	7704.000	6721.000	8716.000	9932.280	7705.56

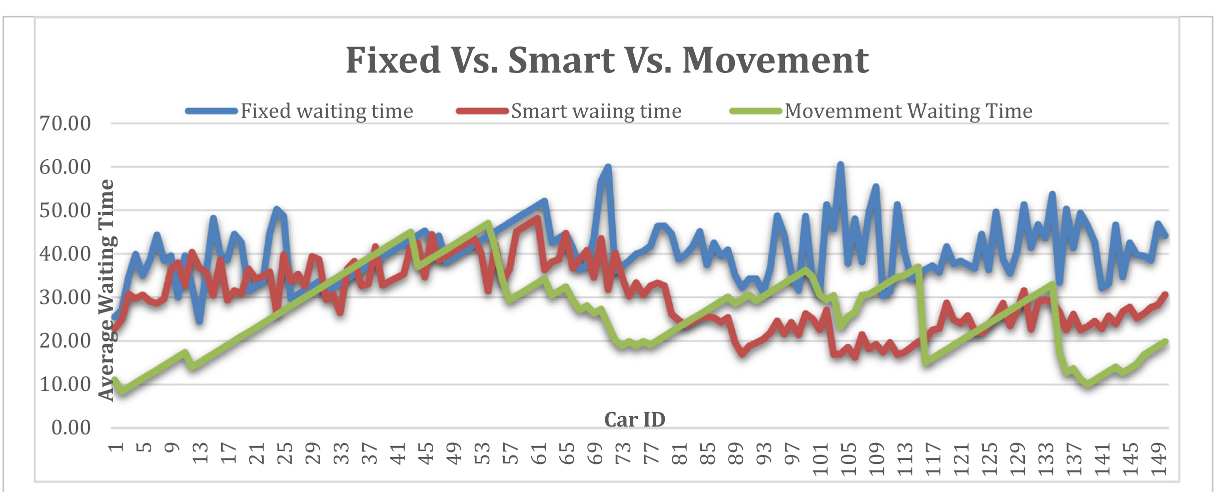


Fig. 11. The proposed algorithm in comparison of fixed cycle control according to total waiting time.

Table 8
Vehicles Trip Time and Average Waiting Time(AWT)- Sample.

Vehicle Id	Trip Time (*Sec.*)	AWT-Fixed (*Sec.*)	AWT-Smart (*Sec.*)	AWT-Movement (*Sec*)
1	235	25.47	22.7	11.00
2	205	27.3	24.87	8.33
3	215	34.67	30.76	9.33
4	334	39.89	29.96	10.33
5	413	35.0	30.54	11.33
6	132	38.56	29.12	12.33
7	514	44.32	28.65	13.33
.	.	.	.	.
.	.	.	.	.
94	392	36.59	21.82	31.23
95	401	48.77	24.60	32.23
96	410	44.32	21.58	33.23
.	.	.	.	.
.	.	.	.	.
146	331	39.67	25.25	14.67
147	288	39.47	26.52	16.80
148	542	38.56	27.66	17.80
149	322	46.56	28.25	18.80
150	331	44.23	30.64	19.80

dictable or incremental behaviour for the network seen in fixed traffic control.

The lane flow and Movement flow appeared very close to each other, as movement control has small improvement than flow control as shown in Fig. 10.

In contrast, the trip time and average waiting time were noted for all of the 150 vehicles for the two systems, as depicted in Table 8. As can be seen in Fig. 10, the suggested method brought about a decrease in the waiting time for every vehicle. According to the findings, the average waiting time computed for traditional fixed cycle control is 40.49 s for all of the 150 vehicles that had an average trip time of 335.44 s and 29.97 s for the suggested system of lane flow control and 26.66 s for the no-interference movement control, where the number of vehicles and the average trip time were the same (See Fig 11).

Consequently, the average waiting time on traffic lights was decreased by the suggested smart system by 25.98 % for lane flow control and 34.16 % for the movement control for the whole traffic in road network. These percentages are higher than other studies carried out with similar goals and environment. When the average waiting time is decreased, there is a decline in gas emission, new infrastructure requirements, time wastage, and so on.

6. Conclusion and future work

In this study, urban traffic-based intelligence approaches for traffic light scheduling are determined based on demand and feasibility of smart traffic optimisation so that vehicle waiting time is decreased and the existing infrastructure undergoes very few changes. Limited indicators and models are presented in this system to enhance the traffic flow for the entire network and decrease the mean waiting time of vehicles for the two methods by 34.16 % and 25.98 %, respectively. When such systems are adopted, the need for new infrastructure is decreased, as well as fuel consumption, drivers' trip time, gas emission, mean waiting time and the environmental impact on flora, fauna and human health. The aim of future studies will be to prototype this system and implement the method on Virtual Traffic Light Technology (VT).

7. Data availability

Data available on request from the authors.

8. Funding statement

No funding to declare.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Authors would like to thank Alzaytoonah University of Jordan for their support.

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