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A real-time adaptive traffic light control algorithm at urban intersections for smart cities

Abstract

This paper investigates the challenges of intelligent traffic light control at urban intersections in the context of the Internet of Things. Increasing vehicle density and mobility have exacerbated traffic congestion and resulted in inefficient use of road infrastructure, particularly at intersections. In addition, the dynamic nature of traffic flow, the unpredictability of human driving behavior, and the complexity of network topologies pose significant obstacles to efficient traffic control. To address these issues, an intelligent control algorithm is proposed that exploits communication between vehicles and infrastructure, as well as between infrastructures. The algorithm incorporates an enhanced version of Dijkstra's algorithm to optimize traffic light operation and minimize vehicle waiting times by dynamically computing shortest paths based on real-time traffic data. Simulation experiments on an urban road network show that the proposed method significantly reduces delays and improves travel efficiency compared to traditional fixed-time traffic control systems. Performance evaluation based on metrics such as average vehicle delay and total travel time confirms significant improvements. In addition, the system demonstrates robustness under varying traffic loads and dynamic road conditions. Future research will focus on extending the approach to highway scenarios and integrating emergency vehicle prioritization mechanisms.

1. INTRODUCTION

For years, intelligent transportation systems (ITS) and their various problems have become a topic of great importance. As a result, researchers around the world are trying to develop a system suitable for smart cities (Kommineni & Baseer, 2024). These efforts are aimed at addressing the improvement in living standards, the sharp increase in the number of vehicles, and the expansion of land-based transportation. This is due to the inefficiency of transport systems and poor infrastructure, which has become a problem for most of the world's population, especially in large cities. One of the serious problems is environmental pollution, because cars that remain on the roads for a long time cause high CO₂ emissions (Tunc & Soylemez, 2023). We also face the problem of accidents that cost the lives of millions of people, not to mention the enormous material losses that result from them.

The biggest problem that has a direct and daily impact is traffic congestion, as it contributes to increasing the level of pollution and often causes accidents and countless human and material losses, especially in emergencies. As mentioned in Table 1 below (Jazib, 2024), the 10 cities with the highest traffic where people spend the most time in traffic, these cities share problems such as urbanization, population growth and poor infrastructure, these problems are the factors that lead to commuter fatigue, loss of time and lives and high levels of pollution. Therefore, reducing the problem of road congestion, or at least mitigating it as much as possible, is considered a necessity to avoid the damage that results from it.

In this paper we have carried out an approach that aims to develop a new algorithm inspired by the Dijkstra algorithm, which controls traffic lights at intersections using two types of communication vehicle to infrastructure (V2I) and infrastructure to infrastructure (I2I) communication to ensure rapid access to information to direct vehicles to the desired destination and reduce both of travel time and waiting time lost in traffic jams.

Tab. 1. Cities where people spent the most time in traffic (Jazib, 2024)

World rank	City	Average travel Time/10 km	Change From 2022	Congestion Level%	Time Lost Per Year (hours)
1 st	London-UK	37 min 20 s	+60 s	45	148
2 nd	Dublin-Ireland	29 min 30 s	+60 s	66	158
3 rd	Toronto-Canada	29 min	+50 s	42	98
4 th	Milan-Italy	2 min 50 s	+20 s	45	137
5 th	Lima-Peru	28 min 30 s	+80 s	61	157
6 th	Bengaluru-India	28 min 10 s	-60 s	63	132
7 th	Pune-India	27 min 50 s	+30 s	57	128
8 th	Bucharest-Romania	27 min 40 s	+20 s	55	150
9 th	Manila-Philippines	27 min 20 s	+20 s	46	105
10 th	Brussels-Belgium	27 min	+20 s	37	104

The paper is organized as follows: Section 2 reviews related work on the traffic light control problem at urban intersections. Section 3 provides a detailed description of the KSTA-IoT algorithm proposed in this study. Section 4 presents an evaluation of the proposed approach through simulations, followed by a discussion of the results. Finally, Section 5 concludes the paper and outlines possible directions for future research.

2. RELATED WORK

A number of works have been proposed in the design of intelligent traffic light control algorithms. These works aim to reduce congestion by automatically adjusting signal durations based on the current state of the intersection, using parameters that vary from one approach to another, sometimes taking into account the presence or absence of emergency vehicles.

Rakesh and Hegde (2022) introduces a real-time algorithm called Capacity Map Generator (CmapGen) that uses image processing techniques to determine the traffic density over the entire area of the traffic signal intersection. This algorithm determines the traffic light durations using the CmapGen method based on the traffic density calculated for the live roadways. The vehicle density is determined using frames extracted from traffic video footage.

Hawi et al. (2017) proposed an approach based on fuzzy logic and wireless sensor networks (WSN) for intelligent traffic control. This approach is designed for an isolated four-lane roundabout, and aims to provide a sustainable solution to the traffic congestion problem that exists in most cities. Traffic data is collected in real time by a WSN integrated into a smart traffic light (STL). The green light duration for each lane is determined by an intelligent algorithm. To evaluate the performance of the Smart Traffic Light (STL) system, a simulation tool was developed in Java to virtually represent the functionalities of the Wireless Sensor Network (WSN) and the Fuzzy Logic Controller (FLC). This method applies simple theoretical concepts to complex problems and demonstrates the robustness of fuzzy control to uncertainties. However, the approach has limitations: implementation and tuning are largely empirical, and no formal theory currently guarantees the stability and robustness of the method.

Ali et al. (2023) constructed a traffic network of signalized intersections within a simulator developed specifically for this study. They also developed algorithms to manage traffic signal state changes to optimize vehicle flow throughout the network. In addition, planning algorithms were developed to control traffic flow dynamics and maximize vehicle movement throughout the network. The obtained results demonstrated a 30% reduction in waiting time compared to the standard traffic model.

Bui and Jung (2018) propose a cooperative game theory approach between agents to improve traffic flow in a network consisting of multiple intersections. A distributed algorithm for dynamic control of traffic lights at intersections is applied to explore how to integrate cooperation among agents. A simulation framework with three intersections was designed to perform the validation by varying different traffic flows, in order to show

the effectiveness of this approach in terms of vehicle waiting times and number of vehicles passing the intersections in one time.

Regragui and Moussa (2018) proposed a real-time path planning method based on the Bellman-Ford algorithm, applied to a scenario derived from a real map. In their approach, real-time traffic information is used to determine the shortest route. To support real-time communication between vehicles, roadside units, and a central server, they used vehicular ad hoc networks (VANETs), allowing each vehicle to send a request and receive its optimal route from the server. Simulation results showed that the proposed planning method efficiently provides reliable routes under varying traffic densities.

Pratama et al. (2018) proposed an adaptive traffic light system where synchronization is based on real-time estimation of road traffic density. The synchronization and control of the traffic lights are managed by a set of algorithms running on a central server, which is responsible for both data collection and traffic light operation. Traffic density is calculated using an image processing method. The proposed system was validated by testing under real traffic conditions.

Hambli et al. (2021) presented an intelligent traffic light control algorithm based on determining the shortest path between a source and a destination to adjust traffic light phases. The algorithm uses the number of vehicles detected in the road network and uses V2I and I2I communication to collect and exchange the necessary information between neighboring intersections. This approach aims to optimize traffic light control by providing the best path for vehicles traversing intersections, and adjusting green light duration accordingly.

Hartanti et al. (2019) propose a more optimal and dynamic traffic light control design based on the Mamdani fuzzy logic method, which allows for multi-stage decision making. The system considers the number and speed of vehicles, queue length, and road width to optimize signal timing according to real-time conditions and avoid unnecessary green phases when there are no queues. A traffic simulation tool has also been developed to optimize lane-specific timing predictions.

Cruz-Piris et al. (2019) presented an automated traffic optimization system for intersections with three mechanisms: modeling of any intersection type, calculation of routes with minimal conflict points between entrances and exits, and optimization of vehicle arrival rates using a genetic algorithm. The system has been validated using the SUMO simulator. Results compared to traditional solutions such as priority-based control and traffic lights demonstrated the effectiveness of the proposed approach.

Jiang et al. (2020) improved a game theory-based algorithm for intersection traffic light control, achieving better real-time performance and higher traffic efficiency. Their approach is based on a mutually exclusive game theory model, where traffic phase selection is determined based on the number of vehicles detected in each lane. Experimental evaluations showed that the proposed method significantly reduces vehicle waiting times during peak hours, alleviates traffic congestion, and dynamically adjusts green light durations according to calculated priority levels without unduly delaying cross-traffic. Comparative analysis showed a 3.4% reduction in vehicle dwell time and a 4.4% reduction in waiting time compared to a fuzzy logic-based polling mechanism.

Naeem and Abbas (2021) propose a computational model aimed at supporting multi-criteria decision making to address traffic congestion challenges. The model starts by identifying the optimal shortcut based on real-time analysis of vehicle density on individual roads using Radio Frequency Identification (RFID) technology. The congestion data is then processed by a specially developed algorithm and software program, which serves as the core of the decision framework.

Yadav et al. (2020) proposed a traffic light management system that combines genetic algorithms (GA) and Internet of Things (IoT) technologies. Their approach involves training a neural network using neuroevolution with genetic algorithms and self-adaptive genetic algorithms to optimize green light timing for each route. This method aims to minimize training time, increase prediction accuracy, and improve generalization performance. Simulations were performed using the SUMO platform under different traffic density scenarios, using queue lengths as input parameters. In order to reduce the network load, snapshots of each route were only taken at green light transition moments. After several generations of training, the model achieved a reduction of the average vehicle waiting time to about two-thirds compared to traditional static time-allocation models.

Sadiqa Jafari et al. (2021) proposed a stable Takagi-Sugeno (TS) fuzzy controller for managing urban traffic at isolated intersections. The stability of the system has been demonstrated using Lyapunov's theorem. The controller uses the queue length and the number of vehicles entering and exiting each lane as input variables. The effectiveness of the proposed controller was validated by simulation results, and an illustrative example was provided to further demonstrate its performance. The method showed superior efficiency compared to conventional fuzzy controllers and fixed-time traffic control systems. By utilizing state-space dynamics, the

proposed system successfully reduced the standard vehicle waiting time and queue length at isolated intersections.

Boppuru et al. (2023) proposed an artificial intelligence-based traffic management methodology to address the problem of excessive waiting times at traffic signals. Their approach uses real-time image acquisition at intersections to accurately estimate traffic density using the YOLOv4 object detection algorithm. YOLOv4 improves the accuracy of detecting multiple vehicles simultaneously. In addition, the system incorporates an intelligent monitoring mechanism combined with a dynamic traffic signal switching algorithm that enables optimized time allocation at intersections. This helps to reduce traffic congestion and improve the overall flow efficiency in urban areas.

The following table consists in comparing the different approaches seen previously, according to the following criteria Method developed, strategy, interaction model, performance indicators and simulation environment.

Tab. 2. Comparison between intersection control research

References	Developed Method	Strategy	Interaction model	Performance Indicators	Simulation environment
(Hawi et al., 2017)	Intelligent traffic light control at roundabouts	Fuzzy logic	V2I/I2I	The amount of traffic, the waiting time for the green light, degree of priority	Urban (<i>java</i>)
(Bui & Jung, 2018)	Optimization of traffic flows for several Intersections	Game-theory	V2I/I2I	Vehicle waiting time, number of vehicles passing intersections	Urban (<i>Netlogo</i>)
(Pratama et al., 2018)	Adaptive traffic lights on road pattern	Image processing method	None	Traffic density and green light duration	Urban (<i>real road condition</i>)
(Regragui & Moussa, 2018)	Time path planning	Bellman-Ford	V2V/I2I	Average travel time, average end-to-end delay	Highway and Urban (<i>VEINS</i>)
(Hartanti et al., 2019)	Traffic light optimization smart to avoid congestion	Fuzzy logic	V2I/I2I	The number of vehicles, the queue size and roadway width	Urban
(Cruz-Piris et al., 2019)	Automated intersection optimization	Genetic Algorithm	V2I/I2I	Density, Total vehicles that arrived at the destination	Urban (<i>SUMO</i>)
(Jiang et al., 2020)	Real-time traffic distribution	Game-theory	V2I/I2I	The number of vehicles on the track, waiting time	Urban
(Yadav et al., 2020)	IoT in traffic light management	Neural networks	V2I/I2I	Density, green light time, queue length	Urban (<i>SUMO</i>)
(Hambli et al., 2021)	Smart control algorithm in traffic lights	Shortest path calculation	V2I/I2I	The number of vehicles, congestion rate.	Urban
(Sadiqa Jafari et al., 2021)	Stable Fuzzy Controller for Single Intersection	Fuzzy logic	None	The queue size and waiting time	Urban

After analyzing the previous works related to the traffic light control problem, the most used metrics are the waiting time and the density of vehicles. Therefore, we decided to use these metrics and add the shortest path to achieve better traffic light control in congested conditions.

3. A REAL-TIME ADAPTIVE TRAFFIC LIGHT CONTROL ALGORITHM

In the following, we introduce our approach, which is called real-time adaptive traffic light control algorithm based on Dijkstra algorithm and Internet of Things (KSTA-IoT), which aims to minimize the waiting time of vehicles at the intersection and reduce the overall travel time from a source to a destination.

3.1. Proposed architecture and assumptions

The road network model used in this study is shown in Figure 1. Each road segment is bi-directional and has two major intersections, labeled A and B, with multiple directions of traffic. Each direction consists of two lanes: the leftmost lane is for left-turning vehicles, while the adjacent lane is for vehicles going straight or turning right. Each intersection is equipped with a controller, which is responsible for determining and implementing the sequence of traffic lights, known as the signal cycle, to regulate vehicle movements. In addition, sensors are installed next to each traffic signal to monitor the number of vehicles passing during the green and yellow signal phases. Additional sensors are also placed at the entrances to each road segment to track the number of vehicles entering the network.

In the proposed scenario, when a vehicle at point D intends to reach a specific destination, the traffic light controller (infrastructure) at point A selects the optimal path for the vehicle to follow. The controller communicates with neighboring controllers (C, E, or B) to request real-time data on traffic density and vehicle speeds along the connected roads. For example, if the driver intends to travel from point A to point C, the controller gathers the necessary information to estimate the travel time. If there is heavy traffic on the direct route AC, the controller will also request information on alternative routes, such as AB and BC, to calculate their respective travel times. If the estimated travel time via the AC route exceeds the combined duration of the AB and BC routes, the system recommends the route with the shortest estimated travel time.

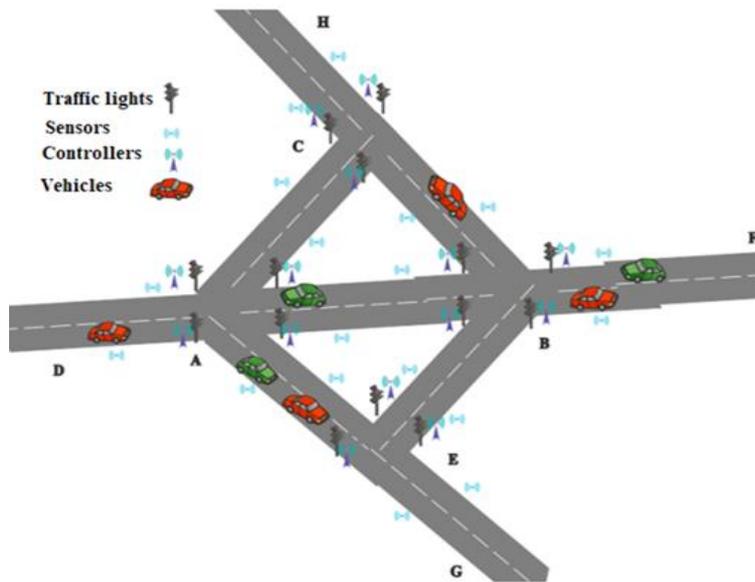


Fig. 1. Urban road network employed in the simulation

3.2. Communication

The transportation infrastructure is equipped with a wireless communication system that allows intersection controllers to receive real-time information from sensors installed along the roadway. In addition, vehicles are equipped with GPS systems that provide enhanced positioning accuracy and communication capabilities. Using the collected data, detectors integrated into each intersection controller are responsible for calculating the number of vehicles passing through the intersection and determining the optimal traffic light control strategy to improve local traffic flow. In addition, intersection controllers communicate with each other to share traffic information and coordinate their strategies. The goal of this inter-controller communication is to optimize the overall flow of vehicles across the network, reduce congestion, and dynamically provide vehicles with the most efficient routes to their destinations.

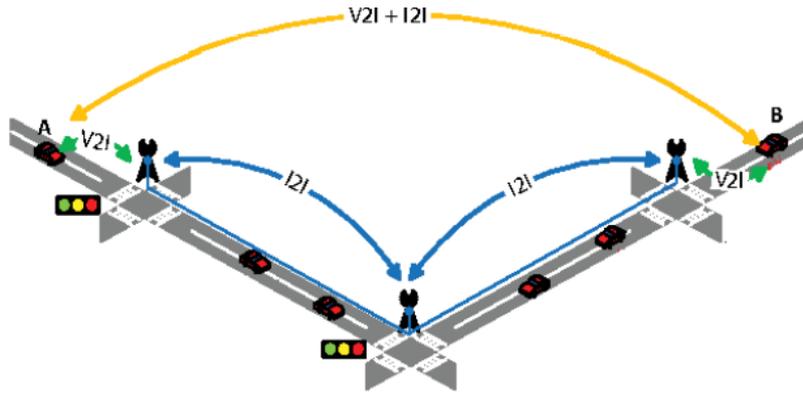


Fig. 2. Illustration of V2I and I2I communication

The sensor receives the signal from the vehicle (its position, destination and speed) that wants to take a space in the next direction to reach its destination, and it sends the necessary information to the controller installed at that intersection.

The controller receives the signals sent by the sensors and processes them based on the vehicle's request (destination) and the current state of the road (number of available spaces). It then polls neighboring controllers to gather additional information needed to compute the shortest path. The latter is determined using the adapted Dijkstra algorithm, where the arc weights are defined by the traffic density values for each direction.

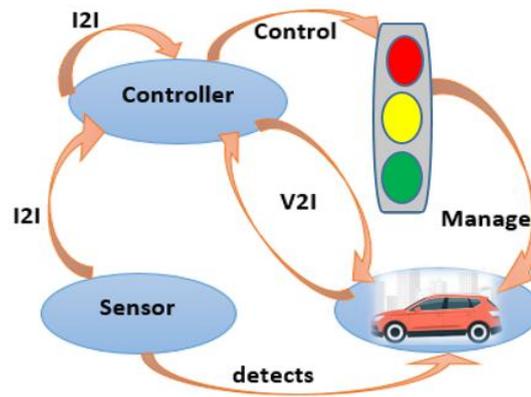


Fig. 3. System architecture of communication and coordination between vehicles, traffic lights, controller and sensors

The proposed algorithm has been developed under the assumption that vehicles are equipped with V2I communication capabilities and can exchange data with the intersection control system. This communication is essential to provide real-time information on vehicle positions and destinations, enabling the system to compute and recommend the optimal route. Without such communication, the system cannot provide guidance because the necessary data would not be available. Dealing with non-cooperative vehicles or heterogeneous traffic scenarios would require alternative approaches, such as sensor-based detection or intent prediction, which are beyond the scope of this study and are left for future research.

3.3. Proposed KSTA-IoT algorithm

The objective of our proposal is to control traffic lights in an efficient way, using communication (V2I) between vehicles and controllers installed at different intersections, and between controllers themselves through communication (I2I). The adapted Dijkstra algorithm is used to determine the shortest path based on the traffic density calculated by the controllers. The result of the shortest path calculation is then used to determine the next route the vehicle should take, along with the corresponding traffic light duration.

The steps of vehicle control from request to shortest path calculation are shown in Figure 4.

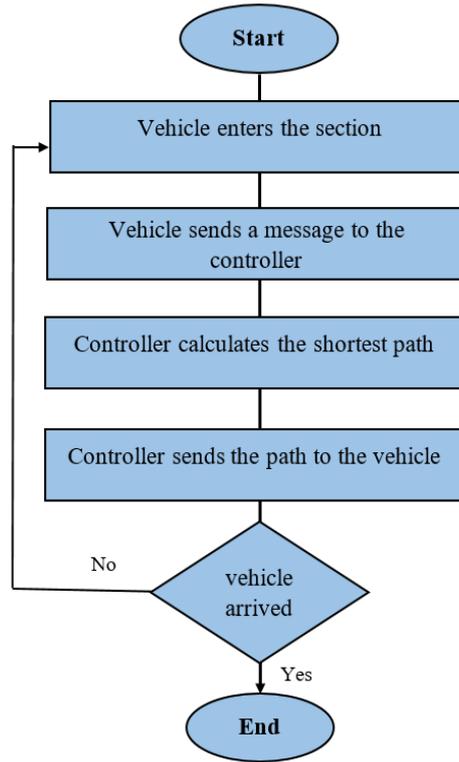


Fig. 4. Flowchart of vehicle steps from entry to exit

The most efficient algorithm for computing the shortest path in a graph with positive weights is the Dijkstra algorithm. In our case, we use this algorithm to determine the shortest path based on travel time rather than distance.

Table 3 shows the vocabulary of graph and its meaning in the vocabulary of our problem.

Tab. 3. Graphs and road vocabulary

The graphs vocabulary	The vocabulary of road
Weighted Graph	Roadway system
Nodes	Town, or traffic intersection
Edge	Road
Arc	One-way road
Weight	Duration

To apply the algorithm, we will first start by defining the sets and variables as follows:

- S represents the set of all vertices of the graph.
- P represents all intersections to be visited, which must be initialized as in (1).

$$P = S - source \quad (1)$$

- T represents the set of intersections for which we already know the minimum duration at the source, which must be initialized as shown in (2).

$$T = source \quad (2)$$

Table 4 shows the definition of the variables used in this approach.

Tab. 4. The description of variables

Variables	Description
Distance (km)	The distance between two points in kilometers
Speed (km/h)	The speed between two points in kilometers for hour
Speed Max (km/h)	The maximum authorized speed kilometers for hour
Capacity	Road capacity.
NbrV	The number of vehicles present on a given road segment.
Density	The number of vehicles occupying a given length of roadway.
Duration (min)	Travel time.
Duration Density (min)	Time when there is density in minutes.
Waiting time (min)	The total time lost at the red light

The core idea of the algorithm is to compute the shortest path through the following set of equations.

$$\text{Duration} = \frac{\text{Distance}}{\text{Speed}_{\text{Max}}} \quad (3)$$

$$\text{Density} = \frac{\text{NbrV}}{\text{Capacity}} \quad (4)$$

$$\text{Duration}_{\text{density}} = \frac{\text{Distance}}{\text{Speed}} \quad (5)$$

$$\text{Waiting}_{\text{time}} = \text{Duration}_{\text{density}} - \text{Duration} \quad (6)$$

- The smaller the time value from source to destination, the better the path.
- The algorithm stops as soon as the destination point is found, it must add a destination point.
- In the proposed routing approach, the cost function is expressed as follows.

$$\text{Cost}(\text{Arc}) = \frac{\text{Distance}}{\text{Speed}} \quad (7)$$

This function represents the estimated travel time required to traverse a given road segment. The cost value directly depends on the current vehicle speed along that road, which reflects real-time traffic conditions. As traffic density increases, the average vehicle speed decreases, resulting in a higher cost value. This relationship allows the system to dynamically prioritize roads with smoother traffic flow and shorter travel times.

The algorithm below represents the adapted Dijkstra algorithm.

<p>Algorithm 1: Adapted Dijkstra algorithm</p> <pre> Begin Initialize T to source Initialize P to S- {source}: the set intersections not visited Duration [source]=0 Path [source]=source Repeat Step1: Look for an unspecified intersection of minimum duration If Duration[s] < +∞ then Add s to T Delete s from P end If For all intersections t of P Do If Duration[s]+ C(s,t) < Duration[t] then Duration [t]= Duration [s]+C(s,t) Path[t]= s end If end for If (P not empty and s ≠ destination) then return to Step1 otherwise End </pre>

At the end of each traffic light cycle - which includes the red, yellow and green phases - the system updates the weight of each road according to the most recent traffic conditions. The update process is as follows.

- Data collection.

Real-time traffic data is collected from connected vehicles and roadside sensors, including the number of vehicles, average speed, and queue length for each street.

- Traffic density calculation.

The system calculates the traffic density for each road based on the ratio of the number of vehicles to the maximum capacity of the road.

$$\text{Density} = \frac{\text{NbrV}}{\text{Capacity}} \quad (4)$$

- Cost recalculation.

The cost of each road is then updated using the cost function.

$$\text{Cost}(\text{Arc}) = \frac{\text{Distance}}{\text{Speed}} \quad (7)$$

- Weight update.

The algorithm assigns the updated cost value as the new weight of the road for the next iteration of route calculation.

- Cycle repetition.

At the beginning of each new signal cycle, the updated weights are used by the routing algorithm to determine optimal paths and signal timing adjustments.

This adaptive weight update mechanism allows the system to dynamically respond to real-time variations in vehicle density and traffic flow, ensuring continuous optimization and improved stability over cycles.

4. RESULTS AND DISCUSSIONS

This part of paper presents the experimental study conducted to validate the KSTA-IoT approach, followed by a comprehensive analysis of the results. The implications of these findings are explored in relation to traffic control and overall system performance.

4.1. Simulation parameters

To evaluate the performance of the KSTA-IoT approach, Java was used to simulate the mobility patterns of vehicles in an urban environment, including both V2I and I2I communication. The simulation was conducted within a 10×10 km² urban area, as shown in Figure 5. The simulation ran for 70 minutes, with a vehicle density ranging from 100 to 300 vehicles, all equipped with GPS and sensor capabilities. During this time, the vehicles sent requests to the controller and received responses.

The key metrics of the simulation are shown in Table 5.

Tab. 5. Simulation Settings

Settings	Data
Simulation zone	10 km × 10 km
Runtime of simulation	70 min
Unit of time	minute
Vehicle count	2500
Vehicle speed	60 km/h
Density of vehicle	100-300

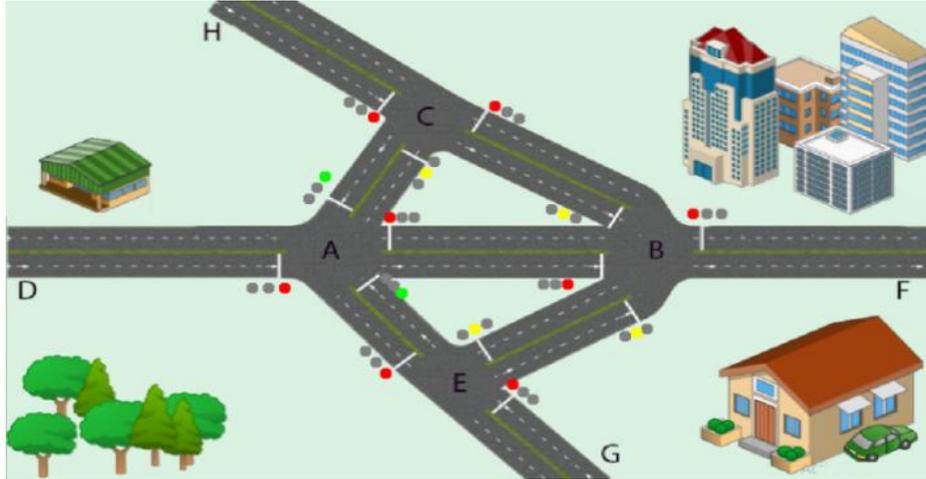


Fig. 5. Simulation interface of the proposed system

4.2. The vehicles density

The weighted graph shown in Figure 6 shows the density in each direction of the road network using the fixed-time traffic light control algorithm and the KSTA-IoT algorithm. Where the values recorded in the graph prove that our approach optimizes the traffic flow by reducing the density of vehicles.

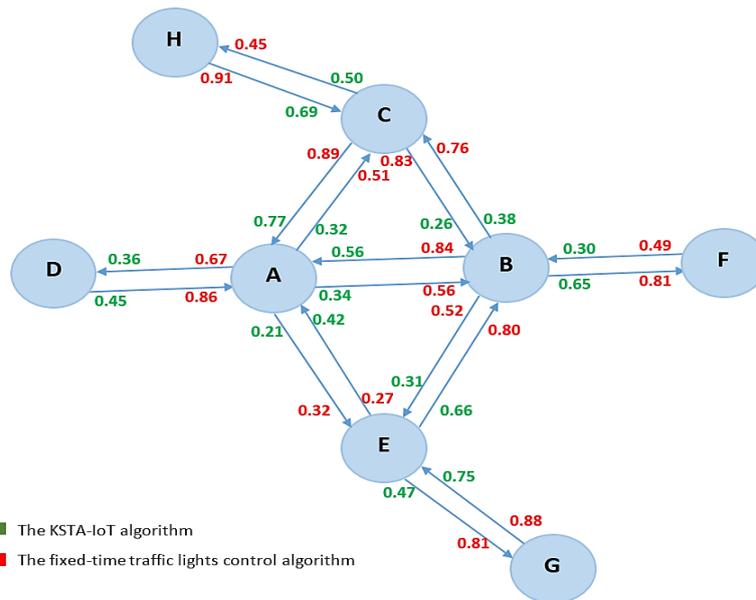


Fig. 6. Weighted Graph representation based on the density of each direction

Figure 7 shows a comparison of the percentage average density values for each direction for the fixed-time traffic signal control algorithm and the KSTA-IoT algorithm. As a result, vehicles using the traditional algorithm spend more time crossing the intersection, resulting in longer waiting times. In contrast, vehicles using the KSTA-IoT algorithm experience shorter wait times. Furthermore, the results show that when intersection controllers communicate with each other, vehicle waiting times across multiple intersections are significantly improved. In this regard, our approach consistently outperforms the fixed-time traffic light control algorithm.

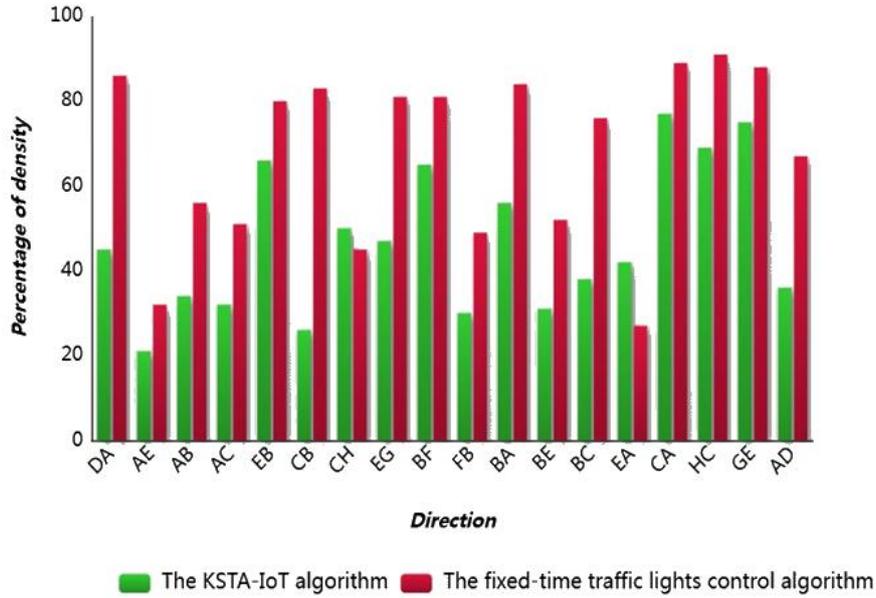


Fig. 7. Percentage distribution of average vehicle density the fixed-time traffic lights control algorithm and the proposed algorithm

4.3. Average waiting time

Figure 8 shows the variation of the waiting time for the fixed time traffic light control algorithm and the KSTA-IoT algorithm. As we observe, the time obtained by applying the proposed algorithm is more interesting compared to that obtained with the traditional algorithm, because the average waiting time of the latter varies from 0 to 40 min (in different densities), while with the new approach the average waiting time varies from 0 to 20 min (in different densities).

This improvement is mainly due to the use of V2I and I2I communications, which facilitate the exchange of traffic state information and thus significantly reduce waiting times, unlike the traditional algorithm, which lacks such communication mechanisms.

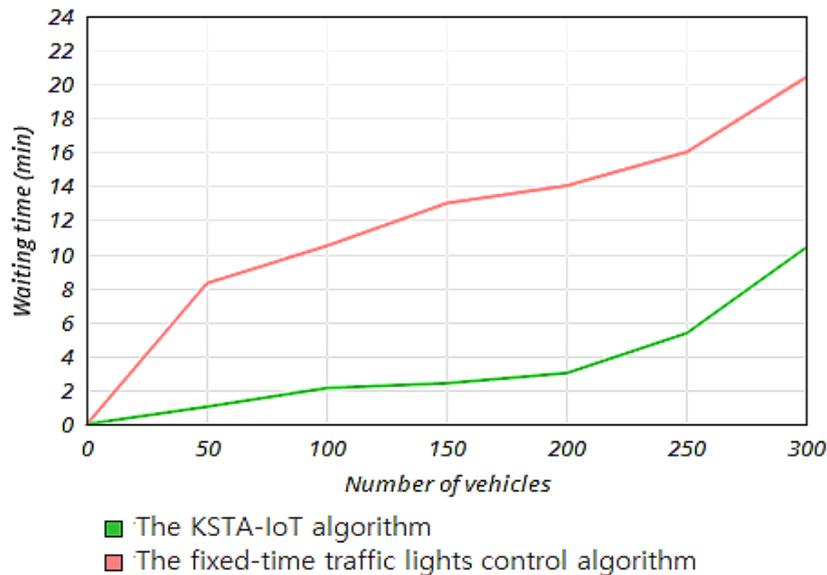


Fig. 8. Average waiting time for the fixed-time traffic lights control algorithm and the proposed algorithm

4.4. The shortest path

The shortest path, as shown in Figure 9, is chosen by comparing the density of vehicles on the segments of each path. Suppose the vehicle is at point D and wants to go to its destination at point G.

In this case, this vehicle requests the best path from controller A, which contacts neighboring controllers to obtain information on the status of the sections, so that controller B provides information on AB and CB, controller C provides information on AC, and controller E provides information on AE and BE.

This information allows it to calculate the density in each section and compare them to provide the best path in terms of waiting time that can be lost by taking that path. Ultimately, the vehicle is provided with the best path to reach its destination as quickly as possible.

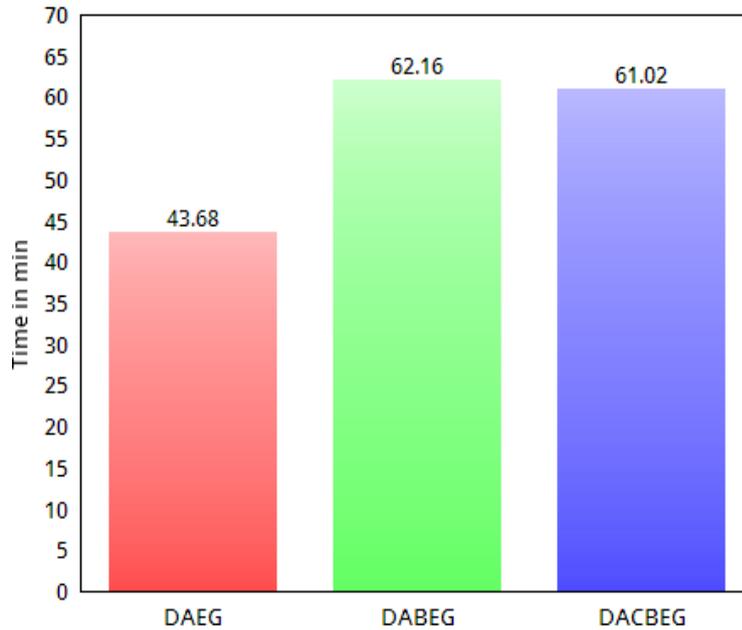


Fig. 9. Evaluation of travel times to identify the shortest path from D to G

To provide a comprehensive evaluation, the evaluation has been extended beyond conventional fixed-time control systems by incorporating adaptive methods based on artificial intelligence (AI). Several intelligent approaches such as fuzzy logic, reinforcement learning, and machine learning-based optimization have been proposed in the literature to improve traffic signal control. Considering these strategies allows for a more robust comparison with the proposed system. Table 6 summarizes the main AI-based methods and compares them with our approach.

In general, the proposed algorithm outperforms the fixed-time traffic light control strategy, demonstrating superior stability and performance even under increasing traffic density. This indicates that the approach provides an efficient and reliable solution for traffic light control, effectively reducing both traffic congestion and travel time. Such improvements underscore the potential of the algorithm to improve traffic flow and optimize urban mobility, representing a significant advancement in the field of intelligent traffic control systems.

Tab. 6. Comparison of traffic signal control approaches

Work	Main Idea	Advantages	Limitations	Scenario
(Hawi et al., 2017)	Smart Traffic Light for roundabout using Wireless Sensor Networks and Fuzzy Logic Controller based on traffic quantity & waiting time.	-Handles uncertainty. -Real-time decisions. -Improves isolated roundabout performance.	-Not scalable to large networks. -Relies on sensor quality.	Single isolated roundabout.
(Shashi et al., 2021)	Uses Deep Q-Network (DQN) with traffic flow information to adaptively control traffic signals and reduce congestion.	-Reduces average vehicle delays. -Adapts to dynamic traffic environments.	-Tested only on limited simulation scenarios. -Focused only on vehicle flow (ignores pedestrians).	Single intersection.
(Wang et al., 2023)	Uses Nash Bargaining Solution to balance green times between vehicles and pedestrians. Compares with actuated signal control.	-Considers both vehicles & pedestrians. -Reduces delay, emissions, and improves fairness.	- Limited to fixed cycle length. -Simulation only in SUMO, no real-world test.	Single/multiple intersections.
(Ming Zhu et al., 2025)	Investigates DQN and DDPG in single and grid road networks. Demonstrates the emergence of 'greenwave' policy as an optimal behavior.	-Scalable to larger networks. -Produces optimal "greenwave" synchronization.	-Requires extensive training data. -Computationally expensive.	Single intersection & grid networks.
(Medvei et al., 2025)	YOLOv8 for vehicle detection at RSUs + PPO-based adaptive control. Secure TLS communication with cloud. Simulation in SUMO shows improved traffic efficiency and emissions reduction.	-Integrates perception (YOLOv8) and control (PPO). -Improves waiting time (~30%) and emissions. - Scalable to different city settings.	-Dependent on RSU infrastructure. -High computation/communication requirements.	Multiple intersections (urban settings).
(Hao et al., 2025)	Introduces Queue Evolution and Delay Model for better delay estimation under oversaturation. Proposes adaptive coordination framework across intersections.	-Accurate delay/queue estimation. -Balances arterial coordination & local optimization. -Validated with hardware-in-the-loop.	-High system complexity. -Needs advanced infrastructure. -Sensitive to update intervals.	Multiple coordinated intersections.
Proposed approach	An enhanced Dijkstra's algorithm uses real-time V2I and I2I data, where road cost depends on traffic density rather than distance. Smart traffic lights update these costs every signal cycle, allowing vehicles to select the fastest and least congested path.	-Simple and explainable method. -Considers real-time traffic density. -Integrates V2I and I2I for adaptive path selection. -Reduces travel time and congestion.	- Not applicable to non-connected vehicles. - Performance depends on accuracy of density estimation.	Multi-intersection scenario with cooperative V2I communication.

However, the implementation of the proposed framework requires careful consideration of several practical factors. First, its effectiveness depends on real-time vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication, which may be limited by the current penetration of these technologies. Second, integration with existing traffic control systems requires addressing interoperability issues and ensuring reliable communication under heterogeneous traffic and network conditions. Finally, large-scale deployment poses challenges related to infrastructure costs, network robustness, and long-term maintenance. Despite these limitations, the modular design of the framework allows for incremental integration into existing urban infrastructures, paving the way for fully networked and adaptive traffic control systems.

5. CONCLUSIONS AND FUTURE WORKS

In this research, we address the challenge of providing intelligent traffic light control to reduce congestion at urban intersections within an Internet of Things (IoT) system. This problem is motivated by two main factors: the increasing mobility and volume of vehicles on the roads, and the crucial importance of real-time data collection and exchange between distributed controllers to enable responsive, intelligent decision-making. To tackle this, we propose a novel control algorithm specifically designed for urban intersections. Our solution utilizes both Vehicle-to-Infrastructure (V2I) and Infrastructure-to-Infrastructure (I2I) communications to gather and share traffic information. By doing so, it dynamically guides vehicles toward the shortest available paths to their destinations. A key contribution of our work is the introduction of an enhanced shortest-path computation method based on the Dijkstra algorithm, optimized to reduce travel delays and minimize vehicle idle times at intersections. We implemented our approach using a Java-based simulation platform and evaluated its performance within an urban road network.

Experimental results demonstrate that our algorithm significantly outperforms traditional fixed-time traffic light control methods. In particular, our approach achieves notable reductions in vehicle waiting times, improves traffic light synchronization, and enhances overall travel efficiency through better route optimization and minimized journey durations.

For future work, we plan to extend the KSTA-IoT algorithm to highway scenarios and integrate mechanisms for prioritizing emergency vehicles. Furthermore, we aim to conduct broader comparative studies against other state-of-the-art intelligent traffic control algorithms suitable for both urban and highway environments.

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Conflicts of interest

The authors declare no conflict of interest.

REFERENCES

- Ali, W., Brek, A., & Bouakkez, F. (2023). Traffic management system and traffic light control in smart city to reduce traffic congestion. *International Journal of automation and Smart Technology*, 13(1). <https://doi.org/10.5875/ausmt.v13i1.2464>
- Boppuru, P. R., Kukatlappalli, P. K., Chowdary, C. R., & Hussain, J. (2013). AI-based YOLO V4 intelligent traffic light control system. *Journal of Automation, Mobile Robotics and Intelligent Systems*, 16(4), 53–61. <https://doi.org/10.14313/JAMRIS/4-2022/33>
- Bui, K. N., & Jung, J. J. (2018). Cooperative game-theoretic approach to traffic flow optimization for several intersections. *Computers & Electrical Engineering*, 71, 1012-1024. <https://doi.org/10.1016/j.compeleceng.2017.10.016>
- Cruz-Piris, L., Lopez-Carmona, M. A., & Marsa-Maestre, I. (2019). Automated optimization of intersections using a genetic algorithm. *IEEE Access*, 7, 15452-15468. <https://doi.org/10.1109/ACCESS.2019.2895370>
- Hambli, C., Amad, M., & Azzaoui, N. (2021). Smart control algorithm in traffic lights at urban intersections. In S. B. Slama, F. Choubani, C. Benavente-Peces, & A. Abdelkarim, *Innovative and Intelligent Technology-Based Services for Smart Environments – Smart Sensing and Artificial Intelligence* (1st edn, pp. 156–162). CRC Press. <https://doi.org/10.1201/9781003181545-23>
- Hao, R., Wang, Y., Wang, Z., Yang, L., & Sun, T. (2025). A coordinated adaptive signal control method based on queue evolution and delay modeling approach. *Applied Sciences*, 15(17), 9294. <https://doi.org/10.3390/app15179294>
- Hartanti, D., Aziza, R. N., & Siswipraptini, P. C. (2019). Optimization of smart traffic lights to prevent traffic congestion using fuzzy logic. *Telkomnika*, 17(1), 320-327. <https://doi.org/10.12928/TELKOMNIKA.v17i1.10129>
- Hawi, R., Okeyo, G., & Kimwele, M. (2017). Smart traffic light control using fuzzy logic and wireless sensor network. *Computing Conference* (pp. 450-460). IEEE. <https://doi.org/10.1109/SAI.2017.8252137>
- Jafari, S., Shahbazi, Z., & Byun, Y. C. (2021). Traffic control prediction design based on fuzzy logic and lyapunov approaches to improve the performance of road intersection. *Processes*, 9(12), 2205. <https://doi.org/10.3390/pr9122205>
- Jazib, M. (2024, 5 February). World's top 10 most congested cities as per avg. travel time. <https://www.jagranjosh.com/general-knowledge/list-of-most-congested-cities-in-the-world-1707117033-1>
- Jiang, J., Peng, F., & Zhao, B. (2020). Mutual exclusion algorithm for real-time traffic dispatching based on game theory. *IOP Conference Series: Materials Science and Engineering* (pp. 032058). IOP Publishing. <https://doi.org/10.1088/1757-899X/782/3/032058>

- Kommineni, M., & Baseer, K. K. (2024). An architecture and review of intelligence based traffic control system for smart cities. *EAI Endorsed Transactions on Energy Web*, 11.
- Medvei, M. M., Bordei, A.-V., Niță, Ș. L., & Țăpuș, N. (2025). DeepSIGNAL-ITS - Deep learning signal intelligence for adaptive traffic signal control in intelligent transportation systems. *Applied Sciences*, 15(17), 9396. <https://doi.org/10.3390/app15179396>
- Naeem, A., & Abbas, J. (2021). A computational model for multi-criteria decision making in traffic jam problem, *Journal of Automation, Mobile Robotics and Intelligent Systems*, 15(2), 39-43. <https://doi.org/10.14313/JAMRIS/2-2021/12>
- Pratama, B., Christanto, J., Hadyantama, M. T., & Muis, A. (2018). Adaptive traffic lights through traffic density calculation on road pattern. *International Conference on Applied Science and Technology (iCAST)* (pp. 82-86). IEEE. <https://doi.org/10.1109/iCAST1.2018.8751540>
- Rakesh, S., & Hegde, N. P. (2022). A new method to control traffic congestion by calculating traffic density. *International Journal of Intelligent Systems and Applications in Engineering*, 10(1S), 1-8.
- Regragui, Y. & Moussa, N. (2018). Investigating the impact of real-time path planning on reducing vehicles traveling time. *International Conference on Advanced Communication Technologies and Networking (CommNet 2018)* (pp. 1-6). IEEE. <https://doi.org/10.1109/COMMNET.2018.8360277>
- Shashi, F. I., Sultan, S. M., Khatun, A., Sultana, T., & Alam, T. (2021). A study on deep reinforcement learning based traffic signal control for mitigating traffic congestion. *The 3rd IEEE Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS)* (pp. 1–6). IEEE. <https://doi.org/10.1109/ECBIOS51820.2021.9510422>
- Tunc, I., & Soylemez, M. T. (2023). Fuzzy logic and deep Q learning based control for traffic lights. *Alexandria Engineering Journal*, 67, 343-359. <https://doi.org/10.1016/j.aej.2022.12.028>
- Wang, A., Zhang, K., Li, M., Shao, J., & Li, S. (2023). Game theory-based signal control considering both pedestrians and vehicles in connected environment. *Sensors*, 23(23), 9438. <https://doi.org/10.3390/s23239438>
- Yadav, R. K., Jain, R., Yadav, S., & Bansal, S. (2020). Dynamic traffic management system using neural network based iot system. *The 4th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 521-526). IEEE. <https://doi.org/10.1109/ICICCS48265.2020.9121066>
- Zhu, M., Liu, X.-Y., Borst, S., & Walid, A. (2025). Deep reinforcement learning for traffic light control in intelligent transportation systems. *ArXiv, abs/2302.03669*. <https://doi.org/10.48550/arXiv.2302.03669>