



# Adaptive Traffic Control Using Cooperative Communication Through Visible Light

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## Abstract

The study aims to create a Visible-Light Communication (VLC) system for secure vehicle management at intersections. This involves enabling communication between vehicles and infrastructure (V2V, V2I, and I2V) using headlights, streetlights, and traffic signals. Mobile optical receivers gather data, determine their location, and read transmitted information through joint transmission. An intersection manager coordinates traffic and communicates with vehicles through embedded Driver Agents. The system utilizes a "mesh/cellular" hybrid network configuration and encodes data into light signals emitted by transmitters. Optical sensors and filtering properties enable reception and decoding. The study demonstrates bidirectional communication, employing queue/request/response mechanisms and relative pose concepts for safe vehicle passage. A deep reinforcement learning model controls traffic light cycles, validated via simulation in a Simulation of Urban Mobility simulator. Results show that this adaptive traffic control system effectively collects detailed vehicle data and ensures secure communication within the short-range mesh network.

**Keywords** Vehicular communication · Traffic control · Light controlled intersection · Queue distance · "Mesh/cellular" hybrid network · Deep reinforcement learning model

## Introduction

The main objective of the Intelligent Transport System (ITS) technology is to optimize traffic safety and efficiency on public roads by increasing situation awareness and mitigating traffic accidents through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [1–3]. The goal is to increase the safety and throughput of traffic intersections using cooperative driving [4, 5]. For self-localization, the precise knowledge of the own motion and position is

important. By knowing, in real time, the location, speed, and direction of nearby vehicles, a considerable improvement in traffic management is expected.

This work focuses directly on the use of Visible-Light Communication (VLC) as a support for the transmission of information providing guidance services and specific information to drivers. VLC is an emerging technology [6, 7] that enables data communication by modulating information on the intensity of the light emitted by LEDs. VLC has significant potential for various applications because of its simple design, efficiency, and wide geographical reach. In the case of vehicular communications, the use of VLC is made easier, because all vehicles, streetlights, and traffic lights are equipped with LEDs that are used for illumination. Here, the communication and localization are performed using the streetlamps, the traffic signaling, and the vehicle front and back lamps, enabling the dual use of exterior automotive and infrastructure lighting for both illumination and communication purposes [8, 9]. VLC enables a more accurate measurement of the distance and position of vehicles with sub-meter resolution given the high directivity of visible light.

The paper is organized as follows. After the introduction where background theory on adaptive traffic control is

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presented and the V-VLC link is explained, in Sect. "Scenario, Environment and Architecture", the V-VLC system is described and the scenario, architecture, communication protocol, and coding/decoding techniques analyzed. In Sect. "VLC Evaluation", the experimental results are reported, and the system evaluation performed. A phasing traffic flow diagram based on V-VLC is developed, as a Proof of Concept (PoC). In Sect. "Intelligent control in V-VLC systems", an agent-based dynamic traffic-controlled simulation based on an urban mobility simulator tool is discussed. Finally, in Sect. Conclusions, the main conclusions are presented.

## Background Theory on Adaptive Traffic Control

The traffic data collected by the current traffic control system, utilizing induction loop detectors and other existing sensors, are limited and based on a non-data-driven approach. This means that decision-making in this approach does not heavily rely on data analysis or insights. Instead, it depends on factors, such as personal experience, intuition, expert opinions, or predetermined rules and heuristics. These approaches are often rooted in established practices, rules of thumb, or traditional methods that have been effective in the past. However, it is important to note that these approaches may not consider the complete range of possibilities or adapt well to rapidly changing circumstances. With the progress of wireless communication technologies and the emergence of V2V and V2I systems, known as Connected Vehicle (CV), better reciprocity between traffic signal control and traffic flow became a reality. Furthermore, technological advancements provide the necessary technological basis for the development of Vehicle-to-X systems and autonomous driving industries. Real-time detection of spatial and temporal data from the network traffic status in urban areas can provide valuable and accurate information for assessing traffic control effectiveness. This data-driven approach enables the development of a closed-loop feedback self-adaptive control system that can better respond to uncertainties and make intelligent decisions. The primary differentiator from current self-adaptive traffic control systems lies in its dependence on traffic control data garnered through thorough data analysis and insight. This involves collecting, analyzing, and interpreting relevant data to make informed decisions, that includes data acquisition, data engineering/filtering, data analysis, and interpretation of results. Statistical analysis, machine learning algorithms, and other data processing techniques are used to uncover patterns, trends, and correlations that guide decision-making. In summary, a data-driven approach utilizes data analysis and derive insights for decision-making, while a non-data-driven approach relies on other factors such as personal experience or predetermined rules.

Our adaptive traffic control strategy aims to dynamically respond to real-time traffic demand by utilizing current and predicted traffic flow data models. In comparison to the limited traffic flow and occupancy information provided by fixed coil detectors in traditional traffic environments, the adaptive traffic control system in a V2X (Vehicle-to-Everything) environment can gather more detailed data. This includes vehicle position, speed, queuing length, and stopping time. While V2V links are crucial for safety features like pre-crash sensing and forward collision warning, I2V (Infrastructure-to-Vehicle) links provide Connected Vehicles with various useful information [10, 11]. Given that the information network of CVs influences driving behavior and the requirement for traffic stream control, further research is needed in the field of multimodal traffic control theory. This research would focus on understanding and optimizing the coordination between different modes of transportation to enhance overall traffic management.

To conduct effective research and achieve reliable results, it is essential to approach the study with meticulous planning, utilize suitable simulation tools, make realistic assumptions, and thoroughly analyze the collected data. The research aims to address the following inquiries: Is it feasible to implement a dependable VLC system using the proposed I2X vehicular visible communication model within controlled intersections? How can VLC be implemented in controlled intersections using a network simulator? Furthermore, what impact does the integration of VLC have on various traffic performance parameters within an urban traffic scenario?

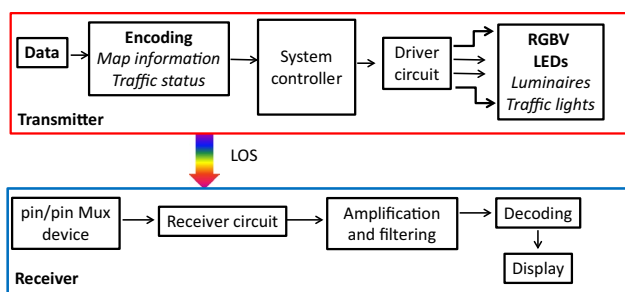
The proposed smart vehicle lighting system considers wireless communication, computer-based algorithms, smart sensor, and optical sources network, which stands out as a transdisciplinary approach framed in cyber-physical systems.

## V-VLC Communication Link

A Vehicular VLC system (V-VLC) consists of a transmitter to generate modulated light and a receiver to detect the received light variation located at the infrastructures and at the driving cars. Both the transmitter and the receiver are connected through the wireless channel. Line of Sight (LoS) is mandatory.

Figure 1 illustrates the basic architecture of a V-VLC system. Both communication modules are software defined, where modulation/ demodulation can be programmed.

The VLC emitter has a dual purpose, emits light, and transmits data instantaneously using the same optical power without any noticeable flickering. The digital VLC emitter module converts the binary data to intensity modulated light waves for transmission. A driving circuit controls the switching of the LED according to the incoming binary data at the



**Fig. 1** Generic design of VLC system: data transmission and reception. Block diagram of the VLC link

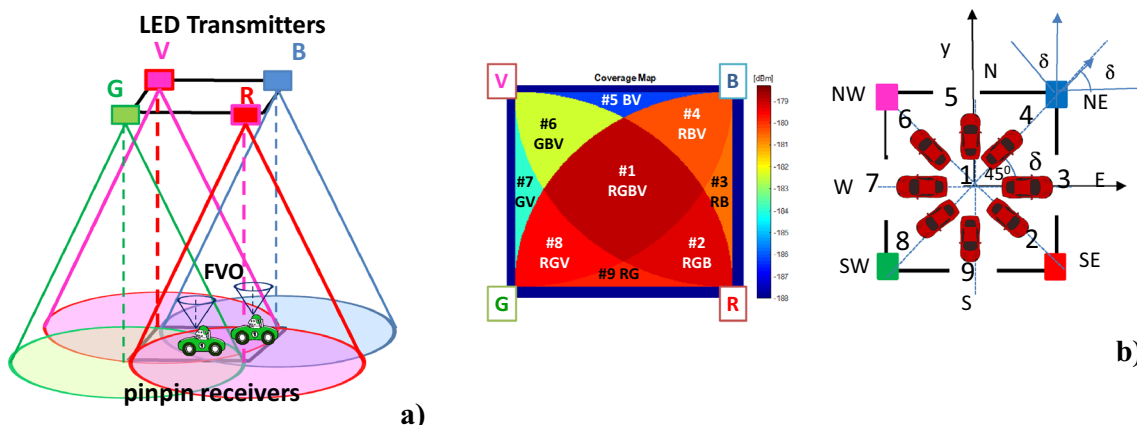
given data rate, generating an amplitude modulated light beam. Here, the light produced by the LED is modulated with ON–OFF-keying (OOK) amplitude modulation [12].

White light tetra-chromatic (WLEDs) sources, positioned at the corners of a square, as shown in Fig. 2a, are employed to offer distinct data channels for each chip. These sources comprise red, green, blue, and violet chips, which are combined in the appropriate ratios to produce white light. At each node, only one chip of the LED is modulated for data transmission, the Red (R: 626 nm), the Green (G: 530 nm), the Blue (B: 470 nm), or the Violet (V: 390 nm). Modulation and digital-to-analog conversion of the information bits are done using signal processing techniques. However, the typical bit rates that can be supported by fast moving vehicles is usually limited by channel conditions, not by the switching speed of the LED.

Transmitters and receiver’s 3D relative positions are displayed in Fig. 2a. The LEDs are modeled as Lambertian sources where the luminance is distributed uniformly in all directions, whereas the luminous intensity is different in all directions [13]. The coverage map for a square unit cell is displayed in Fig. 2b. All the values were converted to decibel

(dB). The nine possible overlaps (#1–#9), defined as fingerprint regions, as well as the possible receiver orientations (steering angles;  $\delta$ ) are also pointed out for the unit square cell. In geolocation, a fingerprint refers to a unique identifier or set of characteristics associated with a specific area. These fingerprints capture the distinct attributes of a location, including the signal strengths and propagation patterns that can be used to determine the geographical coordinates or approximate position of a device or user within that location. Using fingerprints enhances accuracy and provide more precise location information.

The visible light emitted by the LEDs passes through the transmission medium and is received by the MUX photodetector that acts as an active filter for the visible region of the light spectrum [14]. The MUX photodetector multiplexes the different optical channels, perform different filtering processes (amplification, switching, and wavelength conversion) and decode the encoded signals, recovering the transmitted information. The received channel can be expressed as  $y = \mu hx + n$  where  $y$  represents the received signal,  $x$  is the transmitted signal,  $\mu$  is the photoelectric conversion factor which can be normalized as  $\mu = 1$ ,  $h$  is the channel gain, and  $n$  is the additive white Gaussian noise of which the mean is 0. The responsivity of the receiver depends on its physical structure and on the effective area collection. Upon receiving the signal, it undergoes a series of processing steps to prepare it for demodulation. These steps typically involve filtering, amplification, and conversion back to digital format. The device receives multiple signals, finds the centroid of the received coordinates, and stores it as the reference point position. Nine reference points, for each unit cell, are identified giving a fine-grained resolution in the localization of the mobile device across each cell (see Fig. 2b). The input of the guidance system is the coded signal sent by the transmitters to identify the vehicle (I2V), and includes its



**Fig. 2** a Transmitters and receivers’ 3D relative positions. b Illustration of the coverage map in the unit cell: footprint regions (#1–#9) and steering angle codes (2–9)

position in the network  $P(x_i, y_j)$ , inside the unit cell (#1-#9) and the steering angle,  $\delta$  (2-9) that guides the driver orientation across his path.

### Scenario, Environment, and Architecture

#### Scenario Analysis: Traffic Control in an Intersection

Four-legged intersections are usually two-way-two-way intersections (four-legged intersections), which are connected by eight incoming and eight exiting roads to North, West, South, and East. The simulated scenario is a four-legged traffic light-controlled intersection as displayed in Fig. 3.

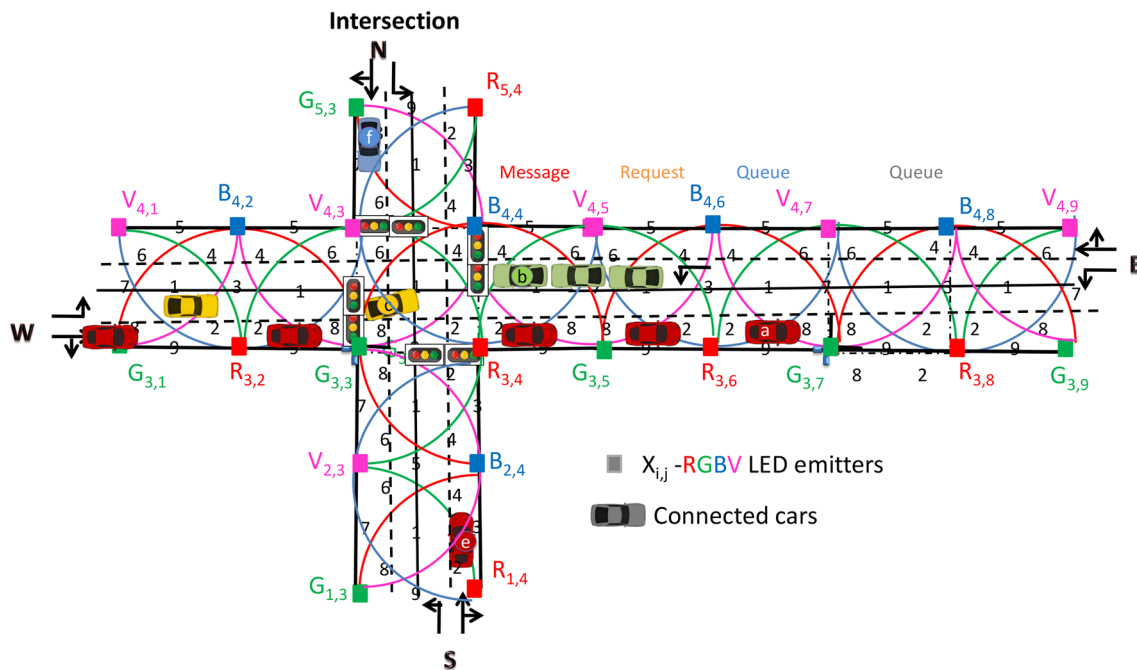
An orthogonal topology based on clusters of square unit cells was considered. The grid size was chosen to avoid an overlap in the receiver from the data in adjacent grid points. Each transmitter,  $X_{i,j}$ , carries its own color, X, (RGBV) as well as its horizontal and vertical ID position in the surrounding network ( $i, j$ ). During the PoC, it was assumed that the crossroad is at the intersection of line 4 and column 3. Located along the roadside are the emitters (streetlamps). Thus, each LED sends an I2V message that includes the synchronism, its physical ID, and the traffic information. When a probe vehicle enters the streetlight’s capture range, the receiver replies to the light signal, and assigns a unique ID and a traffic message [16].

Four traffic flows were considered. One is coming from West (W) with seven vehicles approaching the crossroad: five  $a_i$  Vehicles with straight movement and three  $c_i$  Vehicles with left turn only. In the second flow, three  $b_i$  Vehicles from East (E) approach the intersection with left turn only. In the third flow,  $e$  Vehicle, oncoming from South (S), has right-turn approach. Finally, in the fourth flow,  $f$  Vehicle coming from North, goes straight. Road request and response segments offer a binary (turn left/straight or turn right) choice. According to the simulated scenario, each car represents a percentage of traffic flow.

#### Integration of Architecture and Environment: A Correlative Framework

The term “Intelligent Control System” refers to any combination of hardware and software, which operates autonomously according to the information received and processed. After processing, it is able to act toward the desired control through rational choices. In this case, it is intended to apply an ITS to the CV systems.

The computing and communication workload for CVs may also vary over time and locations, which poses challenges to capacity planning, resource management of computation nodes, and mobility management of the CVs. Thus, a well-designed computing architecture is very important for CV systems. Its implementation will need such processing and storage power that it requires thoughtful management of



**Fig. 3** Simulated scenario: four-legged intersection and environment with the optical infrastructure ( $X_{ij}$ ), the generated footprints (1-9), and the CV

resources, so computation offloading techniques are considered. These will consist of a hierarchy of layers where real-time decisions are made by edge computing nodes, which will be closest to the action and equipped with the necessary processing power, where fog computing and cloud computing will be, respectively, distributed in more distant locations to allocate, process, and analyze larger amounts of data.

Figure 4 presents a draft of a mesh cellular hybrid structure that can be used to create a gateway-free system. As illustrated, the streetlights are equipped with one of two types of nodes: A “mesh” controller that connects with other nodes in its vicinity. These controllers can forward messages to the vehicles (I2V) in the mesh, acting like routers in the network. The other one is the “mesh/cellular” hybrid controller that is also equipped with a modem provides IP base connectivity to the Intersection Manager (IM) services. These nodes act as border-router and can be used for edge computing [15].

This architecture enables edge computing, device-to-cloud communication (I2IM) and peer-to-peer communication (I2I), to exchange information. It performs much of the processing on embedded computing platforms, directly interfacing to sensors and controllers. It supports geo-distribution, local decision-making, and real-time load-balancing.

As depicted in Fig. 5, the movement of vehicles along a lane can be likened to a queue. Vehicles arrive at the lane, wait if the lane is congested, and then resume moving once the congestion subsides. This analogy highlights the sequential and orderly nature of vehicle progression within a lane, similar to how individuals queue up and wait their turn in a line.

For the intersection manager crossing coordination, the vehicle, and the IM exchange information through two types of messages, “request” (V2I) and “response” (I2V). Inside the request distance, an approach “request” is sent, using as emitter the headlights. The “request” contains all the information that is necessary for a vehicle’s space–time

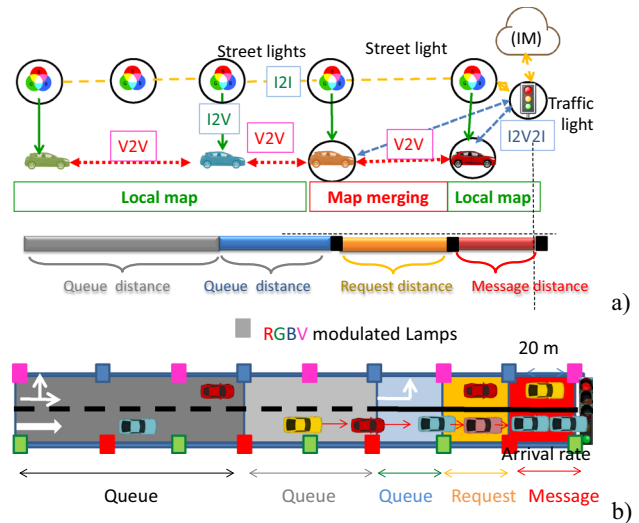


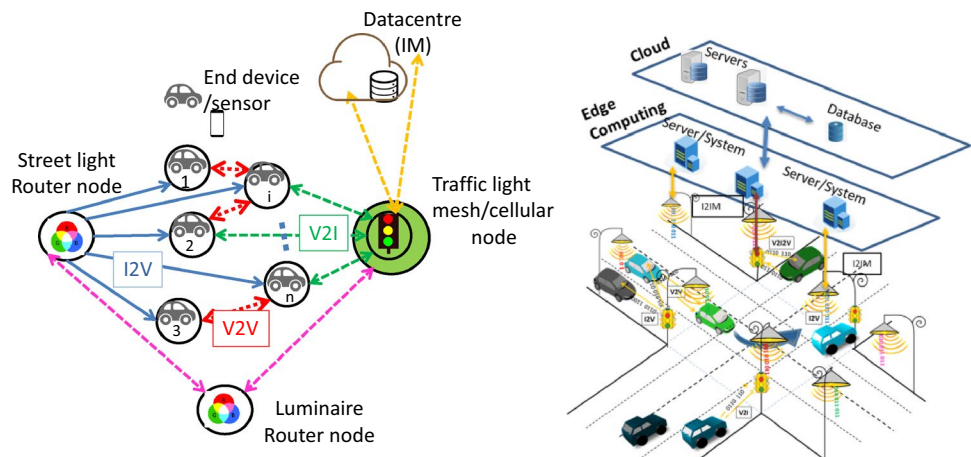
Fig. 5 a Graphical representation of the simultaneous localization as a function of node density, mobility, and transmission range. b Design of the state representation in the west arm of the intersection, with cells length

reservation for its intersection crossing (flow’s direction and its own and followers’ speeds).

The received information in the context of the IM is utilized to convert it into a sequence of timed rectangular spaces. The objective is to let the IM know the position of vehicles inside the environment at each step  $t$ . Each assigned vehicle is then instructed to occupy these spaces within the intersection. This process involves mapping the information received to determine the specific time intervals and physical locations at which each vehicle should be positioned within the intersection area. It includes only spatial information about the vehicles hosted inside the environment, and the cells used to discretize the continuous environment.

A highly congested traffic scenario will be strongly connected. To determine the delay, the number of vehicles

Fig. 4 Representation of the edge computing infrastructure. Mesh and cellular hybrid architecture





queuing in each cell at the beginning and end of the green time is determined by V2V2I observation, as illustrated in Fig. 5. The distance,  $d$ , between vehicles can be calculated based on a truncated exponential distribution [16]. An acknowledgment message, known as an "IM acknowledge," is transmitted from the traffic signal to the in-car application of the leading vehicle. This communication confirms the receipt of information and serves as a response from the traffic signal to the vehicle's application. Once the response is received (message distance in Fig. 5), the vehicle is required to follow the provided occupancy trajectories (footprint regions, see Figs. 2 and 3). If a request has any potential risk of collision with all other vehicles that have already been approved to cross the intersection, the control manager only sends back to the vehicle (V2I) the "response" after the risk of conflict is exceeded.

### Color Phasing Diagram: Visualizing Traffic Movement Patterns

The specification for the phasing plan necessitates the assignment of each traffic movement to a specific timing function. This allocation ensures that the desired sequence of traffic states is produced, accommodating all the required traffic movements in an organized manner. The choice of treatments used will determine which timing functions will be activated and which will be omitted from the phasing plan.

A color phasing diagram for a four-legged intersection is shown in Fig. 6. It was assumed four "color poses" linked with the radial range of the modulated light in the RGBV

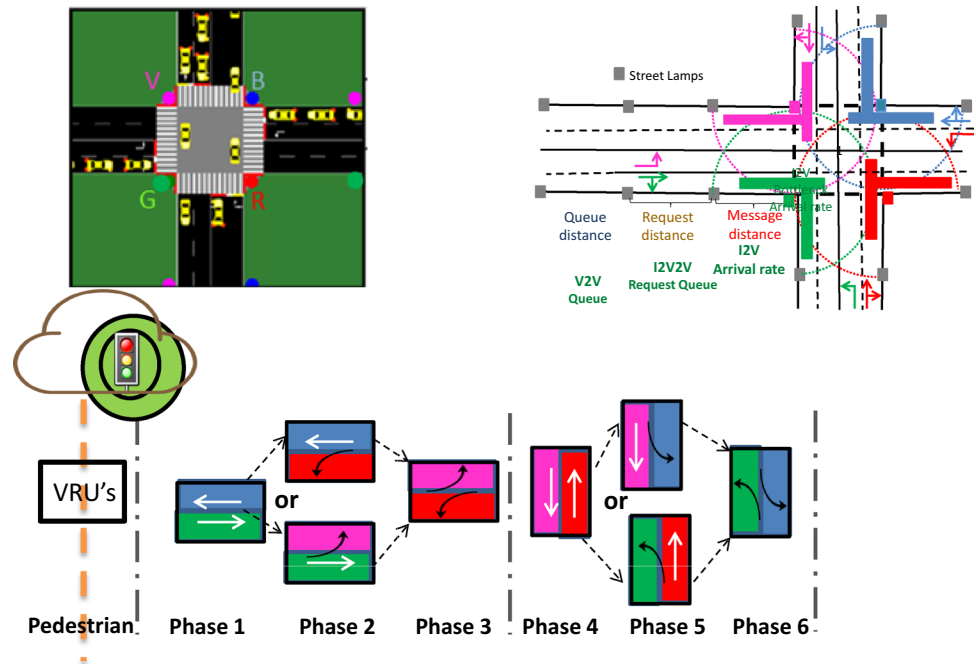
crossroad nodes [13]. The West straight, South left turn, and West right-turn maneuvers correspond to the "Green poses". "Red poses" are related to South straight, East left turn, and South right-turn maneuvers. "Blue poses" are related to East straight, North left turn, and East right-turn maneuvers, and "violet poses" are related to North straight, West left turn, and North right-turn maneuvers. In the phasing diagram, Phase 2 and Phase 5 offer two alternatives. Only one of which may be displayed on any cycle. Vehicles are stopped on all approaches to an intersection, while pedestrians are given a WALK indication, the phasing is referred to as "exclusive". Functional barriers (dash dot lines) exist between exclusive pedestrian and Phase 1 and Phase 6.

The problem that the IM has to solve is, in fact, allocating the reservations among a set of drivers in a way that a specific objective is maximized. Signal timing involves the determination of the appropriate cycle length (i.e., the time required to execute a complete sequence of phases) and apportionment of time among competing movements and phases. The timing allocation is restricted by the minimum green times that need to be enforced to accommodate pedestrians and maintain compliance with motorist expectations. These minimum green times are essential to allow pedestrians to safely cross the intersection and to ensure that drivers have sufficient time to anticipate and react to the traffic signal changes without feeling rushed or caught off guard.

### Multi-vehicle Cooperative Localization

There are critical points where traffic conditions change: the point at which a vehicle begins to decelerate when the traffic

Fig. 6 Color phasing diagram in a four-legged intersection



light turns red (message distance), the point at which it stops and joins the queue (queue distance), the point at which it starts to accelerate when the traffic light turns green (request distance) or the points at which the coming vehicle is slowed by the leaving vehicle (see Fig. 5).

Consequently, by considering the relative positions of vehicles and the current traffic signal phase at intersections, the hindrances to traffic flow can be dynamically computed. This dynamic calculation accounts for the unique conditions of the road network and the interaction between vehicles and traffic signals, enabling a more precise evaluation of factors that impede smooth traffic movement. Through V2I2V communication, it becomes possible to calculate travel time, which in turn influences the channelization of traffic along different routes. This communication enables the collection of real-time data pertaining to speed, spacing, queues, and saturation levels across various distances, including the queue distance, request distance, and message distance. Such data collection and analysis facilitate a comprehensive understanding of traffic conditions and support effective traffic management strategies.

In Fig. 7, the movement of the cars in successive moments is depicted with their colored poses (colored arrows) and  $q_{i,j}$  spatial relative poses (dot lines). We denote  $q(t)$ ,  $q(t')$ ,  $q(t'')$ ,  $q(t''')$  as the vehicle pose estimation at the time  $t$ ,  $t'$ ,  $t''$ ,  $t'''$  (request, response, enter, and exit times), respectively. The vehicle speed can be calculated by measuring the actual traveled distance overtime, using the ID's transmitters tracking. Two measurements are required: distance and elapsed time. The distance is fixed while the elapsed time varies and depends upon the vehicle's speed and is obtained through the instants where the footprint region changes. The receivers compute the geographical position in the successive instants (path) and infer the vehicle's speed. When two vehicles are in neighborhood and in different lanes, the

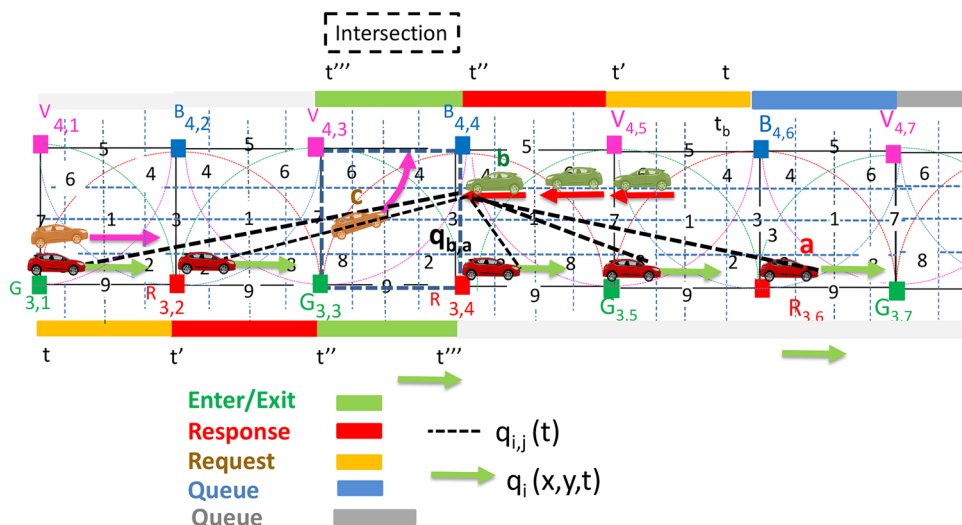
geometric relationship between them ( $q_{i,j}$ ) can be inferred fusing their self-localizations via a chain of geometric relationships among the vehicles poses and the local maps. For a vehicle with several neighboring vehicles, the mesh node (Figs. 3 and 4) uses the indirect V2V relative pose estimations method taking advantage of the data of each neighboring vehicle [17].

In the communication protocol, each request message includes the positions and approach speeds of the vehicles. If there are followers in a vehicle's group, the request message from the group leader includes the position and speed information previously received through Vehicle-to-Vehicle (V2V) communication. This information serves as an alert to the traffic controller regarding subsequent request messages (V2I) that are confirmed by the following vehicle. By including these data, the controller gains insights into the positions, speeds, and group dynamics of vehicles, allowing for more informed decision-making in traffic management.

### VLC Evaluation

In this chapter, we focus on an adaptive traffic control system that utilizes VLC, whereby messages are exchanged between the traffic control system and vehicles to facilitate dynamic and responsive traffic management. The content and nature of these messages are contingent upon the capabilities of the VLC system, the chosen communication protocol, and the specific objectives of the adaptive traffic control system. The underlying purpose of these messages is to enhance communication between the traffic control system and vehicles, enabling effective coordination and enabling a dynamic approach to traffic management. Furthermore, we present experimental results that shed light on the feasibility of implementing Vehicle-to-Vehicle VLC

Fig. 7 Movement of the cars, in the successive moments, with their colorful poses (color arrows) and  $q_{i,j}$  spatial relative poses (dot lines)



(V-VLC) in adaptive traffic control systems. Our primary goal is to showcase the potential of the V-VLC system to either supplement or replace the existing traffic information systems. We also emphasize the significant value of V2V communication in the real-time detection and monitoring of traffic flows. Through these experimental findings, we aim to highlight the capabilities and benefits of integrating V-VLC communication within the domain of adaptive traffic control.

### Communication Protocol and Coding/Decoding Techniques

To code the information, an On–Off keying (OOK) modulation scheme was used, and it was considered a synchronous transmission based on a 64-bit data frame.

As exemplified in the top part of Fig. 8, the frame is divided into four, if the transmitter is a streetlamp or headlamp, or five blocks, if the transmitter is the traffic light. The first block is the synchronization block [10101], the last is the payload data (traffic message), and a stop bit ends the frame. The second block, the ID block, gives the location ( $x, y$  coordinates) of the emitters inside the array ( $X_{i,j}$ ). Cell’s IDs are encoded using a 4-bit binary representation for the decimal number. The  $\delta$  block [steering angle ( $\delta$ )] completes the pose in a frame time  $q(x,y, \delta, t)$ . Eight steering angles along the cardinal points gives the car direction, and are coded with the same number of the footprints in the unit cell (Fig. 2). If the message is diffused by the IM transmitter, a pattern [0000] follows this identification, if it is a request (R) a pattern [00] is used. The traffic message completes the frame.

Because the VLC has four independent emitters, the optical signal generated in the receiver can have one, two, three, or even four optical excitations, resulting in  $2^4$  different

optical combinations and 16 different photocurrent levels at the photodetector.

As an example, in Fig. 8 Vehicle  $c_j$  receives two response MUX signals as it crosses the intersection. This vehicle, driving on the left lane, receives order to enter the intersection in # 7, turning left (NE) and keeps moving in this direction across position #1 toward the North exit (Phase2, violet pose). In the right side, the received channels are identified by its 4-digit binary codes and associated positions in the unit cell. On the top, the transmitted channels’ packets [R, G, B, and V] are decoded.

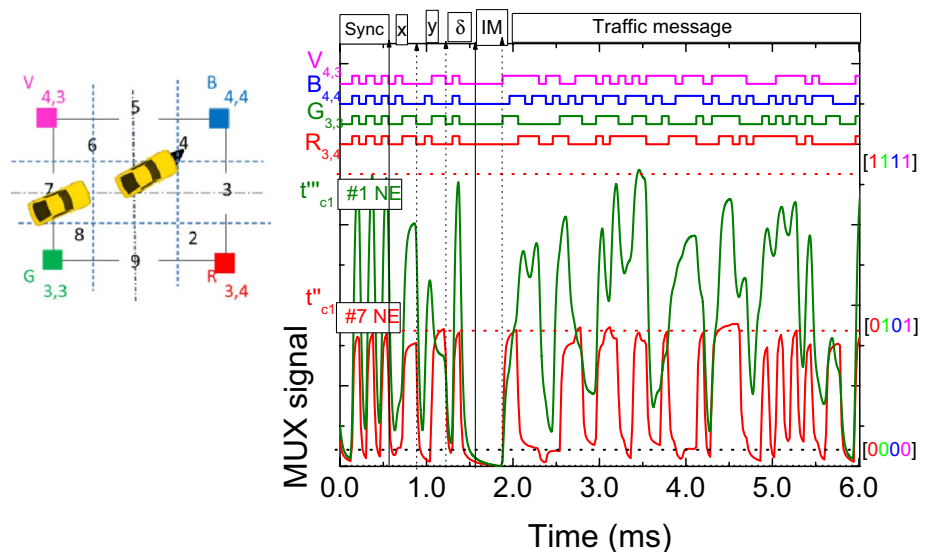
### Adaptive Traffic Control

In the PoC (see Fig. 3), it is assumed that  $a_1, b_1,$  and  $a_2,$  make up the top three requests, followed by  $b_2, a_3,$  and  $c_1$  in fourth, fifth, and sixth places, respectively. In seventh, eighth, and ninth request places are  $b_3, e,$  and  $a_3,$  respectively, followed in tenth place, by  $c_2$ . In penultimate request is  $a_5,$  and in the last one is  $f$ . Therefore,  $t_{a1} < t_{b1} < t_{a2} < t_{b2} < t_{a3} < t_{c1} < t_{b3} < t_e < t_{a4} < t_{c2} < t_{a5} < t_f$ . According to our assumptions, 540 cars approach the intersection per hour, of which 80% come from east and west. Then, 50% of cars will turn left or right at the intersection and the other 50% will continue straight.

In Figs. 9 and 10, the normalized MUX signals and the decoded messages assigned to IM received by Vehicle  $a_1, a_5, b_2, b_3$  at different response times are shown. On the top, the transmitted channels [R, G, B, V] are decoded. In the right side, the received channels for each vehicle are identified by its 4-digit binary codes and associated positions.

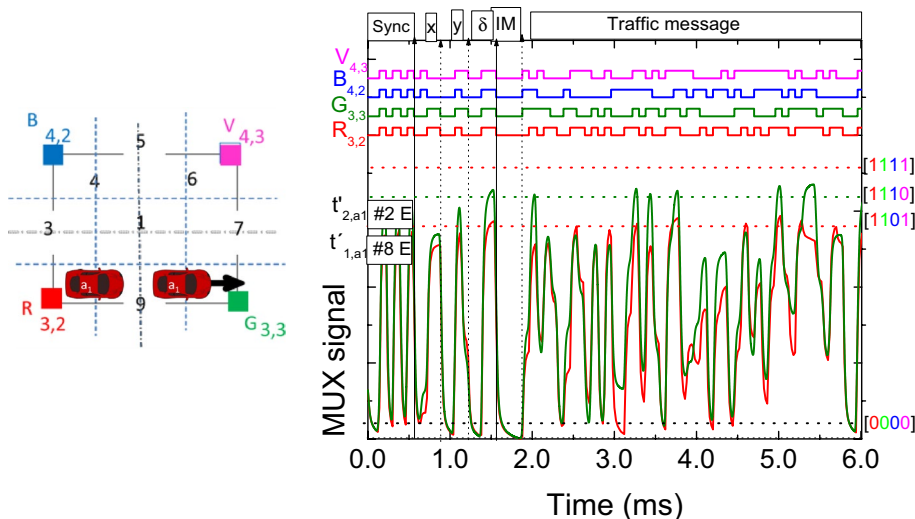
Analyzing Figs. 3 and 6, 9 shows the MUX signals assigned to response messages received by Vehicle  $a_1,$  driving the right lane, that enters Cell  $C_{4,2}$  in #2 ( $t'_1$ , Phase1, green pose), goes straight to E to position #8 ( $t'_2$ , Phase1,

**Fig. 8** MUX signal responses and the assigned decoded inside the intersection; messages acquired by vehicle  $c_j$ , poses #7NE, #1NE. On the top, the transmitted channels packets [R, G, B, V] are decoded

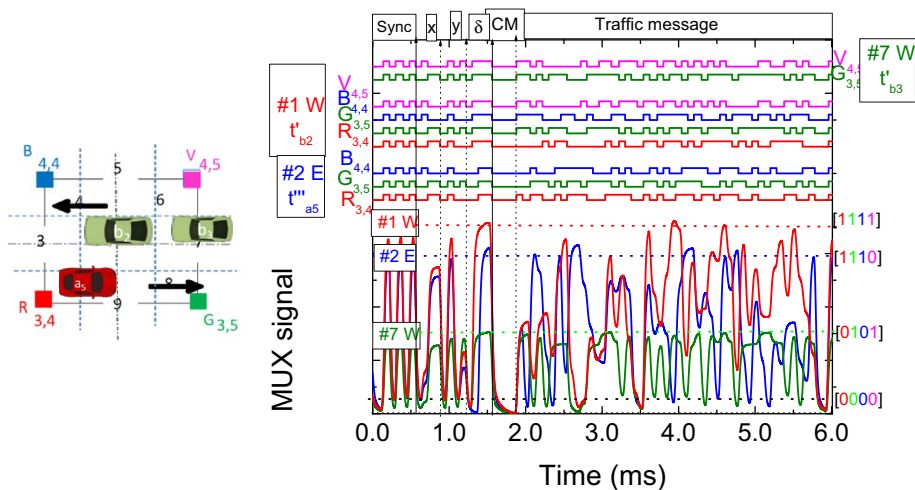




**Fig. 9** Normalized MUX signal responses and the assigned decoded messages acquired by vehicles  $a_1$  at different response times. Message distance, Poses #8E and #2E



**Fig. 10** Normalized MUX signal responses and the assigned decoded messages acquired by vehicles  $a_5, b_2, b_3$  at different response times. Vehicle  $a_5$ , pose #2E, and Vehicle  $b_2$  poses #7W and,  $b_3$  at #1W



green pose). Then, this vehicle enters the crossroad through #8 and leaves it in the exit #2 keeping always the same direction (E).

In Fig. 10, vehicles  $b_2$  and  $b_3$  approach the intersection after having asked permission to cross.

The traffic control system can broadcast messages containing the current signal phase and timing information. This allows vehicles equipped with VLC receivers to be aware of the upcoming signal changes and adjust their speed or behavior accordingly.

In the given scenario, both vehicles ( $b_2$  and  $b_3$ ) intend to make a left turn. Therefore, vehicle  $b_2$  will only be granted authorization to proceed once vehicle  $a_5$  has exited the intersection, which occurs at the end of Phase 2. It is more efficient for traffic management to allow the entire platoon to finish crossing the intersection before granting authorization to vehicle  $b_2$  to make a left turn. This approach minimizes disruptions and optimizes the flow of traffic by allowing

vehicles in the platoon to move through the intersection as a group, rather than interrupting the platoon for a single left-turning vehicle. This sequencing ensures the safe and orderly flow of traffic, allowing one vehicle to exit the intersection before the other is permitted to proceed. Then, Phase 3 begins with vehicle  $b_1$  heading to the intersection (W) (pose red), while vehicles  $a_i$  ( $1 < i < 5$ ) follow its destination toward E (pose green).

**Queuing System: Dynamic Traffic Signal Phasing**

The traffic controller uses queue, request, and response messages, from the  $a_i, b_i, c_i, e_i,$  and  $f_i$  vehicles, fusing the self-localizations  $q_i(t)$  with their space relative poses  $q_{ij}(t)$  to generate phase durations appropriate to accommodate the demand on each cycle.

The following parameters are therefore needed to model the queuing system: The initial arrival time ( $t_0$ ) and velocity

(v) in each the occupied section. The initial time is defined as the time when the vehicles leave the previous section (queue, request, or message distances) and move along the next section,  $q_i(t, t')$ . The service time is calculated using vehicle speed and distance of the section. The number of service units or resources is determined by the capacity of the section,  $n(q_i(x, y, \delta, t))$  and vehicle speed which depends on the number of request services, and on the direction of movement along the lane  $q_i(x, y, \delta, t)$ .

To each driving Vehicle,  $x_i$ , is assigned the unique time at which it must enter the intersection,  $t'[x_i]$ . The phase flow of the PoC intersection is shown in Fig. 11 according to the phasing diagram. In the PoC, it was assumed that  $t_{a1} < t_{b1} < t_{a2} < t_{b2} < t_{a3} < t_{c1} < t_{b3} < t_e < t_{a4} < t_{c2} < t_{a5} < t_f$ .

In this diagram, the cycle length is comprised of 5 out of the 7 phases that are taken into account (refer to Fig. 6). These phases are further divided into 16 time sequences or states. The states marked with an asterisk (\*) are dynamic movable states that vary based on the traffic demand throughout the cycle. These dynamic states can be adjusted or modified to accommodate the changing traffic conditions

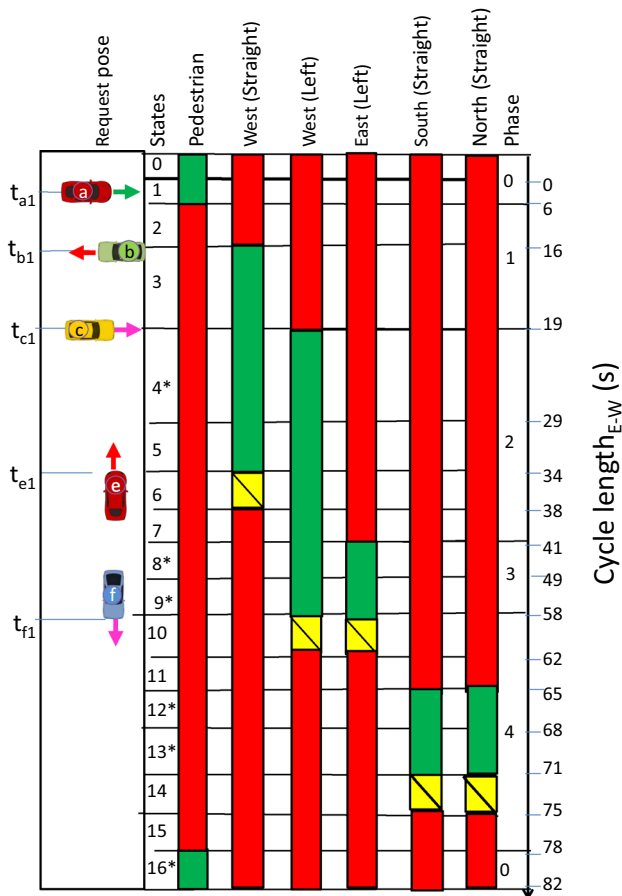


Fig. 11 Requested phasing of traffic flows ( $t_{a1} < t_{b1} < t_{a2} < t_{b2} < t_{a3} < t_{c1} < t_{b3} < t_e < t_{a4} < t_{c2} < t_{a5} < t_f$ )

during the cycle. The exclusive pedestrian phase contains the "0", the "1" and the "16" sequences. The cycle's top synchronization starts with sequences "1". The first, second, third, and fourth phases contain sequences between "2" and "15" and control traffic flow.

The matrix of states allows the traffic light controller to monitor, enter, or modify the division of an intersection into states, as shown in Fig. 12. The matrix shows the durations of the states (sequences) for a given cycle. In this matrix, each element represents the lighting state of the traffic light (if it is selected, the light is green) for the corresponding state. Columns represent the duration of the states in the different arms of the intersection, from cycle minimum [fluid traffic] to cycle maximum [dense traffic]. For a medium-traffic scenario, three distinct cycles are considered based on the higher volume traffic in the request directions (N-S, W-E straight or left). The data are based on the typical values used in an urban light-controlled four-legged intersection.

The column on the right of the matrix is called the column of fixed times.

The Intersection Manager (IM) has the capability to perform several operations based on the requests received. These operations include: modifying cycle durations (the IM can adjust the durations of the entire cycle according to specific requirements or changes in traffic conditions); entering fixed times (for states that have a consistent duration across all cycles in the lighting plan, the IM can input fixed times); changing durations of transportable states (the IM can modify the durations of states that are marked as

Sequences	Low-traffic scenario (s)	N-S medium traffic scenario (s)	E-W medium traffic scenario (Left) (s)	E-W medium traffic scenario (Straight) (s)	High traffic scenario (s)	Fixed time (s)
0	9	3	3	3	3	
1	0	6	6	6	6	
2						10
3						3
4	0	8	7	10	12	
5						5
6						4
7						3
8	3	3	8	8	10	
9	3	3	9	9	8	
10						4
11						3
12	3	6	3	3	7	
13	3	8	3	3	9	
14						4
15						3
16	0	4	4	4	6	
Cycle length	60	80	82	85	100	39

Fig. 12 Matrix of states at a four-legged intersection

transportable at any given time giving flexibility for adjustments based on real-time traffic demands). Also, the IM can make changes to the intersection coordination offset, which affects the timing and synchronization of traffic signals at interconnected intersections. These operations give the IM the ability to adapt and optimize the traffic control system based on real-time data and requests received.

The PoC assumes that all the leaders approach the intersection with similar velocities at different times (Fig. 11). Vehicle  $a_j$  was the first to request to cross the intersection and informed IM about its position and also that four others follow it at their positions with their speeds (see Fig. 9). Phase 1, sequence 3, therefore, begins at  $t'a_j$ . Vehicle  $b_j$  requests access later and includes the mappings of its two followers in its request. As the order to cross conflicts with  $a_i$  movement, he and his followers will pile up on the stop line increasing the total waiting time of the  $b_i$  cars. The fourth sequence is an adaptive sequence (Fig. 12). Due to the presence of a medium E–W traffic scenario, the IM extends the green time to accommodate the passage of all the  $a_i$  followers as well as the simultaneous passage of the arriving  $c_i$  (Fig. 8). From the capacity point of view, it is more efficient, if Vehicle  $c_j$  is given access (Phase 2) before Vehicles  $b_i$ , and Vehicle  $c_2$  is given access before Vehicle  $e$ , forming a west left turn of set of vehicles (platoon) before giving way to the fourth phase with north and south conflicting flows, as stated in Fig. 6. Meanwhile, the speed of Vehicle  $e$  was reduced, increasing the total accumulated time in the S–N arm.

Adaptive sequences 8 and 9 kick off Phase 3 (Fig. 11) and the sequence times will be adjusted according to the variation of  $r_t$  for the left turn of the  $b_i$  cars. A new phase, Phase 4, begins and includes two adaptive sequences, sequence 12 and 13. Their time intervals will be as short as possible, which will free up capacity in the cycle for the E–W flows that are heavily loaded. Taking into account the accumulated total waiting time in each arm, an 85-s cycle is recommended for this type of flow. The times associated with each sequence can be visualized in Fig. 11.

Therefore, the real-time detection of the spatiotemporal data based on urban road network traffic status can provide rich and high-quality basic data and fine-grained assessment of control effects for traffic control.

### Intelligent Control in V-VLC Systems

The purpose here is to develop an intelligent control system model that facilitates safe vehicle management through intersections using Vehicle-to-Vehicle, Vehicle-to-Infrastructure, and Infrastructure-to-Vehicle communications using fundamentals of deep learning, and applied them to a cooperative connected vehicle system.

### Dynamic Traffic Flow Control Simulation

Data-driven paradigms are becoming increasingly popular in modern transportation systems with the aim of obtaining more accurate predictions and advanced control strategies [18]. By utilizing these techniques, both researchers and commercial entities have begun to investigate how traditional transportation problems, such as traffic flow and accident estimation, can be improved or even partially solved. Reinforcement Learning (RL) is a machine learning training method based on rewarding desired behaviors and/or punishing undesired ones [19–21]. In general, a reinforcement learning agent can perceive and interpret its environment, take actions, and learn through trial and error. To incentivize the agent, this technique involves assigning positive values to desired actions and negative values to undesirable behaviors. The key to the agent's success lies in striving for the highest possible long-term reward. As the agent acquires experience, it learns to steer clear of negative situations and prioritize positive actions instead [22].

The simulations were agent-based and they have been carried out in a tool for Simulation of Urban MOBility (SUMO) [23]. In SUMO, the traffic lights are controlled by a learning agent, which makes decisions regarding their operation. The behavior of the traffic lights control agent is guided by a reward system, wherein the agent receives rewards based on its actions. The ultimate objective is to optimize the flow of traffic within the system. Figure 13 illustrates the action-reward feedback loop of a generic RL model. For the best policy, the agent must maximize its total reward while exploring new states. The state of the agent,  $s_t$ , describes a representation of the state of the environment at a particular agentstep  $t$ . For the agent to learn how to optimize traffic effectively, the state should provide adequate information on the distribution of vehicles on each road.

It is possible to detect whether a car has entered the incoming lanes of the intersection by segregating the arms into discrete message, request, and queue cells (Fig. 5). An array will contain all vehicles in simulation at one time, with states assigned to them. “ $v_i$ ” is the state of a vehicle, where

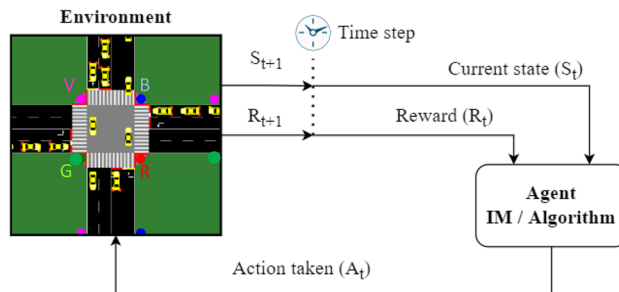


Fig. 13 Illustration of the reinforcement learning’s loop of action-reward feedback

$i$  is the order of the crossing request, and it consists of a string of two digits, one representing the lane the vehicle is in, and the other representing its position in the lane (if it's near or far from the intersection). In Fig. 14a, the assignment of the lanes to the simulated intersection is displayed, and in Fig. 14b, the state representation for the west arm of the intersection is exemplified. Between the beginning of the road and the intersection's stop line, there are 4 cells (0/message, 1/request, 2, 3/queues) per lane (L/0–7). This results in a total of 32 state cells during simulation.

Considering the PoC displayed in Fig. 3, where  $t_{a1} < t_{b1} < t_{a2} < t_{b2} < t_{a3} < t_{c1} < t_{b3} < t_e < t_{a4} < t_{c2} < t_{a5} < t_f$  the states of the leaders  $a_i$  (L0) and  $b_i$  (L4) will be represented as  $v_i = "00"$  and  $v_2 = "50"$ .

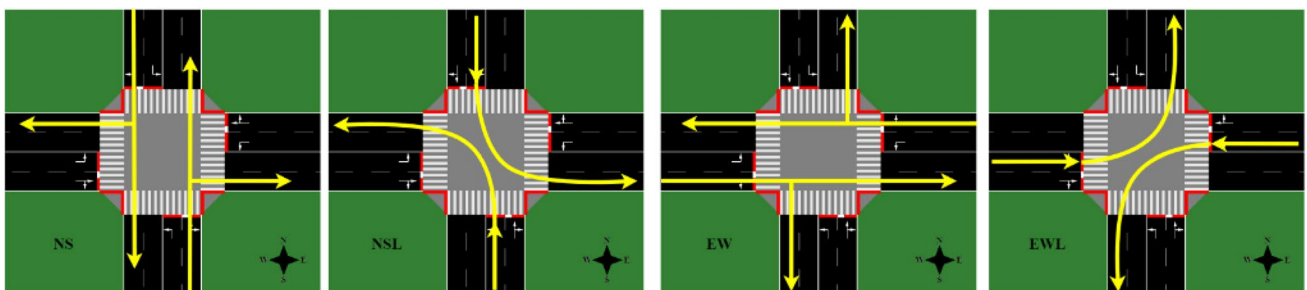
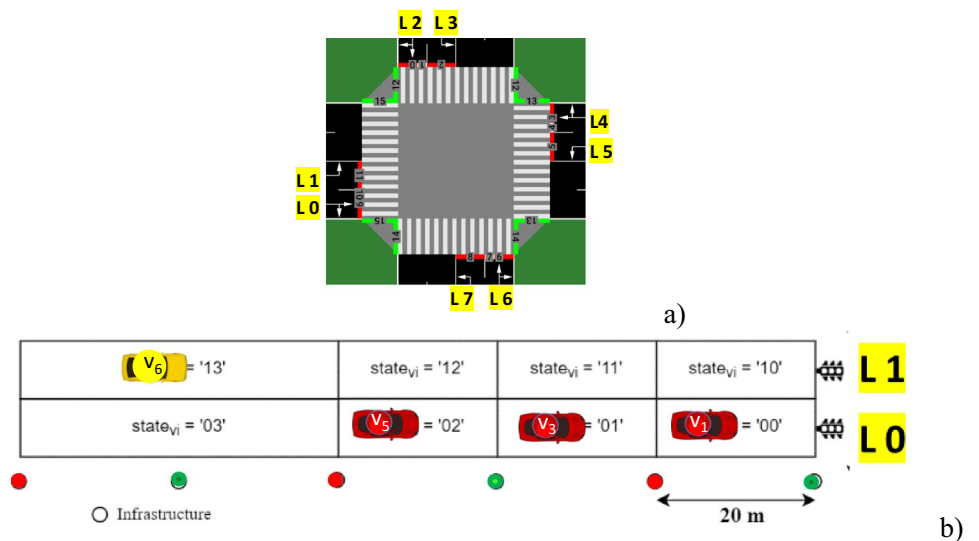
An action is performed when the traffic light system activates a set of lanes for a predetermined time during one of several green phases. The yellow time is set at four seconds, whereas the green time is set at eight. If the action taken in agentstep  $t$  is the same as the action taken in the previous agentstep  $t - 1$ , there is no yellow phase, and the current green phase remains. If the action selected in agentstep  $t$  is not equivalent to the previous action, a 4-s yellow phase

occurs between the two actions. This indicates that there are eight simulation steps between two identical actions, since in SUMO, one simulation step corresponds to one second.

Considering the color phasing diagram (Fig. 6), the four agent's potential actions are displayed in Fig. 15. The main goal is to increase traffic through the intersection over time. Agents use rewards to comprehend the outcome of their actions to improve the model for selecting future actions.

In the learning process, the reward ( $r$ ) represents the response of the environment following the agent's decision. Rewards play a critical role as they provide feedback to the agent, reinforcing both positive and negative outcomes. Positive rewards are given for previous good actions, indicating desirable behavior, while negative rewards stem from previous bad actions, indicating undesired behavior. By incorporating rewards into the learning process, the agent can learn to optimize its decision-making and strive for actions that yield positive outcomes while avoiding actions that result in negative consequences. To accomplish this, the incentive should be based on some traffic efficiency performance metric, allowing the agent to determine whether the action they took reduced or increased intersection efficiency. For

**Fig. 14** a Lanes' assignment. b Agent state ( $s_i$ ) representation in the west arm of the intersection



**Fig. 15** Graphical representation of the agent's four possible options as actions (a)

traffic coordination, in the scenario presented (Fig. 3), the IM receives requests (Fig. 9) for access to the intersection from all the leading cars at different times.  $t_{x_i}$  (Fig. 11). This type of information (V2I) enables the IM to know the precise location (state representation on each cell) and the speed of all the leader vehicles, as well as the location and speed from their followers that was sent to the leaders through V2V. These data help previewing the initial arrival times and speeds at the different sections.

The IM has to minimize accumulated total waiting time  $aTwt$  in each arm of the intersection defined as [24]

$$aTwt_t = \sum_{xi=1}^n (awt)_{xi,t}, \tag{1}$$

where  $awt(x_i,t)$  is the amount of time in seconds a vehicle  $x_i$  has a speed of less than 0.1 m/s at step  $t$  and  $n$  represents the total number of vehicles in the environment at step  $t$ . When the speed is less than 0.1 m/s a queue alert is generated. Defining the reward function,  $r_t$ , as

$$r_t = aTwt_{t-1} - aTwt_t, \tag{2}$$

where  $aTwt_t$  and  $aTwt_{t-1}$  represent the accumulated total waiting time of all the cars in the intersection captured, respectively, at step  $t$  and  $t - 1$ . If  $r_t$  is negative, more vehicles in queues are added compared to the situation in the previous step  $t - 1$ , resulting in higher waiting times compared to the previous step.

The agent determines the reward for the prior action using some indicator of the current traffic situation. Data samples containing details of the latest simulation steps are stored in a memory, which is subsequently extracted for training purposes. After selecting a new action based on the current state of the environment, the agent will begin to simulate until the next interaction takes place. The entire training is divided in multiple episodes. The total number of episodes is specified by the user, with a number of above 100 episodes being the norm. By default, SUMO provides a time frequency of 1 s per step, and the period of each episode is also specified by the user.

### Traffic Generation and Simulated States

Traffic generation is one of the most important elements of a simulated intersection that impacts agent performance.

The simulation needs to have a wide range of traffic flows and patterns to create an adaptive agent capable of genuine environmental adaptation.

Vehicles at the intersection can be defined by modeling vehicles' arrival time at that intersection in the given interval of time. For realism, each episode will use a probability distribution, the Weibull distribution of shape 2, to generate traffic [25].

This distribution simulates the heavy and light traffic volumes during congestion and normal situations. During its early stages, the Weibull distribution shows an increase in traffic, which represents peak traffic hours. As congestion gradually eases, the number of incoming cars declines. In the simulation, all vehicles have identical performance and physical specifications. There are no variations in terms of speed, acceleration, size, or any other physical attributes among the simulated vehicles. This standardization allows for a fair and consistent comparison of the vehicles' behaviors and interactions within the simulated environment.

As a result, the following four different scenarios are defined in Table 1, these being inspired in Fig. 12. These scenarios consider a simulation time of 1.30 h. Each scenario corresponds to a single episode, and they always cycle through in the same order during training.

The considered environment for simulation (Fig. 3), is a four-way intersection, 2 lanes on each arm approach the intersection from compass directions, leaving two lanes on each arm. Each arm is 100 m long. On every arm, each lane defines the possible directions that a vehicle can follow: the right lane enables vehicles to turn right or going straight, while on the left lane, the left turn is the only direction allowed. In the center of the intersection, a traffic light system, controlled by the IM (also known as agent), manages the approaching traffic.

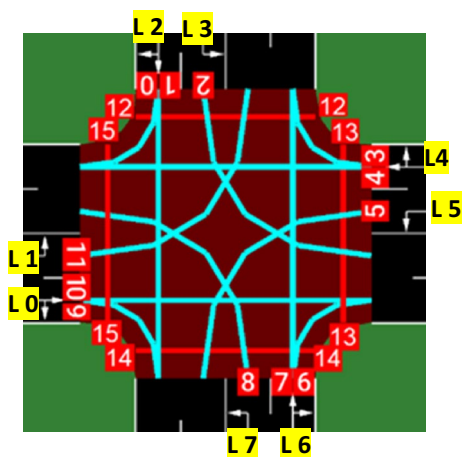
Every lane has a dedicated traffic light (TL) that operates according to the common European regulations, with the only exception being the absence of time between the end of a yellow phase and the start of the next green phase (considering, therefore, that the vehicles will stop on yellow, Y). Figure 16 identifies the number associated to each of the traffic lights and displays all the possible trajectories of the vehicles.

Considering the phase diagram (Fig. 6), a set of states of lights that represent the phases of the system as well as the

**Table 1** Different traffic scenarios defined for training simulation

Traffic scenario		High	Low	NS medium	E-W medium	
Traffic rate per lane (%)	N-S	Straight	37.5	37.5	67.5	7.5
		Left	12.5	12.5	22.5	2.5
	E-W	Straight	37.5	37.5	7.5	67.5
		Left	12.5	12.5	2.5	22.5
Total vehicles (un.)		4000	600	2000	2000	





**Fig. 16** Four-legged intersection. Traffic Lights’ (TL) and Lanes (L) identification and vehicles’ possible trajectories

**Table 2** Description of the different states of the simulated light system. \*—States with variable durations

State ID	Duration	TL ( 0-15) states	Phase	Next
0	–	RRRRRRRRRRRRGGGG	PH0	1
1	8	RRRRRRRRRRRRRRRR	–	2
2	8*	RRRGRRRRGGRRRRR	PH1	3 or 6
3	4	RRYYRRRRGGRRRRR	–	4
4	8*	RRRRRRRRGGGRRRR	PH21	5
5	4	RRRRRRRRYYGRRRR	–	9
6	4	RRGGRRRRYYRRRRR	–	7
7	8*	RRGGGRRRRRRRRRR	PH22	8
8	4	RRYYGRRRRRRRRRR	– 9	
9	8*	RRRRRGRRRRRGRRRR	PH3	10
10	4	RRRRYYRRRRYYRRRR	–	11
11	8*	GRRRRRGRRRRRRRRR	PH4	12 or 15
12	4	GRRRRYYRRRRRRRRR	–	13
13	8	GGRRRRRRRRRRRRRR	PH51	14
14	4	YYGRRRRRRRRRRRRR	–	18
15	4	YYRRRRGGRRRRRRRRR	–	16
16	8*	RRRRRGGGRRRRRRRR	PH52	17
17	4	RRRRRRYYGRRRRRRRR	–	18
18	8*	RRGRRRRRGRRRRRRRR	PH6	19
19	4	RRYRRRRRYRRRRRRRR	–	0

transition between them were considered. This set of color states (TL States) can be seen in Table 2, where it is specified its identification, duration, combination of lights, phase to which it is intended and next state.

The ordering of the combination of lights (TL State) is according to the index of the traffic lights (0–15) shown in Fig. 16, being R—Red, Y—Yellow, and G—Green. Note that the configuration of the states considers that the vehicles stop at the yellow traffic lights.

Some of the states consider variable durations (\*), depending upon the number of vehicles on each road (Table 1). A variable duration has been chosen to improve the traffic flow in each state and the ones that follow. It is also possible for the state duration to be 0 s if there are no vehicles in the lanes in question, also skipping the next yellow state. This sequence of 20 states makes up a complete cycle of phases, starting with the pedestrian phase (Fig. 6). This phase is mandatory for safety reasons and must be separated from the phases intended for vehicle circulation (state 1 with 8 s of pedestrian eviction). Its duration depends upon the existence of vehicles near the intersection, this being a minimum of 6 s. It was also defined 6 s as the minimum that a traffic light should be on. The duration of a minimum signal timing is typically determined based on various factors, including traffic flow characteristics, pedestrian movement, intersection geometry, and safety considerations. The purpose of having a minimum signal timing is to ensure an adequate amount of time for vehicles and pedestrians to safely clear the intersection. The choice of 6 s (or any other specific duration) depends on the clearance time, intersection design, traffic flow, and pedestrian considerations. After phases 1 and 4, a decision is made regarding the best option for the next phase. This decision-making considers a simple comparison of the number of vehicles on the roads. The estimation of the duration also considers static variables/coefficients, which improve it for a given scenario.

### V-VLC Adaptive Traffic Control Evaluation

A static cycle, also known as fixed-time signal control, refers to a predetermined and unchanging sequence of signal phases and timings that repeat continuously. In this approach, the signal timings are set based on historical traffic data. The timings are typically set to provide a balance between different traffic movements and prioritize the efficient flow of vehicles and pedestrians. A dynamic cycle, also referred to as adaptive or responsive signal control, involves adjusting the signal timings in real time based on the prevailing traffic conditions. In this approach, sensors or other data sources (VLC) continuously monitor the traffic flow and provide feedback to a control system. The control system analyzes the traffic data and dynamically adjusts the signal timings to optimize the traffic flow and reduce congestion. The dynamic cycle takes into account the current traffic demand, queue lengths, and traffic patterns to adaptively allocate green time to different movements and phases. By dynamically responding to the changing traffic conditions, the signal timings can be optimized to improve traffic efficiency and reduce delays.

The traffic scenario described in Fig. 3 was simulated for a medium E-W (straight) traffic flow (Table 3). As input parameters the data from Sect. "VLC Evaluation" was

**Table 3** State duration from the first state cycle for different traffic scenarios

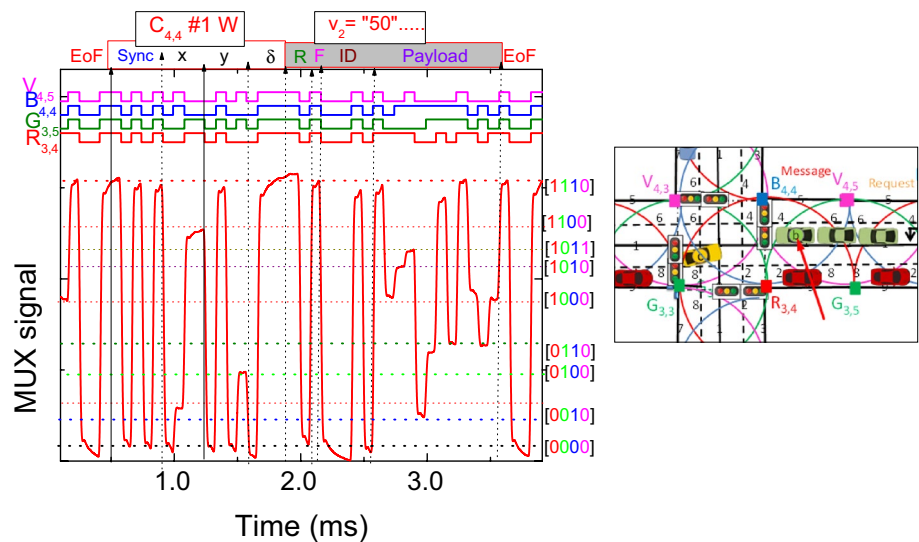
State	Low-traffic scenario (s)	N-S medium-traffic scenario (s)	E-W medium-traffic scenario (Left) (s)	E-W medium-traffic scenario (Straight) (s)	High-traffic scenario (s)	Fixed time (s)
0	9	9	9	9	9	9
1	8	8	8	8	8	8
2	6	6	6	9	6	8
3	4	-	4	4	-	4
4	0	-	2	2	-	8
5	0	-	4	4	-	4
6	-	4	-	-	4	-
7	-	0	-	-	4	-
8	-	0	-	-	4	-
9	0	0	8	0	0	8
10	0	0	4	0	0	4
11	6	9	6	6	9	8
12	-	-	4	4	-	4
13	-	-	0	0	-	8
14	-	-	0	0	-	4
15	4	4	-	-	4	-
16	3	3	-	-	9	-
17	4	4	-	-	4	-
18	0	0	0	0	0	8
19	0	0	0	0	0	4
Cycle length (s)	44	47	55	46	61	89
Average speed (m/s)	6.60	6.76	6.53	7.46	5.1	-

used and compared with results presented in the static case (Fig. 11). When all requests have been resolved and the last vehicle has left the intersection, the simulation ends.

To exemplify the process, in Fig. 17, it is displayed a response to leader vehicle  $b_l$  at  $t_{b_l}$ . In the top of the figure, the decoded signal is displayed, and in the right side, the MUX levels used for in the decoding process are pointed

out. The simulated scenario at the right side serves as tools to guide the eyes and provide visual representations of traffic dynamics. Considering the frame structure, the message contains the location of the vehicle in the network (Sync) and in the cell  $(x, y)$ , the flow direction of the vehicle ( $\delta$ ), and the traffic message. Data in a traffic message include the type of messenger (R, F), the order in which the driver

**Fig. 17** Normalized MUX signal and the assigned and decoded messages acquired by vehicles  $b_l$ . Pose  $C_{4,4}$ , #1W



requested to cross the intersection (ID), and the payload. The End of File (EoF) is also included in the frame. It can be seen from Fig. 8 that the vehicle is in cell  $C_{4,4}$  (message distance), footprint #1, and its flow direction is W (code 7). The agent identified this vehicle with the order number 2. The information obtained from  $t_{b,i}$  indicated that the vehicle belongs to state  $v_2 = "50"$ . For the other vehicles, the process of acquiring the agent's state, represented as "st," is similar (as shown in Fig. 14).

After ensuring all the system settings, we proceed to simulate the system against different traffic flow scenarios. It is important to mention that the simulations end as soon as there are no more vehicles on the network, i.e., after all requests are solved and the last vehicle leaves the vicinity of the intersection. As far as circulation is concerned, the vehicles are all moving at an average of 10 m/s, dropping the speed to 5 m/s when reaching the traffic light at the beginning of the cycle, during pedestrian eviction. Considering this speed, approximately 3 s of green light are estimated to be required for each vehicle to drive through the traffic light.

Different traffic flows were simulated (Table 1) and the state cycles and durations compared. The vehicles were generated 5 s after the start of the simulation to demonstrate the variable duration of phase 0, for pedestrians, and not its minimum duration. Table 3 organizes the state durations for each simulated traffic scenario, as well as the average vehicle speed verified in each state cycle. The durations marked with a dash correspond to states that did not happen during that cycle. The average speed should be seen as a measure that shows whether the scenario is benefited by the previously mentioned state sequence or not.

Results show that the low-traffic scenario corresponds to the lowest cycle duration. In the medium-traffic scenarios, cycle length increases with traffic flow, since the phase duration increases as the flow increases. Two phases are enlarged, one for the N–S traffic (state 11) and one for the E–W (left) traffic scenario (state 9). E–W medium-traffic scenario (straight) is the scenario where the average speed is higher. Here, Phase 1 is destined for E–W traffic straight ahead, and thus, these vehicles are immediately served and do not need to wait for their turn and the total cycle will be lower. In the high-traffic scenario, the vehicle flow duplicates, resulting in the longest cycle and the slowest average speed. Even though there is variation in the cycle length among the different scenarios, it has been observed that all of them are significantly shorter compared to the expected cycle length when using fixed-time states (as shown in Fig. 12). This finding indicates that the adaptive traffic control system is able to dynamically adjust the cycle length based on real-time traffic conditions, resulting in more efficient traffic flow and reduced waiting times compared to a fixed-time control approach.

For the medium E–W (straight) traffic scenario, a state diagram resulting from the SUMO simulation is generated

and presented in Fig. 18. At the top of the diagram, two important elements were included: the environment and the color phasing. The environment represents the external surroundings in which the system operates, while the color phasing refers to the specific sequence or pattern of signal light changes. By including these elements at the top of the diagram, they are given prominence and serve as key factors in the overall system analysis. The arrow points out the scenario represented at this instant. The agent in the system retrieves the current state by considering various requests received, as depicted in Fig. 11. These requests, along with the actions illustrated in Fig. 15, are used to determine the static cycle of the system. The initial proposed phase diagram (Fig. 6) and the set of traffic lights representing each phase (Fig. 16) are also taken into account during this process.

By accumulating the times recorded for each arm of the intersection, the simulation can generate a preview of the phasing diagram. This preview provides insights into the expected timing and sequencing of signal light changes throughout the cycle. Additionally, the simulation calculates the average velocity along the cycle, which helps assess the overall traffic flow efficiency. By incorporating all these elements and calculations, the agent can dynamically adjust the signal timings and optimize the traffic control system to improve the average velocity and overall performance of the intersection. The results show a 55-s cycle length composed of 12 sequential states (TL states, Table 2) that make up the 4 proposed phases (Fig. 6). In each sequential state, the traffic light states (TL) and their green and yellow times are indicated.

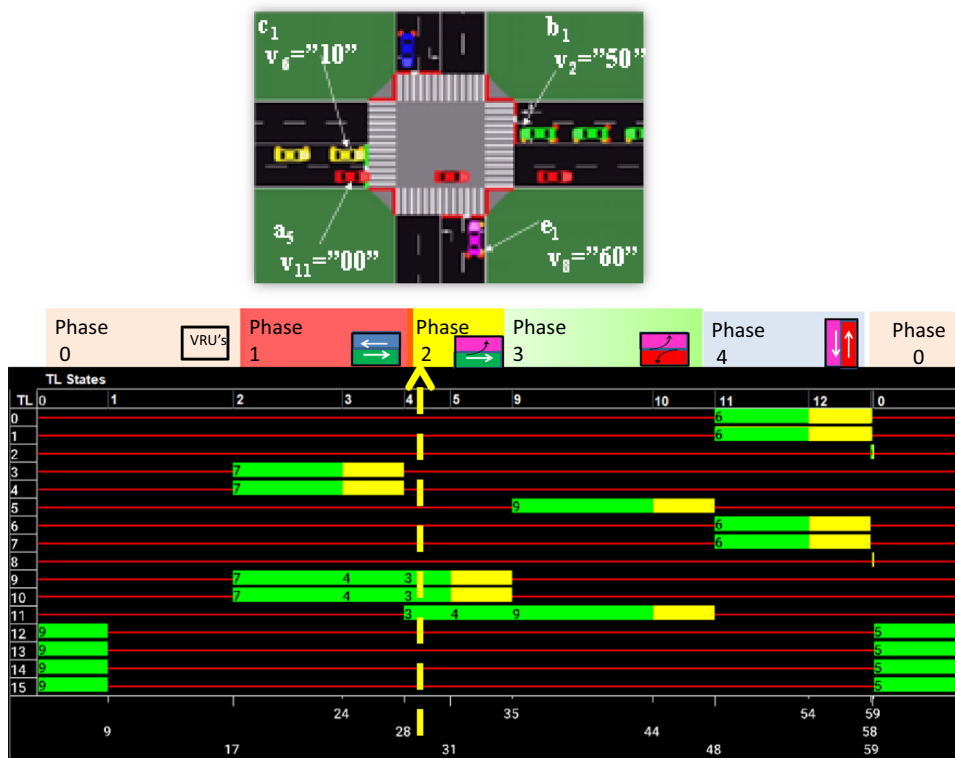
In Fig. 19, the average speed as a function of the simulated time is displayed for the static and a dynamic cycle. The duration of each state is also inserted in the bottom.

As expected, the dynamic system finishes the cycle first by adapting the cycles to shorter durations when necessary. The better temporal management of phases results in better traffic flow and a higher average speed. Although it is still possible to improve its performance, the expected improvements can be seen, managing the flow 15 s faster with the use of dynamic durations in the states.

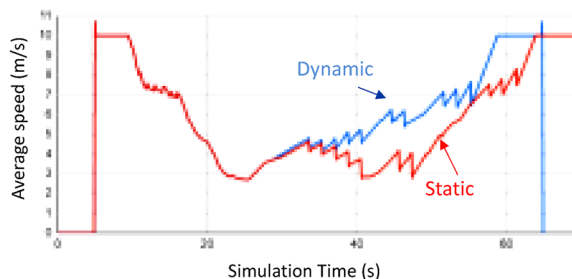
The "dynamic" scenario, characterized by moderate durations due to medium-traffic flow, can be compared to the real static phase diagram shown in Fig. 11. It is observed that the durations chosen in the simulation were significantly lower than those in the static diagram. This observation can be interpreted in two ways:

- *Proper adaptation and optimization*: One interpretation is that the simulator effectively adapted the durations, resulting in an optimization that aligns closely with the ideal scenario. The lower durations may indicate that the simulation intelligently adjusted the signal timings based

**Fig. 18** State diagram resulting from the SUMO simulation. On the top, an insert of environment and the color phasing is inserted



**Fig. 19** Average vehicle speed in simulation for static and dynamic states



	States	0	1	2	3	4	5	9	10	11	12	13	14	18	19	Total duration (s)
Duration (s)	Static cycle	6	8	8	4	8	4	8	4	8	4	8	0	0	0	70
	Dynamic cycle	6	8	7	4	3	4	9	4	6	4	0	0	0	0	55

on the real-time traffic conditions, efficiently allocating green time and minimizing delays. This suggests that the simulation successfully optimized the traffic control system.

- *Unrealistic simulation:* The other interpretation raises the possibility that the simulation may have been unrealistic, failing to consider certain factors that occur in a real traffic context. Factors such as conflicting movements, intersection clearance times for vehicles and pedestrians, queue start times, and "all red" times during phase transitions are critical in real-world traffic control. If the simulation did not adequately account for these factors,

the lower durations might not accurately represent the real-world performance of the system.

### The Intelligent Traffic Control System

To determine which interpretation is more likely, it is important to evaluate the simulation methodology, the accuracy of the input data, and the representation of real-world traffic dynamics. Considering and incorporating the factors mentioned above, along with other relevant aspects, can help ensure a more realistic and reliable simulation of traffic control scenarios.

An intelligent system must be prepared to adapt to any traffic scenario that occurs. For this reason, training the model that describes the system is essential to its performance. Deep learning algorithms should be used to take advantage of the samples collected over time (short or long periods of time) to make decisions and act, or simply collect data for further analysis.

To enable real-time responsiveness to fluctuating traffic flow across different roads, the implementation of machine learning is essential. Specifically, a deep learning (DL) algorithm, among other potential options such as conventional ML algorithms like Support Vector Machine (SVM), can be utilized. While traditional ML algorithms like SVMs still have their merits, especially in scenarios with limited data or when interpretability of the model is crucial, DL's ability to handle large-scale, high-dimensional data and learn complex representations makes it a powerful tool for many modern applications. The choice between DL and traditional ML approaches ultimately depends on the specific task, data availability, interpretability requirements, and the desired level of performance. The Deep Q-Network (DQN) is used as the underlying reinforcement learning algorithm. The DQN approximates the optimal action-value function, which maps states to actions, using a deep neural network. The network is trained through an iterative process of exploration and exploitation to learn the optimal policy. Initially, the system was trained in a simulated environment where traffic conditions could be manipulated. Agents interact with the environment, observe states, take actions, and receive rewards. Through multiple iterations, the DQN learns the optimal policy by updating its network parameters based on the observed rewards and state transitions. Vehicles communicate with each other and with the infrastructure through visible light communication (V2V and V2I). The experimental data were acquired using a simulated scenario, since V-VLC ready connected vehicles are not available yet. This will allow the vehicles to share information about their positions (I2V) intentions (V2I), speeds (V2V), and upcoming maneuvers (I2V). Cooperative behavior is encouraged by enabling vehicles to coordinate actions, such as merging, yielding, or optimizing traffic signal timings. For the test of the algorithms, different models should be trained and the performances compared. The most relevant features for training the models are: total number of trained episodes, total duration of each episode; total number of randomly generated vehicles throughout the simulations; fixed duration for the yellow state, usually 4 s; fixed duration for greens, also serving as the increment duration if the same action is chosen by the agent in the following agent step; number of possible states for the vehicles (Fig. 14); number of choice actions for the agent (Fig. 15). It is also possible to configure the neural network with regard to

the number of hidden layers, layer sizes, and also sample batches' sizes. The learning rate can also be modified.

Overall, using VLC for dynamic traffic control offers advantages, such as real-time adaptability, enhanced traffic management, improved safety, efficient resource utilization, flexibility, scalability, and alignment with smart city initiatives. These benefits make VLC an attractive technology for implementing dynamic and intelligent traffic control systems that can adapt to changing traffic conditions and optimize the overall transportation network. In short, the result demonstrates that the creation of a dynamic system that is adaptive to a specific traffic scenario is achievable and beneficial. Environmental conditions, such as sun, rain, snow, and atmospheric factors, can affect VLC system performance. Direct sunlight causes interference and reduces signal-to-noise ratio. Rain, snow, and fog scatter and attenuate signals, reducing range and introducing errors. Atmospheric conditions like dust or haze also impact signal quality. To overcome these limitations, future techniques include adaptive transmission, adjusting power and modulation based on real-time conditions; advanced signal processing to enhance signal detection and decoding; and hybrid communication systems combining VLC with RF or IR for backup channels when environmental factors compromise VLC performance.

In VLC systems, security, error detection and correction, and limited bandwidth are important considerations. Encryption techniques can safeguard transmitted data, error detection and correction methods enhance reliability, and efficient modulation and coding techniques optimize bandwidth utilization. By addressing these aspects, VLC systems can provide secure and reliable communication. Ongoing research aims to further improve VLC capabilities and overcome challenges in real-world scenarios.

It is important to improve the coding techniques, in the future, to allow only the legitimate receivers to process secure request/response messages. Here, the security is embedded in the physical transmission. In the LoS channel, the eavesdropper remains completely passive, meaning that although the information is technically available to the eavesdropper, it is encrypted and therefore of limited or no usefulness to them. Using the street lamp positions to determine vehicular flow eliminates the need for certificates or passwords from the network and replaces them with statistical secrecy.

## Conclusions

With V-VLC-ready connected cars, we propose optimizing urban traffic network operation by integrating traffic signal control and driving behavior. For managing intersections, the adaptive traffic control system uses a queue/request/response approach. An architecture, scenario, environment,



and hybrid mesh/cellular network configuration were developed and proposed. The V2I2V communications enable real-time monitoring of queues, requests, and messages, along with the travel times necessary to synchronize traffic routing in various routes. To demonstrate the concept, a phasing diagram and matrix of states are proposed. A simulation based on a urban mobility simulator is presented. A comparison between a static case where the green times are fixed and the dynamic where they depend on the accumulated time at each arm is presented.

Our main goal was to show that VLC can be utilized for accurate vehicle localization and positioning. By leveraging the optical signals from streetlights, traffic signals, or other infrastructure, vehicles equipped with VLC receivers can determine their precise location within the network. This capability is valuable for applications such as navigation, collision avoidance, and efficient traffic management. Results show that the adaptive traffic control in a V2X environment can collect more detailed data, such as vehicle position, speed, queue length, and stopping time, than the traffic flow and occupancy information provided by fixed coil detectors. The traffic light phase is adjusted to the traffic scenario and the duration of the traffic light is changed dynamically which reduces travel times and unnecessary waiting for the green phase, leading to optimized traffic flow. The introduction of VLC between connected vehicles and the surrounding infrastructure allows the direct monitoring of critical points that are related to the queue formation and dissipation, relative speed thresholds, and inter-vehicle spacing increasing the safety. Overall, the advantages of using VLC in vehicular communications include high bandwidth, interference-free communication, enhanced security, improved localization and positioning, energy efficiency, reduced electromagnetic interference, and integration with the existing infrastructure. These advantages make VLC a promising technology for enabling reliable and efficient communication in connected vehicle environments. In future, we plan to extend this approach to more complex road networks, with multiple signal intersections, and real-world road data set.

## Future Trends

The future work will delve into expanding the application of V-VLC technology in various traffic scenarios, aiming to enhance traffic flow by integrating this technology into connected cars. The system's queue/request/response approach for intersection management will be further refined and optimized for real-time monitoring of queues and messages. The simulation results have already demonstrated the potential for V-VLC technology to provide detailed data compared to the traditional fixed coil detectors, showcasing its capabilities in improving traffic control.

The next steps will involve dynamic adjustments to traffic light phases and durations based on the collected data, aiming to further reduce travel times and waiting periods at intersections. Additionally, the technology's ability to monitor critical points, such as queue formation and dissipation, will be harnessed to enhance overall traffic safety.

While the initial simulation was conducted in a simple scenario with two intersections, future research will expand testing to more complex and realistic traffic situations. This will provide a deeper understanding of the effectiveness of V-VLC technology in optimizing traffic signal control and its potential for widespread application in urban traffic networks. In conclusion, the study suggests that adaptive traffic control using V-VLC technology holds significant promise for improving traffic flow, and ongoing research will explore and validate its potential in diverse and intricate traffic scenarios.

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## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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