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Research Paper

Development of an IoT based real-time traffic monitoring system for city governance

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ABSTRACT

A significant amount of research work carried out on traffic management systems, but intelligent traffic monitoring is still an active research topic due to the emerging technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI). The integration of these technologies will facilitate the techniques for better decision making and achieve urban growth. However, the existing traffic prediction methods mostly dedicated to highway and urban traffic management, and limited studies focused on collector roads and closed campuses. Besides, reaching out to the public, and establishing active connections to assist them in decision-making is challenging when the users are not equipped with any smart devices. This research proposes an IoT based system model to collect, process, and store real-time traffic data for such a scenario. The objective is to provide real-time traffic updates on traffic congestion and unusual traffic incidents through roadside message units and thereby improve mobility. These early-warning messages will help citizens to save their time, especially during peak hours. Also, the system broadcasts the traffic updates from the administrative authorities. A prototype is implemented to evaluate the feasibility of the model, and the results of the experiments show good accuracy in vehicle detection and a low relative error in road occupancy estimation. The study is part of the Omani-funded research project, investigating Real-Time Feedback for Adaptive Traffic Signals.

1. Introduction

The sustainability and smartness of the smart city concept rely on the technologies adopted to improve the people's quality of life. The smart city governance is one significant aspect of smart city initiatives, which will facilitate the planning techniques for better decision making [11,14]. One of the key elements of the smart city governance framework is the public value generated out of the smart services provided [15].

The government has to work on different aspects of smart city solutions such as smart health care, smart building management, smart traffic management, smart parking solutions, smart transportation, etc. to generate public value for the service they provided. The emergence of the internet of things (IoT) has evolved the concept of smart cities. In a smart city environment, the physical infrastructures of the city are equipped with smart devices, which continuously produce multidimensional data in different spaces and these data are processed to achieve intelligence for the infrastructure [21]. Ultimately, intelligence is applied to improve the socio-economic activities of the society.

Smart traffic infrastructure is an essential component of smart city initiatives because traffic congestion is a severe issue that grows along with city development. Smart traffic management includes intelligent transport systems with integrated components like adaptive traffic signal controls, freeway management, emergency management services, and roadside units [34]. Such systems collect real-time traffic data and take necessary measures to avoid or minimize any social issue created as part road congestions [21]. For example, access to real-time traffic maps will assist the residents in selecting appropriate route to save time and effort.

The widely used mobile applications like Google Maps or Apple

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Maps accurately predict traffic congestion for urban roads based on the sensor data from monitoring devices installed on highways or urban roads [10]. These application providers establish partnerships with various transportation entities to gather traffic information. The transportation governing authorities mostly install the traffic monitoring devices on urban roads, hence such application providers (e.g. Google application programming interface) deliver updates on urban traffic congestion. Besides, such applications also use crowdsourcing with location-based services [1] to improve traffic density prediction. They do expect smart technologies within the vehicle or any smart mobile device with the driver of the vehicle to receive real-time traffic updates. The concern here is that the users require smart devices to access these applications and mostly the services are limited to urban roads.

The traffic pattern of urban roads or highways is different from that of collector roads. The users of collector roads include pedestrians, bicycles, motorbikes, and other vehicles; hence, the traffic pattern is different from the highways. Along with urban roads, the real-time monitoring of collector roads is also essential to improve the mobility of the entire city. The real-time traffic congestion updates, warnings from traffic authorities on non-recurrent traffic incidents such as accidents spilled loads, VIP visits, ambulance services, or any other unusual road incidents will support the collector road drivers in their decision-making. For instance, closed campuses such as universities and hospitals face heavy traffic congestions during peak hours. These campuses will have more collector road segments of different length that will connect to different entry/exit points. The real-time traffic updates of roads that connect to the exit points may help the driver for selecting the most suitable route from his current position. The drivers prefer to know about the congestion state of forthcoming intersections to plan themselves and save their time on the road by choosing alternate ways. The question that arises here is how to provide real-time road congestion updates to drivers even if there are no such smart devices with them or within the car, which is the real motivation of this research.

The recent research efforts in intelligent transport systems show that the IoT paradigm can play an important role in traffic management by connecting the physical devices over the internet to exchange information, tracking, and monitoring traffic movement (Z [38,50,51]. The global positing systems, sensors, probe vehicles, and vehicle to infrastructure communication are a few ways to collect real-time road data. The sensors such as acoustic and magnetic sensors are cost-effective, power-efficient, and most popular among the recent vehicle monitoring solutions [6]. The collected traffic information from multiple sources can be used to predict and manage traffic congestions. Most of the existing solutions deliver real-time traffic updates of urban roads especially through smart mobile devices [10] and limited attention has been given to collector roads. Therefore, this research proposes an IoT-based system model to provide real-time traffic updates through roadside message units. The proposed system is not limited on its application to collector roads.

The system follows a layered architecture with four layers [28,54]: (i) a sensing layer with active things and sensors, (ii) a network layer represents the mode of communication and protocols, (iii) service layer indicates the data analysis and storage, and (iv) application layer describe the end-user applications. The sensing layer collects vehicle data through the sensors installed on roadsides and the WiFi-based microcontroller transfer the real-time data to the service layer. Several open-source cloud IoT platforms are available to manage connected devices, data storage, and analysis. Thinger. io, which is an open-source IoT platform for integrating data fusion applications [13] acts as a service layer in this study. The end-users receive traffic updates through roadside message display units and dashboards. The physical infrastructures such as sensors and message display units are installed on roadsides at selected road intersections. The message units installed at important road intersections substitutes the smart devices and update drivers on the current traffic scenario. The authorities can also send messages on unusual road incidents along with expected clearance time or alternate route suggestions (if any) to assist emergency vehicle handling. The proposed system aims to generate public value by saving the on-road time of drivers through early warning messages. In summary, the proposed system has the following features:

(i) Appropriate to estimate traffic congestions on collector roads using road occupancy measure
(ii) Update residents on real-time traffic messages through roadside display units
(iii) Monitor the road density of smart campuses especially during peak hours and help to improve mobility
(iv) Assist authorities to broadcast important traffic incident messages
(v) Provide a real-time dashboard to monitor the traffic updates

The remainder of this paper is organized as follows: Section 2 presents the related work. Section 3 provides the research methodology followed to accomplish research objectives. Section 4 discusses the proposed system model, technologies required to build the system, and the proposed algorithms for system development. Section 5 demonstrated the system and discusses the experiments. Section 6 presents the evaluation of the system. Section 7 presents a discussion on the pros and cons of the proposed system. Section 8 describes the limitations and future work. Finally, section 9 concludes the paper.

2. Related work

This section first discusses the recent research developments in intelligent traffic management including system models for traffic updates, traffic congestion measures, emergency vehicle handling, and applications of roadside units to deliver messages. Current advances in cost-effective and power-efficient wireless sensor nodes for traffic monitoring follow this. This section also includes specific printed circuit boards based on sensor nodes to detect vehicles, estimate speed, and classify them. The discussion includes the features of these nodes, their pros, and cons.

2.1. Real-time traffic updates

Real-time traffic monitoring systems play a key role in the transition toward smart cities. A considerable amount of literature has been published on intelligent traffic management systems based on the IoT paradigm [25,56,60,61]; Z [38]. Autonomous traffic sensing is at the heart of smart city infrastructures, wherein smart wireless sensors are used to measure traffic flow, predict congestion, and adaptively control traffic routes. Doing so effectively provides an awareness that enables more efficient use of resources and infrastructure.

Identifying and measuring congestion is the very first step in the traffic management process [40]. The flow, occupancy, density is the widely used traffic congestion measures, which are mostly obtained from images or videos captured by vision systems initially [53]. Based on these measures, the traffic warning messages are broadcasted through smartphones, radio, televisions, light signals, dynamic variable message signs, or display units. Among them, the mobile-based web applications received much attention among researchers [18,56].

Most of the recent developments in delivering real-time traffic updates used the congestion estimates to dynamically control the traffic signal [3,27,32,43,59,63]. An IoT based real-time traffic monitoring system is proposed [43] for dynamic handling of traffic signals based on traffic density. The proposed system uses a set of ultrasonic sensors and has two modules: one for vehicle monitoring and other for priority management. The ultrasonic sensors are used to detect vehicles, and the density levels of a given road are sent to an LCD, and the data sent to the server for later usage. In similar research [63], the authors proposed an ultrasonic sensor-based system model specifically for road intersections. In addition to traffic signal lightings, the system alarms on any false vehicle activities such as crossing the red signals. In another research, an IoT based smart traffic management system is proposed [29] to manage real-time traffic through both central and local servers. The data collection layer uses sensors, cameras, and RFIDs. The application layer automatically controls the traffic signal based on traffic density and provides a daily report through a web application. Besides sensors, video monitoring is also used to estimate traffic congestion density [32] and update traffic signals in real-time.

The internet of connected vehicles is another research development in this area [26] to collect real-time traffic data. The connected vehicles support individual vehicle monitoring which enables efficient emergency vehicle management. Integrating roadside units (eg: traffic lights) with the vehicular network to ensure the trustworthiness of traffic events [66]. The emergency vehicle (e.g. Police cars, Fire engines, Ambulances) handling is very critical, the delay of every second matter because of the urgency of the services they are providing. Automatic scheduling of emergency vehicles can be performed by controlling the traffic signals [45,64] to improve the response time [57]. However, these systems are specifically designed for highways.

As this research does not anticipate any smart devices with the drivers, the traffic updates through roadside message units are analyzed in detail. A patented device for displaying traffic conditions [17] is designed to install on the roadside. The graphical message unit displays the upcoming traffic conditions and incidents through messages, signs, or colors. The studies on the impact of dynamic message signs through roadside message units show that it has received acceptance among drivers [23,35,65]. The dynamic message signs can be delivered in permanent mode through roadside message units (installed on bridges, toll plazas, tunnels, etc.) or portable units. The portable units are mainly used to warn about unusual traffic incidents. The roadside units mostly display the messages about over spilled roads, planned activities, environmental updates, traffic flow conditions, etc. The impact analysis of such message units reported that they mainly assist elderly drivers in their decision making [23].

The transportation project for the Beijing Olympics (F [69]. is a great example of providing traffic updates through public message units. The project used changeable message boards, radios, television, internet, and in-vehicle displays to monitor and dispatch traffic updates. However, system development was quite expensive due to advanced programs and devices [5]. After that, several research efforts have been made in this area to provide real-time traffic updates. A system is proposed to display traffic intensity through three different light colors on installed electronic boards at decision points [60]. In this system, the real-time traffic density is calculated from the average vehicle speed determined by vehicle detection systems. The authors apply image processing algorithms to process real-time traffic videos, and the traffic congestion estimation is based on optical flow. Similarly, electronic signboards are used to avoid congestions by setting up different speed limits [21].

The studies discussed above are tested for highways, and real-time updates are delivered through traffic signals or mobile applications. Instead, this research proposes a system model for real-time traffic updates through roadside message units using an IoT platform Nowadays, digital electronic boards are widely used in smart campuses, that can be also reused (if any) to deliver traffic updates during peak hours. Next, discuss the wireless sensors which are mainly used for vehicle detection, classification, speed estimation, etc.

2.2. Wireless sensors for vehicle data collection

This section presents the review of sensors that are used for vehicle detection and classification. The sensors used in intelligent traffic monitoring systems can be on-road sensors or in-vehicle sensors. The on-road traffic sensors can be again classified into two types: intrusive and non-intrusive. The intrusive sensors are paved on the road and are costly compared to non-intrusive sensors. The intrusive sensors provide accurate information; however, they are questioned for the expenses in terms of installation. maintenance, repair costs [22]. The maintenance of such sensors requires road lane closures and traffic disruptions. The non-intrusive sensors can be fixed on different parts of roads/roadsides. This includes magnetic sensors [16,31], ultrasonic sensors [39], infrared sensors [47], acoustic sensors [9,46], video cameras [12]; B [36]. Each sensor has its advantages and disadvantages. The ultrasonic sensors are prone to environmental factors [6]. The video monitoring systems are comparatively costly than other sensors when considering the purchase, installation, and maintenance costs [55]. However, the sensors are relatively less expensive in purchase costs. A comparison of different intrusive and non-intrusive sensors have been already reported in a few kinds of research [44,48,55]. The infrared sensors are sensitive to bad weather; acoustic sensors do not give accurate results during cold temperatures. The magnetic sensors are unable to detect the vehicles which are not moving [44]; however, there is no climatic influence. The magnetic sensors are widely used for vehicle detection and classification because of its easy installation, portability, and low cost [16,72]. The vehicle speed and length can be estimated by one or more magnetic sensors, which will help to approximate the road space occupancy measure.

Besides different types of sensors, a few research efforts have attempted to develop printed circuit boards (PCBs), which can be directly adapted for vehicle detection/speed estimation/classification such as PRS [62], LCTS [72], iVCCS [8], and CPIUS [47]. Fig. 1 shows the PCBs of PRS, LCTS, and iVCCS sensor nodes. The main objective of all these researches is to design and develop inexpensive and portable sensor nodes. On average, a single sensor node costs an average of $30 and operational for many years [6].

PRS is a portable roadside sensor for vehicle detection, counting, classification, and speed estimation [62]. PRS uses a magnetic sensor for vehicle detection. The single PCB board of PRS contains two magnetic sensors (HMC2003). This sensor uses the XBee module for wireless communication. PRS shows an accuracy of 99% in vehicle detection, and the maximum error rate of speed estimation is 2.5% (in a range of 5–27 m/s). Besides, the system also detects the right intersection. The vehicle length and height are estimated from the magnetic length.

LCTS is another low-speed congested traffic sensor node with a magnetic sensor specifically for a single lane road [72]. The sensor node is designed using magnetic sensor HMC5883L. In addition to the magnetic sensor, the node also contains a sound sensor and four infrared sensors. However, the magnetic sensor alone performs vehicle detection and classification. The validation results show a detection accuracy of 99.05% and a classification accuracy of 93.66%.

The iVCCS is an intelligent vehicle counting and classification

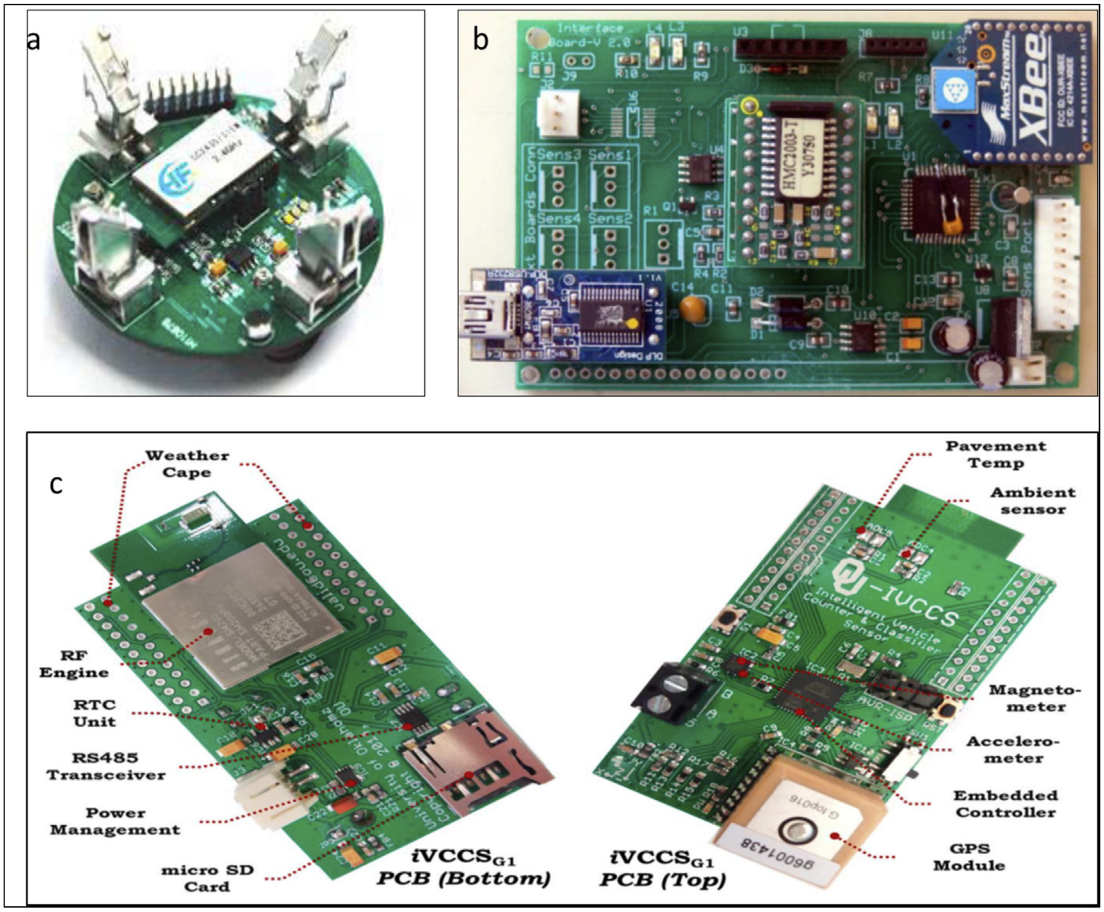

Fig. 1. (a) LCTS Sensor Node [72], (b) PRS Physical Board [47], and (c) iVCCS Physical Board [8].

sensor; the node has different sensors and components such as temperature sensor, accelerometer, magnetic sensor, GPS module, real-time clock unit, memory unit, etc. [8]. The iVCCS is a small battery-powered node with a 6-axis magnetic sensor and accelerometer FXOS8700. It uses a Zigbee wireless communication. The iVCCS nodes are validated in different field trials and exhibit a 99.98% accuracy in vehicle detection, 97% accuracy in vehicle classification, and 97.11% in speed estimation. The consistency of the sensor's output under different conditions is tested and showed high similarity. Besides, the sensor node is portable and can be installed on the road as well as on roadsides.

CPIUS is the combined passive infrared and ultrasonic sensors (CPIUS) for vehicle classification and speed estimation [47]. The measurements from passive infrared sensors and ultrasonic sensors are used for vehicle classification. They produce a high accuracy in vehicle detection (99%), the mean absolute error in speed estimation is approximately 5.87 km/h, and a mean absolute error of 0.73 m in vehicle length estimation. The proposed sensing platform contains one ultrasonic rangefinder and two arrays of six passive infrared sensors (Melexis MLX90614) connected to a microcontroller unit with different components such as an SD card reader, energy monitoring circuit, and flash memory.

The review reveals that magnetic sensors are appropriate for length-based vehicle classification. This is very relevant in the context of this research as the collector roads are mostly occupied with smaller vehicles and a volume to capacity ratio doesn't fit well.

3. The research methodology

A robust research methodology is essential to achieve the research objectives. This research work is carried out in five main phases according to design science research methodology [49]. The five phases are given in Fig. 2: (i) research background study, (ii) objective definition, (iii) design and development of artifacts, (iv) demonstration to show how the artifacts resolve the problems, and (iv) final evaluation.

A research background study is conducted as part of an objective definition. It has been observed that wireless sensor networks are widely applied in traffic management projects and have a significant role in detecting and reducing traffic congestion [16,62,72]. Many kinds of sensors are used for real-time traffic monitoring. The selection criteria for sensors can be power consumption, cost, sensitivity, reliability, etc. [6]. In addition to the traditional traffic monitoring sensors such as magnetic/infrared/ultrasonic sensors, there are dedicated sensors for vehicle detection and classification as discussed in the related work section.

The road occupancy measure is accurate for both highways and collector roads. Collector roads mostly have small vehicles, which has relatively low length hence a length based road occupancy measure is considered in this research. The road space occupancy measure is a spatial measure calculated by considering the length of the vehicle, the safe distance between vehicles, and a buffer length. The safe distance between the two vehicles is 2 m [2]. When a vehicle enters a road segment, the road occupancy measure is increased by the length of the vehicle and decreased when the

Fig. 2. Research methodology.

vehicle exits from that particular road segment. Based on the literature review, this research has decided to go ahead with magnetic sensors (or magnetic sensor-based PCB) for collecting traffic information as they show good accuracy in vehicle detection. The system design and development, demonstration, and evaluation phases are explained in upcoming sections.

4. System design and development

This section discusses the proposed system model, different software and hardware components required, and algorithms to implement the proposed system. The proposed system communication model is presented in Fig. 3, which has components installed at the roadside and a cloud-based central server. The roadside setup includes sensors and message boards. The sensors and boards will be installed between two road segment intersections. The central server includes data storage, cloud services, and interfaces. The components can communicate with each other using WiFi.

4.1. System architecture

An IoT based system architecture mostly contains a sensing layer, network layer, service layer, and an application layer [54]. The sensing layer acquires data from the things, the network layer transfers the collected data from devices to the service layer, the service layer controls the devices and analyzes the collected data, and finally, the application layer which indicates the user interface. The layered architecture is presented in Fig. 4.

The four main system development activities are: (i) populate geographical map details for a given location, (ii) detect vehicle and estimate vehicle length, (iii) determine growing queue, and (iv) display traffic updates. The system components include (i)

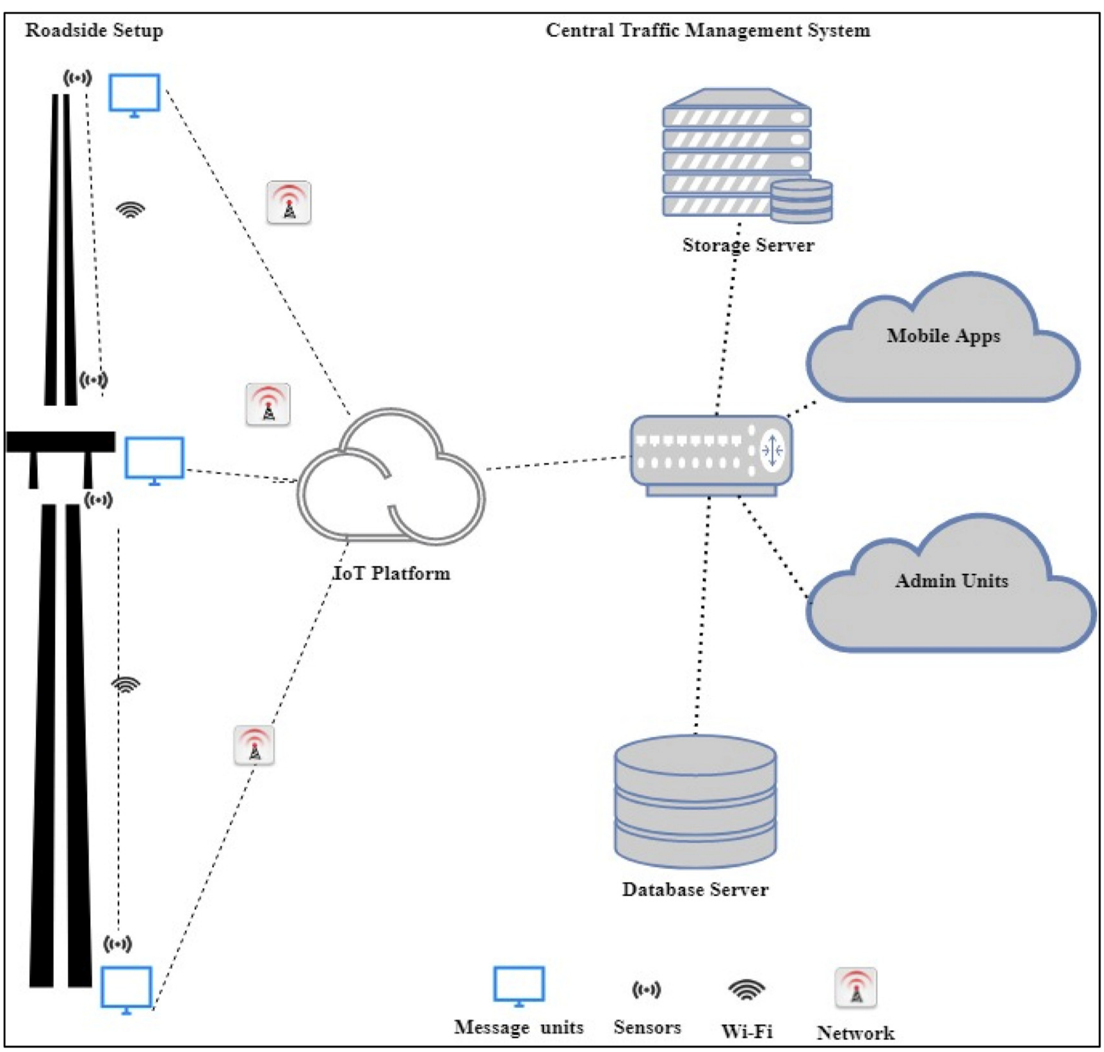

Fig. 3. System communication model.

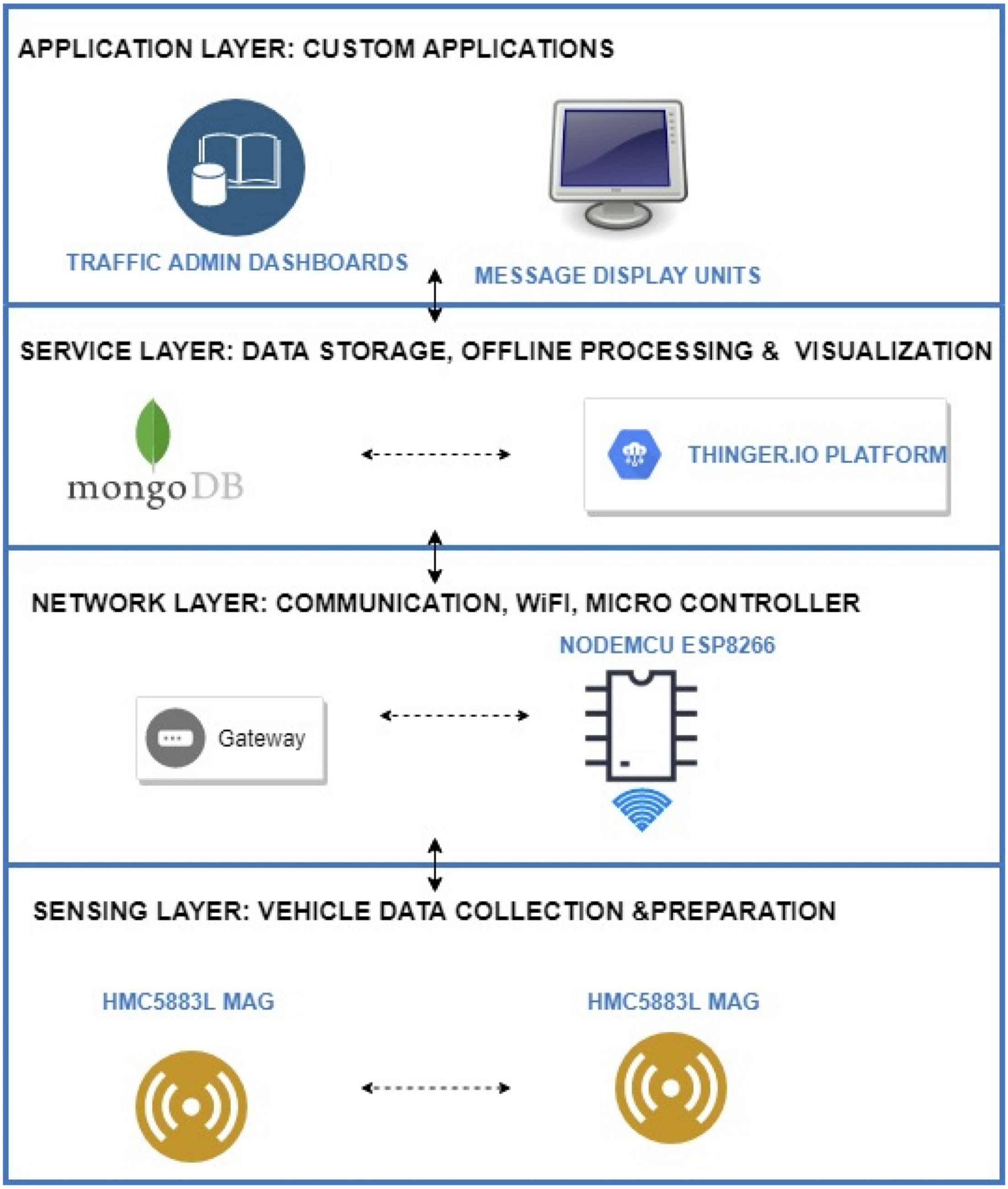

Fig. 4. System architecture.

Geographical map, (ii) Sensors, (iii) Microcontroller, (iv) IoT platform, (v) Database, and (vi) Electronic display units. The activities, the software, and hardware components associated with each activity are given in Fig. 5.

4.2. Hardware and software components

An extensive literature review has been conducted to select various system components and technologies [58]. The hardware and software components used for the system development are given below.

- **OpenStreetMap**: The OpenStreetMap (OSM) is one of the practical projects that provide map data [24]. The map data provided by OSM is free to use (wiki.openstreetmap.org). The individual users are contributed to the development of OSM, and the geographical information contributed by them is the core part of OSM. OSM provides editing, exporting, and uploading functionalities. The export functionality can be used to generate row map data or map images. The raw data can be processed by other systems that use geographical information. The OSM also provides a java interface to edit and work with maps, i.e., Java OpenStreetMap (JOSM) editor, similar to traditional geographic information system packages.
- **MongoDB:** MongoDB (www.mongodb.com) is a document database, and it stores the data from JSON like documents. MongoDB provides flexible access to data and supports nested objects as values. MongoDB has both community and enterprise

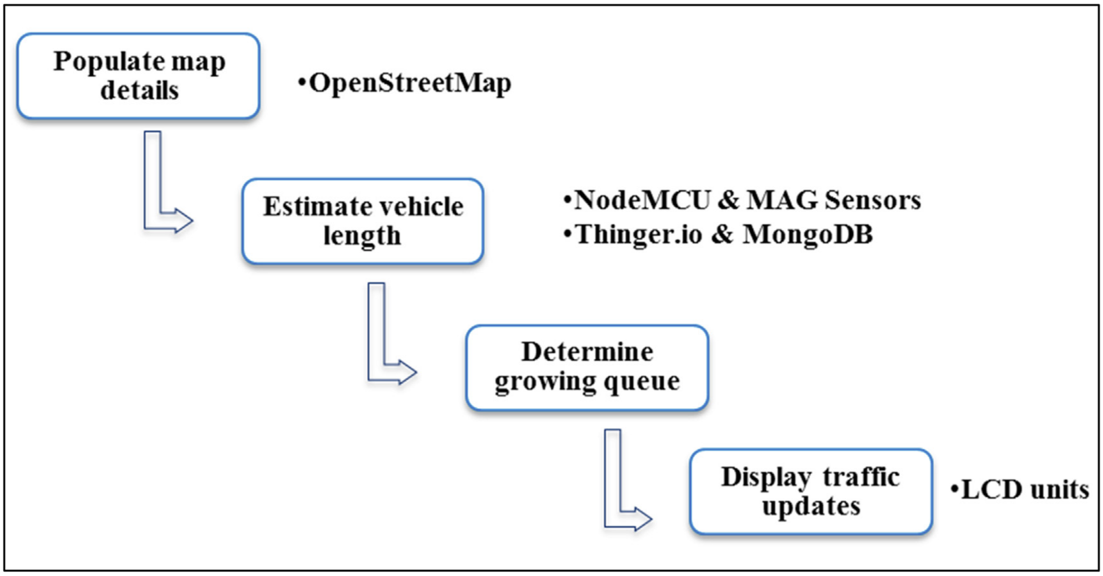

Fig. 5. System development activities.

versions [42]. The community version of MongoDB is used in this research. A record in MongoDB consists of field and value pairs and basically, it is a document. The documents in MongoDB are stored as collections, and similar to tables. The OpenStreetMap downloaded and converted to geojson format and stored in the MongoDB for experiments. We selected MongoDB due to its performance and rich query language.

- **Magnetic Sensors**: The magnetic sensor has the following advantages: (i) it can be easily installed on roadsides, (ii) reduces detection error, (iii) there is no climate influence (Q [71]. Honeywell HMC5883L is a tri-axial magnetic sensor used in many traffic monitoring research due to its high sensitivity (Q [71]. and cost-effectiveness. Hence, this research also used the HMC5883L magnetic sensor to collect vehicle data. It is worth to note that there exist many PCBs with all the necessary components for vehicle detection and classification as discussed in related work, section 2.2. These boards have individual physical sensors as well as the firmware. It is also a good idea to go ahead with these readymade nodes as they are cost-effective and the expected cost of a single node is less than $50.
- **NodeMCU:** NodeMCU is a firmware developed for ESP8266 WiFi system on chip (SoC). It is also an open-source platform. NodeMCU helps to prototype IoT products [33]. ESP8266 has a general-purpose input/output interface [19], hence the sensors/devices can be integrated easily. NodeMCU board has WiFi capability, digital pins (D0-D8), analog pin (A0), and supports serial communication protocols (I2C, UART, etc.). ESP8266 chip is developed by Espressif Systems (www.espressif.com). ESP8266 has 2.4 GHz WiFi, 64 KB boot ROM, 96 KB data RAM, and 64 KB instruction RAM. ESP8266 module can be used for end to end IoT system developments.
- **Thinger. io:** Thinger. io is an open-source IoT platform that supports sensor data collection, management, analysis, and visualization [13]. Thinger. io (www.thinger.io) supports the deployment of data fusion applications with the integration of cloud, IoT technologies, and big data. It supports the remote sensing and actuation of any sensor, and provide readymade services to connect devices. Thinger. io is unique in terms of transmission efficiency by providing an optimized encoding scheme, namely Protoson [13]. Thinger. io is highly interoperable and provides real-time bidirectional communications. The storage management mechanism of Thinger. io is called data buckets and supports document storages such as MongoDB. The Thinger. io platform offers an interface to configure devices, create data buckets, and model devices in this research.
- **LCD Unit:** The message board unit can be a WiFi-enabled character type LCD unit. However, to experiment, a 16 x 02 LCD unit was used that can display only 32 characters.

4.3. System development activities

The proposed algorithms for system development activities presented in Fig. 5 are discussed in this section.

4.3.1. Geographical map data processing

The geographical map provides the road segment information, intersections, and routes. The maps are processed to load the road information to the database as well as to extract the message board locations. The user-generated map can be used to find the message board location [24]. The road junctions that have more connected road segments are the best locations to display traffic-warning messages. The message board locations are selected based on its exposure to maximize message visibility. The message board selection is considered as a maximization problem because the objective is to maximize the visibility of the message. The idea of billboard advertising can be applied here to maximize the strength of message exposure (L [70]. Also, the major parking slots in a closed campus can be selected to reach the messages to the maximum. The number of connected roads is one parameter that decides the strength of message exposure. Besides, the earlier patterns of traffic density can also be selected while determining the message unit location. The strength of message exposure at a junction j is defined as the function below.

$$f(x) = n \times K \tag{1}$$

$$n \geq 2, \quad K > 0$$

$$where\ n = number\ of\ connected\ roads\ in\ a\ junction,$$

$$K = weighted\ average\ of\ traffic\ density\ of\ all\ connected\ road\ in\ junction\ j$$

The OSM map for a given location can be downloaded from the OpenStreetMap website. The OSM file follows XML format and there are three key elements: nodes, ways, and relations. There is a different tag to identify each type of road. The highway key can have different values such as a motorway, trunk, primary, residential, etc. Similarly, the link roads also can be identified. The junctions key can be used together with highways, and particular types of junctions are roundabouts, circular, filter, and jughandle. These keys help to extract the relevant information on a street. The flowchart to process the OSM file is presented in Fig. 6.

The process begins with geographical map format conversion and database loading. The second step is to identify the message

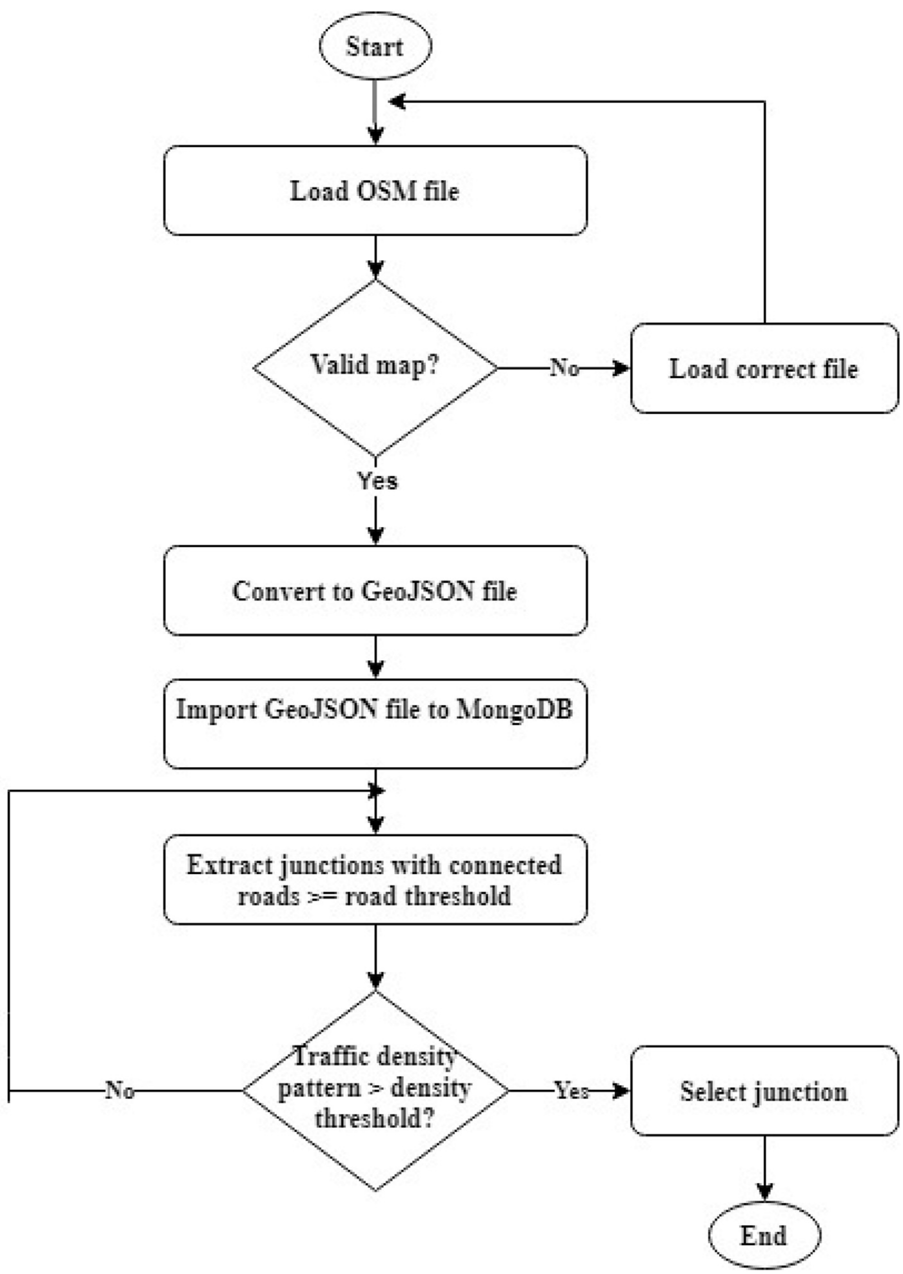

Fig. 6. Map processing.

board locations based on previous traffic density at intersections and the number of connected roads.

4.3.2. Vehicle detection and physical length estimation

The real-time vehicle data captured by magnetic sensors are used to detect vehicle and estimate the vehicle length. The predicted vehicle speed is a parameter that is mostly used to determine the length of the vehicle [8,72]. Magnetic sensors detect the disturbance in the earth's magnetic field caused by moving vehicles and measured as vehicle magnetic length [16]. The vehicle magnetic length (VML) is used to estimate vehicle physical length [30,62]. The studies reported that a single magnetic sensor can be used for vehicle detection with 99% accuracy (H. [37], one or two sensors for vehicle speed estimation, more than two magnetic sensors for vehicle classification. Hence vehicle detection and length estimation algorithm [8] is adopted in this research as it has 99% accuracy in speed estimation, 97.8% accuracy in vehicle classification. The vehicle detection occurs when the magnetic field intensity is higher than the threshold. The magnetic field intensity of the signal and measured as:

$$f(k) = \sqrt{x(k)^2 + y(k)^2 + z(k)^2}\ , \tag{2}$$

where $x,\ y,$ and z are the geomagnetic field components

The vehicle speed estimation using two magnetic sensors has shown high accuracy than a single sensor. This research followed the assumptions adopted in [7], i.e., the sensors are installed between a distance '*d*' and no lane changing happens. The speed is calculated from the travel time between two horizontally placed magnetic sensor nodes A and B with a distance '*d*'. The arrival (arr) and departure (dep) time are stored when the intensity goes over and drop down the threshold, respectively. The estimated speed of ith vehicle is calculated as

$$v_i \approx \frac{d_{A-B}}{\left(\left(T^B_{arr} - T^A_{arr}\right) + \left(T^B_{dep} - T^A_{dep}\right)\right)/2} \tag{3}$$

Where T^A_{arr} is arrival time at node A,
T^A_{dep} is departure time at node A T^B_{arr} is arrival time at node B,
T^B_{dep} is departure time at node B

VML is estimated from vehicle speed and sensor occupancy time. VML is always greater than the actual length of the vehicle. The sensor occupancy time ot_i is calculated as

$$ot_i = \left(\left(T^A_{dep} - T^A_{arr}\right) + \left(T^B_{dep} - T^B_{arr}\right)\right)/2 \tag{4}$$

The vehicle magnetic length for ith vehicle is calculated as

$$vml_i \approx v_i * ot_i \tag{5}$$

The vehicle physical length (VPL) can be calculated in different ways; however, there are challenges in estimating exact VPL [8]. The physical length is estimated as a derivative of sensor signals [41], signal gradient [20], and from the mean estimate of a set of sensors [68]. One another way to estimate VPL is to subtract the length of the sensor detection zone from VML.

$$vpl_i \approx vml_i - ldz \tag{6}$$

where $ldz = v_i * (T^A_{dep} - T^A_{arr}) - d_{A-B}$

The length of the sensor detection zone can be estimated from the vehicle speed, arrival and departure time at sensor nodes A and B. The microcontroller of sensor node B estimates the physical lengths from the given input. Fig. 7 (a) presents the flowchart for vehicle length estimation. The given equations are used to estimate the speed, magnetic, length, length of the detection zone for ith vehicle. These values are used to estimate the physical length in the final step of the algorithm.

4.3.3. Road occupancy and growing queues

The traffic congestion measures are mostly based on parameters such as speed, time and delay, reliability, service, space, etc. The road space occupancy is one such measure to determine the growing traffic queue and Fig. 7 (b) shows the flowchart on how to determine the road congestion using occupancy measure. Fig. 8 illustrates how the road occupancy measure is calculated. The VPL is estimated by the sensors when the vehicle crosses the sensor nodes, the physical length is added to the road occupancy measure and subtracts the length when the vehicle departs at exit points as in Fig. 8. When sensor C detects a vehicle, sensor node D will estimate the physical length and send it to sensor B. The microcontroller associated with sensor B holds the occupancy measure and sends real-time traffic updates.

The road occupancy measure is estimated from vehicle physical length at the entrance and exit of the road segment. The algorithm in Fig. 7 (b) is implemented as firmware for the sensor node B in Fig. 8. The sensor node D only estimates the physical length and sends it to node A, which acts as the server here and sends the message to the display unit as well as it will load the data to the IoT platform wirelessly.

4.3.4. Display warning messages

The traffic warning message can be of two types: (i) real-time updates on traffic density, (ii) messages on unusual road incidents by authorities. These updates can be accessed by drivers while driving through different modes such as smart mobile applications, radios, televisions, etc. Another method is to use roadside message boards at significant intersections. These units will reach the maximum public and help them to take alternate routes.

5. Experiments and discussions

An experiment has been conducted to demonstrate the feasibility and applicability of the proposed system. A proof of concept system is developed. The experiment execution steps are (i) load geographical map details, (ii) conduct on the road test for vehicle detection, vehicle length estimation, and road occupancy measurement, and (iii) traffic dashboard creation from real-time data. The communication model of the prototype is given in Fig. 9. The experiment used a single node for vehicle detection and a simulation scenario for road occupancy measurement.

The hardware and software components used for the prototype implementation is discussed in detail under section 4.2. The hardware and software components required to set up the experiment are:

- HMC5883L, NodeMCU ESP8266, LCD unit, Breadboard, Jumper wires, USB cable
- Arduino IDE, Thinger. io, MongoDB, OSM file

The Arduino IDE (www.arduino.cc) is used for NodeMCU programming. The libraries required for thinger. io are imported to Arduino IDE using the import libraries feature. The sensors are registered to the Thinger. io interface.

The experiment is conducted in the Sultan Qaboos University campus. The road occupancy rate of campus will be very high during peak hours and has three entry and exit points. Consider the real scenario is shown in Fig. 10, (a) the empty road and junction, (b) vehicle are approaching the junction, (c) vehicles are exiting the junction. The message display unit at this junction will provide the

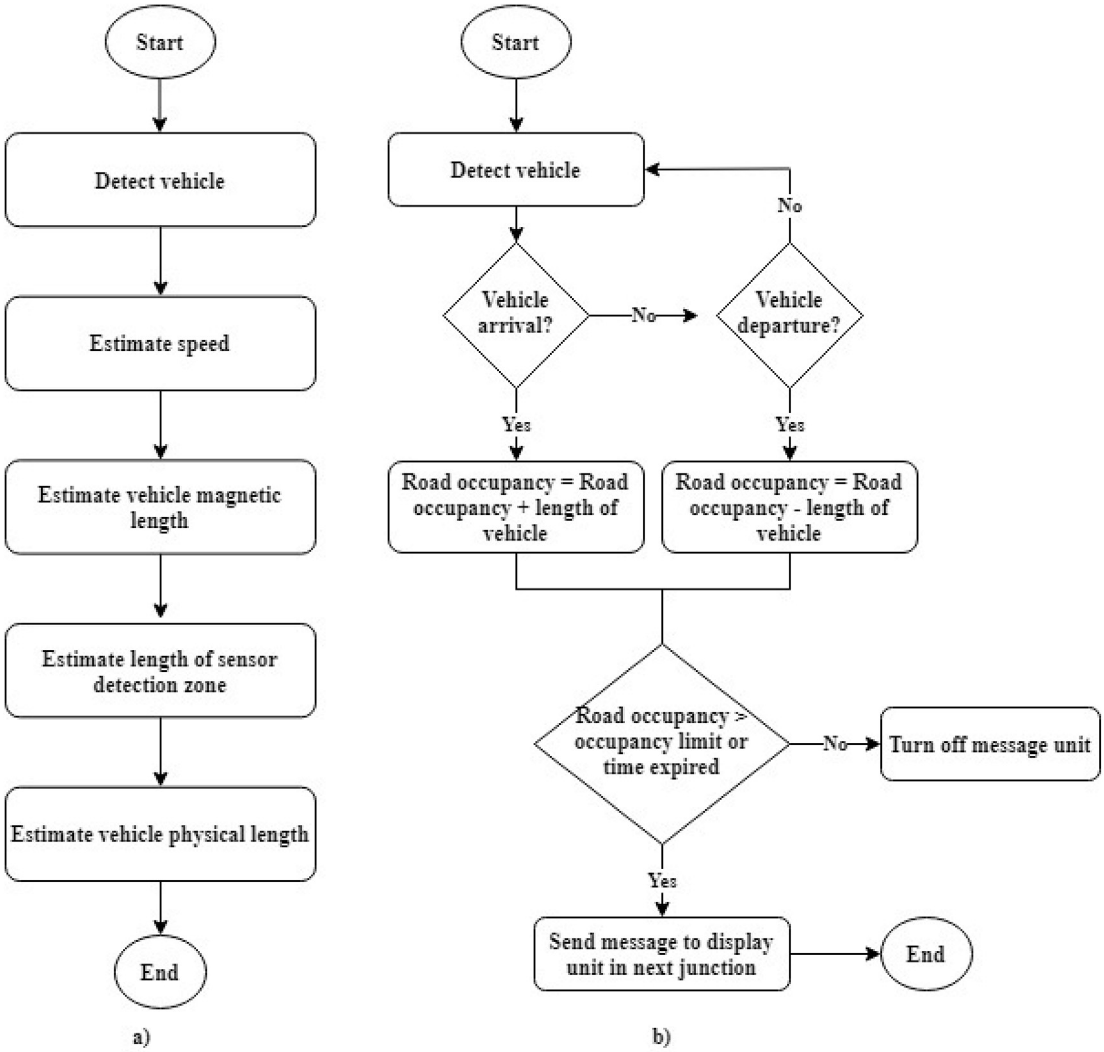

Fig. 7. (a) Vehicle length estimation, (b) Send traffic update on occupancy.

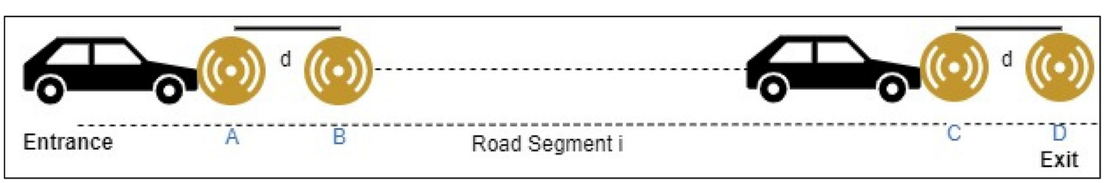

Fig. 8. Scenario to estimate road occupancy.

traffic information of the next upcoming junctions, so the drivers can decide to choose another path to the exit gate.

The geographical map processing is a preprocessing step to execute the road experiment. The experiments are based on three roads in the university Road i.e. A, B, and C. The vehicle detection is verified as part of a real-time experiment on these roads. The road occupancy estimation is tested using a simulation scenario. The field trials for vehicle detection are conducted at Road A, B, and C to evaluate the vehicle detection step. Then, the road occupancy measure is calculated by considering a fixed-length road segment of road A, B, and C. The simulation scenario is built on a 300-m road segment on road A, 200-m on road B, and a 400-m segment of road C. The results of the experiments and the evaluation are detailed in the next section.

6. Evaluation

A step-by-step evaluation process has been executed to validate three main functionalities: (i) map processing and selection of message board location, (ii) vehicle data collection and processing, and (iii) dashboards.

6.1. Selection of message board location

The map of the university is downloaded from the OpenStreetMap website. The OSM files are converted and loaded to

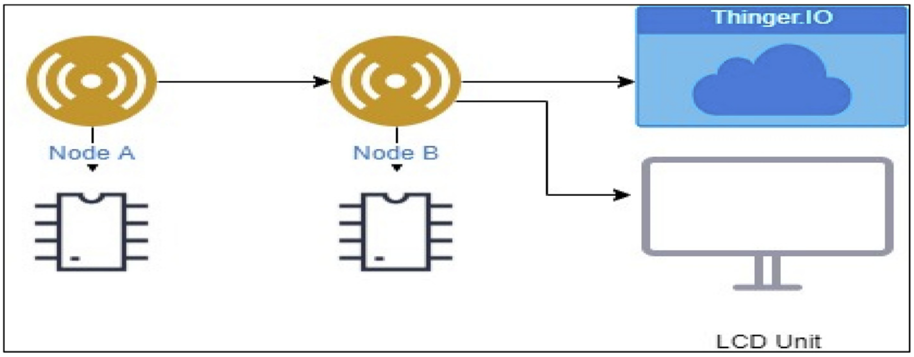

Fig. 9. Prototype communication model.

Fig. 10. University scenario.

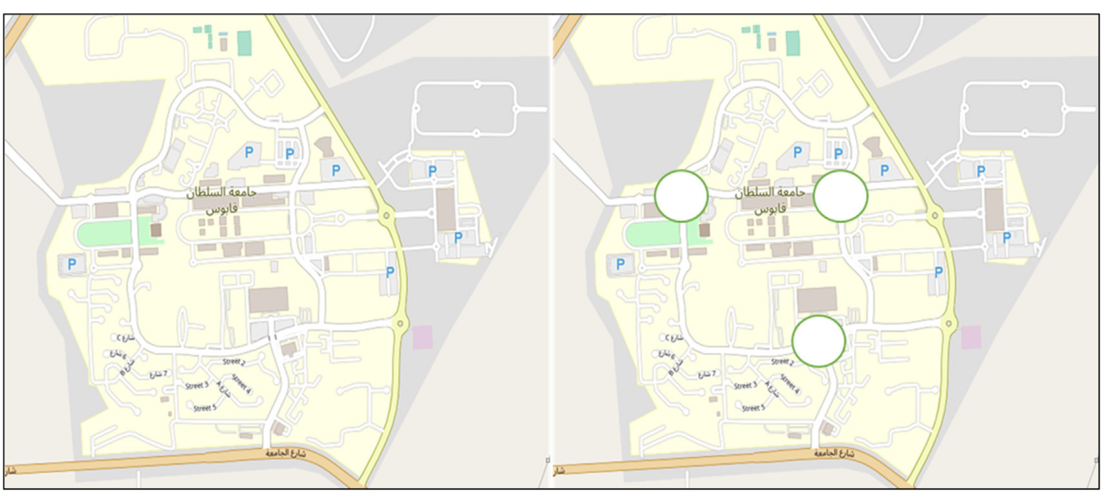

Fig. 11. University map.

Table 1
Map processing evaluation.

Maximum roads Threshold	Junctions Retrieved	Relevant Junctions	Precision	Recall
4	3	3	100%	100%

MongoDB and the pictorial view is presented in Fig. 11. The original map is on the left and expected junctions are marked on the right.

The accuracy of the map processing script is measured through precision and recall metrics. These metrics are used to evaluate the effectiveness of information retrieval.

Precision % = (Number of relevant junctions retrieved/Number of junctions retrieved) * 100%
Recall %= (Number of relevant junctions retrieved/Number of relevant junctions in the map) * 100%

The script expects to retrieve the message board location according to the given threshold for the number of connected roads. The OSM map is manually compared with the image from another map tool Mapcarta (www.mapcarta.com). The results of the university map processed are given in Table 1.

The high precision and recall indicate the map processing script works as expected. Three intersections are identified as the locations for the message board location based on the exposure of message visibility.

6.2. Vehicle detection and road occupancy estimation

The vehicle detection has been tested using a single roadside node. Fig. 11 shows the experiment setup and the magnetic field fluctuations of a Renault Duster car when the sensor is placed at a distance of 100 cm. The earth's magnetic field flux intensity f, the geomagnetic field components x, y, z when the sensor detects a vehicle is shown in Fig. 11.

The relative error (RE) metric is used to evaluate both vehicle detection and road occupancy estimation. The system detected 30 vehicles and the accuracy of detection is 100%. The detection accuracy of this setup and the vehicles detected in an experiment at Road A, Road B, and Road C are given in Table 2.

$$RE = |Detected - Actual|*100 / Actual$$

Sensor node B estimates the vehicle speed, magnetic length, physical length, road occupancy, and sends the data to the Thinger. io platform. This study has not detailed the validation of speed/ length estimation as they are already proven in [8]. The road occupancy measure calculated from the physical length of the vehicle is given in Table 3.

The system shows an average relative error of 6.35%. These results are achieved for passenger cars. The medium, medium-long, or long vehicles are not considered, which is a limitation of this evaluation. As the length of the road increases, the error percentage also decreases. Hence, the system is expected to perform better in real road scenarios.

6.3. Dashboards

The communication between sensor node B and Thinger. io has been established to build the dashboard and store real-time traffic data for the future. A simple dashboard to find the occupancy of road A, B, and C at different timings is given in Fig. 12 (see Fig. 13).

The dashboarding tools can be evaluated from different user perspectives, such as the consumers of information, administrators, and developers. In this section, the dashboard is evaluated from a user's view according to the dashboard evaluation criteria defined [4]. Table 4 presents the attributes, description, and compliance.

Table 2
Vehicle detection evaluation.

Road	Actual	Detected	Relative Error
A	12	12	0%
B	8	8	0%
C	10	10	0%

The compliance value can be true or false based on the attribute is supported or not, compliance = {0,1}.

The Thinger. io dashboards comply with most of the dashboard evaluation attributes except the ability to subscribe, export, or toggle. These criteria are not too relevant in this context as the dashboards are created from the real-time data loaded to the IoT platform.

6.4. System comparison

The proposed system model is compared with existing systems discussed in the related works section based on functional aspects. The functionality is evaluated with respect to research objectives. The real-time monitoring of traffic scenarios and reach out to the public through traffic updates is the main objective of the proposed system. Hence, the three parameters 'real-time monitoring', 'real-time signal controlling', 'real-time public updates' are defined as parameters to evaluate the functionality. Similarly, another objective is to support message broadcasting by administrators on any unusual traffic incidents and monitoring dashboards for administrators, this leads to the fourth parameter 'administrator updates'. The final parameter is 'System scalability' indicates the integration of additional hardware/software components. To evaluate the proposed system models, the defined parameters are assigned 3 values between 0 and 5: (i) 'not addressed' = 0, 'partially addressed' = 3, 'completely addressed' = 5. The 'partially addressed' and 'completely addressed' parameters are defined to differentiate the intensity of the functional requirements covered in the study. The 'partially addressed' parameter indicates that the study support only minimum functionality, whereas the 'completely addressed' parameter, indicates the support to different functional requirements. For eg, the functionality of real-time traffic update is only through traffic signals in studies 3, 4, and 5, whereas study 1 and 2 also provide the update on the intensity of traffic congestion. Similarly, study 5 provides a few kinds of administrative reports through the application layer and the system design uses fixed surveillance cameras; however, it does not provide a real-time dashboard. Considering this, the 'partially addressed' score has been assigned to the system for administrator updates and system scalability parameters. The evaluation results are given in Table 5.

Table 5 shows that the proposed system achieves the objectives and outperforms the similar system models discussed in the related works section.

7. Discussion

The study proposed a system model for real-time traffic updates in an IoT context to assist drivers. The system has three main functionalities: (i) map processing, (ii) traffic data collection, (iii) visualization, and storage. The system uses an existing free wiki map to collect the road information and extract the message unit location. The data collection layer is built on magnetic sensors to detect vehicles and estimate the length of the vehicle and road occupancy. The feasibility of the system is demonstrated through a prototype. Each of the modules is evaluated individually, and the results of the evaluation are satisfactory in terms of accuracy. The system architecture establishes a WiFi-based communication model between sensors and the IoT platform. The roadside magnetic sensors and the micro-controller follows a client-server WiFi communication. The sensor nodes A and C act as client and sensor nodes B and D as the server to estimate vehicle length at entry and exit points of the road segment. The sensor node B acts as a server and sensor node A acts as a client while estimating the road occupancy measure. The sensor node B sends the message to the

Table 3
Road occupancy evaluation.

Road	Road Length	Actual Occupancy	Estimated Occupancy	Relative Error
A	300 M	240 M	254 M	5.8%
B	200 M	170 M	182 M	7.5%
C	400 M	320 M	338 M	5.6%
Total	900 M	730 M	774 M	Average = 6.35%

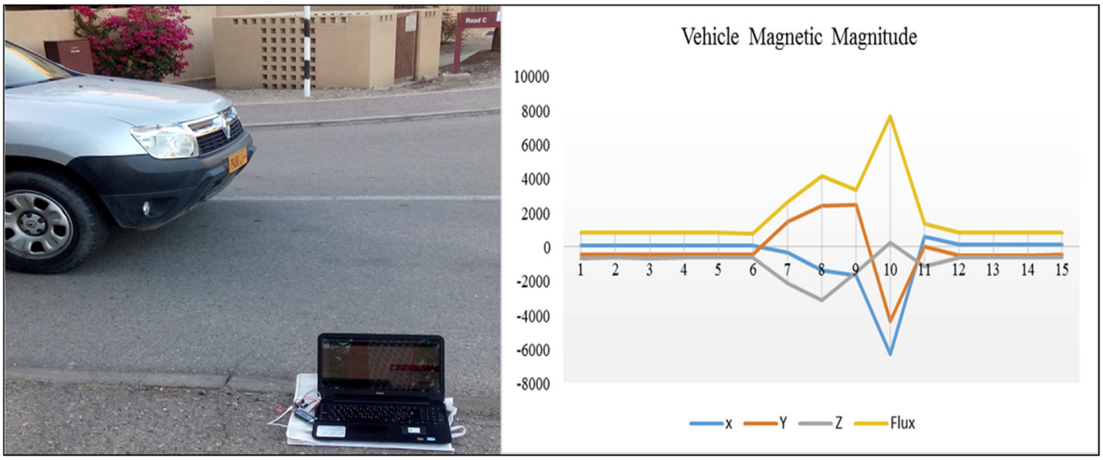

Fig. 12. Vehicle detection.

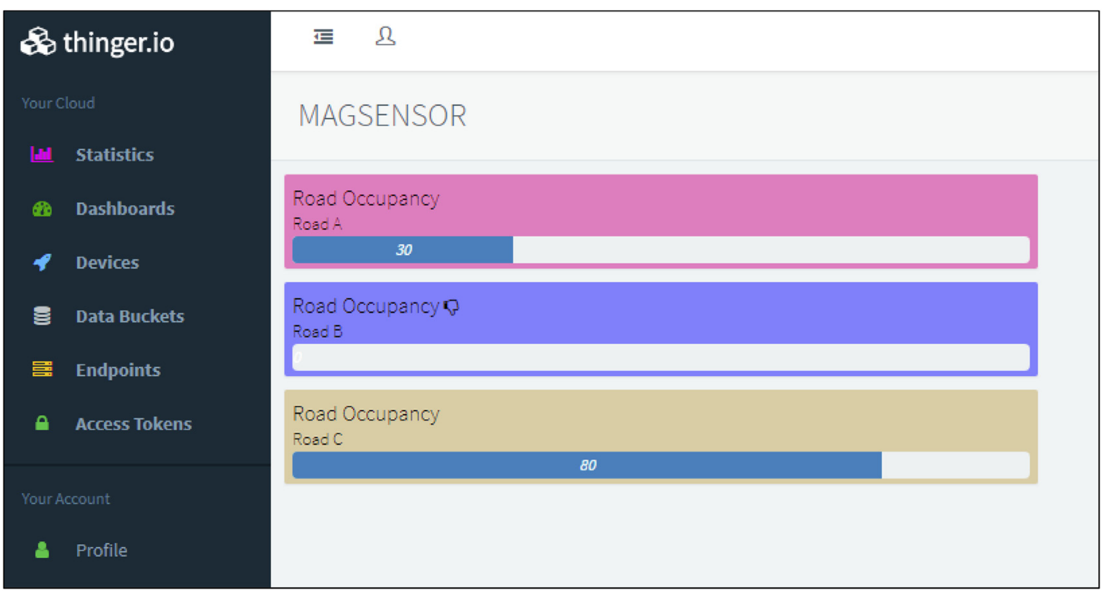

Fig. 13. Thinger. io dashboard.

roadside unit through WiFi and to the real-time data to the IoT platform. As part of the prototype, the Nodemcu microcontroller is used and a more powerful unit can be used in real-time. The central traffic management system can also connect to the IoT platform in the same way, which is beyond the scope of this work. This research selected a magnetic sensor for prototype implementation due to its low cost and availability. In an end-to-end real-time implementation, the readymade PCBs (e.g., iVCCS, PRS, etc.) can be used instead of magnetic sensors as all of them are already proven and have shown high accuracy in vehicle detection, speed estimation, magnetic length estimation, and physical length estimation/vehicle classification.

Estimating road occupancy based on vehicle length is the main concern of this work. The experimental test shows a 100% accuracy in vehicle detection. The experiments also confirmed that high accuracy of 97% in both speed estimation and length based vehicle classification and a relatively low error rate in road occupancy estimation. However, it has to be noted that the physical length estimation has been performed for vehicles of length between 1.5 M and 5.48 M because they are widely used in such campuses. The road segments between 200 and 500 m are considered for evaluation. The test results indicate that the road length is inversely

Table 4
Dashboard evaluation.

Parameters	Description	Compliance
Customization	Are different layouts supported?	1
Interaction	Can interact with different dashboards/components?	1
Response time	Is the information presented within a minimum response time?	1
Ability to drill down	Does the dashboard provide the ability to drill down and see further details?	1
Subscribe/Unsubscribe	Can the dashboards be subscribed?	0
Easy navigation	Is it easy to navigate through the dashboard?	1
Minimum training	Is it easy to educate the users?	1
Ability to export	Is it exportable?	0
Ability to toggle	Can we toggle the display formats?	0
Support resize	Are the dashboards resizable?	1
Compliance % = 70%	ΣA = 10	ΣC = 7

Table 5
Functionality evaluation.

System	Real-time monitoring	Real-time traffic updates	Real-time Signal control	Administrator updates	System scalability	Total (score/25)*100
1. Proposed System	5	5	0	5	5	80%
2 [60].	5	5	0	0	5	60%
3 [43].	5	3	5	0	5	72%
4 [63].	5	3	5	0	5	72%
5 [29].	5	3	5	3	3	76%

proportional to the error rate. Hence, the proposed system model is expected to perform well in real road scenarios.

8. Limitations and future work

There are some limitations on the proposed model, which need to be enhanced further. The proposed system uses WiFi to communicate between devices; however, their energy consumptions and solutions to recharge them are not considered in this study. Alternate solutions such as solar charging or charging from street lights can be further looked at. Similarly, the proposed model is tested only in the context of the single-lane road as intended. However, it would be useful to test the system in a multi-lane scenario to identify the false detections.

For future directions, the proposed system could be further improved considering different aspects. The first dimension is suggesting an optimal route for the drivers based on real-time data.

The dynamic traffic signal control functionality is also considered as future work. In this case, the communication of roadside display units and traffic signals have to be established. Another aspect is the real-time implementation of the system including the IoT security features [1,52] in the communication layer; the prototype has to be extended to a complete end-to-end system with central server communication. Moreover, the integration of IoT security, communication between display units, and traffic signals will be investigated in future research.

9. Conclusion

This research proposed an IoT based system model to collect, process, and store real-time traffic data. This research provided real-time traffic monitoring for traffic updates through roadside message units. The traffic authorities can also broadcast messages on VIP visits, medical emergencies, accidents, etc. to corresponding message units, which will assist the public in decision making and save their time on roads. The proposed system uses magnetic sensor nodes to collect real-time vehicle information. The real-time data is processed by WiFi-enabled microcontrollers and sends to an IoT platform for further actions. Whereas, the proposed system does not expect any smart equipped devices with the driver of the car or within the car such as sensors, GPS, WiFi, etc. and which makes this model unique. The proposed system is expected to be considered in any smart city initiatives such as a smart university campus or any closed smart premises. As a prototype was implemented to demonstrate the feasibility of the proposed model, the results of the prototype demonstration showed good accuracy in vehicle detection and a low relative error in road occupancy estimation. Thus, the proposed model can help citizens to save their time based on the early-warning messages displayed in the message unit, especially during peak hours. The traffic administration can send priority messages to the citizens; hence, the traffic congestion due to accidents or any such unusual incidents can be avoided.

CRediT authorship contribution statement

Mohammed Sarrab: Conceptualization, Supervision, Investigation, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Supriya Pulparambil:** Methodology, Investigation, Validation, Writing - original draft. **Medhat Awadalla:** Conceptualization, Supervision, Writing - review & editing.

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References

[1] Z.A. Almusaylim, N.Z. Jhanjhi, Comprehensive review: privacy protection of user in location-aware services of mobile cloud computing, Wireless Pers. Commun. 111 (1) (2020) 541–564.
[2] V.T. Arasan, G. Dhivya, Measuring heterogeneous traffic density, Int. J. Civ. Environ. Eng. 2 (10) (2008) 342–346.
[3] A. Atta, S. Abbas, M.A. Khan, G. Ahmed, U. Farooq, An adaptive approach: smart traffic congestion control system, Journal of King Saud University - Computer and Information Sciences (2018), https://doi.org/10.1016/j.jksuci.2018.10.011.
[4] B. Austin, Checklist for evaluating dashboarding tools. https://bennyaustin.com/2010/03/20/checklist-for-evaluating-dashboarding-tools/, 2010.
[5] M.H.A. Awadalla, Design of a smart traffic information system, in: *2017*

International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), 2017, pp. 757–762.
[6] W. Balid, Fully-Autonomous Self-Powered Intelligent Wireless Sensor for Real-Time Traffic Surveillance in Smart Cities, University of Oklahoma, 2016.
[7] W. Balid, H.H. Refai, Real-time magnetic length-based vehicle classification: case study for inductive loops and wireless magnetometer sensors in Oklahoma state, Transport. Res. Rec. 2672 (19) (2018) 102–111, https://doi.org/10.1177/0361198118791612.
[8] W. Balid, H. Tafish, H.H. Refai, Intelligent vehicle counting and classification sensor for real-time traffic surveillance, IEEE Trans. Intell. Transport. Syst. 19 (6) (2018) 1784–1794, https://doi.org/10.1109/TITS.2017.2741507.
[9] B. Barbagli, G. Manes, R. Facchini, S. Marta, A. Manes, Acoustic Sensor Network for Vehicle Traffic Monitoring, in: VEHICULAR 2012 : the First International Conference on Advances in Vehicular Systems, Technologies and Applications, 2012, pp. 1–6. *May*, http://www.thinkmind.org/index.php?view=article&articleid=vehicular_2012_1_10_60034.
[10] B. Brindle, How does Google maps predict traffic?. https://electronics.howstuffworks.com/how-does-google-maps-predict-traffic.htm, 2020.
[11] L. Broccardo, F. Culasso, S.G. Mauro, Smart city governance: exploring the institutional work of multiple actors towards collaboration, Int. J. Public Sect. Manag. 32 (4) (2019) 367–387, https://doi.org/10.1108/IJPSM-05-2018-0126.
[12] N. Buch, S.A. Velastin, J. Orwell, A review of computer vision techniques for the analysis of urban traffic, IEEE Trans. Intell. Transport. Syst. 12 (3) (2011) 920–939, https://doi.org/10.1109/TITS.2011.2119372.
[13] A.L. Bustamante, M.A. Patricio, J.M. Molina, Thinger.io: an open source platform for deploying data fusion applications in IoT environments, Sensors 19 (5) (2019), https://doi.org/10.3390/s19051044.
[14] A. Camero, E. Alba, Smart City and information technology: a review, Cities 93 (May) (2019) 84–94, https://doi.org/10.1016/j.cities.2019.04.014.
[15] W. Castelnovo, G. Misuraca, A. Savoldelli, Smart cities governance: the need for a holistic approach to assessing urban participatory policy making, Soc. Sci. Comput. Rev. 34 (6) (2016) 724–739, https://doi.org/10.1177/0894439315611103.
[16] S. Cheung, S. Coleri, B. Dundar, S. Ganesh, C.-W. Tan, P. Varaiya, Traffic measurement and vehicle classification with single magnetic sensor, Transport. Res. Rec.: Journal of the Transportation Research Board 1917 (January) (2005) 173–181, https://doi.org/10.3141/1917-19.
[17] J.-H. Dokko, Traffic condition displaying system (Patent No. 5,892,461), https://patentimages.storage.googleapis.com/03/b7/a0/5eddd9975c52af/US5892461.pdf, 1999.
[18] A. Dubey, Akshdeep, S. Rane, Implementation of an intelligent traffic control system and real time traffic statistics broadcasting, in: Proceedings of the International Conference on Electronics, Communication and Aerospace Technology, 2017, pp. 33–37, https://doi.org/10.1109/ICECA.2017.8212827. *ICECA 2017*, *2017-Janua*.
[19] Espressif, ESP8266 technical reference (issue february). www.espressif.com, 2019.
[20] G. Feltrin, N. Popovic, M. Wojtera, A sentinel node for event-driven structural monitoring of road bridges using wireless sensor networks, Journal of Sensors 2019 (2019), https://doi.org/10.1155/2019/8652527.
[21] M. Gohar, M. Muzammal, A. Ur Rahman, Smart TSS: defining transportation system behavior using big data analytics in smart cities, Sustainable Cities and Society 41 (August 2017) (2018) 114–119, https://doi.org/10.1016/j.scs.2018.05.008.
[22] J. Guerrero-Ibáñez, S. Zeadally, J. Contreras-Castillo, Sensor technologies for intelligent transportation systems, Sensors 18 (4) (2018) 1–24, https://doi.org/10.3390/s18041212.
[23] A. Haghani, M. Hamedi, A. Nouruzi, M.O. Malley, A.G. Brown, L. Governor, D.B. Mobley, M.B. Peters, R.L. Fish, State Highway Administration Research Report Evaluation of Dynamic Message Signs and Their Potential Impact on Traffic Flow, 2013. https://www.roads.maryland.gov/OPR_Research/MD-13-SP109B4C_Impact-of-DMS-Messages_Report.pdf.
[24] M. Haklay, P. Weber, OpenStreet map: user-generated street maps, IEEE Pervasive Computing 7 (4) (2008) 12–18, https://doi.org/10.1109/MPRV.2008.80.
[25] G.J. Horng, S.T. Cheng, Using intelligent vehicle infrastructure integration for reducing congestion in smart city, Wireless Pers. Commun. 91 (2) (2016) 861–883, https://doi.org/10.1007/s11277-016-3501-8.
[26] Y. Huang, J. Wang, C. Jiang, H. Zhang, V.C.M. Leung, Vehicular network based reliable traffic density estimation, in: IEEE Vehicular Technology Conference, 2016, pp. 1–5, https://doi.org/10.1109/VTCSpring.2016.7504527. 2016-July.
[27] M.R. Islam, N.I. Shahid, D.T. Ul Karim, A. Al Mamun, M.K. Rhaman, An efficient algorithm for detecting traffic congestion and a framework for smart traffic control system, in: International Conference on Advanced Communication Technology, ICACT, 2016, pp. 802–807, https://doi.org/10.1109/ICACT.2016.7423566. 2016-March.
[28] S. Jagtap, S. Rahimifard, Utilization of internet of things to improve resource efficiency of food supply chains, in: CEUR Workshop Proceedings, 2017, pp. 8–19. *2030*.
[29] S. Javaid, A. Sufian, S. Pervaiz, M. Tanveer, Smart traffic management system using Internet of Things, in: International Conference on Advanced Communication Technology, ICACT, 2018, pp. 393–398, https://doi.org/10.23919/ICACT.2018.8323770. 2018-Febru.
[30] S. Kaewkamnerd, J. Chinrungrueng, R. Pongthornseri, S. Dumnin, Vehicle classification based on magnetic sensor signal, in: 2010 IEEE International Conference on Information and Automation, ICIA 2010, 2010, pp. 935–939, https://doi.org/10.1109/ICINFA.2010.5512140. *June*.
[31] P. Kanathantip, W. Kumwilaisak, J. Chinrungrueng, Robust vehicle detection algorithm with magnetic sensor, in: ECTI-CON 2010 - the 2010 ECTI International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, 2010, pp. 1060–1064. January *2010*.
[32] A. Kanungo, A. Sharma, C. Singla, Smart traffic lights switching and traffic density calculation using video processing, in: *2014* Recent Advances in Engineering and Computational Sciences, RAECS 2014, 2014, pp. 1–6, https://doi.org/10.1109/RAECS.2014.6799542.
[33] R.K. Kodali, V.S.K. Gorantla, RESTful motion detection and notification using IoT, in: 2018 International Conference on Computer Communication and Informatics, ICCCI *2018*, 2018, pp. 1–5, https://doi.org/10.1109/ICCCI.2018.8441423.
[34] W.H. Lee, C.Y. Chiu, Design and implementation of a smart traffic signal control system for smart city applications, Sensors 20 (2) (2020), https://doi.org/10.3390/s20020508.
[35] D.M. Levinson, Effectiveness of variable message signs, SSRN Electronic Journal (2012), https://doi.org/10.2139/ssrn.1748577.
[36] B. Li, Y. Liu, J. Ren, Y. Chen, L. Xin, J. Shi, Detecting and positioning of traffic incidents via video-based analysis of traffic states in a road segment, IET Intell. Transp. Syst. 10 (6) (2016) 428–437, https://doi.org/10.1049/iet-its.2015.0022.
[37] H. Li, H. Dong, L. Jia, D. Xu, Y. Qin, Some practical vehicle speed estimation methods by a single traffic magnetic sensor, in: IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, October, 2011, pp. 1566–1573, https://doi.org/10.1109/ITSC.2011.6083076.
[38] Z. Li, R. Al Hassan, M. Shahidehpour, S. Bahramirad, A. Khodaei, A hierarchical framework for intelligent traffic management in smart cities, IEEE Transactions on Smart Grid 10 (1) (2019) 691–701, https://doi.org/10.1109/TSG.2017.2750542.
[39] E. Likotiko, D. Petrov, J. Mwangoka, U. Hilleringmann, Real time solid waste monitoring using cloud and sensors technologies, Tosjat 8 (1) (2018) 106–116.
[40] T.J. Lomax, Quantifying Congestion (Issue 398), Transportation Research Board, 1997.
[41] V. Markevicius, D. Navikas, A. Idzkowski, D. Miklusis, D. Andriukaitis, A. Valinevicius, M. Zilys, M. Cepenas, W. Walendziuk, Vehicle speed and length estimation errors using the intelligent transportation system with a set of anisotropic magneto-resistive (AMR) sensors, Sensors 19 (23) (2019), https://doi.org/10.3390/s19235234.
[42] MongoDB, The MongoDB 4.2 manual. https://docs.mongodb.com/manual/, 2019.
[43] V.S. Nagmode, An intelligent framework for vehicle traffic monitoring system using IoT 7–10 (2017).
[44] K. Nellore, G.P. Hancke, A survey on urban traffic management system using wireless sensor networks, Sensors 16 (2) (2016a), https://doi.org/10.3390/s16020157.
[45] K. Nellore, G.P. Hancke, Traffic Management for Emergency Vehicle Priority Based on Visual Sensing, 2016, https://doi.org/10.3390/s16111892.
[46] S. Ntalampiras, Moving vehicle classification using wireless acoustic sensor networks, IEEE Transactions on Emerging Topics in Computational Intelligence 2 (2) (2018) 129–138, https://doi.org/10.1109/tetci.2017.2783340.
[47] E. Odat, J.S. Shamma, C. Claudel, Vehicle classification and speed estimation using combined passive infrared/ultrasonic sensors, IEEE Trans. Intell. Transport. Syst. 19 (5) (2018) 1593–1606, https://doi.org/10.1109/TITS.2017.2727224.
[48] A. Pascale, M. Nicoli, F. Deflorio, B. Dalla Chiara, U. Spagnolini, Wireless sensor networks for traffic management and road safety, IET Intell. Transp. Syst. 6 (1) (2012) 67–77, https://doi.org/10.1049/iet-its.2010.0129.
[49] K. Peffers, T. Tuunanen, M. Rothenberger, S. Chatterjee, A design science research methodology for information systems research, J. Manag. Inf. Syst. 24 (3) (2007) 45–78, https://doi.org/10.2753/MIS0742-1222240302.
[50] Y. Qian, D. Wu, W. Bao, P. Lorenz, The internet of things for smart cities: technologies and applications, IEEE Network 33 (2) (2019) 4–5, https://doi.org/10.1109/MNET.2019.8675165.
[51] J. Qiu, L. Du, D. Zhang, S. Su, Z. Tian, Nei-TTE: intelligent traffic time estimation based on fine-grained time derivation of road segments for smart city, IEEE Transactions on Industrial Informatics 16 (4) (2019) 2659–2666.
[52] J. Qiu, Z. Tian, C. Du, Q. Zuo, S. Su, B. Fang, A survey on access control in the age of internet of things, IEEE Internet of Things Journal 7 (6) (2020).
[53] A.M. Rao, K.R. Rao, Measuring urban traffic congestion – a review, Int. J. Traffic Transport. Eng. 2 (4) (2012) 286–305, https://doi.org/10.7708/ijtte.2012.2(4).01.
[54] P.P. Ray, A survey on Internet of Things architectures, Journal of King Saud University - Computer and Information Sciences 30 (3) (2018) 291–319, https://doi.org/10.1016/j.jksuci.2016.10.003.
[55] D.D. Romero, A.S. Prabuwono, Taufik, A. Hasniaty, A review of sensing techniques for real-time traffic surveillance, J. Appl. Sci. 11 (2010) 192–198.
[56] A. Saikar, M. Parulekar, A. Badve, S. Thakkar, A. Deshmukh, TrafficIntel: smart traffic management for smart cities, in: *2017* International Conference on Emerging Trends and Innovation in ICT, ICEI 2017, 2017, pp. 46–50, https://doi.org/10.1109/ETIICT.2017.7977008.
[57] S.B. Sangamesh, D.H. Sanjay, S. Meghana, M.N. Thippeswamy, Advanced traffic

signal control system for emergency vehicles, 3, 2019, pp. 1242–1246, https://doi.org/10.35940/ijrte.C4323.098319.
[58] M. Sarrab, S. Pulparambil, N. Kraiem, M. Al-Badawi, Real-time traffic monitoring systems based on magnetic sensor integration, International Conference on Smart City and Informatization (2019) 447–460.
[59] A. Simdiankin, I. Uspensky, L. Belyu, K. Ratnikov, A method to assess congestion in various traffic directions, Transportation Research Procedia 36 (2018) 725–731, https://doi.org/10.1016/j.trpro.2018.12.099.
[60] A. Sodagaran, N. Zarei, Z. Azimifar, Intelligent traffic information system a real-time traffic information system on the shiraz bypass, MATEC Web of Conferences 81 (2016), 04003, https://doi.org/10.1051/matecconf/20168104003.
[61] L. Sumi, V. Ranga, An IoT-VANET-based traffic management system for emergency vehicles in a smart city, Advances in Intelligent Systems and Computing 708 (2) (2018) 23–31, https://doi.org/10.1007/978-981-10-8636-6_3.
[62] S. Taghvaeeyan, R. Rajamani, Portable roadside sensors for vehicle counting, classification, and speed measurement, IEEE Trans. Intell. Transport. Syst. 15 (1) (2014) 73–83, https://doi.org/10.1109/TITS.2013.2273876.
[63] M.Z. Talukder, S.S. Towqir, A.R. Remon, H.U. Zaman, An IoT based automated traffic control system with real-time update capability, in: 8th International Conference on Computing, Communications and Networking Technologies, 2017, pp. 1–6, https://doi.org/10.1109/ICCCNT.2017.8204095. ICCCNT *2017*.
[64] M.A. Tank, Review on Smart Traffic Control for Emergency Vehicles 112 (7) (2015) 1–3.
[65] R. Tay, A.G. De Barros, Public perceptions of the use of dynamic message signs, J. Adv. Transport. 42 (1) (2008) 95–110, https://doi.org/10.1002/atr.5670420107.
[66] Z. Tian, X. Gao, S. Su, J. Qiu, Vcash: a novel reputation framework for identifying denial of traffic service in Internet of connected vehicles, IEEE Internet of Things Journal 7 (5) (2019) 3901–3909.
[68] V. Velisavljevic, E. Cano, V. Dyo, B. Allen, Wireless magnetic sensor network for road traffic monitoring and vehicle classification, Transport and Telecommunication 17 (4) (2016) 274–288, https://doi.org/10.1515/ttj-2016-0024.
[69] F. Wang, S. Tang, Y. Sui, X. Wang, Towards Intelligent Transportation Systems for the 2008 Olympics, 2008, pp. 8–11.
[70] L. Wang, Z. Yu, D. Yang, H. Ma, H. Sheng, Efficiently targeted billboard advertising using crowdsensing vehicle trajectory data, IEEE Transactions on Industrial Informatics 16 (2) (2019), https://doi.org/10.1109/tii.2019.2891258. PP(January), 1–1.
[71] Q. Wang, J. Zheng, H. Xu, B. Xu, R. Chen, Roadside magnetic sensor system for vehicle detection in urban environments, IEEE Trans. Intell. Transport. Syst. 19 (5) (2018) 1365–1374, https://doi.org/10.1109/TITS.2017.2723908.
[72] B. Yang, Y. Lei, Vehicle detection and classification for low-speed congested traffic with anisotropic magnetoresistive sensor, IEEE Sensor. J. 15 (2) (2014) 1132–1138, https://doi.org/10.1109/jsen.2014.2359014.