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DTCMS: Dynamic traffic congestion management in Social Internet of Vehicles (SIoV)

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ABSTRACT

With the augmentation of traffic exponentially, we observe that traffic congestion does not guarantee road safety or enhance the driving experience. In the recent past, Social Internet of Vehicles (SIoV), a social network paradigm permits social relationships among every vehicle in the network or with any road infrastructure to render a radically useful environment. SIoV is beneficial for the drivers, in improving road safety, avoiding mishaps, and providing a friendly-driving experience. In this paper, we propose a traffic scheduling algorithm to gain the maximum throughput for the flow of vehicles at a road intersection with the formation of social relationships among the vehicles and with the Road Side Units (RSUs). The algorithm estimates the flow rate of vehicles for lanes at the intersections exploiting the volume of traffic moving through the given road. A condition matrix is designed for the consistent movement of traffic considering different routes on the road segments. Social relationships are devised on various aspects of travel needs for a safe, agile, and better driving experience. Simulation results illustrate the efficacy of the proposed scheme with high traffic throughput, service rate and reduce the total travelling time, delay time, and average waiting time in comparison with Dynamic Throughput Maximization Framework and Adaptive Traffic Control Algorithm.

1. Introduction

The number of vehicles plying on the roads is proliferating with the increase in population. Almost all the significant urban cities experience massive traffic during peak hours. An unfortunate accident or a maintenance task on a small road can lead to an enormous hold-up and further setbacks [1]. Approximately 1.35 million people die each year as a result of

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road traffic crashes [2]. On travelling during peak hours, the traffic takes a normal of 162% additional time than the same distance travelled during off-peak hours [3]. The traffic congestion incorporates social expenses like time delays, more fuel consumption, costs due to traffic accidents, vehicle misfortune, wear and tear, and environmental issues. Gravely structured traffic signals produce frequent disturbances to the traffic flows and increase the delays. Prior attempts have been made to increase the traffic flows in urban arterial roads [4], mitigate the hold-up time at intersections and steer the vehicles on congested roads [5].

The traffic density pattern remains irregular until the end of the day. The traffic congestion rate relies upon the control on the traffic flow and on the signal timer. Congestion can be controlled by efficiently collecting the data from the traffic flow structure, utilizing various models, like vehicle detectors and sensors [6]. With the proper setting of signal timers and traffic flow prediction, traffic congestion can be controlled efficiently.

Social Internet of Things (SIoT) has surfaced after the integration of social networking notions in the Internet of Things (IoT) [7]. It is interdisciplinarily aimed at making a connected, smarter world. An instance of SIoT, called Social Internet of Vehicles (SIoV), has emerged to socialize the vehicles, commuters, and transportation infrastructure [8]. The SIoV model is applied in various areas and is developing rapidly in the digital world [9]. Presently, vehicles are advancing towards the communication technology moving towards the idea of making a smart city by connecting every object.

In SIoV, objects interact with each other by sharing details of common interests [10] to avoid the mishaps occurring on the road by allowing the commuters to share their turning intentions with traffic controllers and to abstain from any unfortunate accidents. The rapid expansion of technologies in detecting, computing, and networking, develops the massive volumes of data in a city-wide system. It includes real-time traffic information, human mobility information, and socialized connections [11]. Therefore, SIoV comes into view, aiming to successfully handle real-time traffic data, provide road safety with the Intelligent Transportation System (ITS), and make use of data processing and mining techniques for information distribution [12].

The SIoV system deals with delivering different kinds of information to several stakeholders of the transportation system (drivers, passengers, *etc.*), like emergency information [13], receiving the On-Board Diagnostics (OBD) parameters from vehicles [14] *etc*. It also communicates with the Road Side Units (RSUs) to provide the traffic patterns and vehicular flow for a safe and clear ride. This system utilizes social connections among the entities to encourage diverse communications and store the accumulated data, including performance and safety information. Thus, SIoV system leverages the traditional Vehicular Ad-hoc Networks (VANETs) mechanics [15], as it could be challenging for VANETs to work with vehicles with high mobility which cause the rapid change of network topology.

Generally, smart vehicles are furnished with cutting-edge technologies to establish Vehicle-to-Vehicle (V2V) communications with the vehicles close-by. There also exists Vehicle-to-Infrastructure (V2I) communications where the vehicles communicate with RSU to exchange meaningful information, as mentioned earlier. The smart vehicles form social relationships with RSUs and other vehicles [16] and assist in understanding the way the vehicles and RSUs connect better. The relationships among the smart vehicles and RSUs form a systematic flow for a pre-planned context [17] and avoids a misfortune, delay or congestion on the road.

With the devices being connected in IoT, SIoT, or SIoV, each of the devices' response is swift to perform the computation. These frameworks involve necessary service requirements to be satisfied by the cloud in delivering the information. The cloud cannot meet these requirements due to low latency, mobility, dissemination, scalability, limited resources *etc*. To mitigate the communication and processing delays that follow the operation, handling the data and its functions are set out nearer to the data sources using fog computing [18]. Fog computing can prevent the issues of resource scarcity in IoT, SIoT, and SIoV and improvises the effectiveness of the data sharing.

The contributions of the paper are summarized as follows:

(i) We propose a dynamic traffic control algorithm through social features by analyzing the attributes of the vehicles and their movement types to maximize the traffic flow at the intersection and give a fair chance for the higher priority vehicles.
(ii) We have defined various social relationships to inspect the absolute internal similarity among the vehicles and increase the vehicle flowing rate at the intersections over a road network.
(iii) We have analyzed the performance of the traffic conditions to optimize the traffic flow metrics such as traffic throughput, total travelling time, average waiting time, delay time, and service rate under different vehicle arrival rates.

The rest of the paper is organized as follows. A brief description of related works is presented in Section 2. Problem statement is discussed in Section 3. The traffic scheduling algorithm for Dynamic Traffic Congestion Management in SIoV (DTCMS) is presented in Section 4. The implementation of DTCMS algorithm to enhance the signal scheduling scheme is demonstrated in Section 5. The performance analysis is explained in Sections 6 and 7 contains the conclusions.

2. Related work

In this section, we present the recent related works in traffic control systems, traffic congestion, IoT, IoV, SIoT, and SIoV. Since the early 1800s, people have been thinking of machines communicating with each other. This has led to the development of IoT, which now can be described as a system of interrelated physical devices that include digital or mechanical objects and other computing devices capable of transferring data over the network without human intervention.

SIoT has emerged, enabling different devices to be connected and form relationships to achieve a common goal. Internet of Vehicles (IoV) is an extension of the concept of SIoT, leading to Social IoV (SIoV). In SIoV, smart vehicles are the objects of SIoT, that build social relationships, exchange information to enhance the driving knowledge, and give various services to the drivers.

Traffic control systems are regarded as beneficial solutions to control and manage the traffic, passing the intersections to improve road safety and traffic performance. To optimize the throughput, the traffic controller at the intersection employs turning intentions and the lane positions of the vehicles that maximize the flow of vehicles on the road segment [19]. The new method to compute the green duration and phase selection that increases the traffic flow considers waiting time, passing time, the volume of the incoming traffic, and the delay in the two subsequent phases [5].

Traffic congestion is a situation that generally takes place when the traffic flow is greater than the magnitude of the roadway [20,21]. It causes harmful effects on the environment, like increased pollutants and emission of harmful carbon in large volumes and further effects in slow delivery services at emergency responses. New approaches for collecting traffic congestion information may involve constructing the best intersection to control the congestion *via* decision making, vehicle clustering, and fuzzy assessment techniques [22,23]. The proposition of route reservation architecture and congestion-avoidance routing algorithm also helps in traffic optimization in urban simulations [24,25].

IoT is the augmentation of internet connectivity into everyday items and physical devices. IoT has advanced due to various technologies, ongoing investigation, embedded systems, machine learning, product sensors, and installed frameworks [26,27]. IoT paradigm stretches out to all aspects of the transportation system (for instance, the vehicle, the driver, or client). The dynamic collaboration of a vehicular system empowers inter and intra vehicular communication, smart traffic control, vehicle control, and road assistance. The various techniques involved in forming the relationships among objects are presented by developing a cloud-based IoT platform [28], and generating secure IoT based traffic signalling system architecture and machine learning intelligence for examining the traffic data patterns [29]. These techniques help in building up a social relationship in an autonomous manner for finding the relevant data.

IoV allows vehicles to trade information, maintain the efficiency and safety with others, and the infrastructures using Vehicular Ad Hoc Networks (VANETs). It is an advancement of conventional VANET. To predict the traffic flow and improve the performance of traffic, there are different methods which have come into existence, for example, Traffic Flow Prediction for IoV based on Deep Belief Networks [34], the vehicular communication-based technique to control the traffic signal cost-effectively [35], fog computing with a decentralized traffic management system [36] and routing protocols to provide information regarding the traffic conditions for prior decisions [37].

SIoT is portrayed as a developing paradigm of IoT where things are equipped for setting up social relationships with different objects and users. Depending on the type of the objects involved in the relationship, various types of user-object and object-object relationships [38,39]. Different strategies proposed using the SIoT include, a prediction system [40], traffic information sharing system with fog computing [41], and a trust model tailored to SIoT [42]. These strategies emphasize effectively discovering objects and services and sharing information to provide awareness in the vicinity, to minimize road accidents.

SIoV is a vehicular instance of the Social IoT (SIoT), where vehicles are the primary social segments in the machine-to-machine vehicular social networks. It is a network that validates social interactions among vehicles and commuters. SIoV is beneficial for road safety applications, traffic administration, and sharing of various other information in the smart cities [43].

Ning et al., [15] have proposed a service access method in SIoV that emphasizes on an unwavering quality assurance technique and quality enhancement strategy. The exhibited cooperative quality-aware system model considers the service discovery, network access, and routing in SIoVs and characterizes the primary social relationships among vehicles and introduced a Quality of Service (QoS) priority routing strategy algorithm. It does not address the social relationship established among the vehicles extensively and their purposes.

Silva et al. [8] have surveyed the wider SIoV system with the V2V and V2I communications to improvise the traffic efficiency and road safety. Besides, they emphasize on the ethical guidelines in designing and deploying of the SIoV frameworks. However, the system accomplishes the considerable performance; it is not intelligent to proficiently deal with the network system among smart vehicles with high-level agility in IoV systems.

Atzori et al. [30] have portrayed the implementation of SIoV on the cloud-based IoT platform. They distinguish the relationships formed among the vehicles, considering the realistic execution utilizing either Bluetooth (BT), 802.11p, or Wi-Fi advancements to influence vehicles to identify one another and make social relationships. The 802.11p protocol examination is difficult, as there are comparatively few appropriate products in the market.

Lin et al. [31] have proposed a route selection method of social vehicle, to mitigate traffic gridlock and accomplish the aim behind traffic flow control. The vehicles are separated into different clusters depending on the present and historical driving data and decide the optimal route using game evolution. Emphasis on incorporating the drivers' personal factors for traffic control, online processing information, and the design of artificial intelligence algorithms for extensive data has to be addressed.

Jain et al. [32] have presented a SIoV system architecture that incorporates several sensors to control traffic congestion and ensure road safety. A Vehicular Social Network Protocol based on wireless sensor networks achieves a global communication optimum, and an analytical cross-layer model assigns valid time slots to traffic lights. It utilizes the various benefits of heterogeneity and improves the throughput parameters for an effective IoV.

Table 1
Summary of Research Works in SIoV.

Research publication	Propose model	Technique	Operational Parameter	Relationship Type	Performance Parameter	Experimental Testbed/Simulation
Ning et al. [15] 2017	Cooperative quality-aware service access system	Service discovery, Service routing selection strategy and Quality aware access service	Access service evaluation, Social relationship evaluation, Interaction time prediction	Co-Location, Co-Work, Parental, and Social	Quality of service, request success rate, and average request cost	MATLAB Simulation
Silva et al. [8] 2018	Ethical guidelines	Ethical SIoV architecture	Years of Life Lost, Years Lost due to Disability and Disability Adjusted Life Year	Common interests	Privacy, Accuracy, Property, and Accessibility	Computational Implementation (Utilitarian Force)
Atzori et al. [30] 2018	Cloud based platform	Intelligent Transportation System Station Architecture	Vehicles radio visibility	Parental, Social, Co-Work and Ownership	Visibility distance and Friendship establishment time	Raspberry Pi 3, Telit SL869
Lin et al. [31] 2018	Social Vehicle Route Selection algorithm	Social Clustering and Game Evolution	Current and Historical driving data, evolution game model(Participants, Strategies and Clusters)	Social correlations	Social clustering and traffic congestion	Vehicles in a city of United States of America imported from OpenStreetMap
Jain et al. [32] 2018	Cross layer model for traffic management	Dynamic duty cycle control approach	Static and dynamic time zone	Common interests	Energy consumption, throughput, network lifetime and delay	MATLAB
Zia et al. [33] 2020	Agent-based model of information sharing	Context based Recommendation	Vehicle, person, and point of interest	Co-location	Good visit, Bad visit, and No visit	NetLogo

Zia et al. [33] have introduced an agent-based model of data sharing on a general populace of smart vehicles. The proposed model can depict a multi-scale recommendation system using the combination of typical Social Network (SN) and SIoV. It highlights the activity life cycle, quality update mechanism for the Point of Interest, activity replacement strategies, and a social network model.

The Table 1 summarizes the research works published in SIoV, with the proposed model, techniques, operational parameters for the data that are modelled, relation type to identify the social intersection, performance parameter and the configuration of the experimental testbed to test the environment.

The State-of-the-art research works presented above utilizes many diverse methods to provide safety and security for the flow of traffic that have proven to be productive by employing techniques like fuzzy assessment, decision-making, machine learning, routing in the networks [44,45] *etc*. The methods mentioned above intended to resolve the issues like maintaining vehicle routing decisions, detecting and evading congestion, sharing traffic information, and dealing with the vehicles' social activities. These distinguishing features assist in building better solutions for the problems not addressed previously.

3. Problem statement

In this section, we define the problem statement for traffic congestion management.

3.1. Problem statement

The dynamic traffic signal management problem is defined as follows. At an intersection, each road segment has traffic flows consisting of *right_only, left_only, go_straight, straight_right, left_diagonal, right_diagonal, all_ through, and straight_left* movement vehicles. Green signs are to be assigned for traffic movement at the intersection, which does not result in any collision or cause congestion and provide a quality-of-service to higher priority vehicles. The objectives are to (i) estimate the Flow Count to improvise the traffic flow by adding a trace of social parameters, (ii) design the condition matrix independent of the lanes or movement types and left/right-hand driven vehicles, and (iii) determine the next non-colliding flow and choose to assign the green sign for the traffic that can pass the intersection, and address the following.

(i) Maximize the traffic throughput and service rate with the allocation of green signs for the specific road segment and increase the traffic flow with the formation of social relationships between the vehicles, RSUs, and commuters.
(ii) Minimize the total travelling time, average waiting time, and delay time of vehicles at the intersection under different vehicle arrival rates.

3.2. Assumptions

1. Vehicles are assumed to have Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) connectivity.
2. The vehicles are not permitted to make U-turns.
3. The vehicles register and disseminate their information, like location, acceleration, drivers reaction time, and turning intentions to the traffic controller at the intersections.
4. Legislation and Security are not considered to model the vehicles.
5. The optimization scheme does not take into account pedestrian and crosswalks at the Intersections.

4. Traffic signal scheduling through social features

In this section, we describe the system model, system design and the signal scheduling algorithm to maximize the traffic flow. The algorithm applies the social features to control the green signal, which effectively manages the congestion at the intersection.

4.1. System design

The proposed road network model is demonstrated in Fig. 1 with Intersection *I* and an adjacent Intersection *J*. The Intersection *I* consists of a six-road segment that connects a crossing of vertical, horizontal, and diagonal tracks and the Intersection *J* comprises four road segments with two lanes. As the figure describes the layout of an intersection, we specify the components present on the road and its further details in Fig. 2. At the intersection side, there is a traffic controller with a network interface and microprocessor. At the roadside, the vehicles are equipped with the network interface, GPS receiver, and an On-Board Diagnostic (OBD) interface [46]. The network interface manages the communication between traffic controllers, vehicles, and GPS receiver; the microprocessor controls the traffic signs, and the GPS receiver calculates the locations. The OBD interface captures the current vehicle status, like vehicle type, length, speed, drivers turning intention, and acceleration habit. The segment of SIoV comes into play, where we tend to determine the purpose of a vehicle choosing a particular road from the historical data and calibrate the traffic based on the prediction. We can anticipate how regularly a specific vehicle crosses that road and its needs from the various amenities it halts at.

In SIoV, a vehicle which is a mobile node comprises of On-Board Unit (OBU) whose essential job is detecting and creating vehicular communication. Also, there exists a static node called as a Road Side Unit (RSU) or Traffic Controller (TC), where

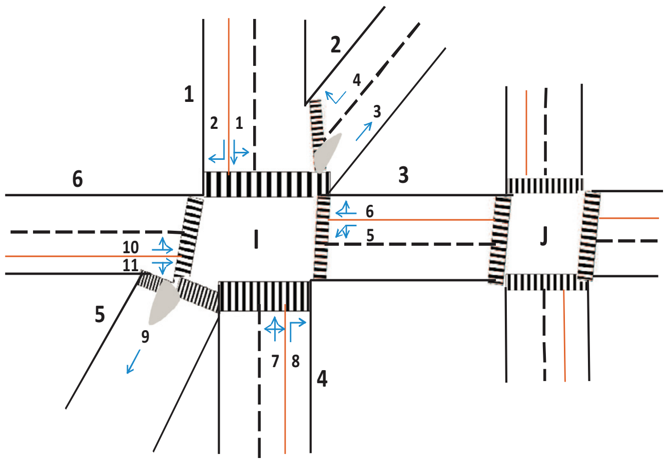


Fig. 1. Road Network Model in the Proposed Work.

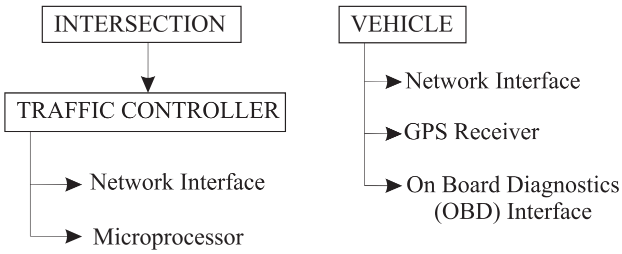


Fig. 2. Components of the Road Network.

it has its geographical location, storage device, and atleast two network interfaces that constitute the roadside infrastructure [30]. The communication between these bodies describes the Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) information. Based on the communication between the vehicles and the RSUs, we can define the following social relationships.

(i) *Approach Object Relationship (AOR)* - AOR exists between vehicles present in the same physical geography intending to share the public information and messages. When a vehicle (*i.e.* OBU) come in contact with another vehicle, based on the message exchange, an AOR is created between the vehicles.
(ii) *Group Object Relationship (GROR)* - GROR is formed where vehicles obtain updated information from a group of social friends travelling through the same routes about traffic conditions [30].
(iii) *Priority Object Relationship (PROR)* - When a higher priority vehicle, for example, an ambulance, proceeds towards a vehicle, this vehicle establishes the PROR for which it gets in contact with the ambulance and allows it to give a clear run down the middle of the road.
(iv) *Distant Object Relationship (DOR)* - Vehicles from the same producer come in contact with others to know if they had faced a similar issue and identify the way they have resolved it. For example, a service for diagnosis helped a vehicle to get immediate recovery; this can be shared with the requesting vehicle; another could be faraway maintenance from the manufacturer himself [30].
(v) *Visited Object Relationship (VOR)* - When a vehicles pass through or come in contact with a premise or a building previously visited (from the historical data of the vehicle) it forms a VOR and with the aid of Ownership Object Relationship (OOR) [39] gathers the different information from the connected devices under the same owner and stores this new information.
(vi) *Resource Object Relationship (ROR)* - A public transport vehicle, *e.g.* a bus establishes a ROR with other coaches, this relationship executes the resource request by coordinating the same resource configuration. Every public transport vehicle in the network by itself forms various types of relationships and uses the resulting connection for network navigation.
(vii) *Possession Object Relationship (PSOR)* - PSOR is formed between different objects, like smartphones, tablets, smartwatches *etc.* of the single user and connects these computing devices to his/her vehicle establishing a relationship between these objects with the vehicle he possesses. For example, in Freight Transportation, as mentioned in [39], the carrier vehicle retrieves the information from the devices it has formed a relationship to determine the unloading of the merchandise from the truckload.

Table 2
Relationship Types among Vehicles and with RSUs.

Relationship type	Type	Characteristics	Participating entities	Weighting factor (w_R)	Maximum Relationship Score ($R_{\max}$)
AOR, PROR, ROR	TYPE 1	The usual set of circumstances occurring on the road, where one vehicle crosses another	Vehicle and Vehicle	0.4	2
GROR, DOR, ADOR	TYPE 2	Vehicles get assistance from friend vehicle or a static node *e.g.*, RSU	Vehicle and a Friend Vehicle / RSU	0.3	3
PSOR, PKOR, VOR	TYPE 3	Vehicles establish relationships with other vehicles/devices to attain a common service	Vehicle and Computing Devices	0.2	4
LOR	TYPE 4	Vehicle collaborates with other vehicles to achieve a goal	Vehicle and Vehicle	0.1	9

(viii) *Parking Object Relationship (PKOR)* - PKOR is established between the vehicles' GPS receiver, smartphone navigator, and a sensor service platform. It enables a vehicle and its driver to obtain available parking spaces from the data collected in the real-time. The vehicle creates a relationship with the sensors, smartphones, smart parking meters, and a parking provider. Thus, operating in reduced traffic, increased service and optimized parking during traffic congestion.

(ix) *Administrator Object Relationship (ADOR)* - Here, the RSU acts as the preserver of the OBU in case of any extremity and forms a relationship with OBU by apprising it with the needful information during the crisis. This relationship assists the OBU in gaining acquaintance about the condition ahead and cleverly refrains from it.

(x) *Lane Object Relationship (LOR)* - Suppose a vehicle wishes to change its lane from an arterial road to a service road. In that case, it forms a LOR relationship with the vehicles around it, for them to assist it in changing the lane without causing any congestion or delay in the flow of traffic.

These relationships among the vehicles and the RSUs are dynamic and short-lived based on the instantaneous position of the vehicles. The various relationships among the entities involved in providing services to one another is outlined in Table 2. Every relationship works in-order to achieve a distinct goal and increase the service quality to improve the whole user experience. To enhance the service quality, the higher priority value is specified to the services with the outstanding quality and connections due to its vast dependability. Various vehicles with distinct features can be grouped to form clusters, and they establish social relationships to perform a common task. The weighting factor is assigned to a range of relationships that have common characteristics to provide better facilities to the entities. Each of the relationship types that can be tied among the groups of vehicles and the RSUs on each lane of the road segments is fixed with the maximum relationship score.

Out of the four types of relationships defined, *TYPE 1* is given a top weighting factor because it contains the relationships which offer more service. For example, a higher preference vehicle like an ambulance, would cross paths with other vehicles and given more priority by the others. Thus the relationship holds to have a weighting factor of 0.4. Similarly, the *TYPE 2* relationships obtain assistance from others to solve a problem; hence these relationships are given the next higher weighting factor of 0.3. The same follows with the rest of the relationship types. For the maximum relationship score, *TYPE 1* is assigned with the least score because we assume that at most two higher preference vehicles can be seen on each lane at the same instance. *TYPE 4* is given the highest score with 9, indicating that a maximum of nine *LOR* relationships can be established among the vehicles on each lane of the road segment.

4.2. System model

Consider a road network with an intersection I, which has the adjacent intersections. Each intersection has p road segments, where $I = \{Rs_1, Rs_2, Rs_3, \ldots Rs_p\}$, comprising r lanes. If there are k lanes on each road segment i then $Rs_i = \{L_1, L_2, L_3, \ldots, L_k\}$.

Each lane k on road segment i has a different traffic flows, such as {*left turn, right turn, go straight, left diagonal and right diagonal* }. For each road segment i, we define q movement types, *i.e.MovementTypes*= {①*right_only*, ②*left_only*, ③*go_straight,....* ⓠ }.

The MovementType j that is non-colliding with the road segments p are considered as the permitted movements and are combined together to form a set of candidate condition matrices $M = (M^1,\ M^2 .... M^c)$.

The next step is to choose the most appropriate condition matrix that yields the highest flow count *i.e.* $M_{\max} \in M$.

The green sign is assigned simultaneously to all the lanes r that belong to the permitted movements in the condition matrix $M_{\max}$ *i.e.* the traffic with the maximum flow count. The highest flow time among all the permitted lanes is selected as the green duration S_{green}.

4.2.1. Traffic flow queue

Let there be three types of queue approaching the intersection I on each lane of the road segments, enumerated as follows:

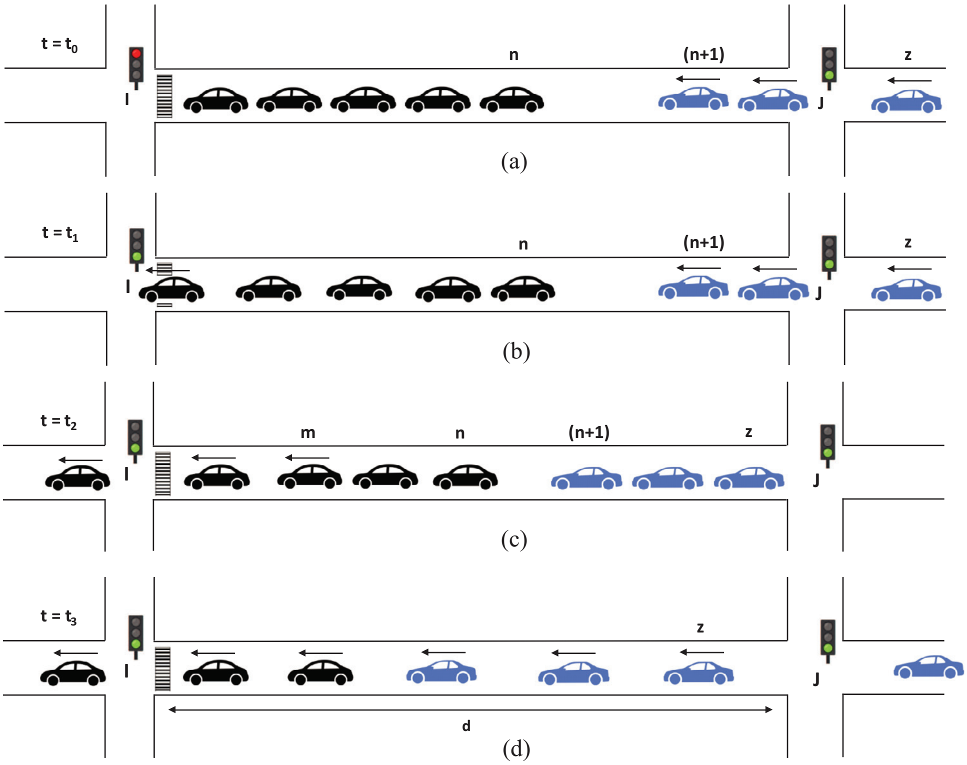


Fig. 3. Instance of Traffic Flow Queue for *(Q1, AQ1)* for Timeline (a) $t = t_0$, (b) $t = t_1$, (c) $t = t_2$, and (d) $t = t_3$.

Q1: *Non-Moving Queue*: All the vehicles in the queue are not moving due to the red signal and are waiting to cross the Intersection *I*.

Q2: *Moving Queue with Non-moving Vehicles*: The vehicles in the front portion of the queue have begun to move when green light has just fallen, while few in the rear portion are still stopped at the Intersection *I*.

Q3: *Moving Queue Without Non-moving Vehicles*: All the vehicles in the queue have started to move when the green light has given for a while and no vehicles are stopped at the Intersection *I*.

Next, considering the traffic flow from the adjacent intersection *J* to the Intersection *I*. We classify the queues arriving from *J* to *I* into three types according to the changing status of the queue, *i.e* when the front portion of the queue from *J* reaches the end of the queue at *I*.

AQ1: *Wait-First Queue Without Move Forward Vehicles*: When the queue from *J* advances towards the queue at *I*, all the vehicles from *J* will stop at the beginning and then move ahead.

AQ2: *Wait-First Queue With Move Forward Vehicles*: When the queue from *J* advances towards the queue at *I*, the front portion of the queue from *J* will stop first and then move forward. But the rear portion continues to move without completely stopping.

AQ3: *Move Forward Queue*: When the queue from *J* advances towards the queue at *I*, all the vehicles from *J* will continue moving ahead without completely stopping.

Suppose that at time $t = t_0$, Intersection I is scheduling to choose the next cycle at time $t = t_1$, where the time interval $(t_1 - t_0)$ is very short. Fig. 3 shows an instance of the traffic flow with queue *Q1* at the Intersection *I* and queue *AQ1* at Intersection *J*. At time $t = t_0$, let n be the last vehicle in the queue *Q1* at the Intersection *I*, *n+1* is the first vehicle in the queue *AQ1* which has crossed the Intersection *J*, and *z* is the last vehicle in the queue *AQ1* which has not crossed the Intersection *J*, where $n < n+1 \leqslant z$. Assume that at time $t = t_1$, the red signal at the Intersection *I* changes to green and all the vehicles at *I* starts to move. At time $t = t_2$, the *z*th vehicle has crossed the Intersection *J*and gets to a stop blocked by few vehicles in the front. During this interval, *m-1* vehicles has continued moving forward and the *m*th vehicle is just began to move, which indicates that the *z*th vehicle has taken $\sum_{x=1}^{m} \Delta r_x$ seconds to stop. Finally, at time $t = t_3$ the *z*th vehicle starts moving after $\sum_{x=m+1}^{z} \Delta r_x$ seconds. Then the anticipated flow time of the *z*th vehicle to pass the Intersection *I*is determined by $\Delta t_I(z) = ((-v + \sqrt{(v^2 + 2ad)})/(a)) + \sum_{x=1}^{m} \Delta r_x + \sum_{x=m+1}^{z} \Delta r_x$, where v is the velocity of the *z*th vehicle while crossing I, $d = \sum_{x=m}^{z} l_x + d_x$, where l_x is the length of the xth vehicle and d_x is the distance from mth vehicle to the vehicle in the front that is stopped, hence aggregation is the distance from the mth vehicle to zth vehicle, $a$is the acceleration between the vehicles m to the z, and Δr_x is the drivers reaction time of the xth vehicle. Thus depending on the type of the queue that arrives at the intersection, the anticipated flow time of the zth vehicle can be derived for different instances of queues *(Qi, AQj)*[19].

4.3. DTCMS Algorithm

The Algorithm 1 , DTCMS (Dynamic Traffic Congestion Management in SIoV) consists of five phases:

Algorithm 1: DTCMS: Dynamic Traffic Congestion Management in SIoV.

Input: Information of vehicles passing the Intersection
Output: Condition Matrix with the Maximum Aggregated Flow Count ($M_{\max}$)
begin
  Phase I : Determine the Flow Count incorporating Social Attributes
  for $i \leftarrow 1$ *to* p **do**
    for $k \leftarrow 1$ *to* L_i **do**
      Compute $c_{ik} = \frac{n}{\Delta t_{ik}} + c_{PRI} + \alpha w_R$
  Phase II : Computation of Drift Attribute of Lanes
  for $i \leftarrow 1$ *to* p **do**
    for $j \leftarrow 1$ *to* q **do**
      for $k \leftarrow 1$ *to* L_i **do**
        if *vehicle turning intention on the lane* (k) *of road segment* (i) *is complaint to movement type* (j) **then**
          $D^k_{i,j} = 1$
        else
          $D^k_{i,j} = 0$
  Phase III : Determine the Total Flow Count
  for $i \leftarrow 1$ *to* p **do**
    for $j \leftarrow 1$ *to* q **do**
      Compute $C_{ij} = \sum_{k=1}^{L_i} c_{ik} \times D^k_{ij}$
  Phase IV : Generate Condition Matrix for Road Segments
  for $i \leftarrow 1$ *to* p **do**
    for $j \leftarrow 1$ *to* q **do**
      if *MovementType j on RoadSegment i is non-colliding and allowed concurrently with MovementTypes* $(j, j+1, \ldots q)$ *of other RoadSegments* $(i+1, \ldots p)$ **then**
        $M_{ij} = 1$
      else
        $M_{ij} = 0$
  for $i \leftarrow 1$ *to* p **do**
    for $j \leftarrow 1$ *to* q **do**
      Output $M^1 = M_{ij}$
  Phase V : Determine the Aggregated Flow Count
  for $n \leftarrow 1$ *to* N **do**
    Compute $A^c = \sum_{i=1}^{p} \sum_{j=1}^{q} C_{ij} \times M^n_{ij}$
  Choose Condition Matrix with the Maximum Aggregated Flow Count ($M_{\max}$)
  return $M_{\max}$

Phase I : Determine the Flow Count incorporating Social Attributes.
Phase II : Computation of Drift Attribute of Lanes.
Phase III : Determine the total Flow Count.
Phase IV : Generate the Condition Matrix.
Phase V : Determine the Aggregated Flow Count.
The Notations used in the Algorithm is listed in Table 3. The flowchart of the proposed DTCMS is shown in Figure. 4.

Table 3
Notations used in the Algorithm.

Notation	Description
I	Road Intersection
i	RoadSegment
p	Total number of RoadSegments at Intersection I
j	MovementType
q	Total number of MovementTypes
k	Lane
r	Total number of Lanes on RoadSegment i
c_{ik}	Flow Count for the lane k on Road Segment i at an Intersection I
c_{PRI}	Flow Count with Priority Vehicles
w_R	Weighting Factor for Relationships
$R_{\max}$	Maximum relationship types allowed among vehicles and RSUs on each lane at the same instance
R	Number of relationship types tied among vehicles and RSUs on each lane of the road segment at the same instance
α	Scaling Factor
L_i	Number of lanes on RoadSegment i
M_{ij}	Condition Matrix for the MovementType j on the RoadSegment i
D_{ij}^{k}	Drift Attribute of the k^{th} lane of RoadSegment i for the MovementType j
C_{ij}	Total Flow Count for each RoadSegment i given MovementType j
A^c	Aggregated Flow Count

4.3.1. Phase I : determine the flow count incorporating social attributes

The Flow count describes the amount of traffic allowed in a lane to pass through the intersection. Consider the lane k on road segment i, the flow count for this lane at an Intersection I is computed by Eq. (1).

$$c_{ik} = \frac{n}{\Delta t_{ik}} + c_{PRI} + \alpha w_R \tag{1}$$

Where n is the number of vehicles in the queue waiting to pass the intersection, estimated by the traffic controller *via ADOR* relationship and Δt_{ik} is the anticipated time required by the last (*i.e.* n^{th}) vehicle in the lane $k$on road segment i to pass the intersection called as the flow time, must satisfy the Eq. (2).

$$\Delta t_{ik} = \frac{-v + \sqrt{(v^2 + 2ad)}}{a} + \sum_{m=k}^{n} \Delta r_m \tag{2}$$

The flow time is derived from the kinematic equation [47] that takes into account measures such as the vehicles velocity (v), acceleration (a), distance to the intersection (d) and the drivers reaction time Δr_m for the mth vehicle with $s$being the first stationary vehicle in the queue, $1 \leqslant s \leqslant m \leqslant n$. Incorporating the aspects of social attributes and establishing the *ADOR*relationships, we acquire the vehicles position, acceleration, their social needs *etc*, to achieve accuracy, where c_{PRI} is the vehicle flow count with the priority assigned to it if any. c_{PRI} is set to *1* with the priority vehicles on the lane, and with no priority vehicles, it is set to *0*. The weighting factor (w_R) for the relationship type among the vehicles and RSUs is as described in Table 2. Suppose, if there exist two different types of relationships on the same lane of the road segment, then the weighting factor of the higher priority relationship type is chosen. The scaling factor α is considered in the range of 0–1 to regulate the decision of the weighting factor. The scaling factor synchronizes with the weighting factor based on the category and the number of the relationship types (R) that exist among vehicles, given by $\alpha = w_R \times R$; $0 < R \leqslant R_{\max}$.

4.3.2. Phase II : computation of drift attribute of lanes

After computing the flow count for each lane, the right-of-way for the lanes on the road segments needs to be scheduled with various movement types. All the possible movement types of the vehicle for each lane k on the road segments i are: ①*right_only*, ②*left_only*, ③*go_straight*, ④*straight_right*, ⑤*left_diagonal*, ⑥*right_diagonal*, ⑦*all_ through*, and ⑧*straight_left* movements as shown in the Fig. 5. The Drift attribute of lanes is composed of three-dimensional *RoadSegment-Lane-MovementType* binary element, whose value rely upon the vehicles turning intention *i.e.* the movement type that the drivers intend to turn at the intersections and it is denoted by D_{ij}^{k} of the kth lane of road segment i for the movement type j. The vehicles turning intention is registered to the traffic controller based on *ADOR* relationship. When the turning intention of vehicles on the kth lane of road segment $i$is compliant to movement type j, then D_{ij}^{k} is set to *1*, if not, it is set to *0*. The lanes on the road segment i are denoted by L_i and are numbered from left-to-right in the left hand operated vehicles that drive on the right side of the road, and right-to-left in the right hand operated vehicles that drive on the left side of the road. The Drift Attribute is computed based on the following strategies:

(i) If the leftmost lane has no *go_straight* intention vehicles, then *left_only* is set to the leftmost lane, and *straight_right* is set to all-other lanes of the road segment.

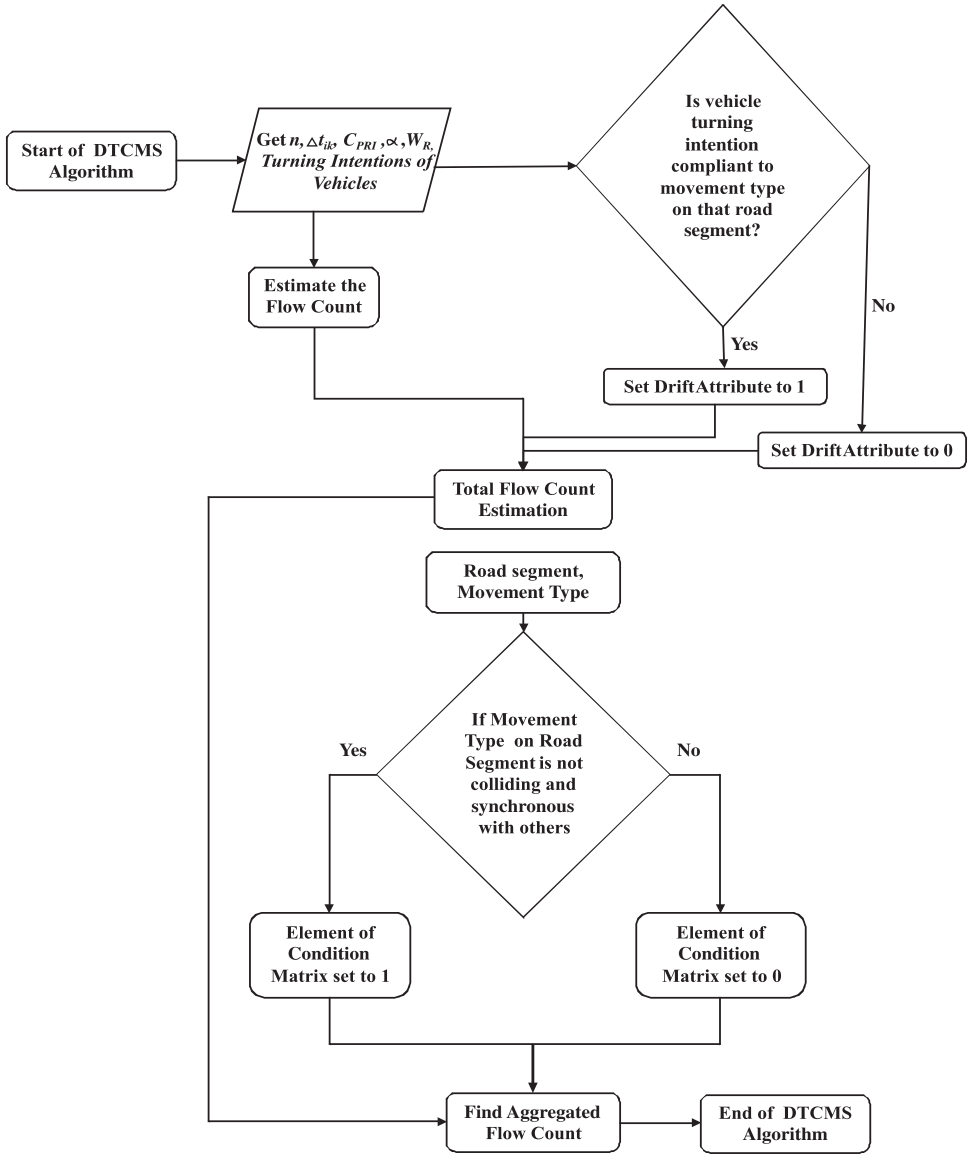


Fig. 4. Flowchart for the proposed DTCMS.

(ii) If the leftmost lane has only *go_straight* intention vehicles, then *straight_right* is set to leftmost lane and to all-other lanes of the road segment.
(iii) If the leftmost lane has both *go_straight* and *left_turn* intention vehicles, then *straight_left* is set to leftmost lane and *right_diagonal* or *all_through* is set to all-other lanes of the road segment.
(iv) If the rightmost lane has no *go_straight* intention vehicles, then *right_only* is set to the rightmost lane, and *straight_left* is set to the other lanes of the road segment.
(v) If the rightmost lane has only *go_straight* intention vehicles, then *straight_left* is set to rightmost lane and to all-other lanes of the road segment.
(vi) If the rightmost lane has both *go_straight* and *right_turn* intention vehicles, then *straight_right* is set to rightmost lane, and the *left_diagonal* or *all_through* is set to all-other lanes of the road segment.

The strategies for assigning drift attribute of lanes are listed in Table 4 and it can be applied to any road segment with the different number of lanes for both left, and right hand drove vehicles.

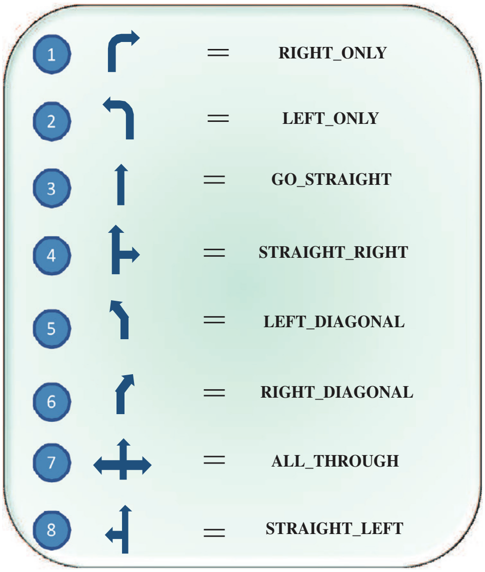


Fig. 5. Vehicle Movement Types for each Road Segments.

Table 4
Strategy to Assign Drift Attribute.

Vehicle Operation	Turning Intention	leftmost lane	all-other lanes
Left Hand **1, 2, ..., L_i**	↗	② ↰ $D^1_{i2}=1$	④ $D^r_{i4}=1,\ for\ \ r=2,3,....,L_i$
	↑	④ $D^1_{i4}=1$	④ $D^r_{i4}=1 for r=2,3,....,L_i$
	↑ + ↰	⑧ $D^1_{i8}=1$	⑦ $D^r_{i7}=1 for r=2,3,....,L_i$ OR ⑥ $D^r_{i6}=1 for r=2,3,....,L_i$
Vehicle Operation	Turning Intention	rightmost lane	all-other lanes
Right Hand L_i**, ... ,2,1**	↗	① ↱ $D^1_{i1}=1$	⑧ $D^r_{i8}=1,\ for\ \ r=2,3,....,L_i$
	↑	⑧ $D^1_{i8}=1$	⑧ $D^r_{i8}=1,\ for\ \ r=2,3,....,L_i$
	↑ + ↱	④ $D^1_{i4}=1$	⑦ $D^r_{i7}=1,\ for\ \ r=2,3,....,L_i$ OR ⑤ $D^r_{i5}=1,\ for\ \ r=2,3,....,L_i$

Movement Types / Road Segments

$$
\begin{array}{c}
\\ 1 \\ 2 \\ \vdots \\ i \\ \vdots \\ p
\end{array}
\begin{array}{c}
\begin{array}{ccccccc} 1 & 2 & \cdots & j & \cdots & q \end{array} \\
\begin{bmatrix}
M_{11} & M_{12} & \cdots & M_{1j} & \cdots & M_{1q} \\
M_{21} & M_{22} & \cdots & M_{2j} & \cdots & M_{2q} \\
\vdots & \vdots & & \vdots & & \vdots \\
M_{i1} & M_{i2} & \cdots & M_{ij} & \cdots & M_{iq} \\
\vdots & & & & & \\
M_{p1} & M_{p2} & \cdots & M_{pj} & \cdots & M_{pq}
\end{bmatrix}
\end{array}
$$

Fig. 6. Condition Matrix with Non-colliding Movements for the Road Segments.

4.3.3. Phase III : determine the total flow count

After assigning the drift attribute to all the lanes, the Total Flow Count C_{ij} for each road segment i given movement type j is computed by Eq. (3).

$$C_{ij} = \sum_{k=1}^{L_i} c_{ik} \times D_{ij}^{k} \tag{3}$$

where c_{ik} is the Flow Count estimated by Eq. (1) and D_{ij}^{k} is the Drift Attribute for the lane k of road segment i given movement type j. The Total Flow Count computation is performed to obtain the maximum flowing rate of vehicles in a lane.

4.3.4. Phase IV : generate the condition matrix for road segments

After determining the flowing rate of vehicles for each lane k of the road segment i, a condition matrix is designed that indicates the qualified non-colliding movements for the road segments of Intersection I. As depicted in Fig. 6, for the vehicles to pass an intersection compose of a *RoadSegment-MovementType* Condition Matrix, where M_{ij} represent the *RoadSegement i*'s permitted *MovementType* is j. M_{ij} is set to 1, if the *MovementTypes* on the *RoadSegment i* is non-colliding and allowed simultaneously with *MovementTypes* of the other *RoadSegments p*, if not, it is set to 0. A set of all possible candidate condition matrices $M = (M^1, M^2....M^N)$ to be qualified to pass an intersection is generated by combining the non-colliding and allowed movements. The traffic controller present at the intersection manages to select an appropriate non-colliding condition matrix from the set of the candidate condition matrices $M$and apply it to the current traffic pattern so that the lanes that belong to these permitted movements are allowed with green signs simultaneously.

4.3.5. Phase V : determine the aggregated flow count

The condition matrix expresses the possible scheduling of green signs for road segments at intersection I. To maximize the traffic flow at an intersection, we have to choose the condition matrix such that the Total Flow Count of all the permitted lanes should be maximized to pass the heavy traffic in a fair way at every cycle of traffic lights.

Consider the condition matrix $M^c \in M$ is chosen, then the aggregated flow count is measured by the Eq. (4).

$$A^c = \sum_{i=1}^{p} \sum_{j=1}^{q} C_{ij} \times M_{ij}^{c} \tag{4}$$

Where M_{ij}^{c} is the (i, j)th element of the condition matrix M^c with size $p \times q$. Here C_{ij} is the Total Flow Count of road segment i given movement type j, we consider to determine it with the aid of the drift attribute D_{ij}^{k} of the kth lane of road segment $i$for movement type j as in Eq. (3). The condition matrix with the maximum aggregated flow count $M_{\max}$ is chosen to schedule the green sign to the current cycle of traffic lights for all the road segments at intersection I. Among all the permitted lanes the one with highest flow time is selected as the duration of the green sign S_{green}. The next condition matrix with the maximum aggregated flow count $M_{\max}$ is determined before the completion of the current green-sign duration to pass vehicles in the next cycle. The condition matrix that is generated for the next cycle may be the same as the current cycle, thus extending or shortening the green sign duration S_{green}. To avoid this, S_{green} is bound in the range of $[S_{\min}, S_{\max}]$. If $S_{green} < S_{\min}$, it is set to $S_{\min}$ and if $S_{green} > S_{\min}$, S_{green} is set to $S_{\max}$. The computations described in Algorithm *DTCMS*are performed to get the maximum value for passing the vehicles in a lane, to prevent long waits, and to assign a green sign for non-colliding movements.

4.4. Complexity analysis of DTCMS algorithm

In this subsection, we evaluate the communication and the runtime complexity of *DTCMS* algorithm, which operates at the traffic controller present at the intersection. Let N_v be the maximum number of vehicles waiting to pass the intersection,

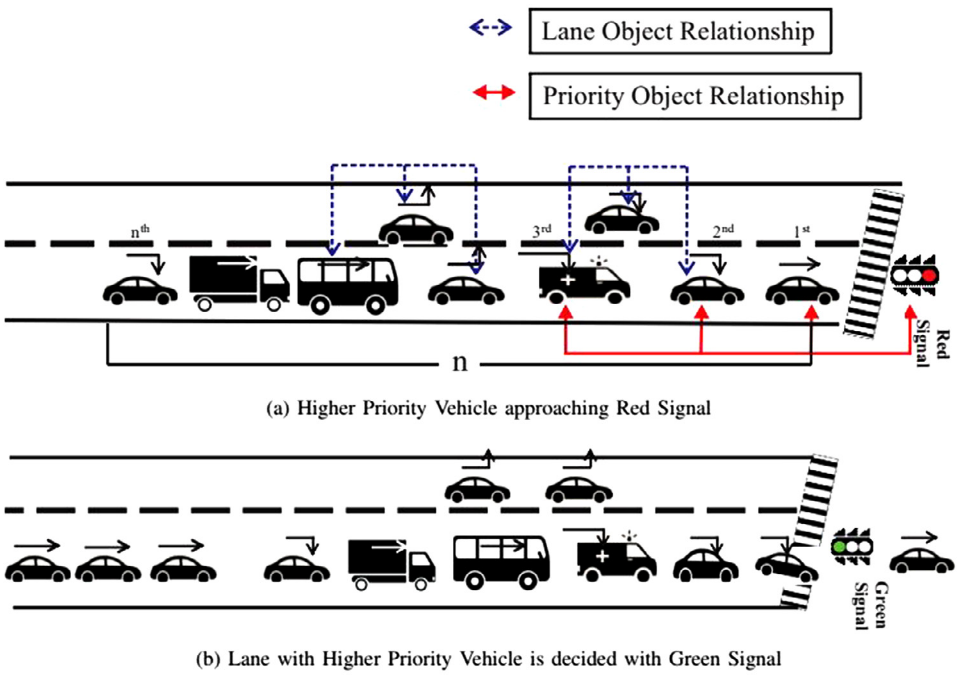


Fig. 7. Vehicles at the intersection forming Priority Object Relationship and Lane Object Relationship.

p is the total number of roadsegments at the intersection, q is all the possible movement types on the roadsegment, and L is the total number of lanes on all the road segments.

1. *Communication Complexity*: The communication overhead of *DTCMS* is bounded on two factors executed at each cycle of traffic lights: these factors are messages per vehicle stopped at the intersection to publish its arrival to the traffic controller *i.e.* $O(N_v /L)$ and the $O(1)$ messages to disseminate the update time of traffic light through *ADOR* relationship. Thus its complexity is $O(N_v/L)$.
2. *Runtime Complexity*: The runtime overhead of *DTCMS* is decided by five phases performed at each cycle of traffic lights.
   The *Phase I* determines the amount of traffic permitted to pass the intersection on lanes of all roadsegments. The complexity of *Phase I* is bound to $O(L)$
   The *Phase II* relies on the movement types that the drivers intend to turn at the intersection on each lane of all roadsegments. Thus its complexity is $O(qL)$.
   The complexity of *Phase III* is $O(L)$, since it is performed to obtain the maximum flowing rate of vehicles on lanes of all road segments.
   The *Phase IV* generates the non-colliding and allowed movements for the roadsegments. Thus, the complexity is bound to $O(pq)$.
   The *Phase V* chooses the condition matrix that has the maximum aggregated flow count from the set of N candidate condition matrices. The complexity of *Phase V* is $O(N)$.

Thus, the overall time complexity of DTCMS algorithm at each intersection is confined to $O(pqLN)$.

5. Implementation of DTCMS algorithm

In this section, we discuss the implementation of DTCMS algorithm by an illustration under different traffic network to schedule the green sign.

5.0.1. Example

Fig. 7 (a) depicts the vehicles in the queue at an intersection, waiting to pass the signal (red light). During this period, they form relationships with each other and act according to the type of relationship formed. Fig. 7 (b) shows the vehicles moving in their respective directions (green light), and react according to the interpretation of the relationships. Different types of relationships can be formed among the vehicles and traffic controller, as discussed at the beginning of this section, that socially connects the vehicles and the drivers of other vehicles. It makes the traffic flow easier, mitigating the congestion rate, and giving priority to the vehicles when they are socially connected and the vehicle to communicate with others of its requirement. When a vehicle passes a traffic controller, it shares its information with it, and this traffic controller can alert the vehicles at the forefront of any future vehicles of the one in consideration.

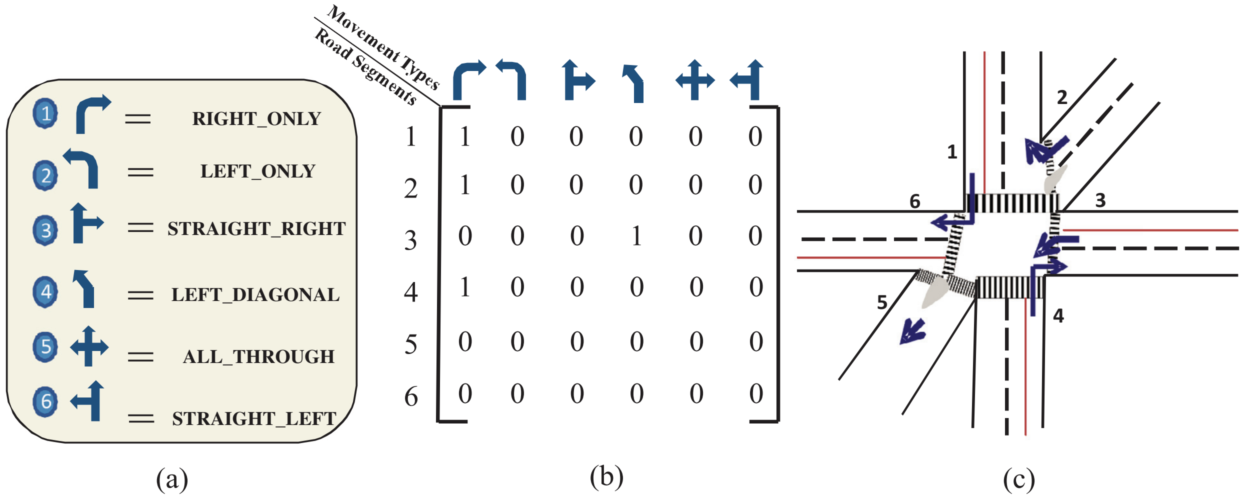


Fig. 8. Types of Movements and a Condition Matrix with non-colliding movements for six road segment. (a) Types of Movements (b) Condition Matrix (c) Non-colliding movements.

As seen in Fig. 7 (a), suppose we consider the lanes *10* and *11* of the road segment *6* of the road intersection in Fig. 1, each phase of the DTCMS algorithm is performed as follows:

(i) *Phase I:* The amount of traffic allowed on a lane to pass through the intersection *i.e.* the flow count of the lane is computed using Eq. (1). There are seven vehicles on the lane *11*, at a flow time of *400* ms (considering the velocity, acceleration, distance, and drivers reaction time), with the priority vehicles on the lane, we set c_{PRI} to 1. The weighting factor is assigned with 0.4, and α is scaled to 0.4 based on the weighting factor and the number of relationship types tied among vehicles with one priority vehicle on lane *i.e.* R is set to 1.

(ii) *Phase II:* Each road segment has six movement types: *right_only, left_only, straight_right, left_diagonal, all_through, and straight_left* as shown in Fig. 8 (a). The drift attribute is assigned for each lane for the given movement types. The lanes are number from left to right, since the vehicles drive on the right side of the road. The leftmost lane *10* has no *go_straight* intention vehicles, *left_only* is set to lane *10* and *straight_right* is set to lane *11, i.e.* $D^{10}_{6,2} = 1$ and $D^{11}_{6,3} = 1$.

(iii) *Phase III:* With the aid of the drift attribute of the lanes *10* and *11* the Total Flow Count for the road segment *6*, given a movement type is obtained by the Eq. (3).

(iv) *Phase IV:* The condition matrices are designed to schedule the road segments with non-colliding movement type. A sample 6X6 condition matrix, shown in Fig. 8 (b) indicates the permitted non-colliding movement types, where *1* means allowed and *0* means not allowed movements for the six road segments of Intersection *I*. For instance, the condition matrix in Fig. 8 (b) means that road segments *1, 2* and *4* can turn right and the road segment *3* can go left diagonal. Fig. 8 (c) shows the non-colliding movement directions followed for the six road segment. After linking as many non-colliding types of movements as possible the set of condition matrices $M = (M^1,\ M^2 ....M^c)$ generated for the six road segment, with $c = 31$ to be qualified to pass an intersection is as shown below

$$M^1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} M^2 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$M^3 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} M^4 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Table 5
Road Network Information for Parameters used in Simulation.

Parameter	Six RoadSegments	Four RoadSegments
Total number of Edges	213	16
Total number of Lanes	864	48
Total Edge length (km)	11.49	0.80
Total Lane length (km)	14.02	2.4
Number of Traffic Lights	11	2

(a) (b) (c)

Fig. 9. Scenario 1: Traffic Network with six RoadSegments (a) Browser interface for the OpenStreeMap (b) GoogleMap view (c) Imported Real Road map from Dupont circle Washington DC area (971x660 m^2).

$$
\ldots\ldots\ldots M^{31} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
$$

(v) *Phase V:* To increase the traffic flow and pass the heavy traffic at an intersection in a fair way, the traffic controller has to choose the condition matrix that has the maximum aggregated flow count computed by Eq. (4), to set the current green sign.

5.0.2. Case study

The algorithm is implemented in two different scenarios with a varying number of lanes and road segments merging at the intersection. To simulate a realistic scenario, we build a simulation model by importing the traffic network from the OpenStreetMap [48] platform for random traffic. In the second scenario, the traffic model and vehicle routes are created manually. The road network information for different parameters used in six and four roadsegments simulation is enumerated in Table 5.

(i) *Traffic Network for six RoadSegments:* A road intersection used for the first simulation has six road segments in which the horizontal and the vertical roads have two edges, and each edge has two lanes. In contrast, the diagonal roads have one edge with just one lane. The road network is obtained from the *U Street Northwest, Dupont Circle, Washington D.C., United States of America* imported from the OpenStreetMap, which has left-hand operated vehicles that drive on the right side of the road platform. Fig. 9 (a) shows the Browser interface for the OpenStreetMap, (b) GoogleMap View, (c) Imported real road map and Fig. 10 shows the traffic simulation in sumo. We consider seven movement types: *right_only, left_only, straight_right, left_diagonal, right_diagonal, all_through, and straight_left* for each road segments and construct thirty six condition matrices of dimension *6X7* that indicates the allowed non-conflicting movement types for the of intersection with six road segments.
(ii) *Traffic Network for four RoadSegments:* A road intersection used for the second simulation has four road segments in which the horizontal and the vertical roads have two edges, and each edge has three lanes. The road network and the vehicle routes are created manually, which has right hand-operated vehicles that drive on the left side of the road platform. Fig. 11 shows the traffic simulation in sumo, with four movement types *i.e. right_only, left_only, straight_right, and straight_left*. We construct sixteen condition matrices of size *4X4* that indicates the allowed non-conflicting movement types for the intersection with four road segments.

The complete code of DTCMS algorithm for traffic network with six and four road segments is available online at public repository [49].

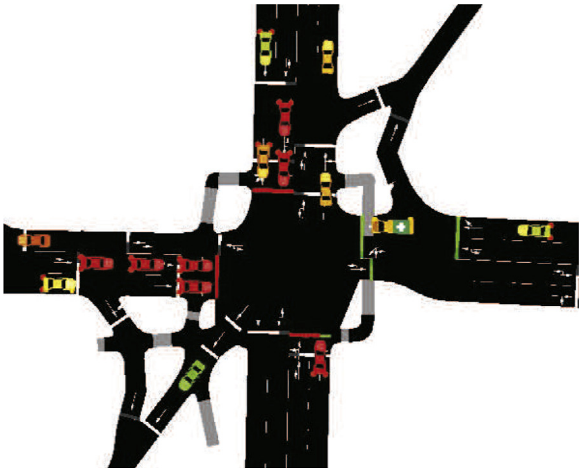


Fig. 10. Scenario 1: Traffic Network for six RoadSegments with two lanes in Sumo Simulation.

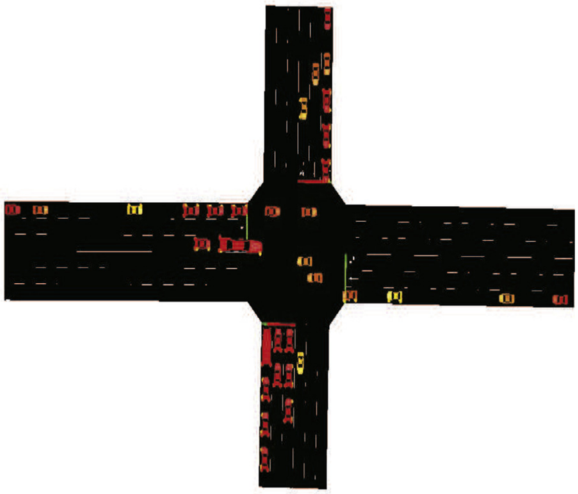


Fig. 11. Scenario 2: Traffic Network for four RoadSegments with three lanes in Sumo Simulation.

6. Performance analysis

The proposed DTCMS algorithm is verified by simulation. In this section, we discuss the simulation setup, traffic flow metrics, baseline methods, and the simulation results.

6.1. Simulation setup

We validate the performance of the DTCMS algorithm through a traffic simulation software called Simulation of Urban Mobility (SUMO) [50], which is applied to model multiple traffic flows consisting of vehicles on a given road network. We generate the traffic demands *via* Traffic Control Interface (TraCI) protocol that controls traffic signs, and the traffic demands are developed based on vehicle turning ratios using the *JTRROUTER* tool. The TraCI protocol is included in the python program to interact with SUMO and facilitates the overall movement of the traffic for *Lane-Priority* and *Lane-Changing Model* [51]. For the simulation, six types of vehicles, car, bus, truck, police car, ambulance, and fire brigade are assumed with three kinds of relationships, such as *PROR, LOR*, and *ADOR* among the vehicles and the traffic controller. The simulation parameters of vehicles are summarized in Table 6. The traffic condition is regulated by setting an arrival rate of vehicles included in the road network per simulation time. Each simulation is carried out for 3600 seconds. The vehicle arrival is based on an exponential distribution with the inter-arrival time between two consecutive arrivals. To simulate the multiple levels of congestion on the road network, the inter-arrival rate of vehicles is varied and selected in the range of [1.8, 3.3] under different turning intentions of vehicles. For example, if the inter-arrival rate is set to 0.6 seconds, then an average of 6000 vehicles

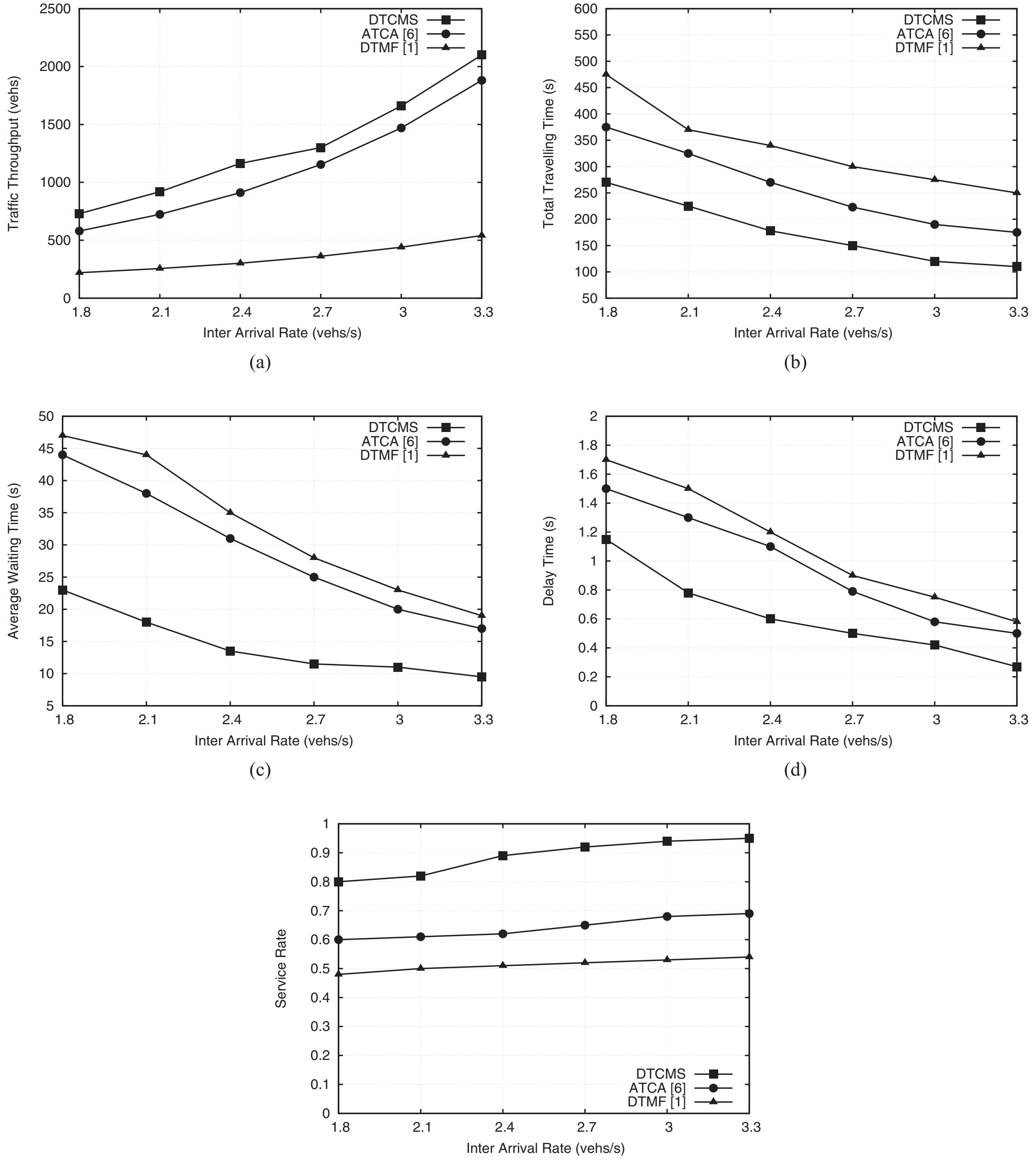


Fig. 12. Performance Comparison of Traffic Network with six RoadSegments (a) Traffic Throughput, (b) Total Traveling Time, (c) Average Waiting Time, (d) Delay Time and (e) Service Rate.

Table 6
Vehicles Simulation Parameters.

Vehicle Type	Length (m)	Acceleration (m/s^2)	Deceleration (m/s^2)	Max. Speed (m/s)
Car	4.3	2.9	7.5	50
Bus	12	1.2	4	23.61
Truck	7.1	1.3	4	36.11
Police Car	4.7	2.9	7.5	50
Ambulance	6.5	2.9	7.5	50
Fire Bridge	6.5	2.9	7.5	50

are accumulated into the road network during the simulation time of 3600 seconds. The simulation results are obtained from the summary-file and averaged the individual experiments over 10 runs by SUMO tool.

6.2. Traffic flow metrics

The performance of DTCMS is evaluated at the target intersection in terms of the following six traffic flow metrics [52].

1. *Traffic Throughput (TT)*: It is the number of vehicles (V) that crosses the road intersection per unit time. Assuming the time interval of $t$sec, then $TT = (V)/t$.
2. *Total Traveling Time (TTT)*: It is the time that the vehicle arrives at the road network to the time it departs from the road network. Let A_{v_i} is the arrival time and D_{v_i} is the departure time of the vehicle v_i, then $TTT = D_{v_i} - A_{v_i}$. The main goal is to minimize the average traveling time of vehicles passing the intersection.
3. *Average Waiting Time (AWT)*: It is the total stopover time at the intersection per vehicle. Let w_i is the waiting time of the vehicle v_i, where $v_i \in [1, 2.V]$ and V is the number of vehicles, then $AWT = \sum_i w_i/V$.
4. *Delay Time (DT)*: It is the difference between the actual travel time and the anticipated travel time under the free-flow speed. It is equal to the distance (d) a vehicle travels from the start of the simulation divided by the vehicle speed limit (s) *i.e.* $t = d/s$.
5. *Service Rate (SR)*: It is the ratio of the number of vehicles (V) inside the road network from the total vehicles (V_{Total}) attempting to enter the road network, *i.e.*$SR = V/V_{Total}$.

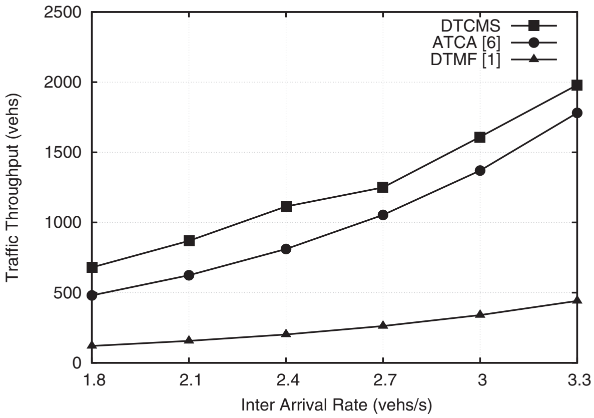
6.3. Baseline methods

The performance of DTCMS is compared with the two baseline methods, namely, Dynamic Throughput Maximization Framework DTMF [19], and Adaptive Traffic Control Algorithm ATCA [5]. The objective of the two baseline methods is the same as DTCMS, to maximize the traffic throughput and minimize the average waiting time by dynamically controlling the traffic light at the intersections. Each of these methods applies distinct factors to achieve the purpose and ultimately ends with the varied results. DTMF uses turning intentions and the lane positions of the vehicles to increase the traffic flow considering only four movement types of vehicles for a four road segment intersection. ATCA maximizes the traffic flow considering waiting, passing, incoming traffic volume, and the delay in two subsequent phases for computing green duration and phase selection. However, the two baselines present the idea of a vehicle waiting at a signal for a longer time to get the priority to pass the intersection and do not provide the quality-of-service to improve the whole user experience and to higher priority vehicles, like ambulances, fire trucks, police cars, *etc.* resulting in inappropriate traffic flow. The factors that set DTCMS unique are, the turning intention of vehicles with more movement types to allow vehicles to simultaneously pass through intersections, social features to improve traffic flow and enhance the fairness utilizing relationship types, and a rational provision to improve the signal scheduling by giving accurate priorities incorporating the social attributes.

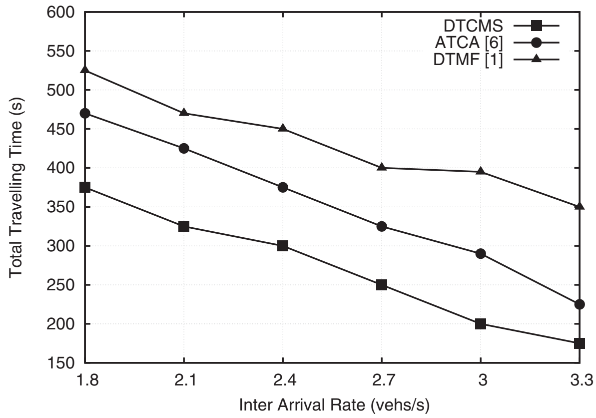
6.4. Simulation results

The performance of DTCMS is validated in both six Roadsegments and four Roadsegments traffic network in terms of traffic throughput, total traveling time, average waiting time, delay time, and service rate. The simulation experiment is performed under different traffic conditions; the rationale is that real traffic data does not cover all possible traffic scenarios. To simulate the various levels of congestion on the configured road network, the inter-arrival rate is varied between 1.8 and 3.3, with an increment of 0.3. A total of 2000 vehicles are loaded into the network during the simulation time of 3600 seconds.

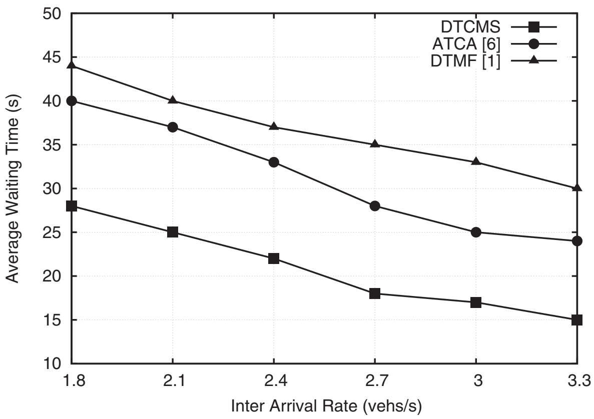
1. *Performance comparison of traffic network with six RoadSegments*:
   Fig. 12 represent the performance comparison of DTCMS algorithm to DTMF and ATCA in a road traffic network for six roadsegments comprising two lanes at different inter-arrival rates under 75% *go_straight*, 15% *right_only*, and 10% *left_only* turn vehicles that drive on the right side of the road.
   Fig. 12 (a) shows that DTCMS achieves higher traffic throughput irrespective of congestion levels in the road network. The performance gap between DTCMS and DTMF becomes larger as the inter-arrival rate rises and the traffic gets smooth.



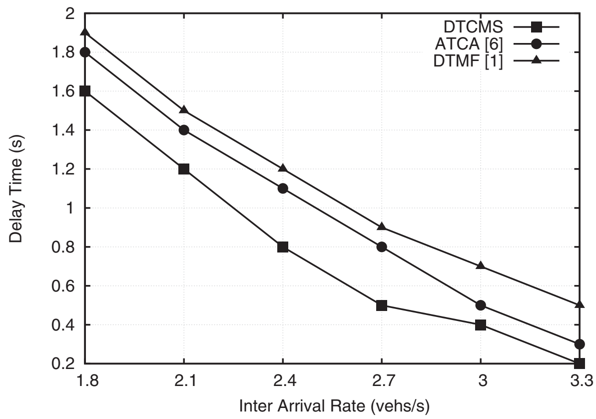
(a)



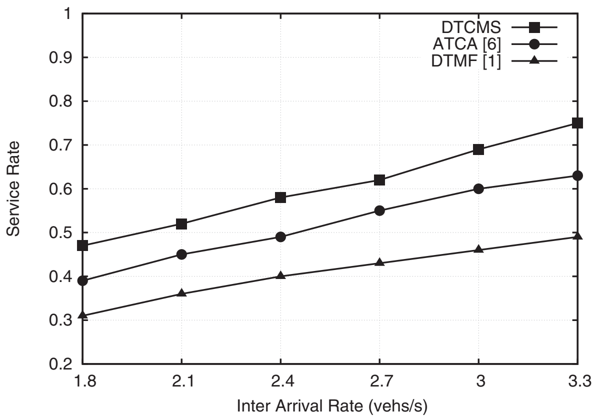
(b)



(c)

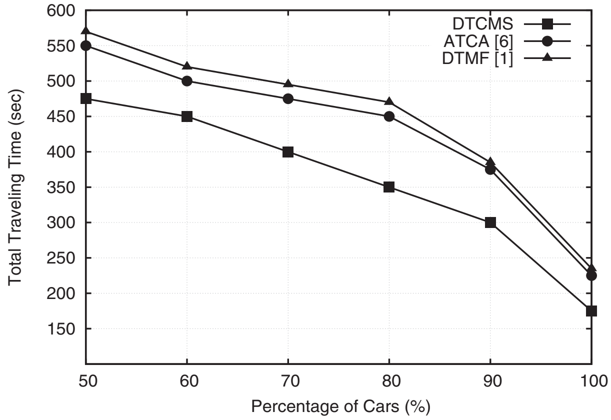


(d)

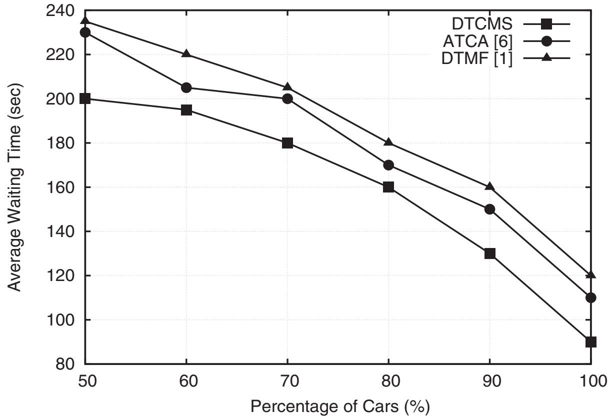


(e)

Fig. 13. Performance Comparison of Traffic Network with four RoadSegments (a) Traffic Throughput, (b) Total Traveling Time, (c) Average Waiting Time, (d) Delay Time and (e) Service Rate.



(a)



(b)

Fig. 14. Efficiency Comparison of DTCMS to DTMF and ATCA for Traffic Network with four RoadSegments (a) Total Traveling Time and (c) Average Waiting Time.

When the inter-arrival rate is between 1.8 to 2.4 the gain is smaller since the load on the network is high as the inter-arrival rate increases when the road network is very much free the throughput gradually increases and remains constant. This is because DTCMS considers all possible combinations of movement types to simultaneously cross the intersections. Fig. 12 (b) illustrates the comparison of total traveling time of vehicles for different levels of congestion. When traffic signals are managed by DTCMS algorithm, vehicles travel 75% faster than DTMF at inter-arrival rate 3.3 and the traveling time of vehicles is longer at the congested roads at inter-arrival rate of 1.8.

Fig. 12 (c) and (d) shows average waiting time and the delay time for vehicles at the intersections. When roads are congested at inter-arrival rate of 1.8, DTCMS shows about 57% performance improvement than ATCA and 67% improvement than DTMS for average waiting time. The delay time of DTCMS is reduced by 55% and 65% compared to ATCA and DTMF at inter-arrival rate of 3.3. Thus, DTCMS enables higher movement speeds of vehicles resulting in shorter queues at intersections. DTCMS diminishes the delay time and the average waiting time of vehicles compared to the baseline methods. DTCMS's such distinct performance is attributed to analyzing vehicles turning intentions and all movement type combinations while creating a condition matrix and allocating green sign to congested flows; this benefits in reducing the delay and the average number of vehicles waiting in the green signal to move. Fig. 12 (e) shows that DTCMS exceeds the baseline methods in terms of the service rate irrespective of congestion in the road network. DTCMS attains 80% service rate with the inter-arrival rate of 1.8 vehicles per second, which produces the maximum congestion on the roads. At the same inter-arrival rate ATCA and DTMF show nearly 49% and 60% of service rate.

Compared with DTMS and ATCA, DTCMS maximize the number of vehicles crossing the intersections by considering the vehicles both in the current intersection and the adjacent intersections to determine the flow count for signal scheduling and the turning intentions of vehicles that drive on the right side of the road to compute drift attribute.

2. *Performance comparison of traffic network with four RoadSegments*:
We have extended the performance study by varying the number of roadsegments and the lanes at the intersection. Fig. 13 shows the performance result in a road traffic network for four Roadsegments comprising three lanes at different inter-arrival rates under 75% *go_straight*, 15% *left_only*, and 10% *right_only* turn vehicles that drive on the left side of the road.
Fig. 13 (a)–(e) depicts the throughput, total traveling time, average waiting time, delay time, and the service rate analysis for the different inter-arrival rate of vehicles. Similar to the six Roadsegments network with two lanes, DTCMS shows higher throughput, yields better results for total traveling time, drops the average waiting time and the delay time, and achieves higher service rate compared to ATCA and DTMF.
Comparing Fig. 12 (a)–(e) with Fig. 13 (a)–(e) the performance results in six Roadsegments are more superior compared to six Roadsegments, this is due to the increased capacity of the road network.
3. *Driving Efficiency Comparison*: The same experiments are carried out to estimate the driving efficiency of the vehicles under 50%, 60%, 70%, 80%, 90%, and 100% of cars, with 1% priority vehicle and 2% lane changing vehicles and the rest are buses. The arrival rate of the vehicle is set to 3 vehicles per second with turning percentages for *go_straight, left_only, and right_only* directions are fixed to 75%, 15%, and 10%, respectively.
Fig. 14 (a) and (b) show the driving efficiency comparison for total traveling time and the average waiting time in four Roadsegments traffic network. DTCMS outperforms the other baseline methods. This is because, the simulations are carried out for vehicles of different lengths, acceleration, deceleration, and maximum speeds to increase the number of vehicles that pass the intersection. Furthermore, signal scheduling in DTCMS considers the vehicles arriving from the adjacent intersections and thus increases the vehicle flow rate at the intersection within the same green duration. To

achieve better driving efficiency, DTCMS utilizes social relationships such as *PROR*, *LOR*, or *AOR* among vehicles, commuters, and RSUs. When an emergency vehicle or a lane-changing vehicle proceed towards the other vehicles on the lane, it establishes *PROR* or *LOR* relationship and increases the priority of the lane, that have a higher possibility to get the right-of-the way in the intersection.

From the above performance results, we conclude that the proposed DTCMS can be utilized for the varied number of road segments and lanes on the road network and the vehicles that operate on the right and left side of the road. This confirms the scalability of DTCMS algorithm for large road networks for both the left and right hand-operated vehicles.

Based on the traffic demand set in the program, we have simulated the proposed DTCMS algorithm with the throughput maximization to control the traffic signal and to increase the flow count of the vehicles at the intersection.

7. Conclusions

In this paper, we have proposed DTCMS, a dynamic traffic congestion management algorithm by applying the concept of SIoV, which describes the social interactions among the vehicle and commuters. We define social, behavioral, and preference-based relationships to exhibit the smooth flow of traffic and manage the flowing rate of vehicles at the intersections. DTCMS is verified by extensive simulations using the road networks with six and four roadsegments for the different number of lanes. The simulation results have shown that DTCMS optimize the traffic flow metrics such as traffic throughput, total traveling time, average waiting time, delay time, and service rate for different vehicle arrival rates. The traffic flow metrics optimization for the fairness scheduling is investigated for the road network with multiple intersections to provide an even better result for the traffic allowance regarding the vehicles arriving from the adjacent junctions.

In the future, we intend to exploit the other relationships among OBUs and RSUs maintained in SIoV and consider the green duration for pedestrians to cross roads in the optimization procedure. We further aim to enhance the process of storing the vehicle data in the cloud using fog computing and make it available for the large distant RSUs. To address the RSUs ability to synchronize with the navigation of vehicles at a route, and provide them alternates to reduce the congestion at a single road is also an exciting direction. Strategies to manage accidents and allow to reschedule the vehicles on demand reacting to accidents is another possible future work. Besides, we aim to consider the issues that are likely to arise in SIoV, such as security, privacy, and trust.

Declaration of Competing Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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