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An Infrastructure-Assisted Crowdsensing Approach for On-Demand Traffic Condition Estimation

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ABSTRACT With the widespread use of smartphones and the continuous increase of their capabilities, a new sensing paradigm has emerged: mobile crowdsensing. The concept of crowdsensing implies the reliance on the crowd to perform sensing tasks and collect data about a phenomena of interest. Due to the benefits it offers in terms of time and cost savings in terms of sensors' deployment and maintenance, the concept of mobile crowdsensing is now being adopted in the area of intelligent transportation. In this context, drivers or pedestrians equipped with sensor enabled smartphones collaborate to collect information about roads and traffic. However, the current solutions proposed for the use of crowdsensing for the collection of traffic related data adopt an opportunistic continuous sensing approach, which entails high resource consumption on the server and mobile device side, a high communication overhead, while offering little control of the users over the sensing activity. In this paper, we address these limitations by proposing an infrastructure-assisted on-demand crowdsensing approach for the real time detection and prediction of traffic conditions in an area of interest. Our approach combines the strengths of mobile crowdsensing, with the support of the mobile infrastructure, a multi-criteria algorithm for the participants' selection, and a deductive rule-based model for traffic condition estimation. The proposed solution was validated through a combination of prototyping and simulated traffic traces, and the results show a significant reduction in terms of resources' consumption and network overhead, while reaching high accuracy for the traffic condition estimation.

INDEX TERMS Intelligent transportation system, mobile infrastructure, traffic condition classification, crowdsensing, deductive rule-based logic.

I. INTRODUCTION

Populations' concentration in urban areas and the increased need for mobility are posing important challenges to cities and transportation infrastructures. Indeed, with the overcrowding of cities and the increase in the number of vehicles sharing the roads, citizens are witnessing increasing congestions, road side accidents, and traffic emergencies. Intelligent Transportation Systems (ITS) are being contemplated as mean to enhance the efficiency, safety, and productivity of transportation services [11]. Leveraging communication, sensory, and data analysis technologies, ITS are expected to offer a multitude of useful applications such as route planning and optimization, road safety support, and traffic condition monitoring applications. One of the challenges associated with ITS applications refers to the collection of real time traffic information. Without accurate traffic information collected in real time, offering such ITS applications would not be possible.

Typically, traffic related information is collected using dedicated sensing infrastructures such as road surveillance cameras [32] or loop detectors [50]. While such infrastructures can provide rich and dense data about ongoing traffic, the cost associated with their deployment and maintenance is very high, which prevents their usage in countries with limited resources and their deployment on a global scale [51]. Recently, an alternative method for traffic data collection has attracted attention, namely: mobile crowdsensing [12], [25]. In this new approach, regular users carrying sensors-embedded smartphones collaborate to collect data about a

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phenomena of interest (e.g. traffic condition), in a participatory [15] or an opportunistic mode [39]. In participatory crowdsensing, users actively participate in collecting data, while opportunistic crowdsensing occurs automatically by tapping into phones' sensors, without users' involvement.

In the context of ITS, the idea of relying on drivers or pedestrians when collecting real-time traffic related data can bring significant benefits. The first one is the ability of easily deploying global network of mobile sensors [31] when needed, as millions of users carry smartphones everyday while conducting their daily activities. Another benefit is the time and cost savings that could be achieved in terms of deployment and maintenance, when compared to the traditional sensing infrastructures. Due to these benefits, several crowdsensing based traffic monitoring solutions have been proposed in industry and academia, including: Waze [44], Google Traffic [30], Microsoft Research's Nericell [35], and MIT's CarTel [22]. Despite the merits of those solutions, they all follow an approach where, with no explicit participation of the users, data is continually sensed from all vehicles on all roads, to be sent and processed on the server side. This continuous sensing approach [56] lacks efficiency since it produced large amounts of data, which consumes a lot of resources on the client side, requires extensive processing on the server side, and entails signification communication overhead on mobile networks. Moreover, the opportunistic mode of data collection employed rises mobile user concerns about privacy, as they have to share some sensitive data such as their exact locations or speeds along their trip.

In the area of vehicular networks, solutions were proposed to address different challenges. In [49], the authors proposed a QoS-aware node clustering algorithm that aims at maintaining stability of communication during high mobility and link failure scenarios. In [48], the authors proposed the use of machine learning for the classification of nodes in vehicular area networks as cooperative or malicious. In [37], the authors focused on the analysis of Arabic social media content generated by drivers to identify traffic conditions and the causes of traffic related events. In [2], the authors explored the idea of traffic offloading via device-to-device communications as means to meet the target rate per served user, over long and short-range connections. In [14], the authors proposed the use of unmanned aerial vehicles (UAVs) as store-carry-forward nodes to enhance the connectivity path in vehicular ad hoc networks. In [43], the authors proposed device-to-device cooperation to ensure scalability and failure recovery in wireless content distribution networks. In [47], the authors adopted the mobile cloud-computing model and propose an efficient model for computation offloading to mobile devices. Addressing autonomous vehicle management at intersections, the work in [24] proposed an approach for allowing the vehicles to make autonomous decisions based on sensory information without the need for vehicle to vehicle or vehicle to infrastructure communication. In [13], the authors proposed the integration of UAVs as moving relays in relay-assisted FSO systems. In [6], a solution is proposed to enable the delay optimal scheduling of electric vehicle charging, at several charging stations. In [52], the authors proposed real-time system based on crowdsourcing approach for sharing visual information at a desired location. The proposed system requires capturing street images from users' smartphones and uploading them on a cloud server.

As contribution to the area of mobile crowdsensing, we have previously proposed a participatory on-demand sensing approach to monitor the traffic status [5]. Our approach leverages the concept of Mobile Sensing as a Service (MSaaS) [34] in which sensing capabilities of mobile devices are offered as services by their users, in a participatory fashion. Moreover, in another previously proposed solution [41], traffic data is collected only when needed and triggered by a user's request (instead of continuous collection), and the data is collected on the specific street segment targeted, instead of collection from all roads. Furthermore, data collectors control their involvement in the process via an ability to accept or reject a sensing request. While our participatory infrastructure-less on-demand approach represents benefits when compared to the existing opportunistic continuous sensing approaches, in terms of efficiency of resource consumption and increased control of end users, it still required the periodic publishing of phones' geographic location information for the proper functioning of the system, which is still a limitation in a fully on-demand model. Moreover, the response obtained from the system consists of the estimated traffic speed (in Km/h) on the road targeted. While this information is useful, users would be more interested in knowing the traffic condition (e.g. congested road) than the estimated traffic speed on the road (e.g. mean speed = 55 km/h), as it would give them a quick indication about the state of traffic in that area.

In this work, we address those limitations by proposing an optimized on-demand traffic sensing approach that combines the capabilities of mobile devices with the support of mobile infrastructures to achieve an accurate real-time detection of traffic conditions. In our proposed approach, data is collected on demand about an area of interest. Moreover, phones' locations are determined with the support of the mobile infrastructure, thus not requiring any regular publication of geographic locations by participating phones/users. Once a set of potential data collectors located in the area of interest is determined, our multi-criteria matching algorithm is used to select the best participants based on their phones' sensing capabilities, the users' reputation, the phones' battery level, and the accuracy of the data they provide. Moreover, a dual criteria traffic estimation model is used to categorize the traffic condition as free flowing, moderately congested, or traffic Jam, based on the traffic mean speed and traffic density. If a conflict occurs between the mean speed and the density values, inference rules based on deductive logic are used to make the final traffic condition estimation. To validate our solution and evaluate its performance, we used a combination of prototyping and simulated traffic traces, and conducted various performance tests in order to measure the

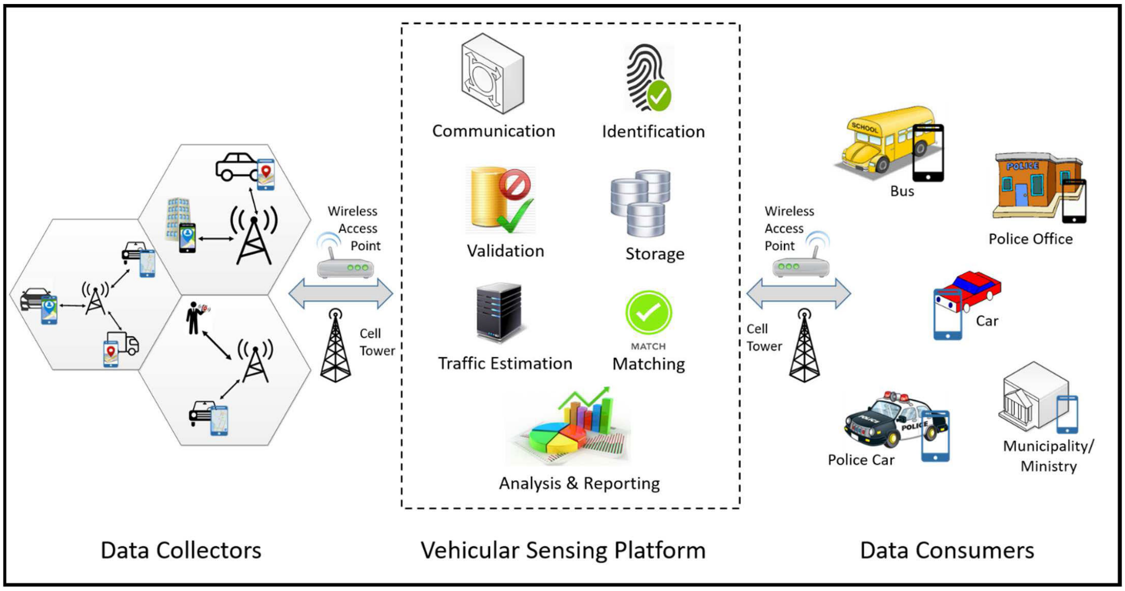

FIGURE 1. **Framework architecture.**

traffic condition estimation accuracy, the network load, and the response time. Moreover, we compared the performance of the continuous sensing approach, the infrastructure-less on-demand sensing approach, and the infrastructure-assisted on-demand sensing approach.

The contributions of our infrastructure-assisted on-demand sensing approach can be summarized as follows:

- **Optimized on-demand collection of real time traffic data with the support of mobile infrastructure**: Unlike existing models that depend on the continuous sensory data collection, our sensing approach supports optimized on-demand system for the monitoring of traffic condition. The use of cellular towers helps satisfy the on-demand sensing requests without requiring any period location updates by participating users needed in the current participatory approaches.
- **Novel rule-based classification model for inferring traffic condition**: The proposed solution is able to accurately infer the current traffic status on a specific road, when requested by a user. The experimental results show high accuracy for the classification of the traffic condition in all cases: Free Flowing, Moderate Congestion, and Traffic Jam. The inferred traffic condition is estimated based on a combination of two traffic properties: the traffic mean speed and the traffic density. Moreover, in the case of conflict between the mean speed and density models, the proposed rule-based classification model infers the traffic status based on the elaborated deductive logic.
- **Efficient resource utilization**: Due to the infrastructure assisted, on-demand, participatory sensing approach used, extensive data processing on the server side can be reduced, mobile device resource consumption such as mobile battery can be reduced, and minimal communication overhead on mobile networks can be achieved. Our approach thus offers important resources' savings when compared to the traditional continuous sensing approach as well as the infrastructure-less on-demand sensing approach.

The rest of the paper is organized as follows. In section II, we describe our proposed infrastructure-assisted on-demand sensing framework. Our participants' matching, traffic condition estimation, and deductive rule-based models are detailed in Sections III, IV, and V respectively, followed by our experimental results in Section VI. The related work is presented in Section VII. We end the paper with our conclusions in Section VIII.

II. APPROACH OVERVIEW

The high-level architecture of our vehicular sensing based framework is presented in Figure 1. Our system consists of three core components: Data consumers, data collectors, and vehicular sensing platform. The communication between the different components can be achieved through mobile communication infrastructures (e.g. 3G/4G mobile networks) or over public WiFi hotspots if available (e.g. in smart cities). First, a data consumer sends to the vehicular sensing platform sensing request for traffic condition in a particular area. The platform then processes the received request and matches it with the most suitable set of data collectors, locating in the targeted area and satisfying several selection criteria. Using their devices capabilities for data collection, the selected data collectors sends the needed data to the platform, which estimates the traffic condition to be sent to the requester. In the sequel, we present the function of each component in details.

- **Data Consumer:** Being in his own car, a school bus, a municipality ministry or even at home, any user interested in sensing activities and intends to know the traffic status in a specific area is considered as a data consumer. To acquire such road data, the user must initially be a member of the community by subscribing to the platform application. Then, the consumer can specify at any time a certain road from the map to request its traffic condition from the platform.

- **Data Collector:** Any user who tends to be involved in the sensing activities must hold sensor-enabled phones and subscribe to the platform application to become a data collector. Whenever the collectors receive sensing task, they share with the platform their phones data sensing capabilities determining their exact location.
- **Vehicular Sensing Platform:** The vehicular sensing platform is where sensed data is aggregated, validated and processed to predict the traffic status of the roads, which make the vehicular platform the key component in our architecture. Many modules are implemented to help achieving any consumer request:
  - The communication module is in charge of handling the exchanged messages between the platform and both the consumers and collectors. As multiple sensing requests could be received simultaneously from different data consumers, we use RESTful [1] which enable services to work best on the web-based applications and mobile web services.
  - The identification module is in charge of allocating IDs to the participating data consumers as well as data collectors, in addition to the generated traffic status reports.
  - The validation module is in charge of detecting inconsistencies in the consumer requested data before being processed. Moreover, this module helps detecting whether the collector sensed data comes from a pedestrian or a user taking a ride.
  - The storage module is in charge of storing the collectors data location along with the time of the sensing and the traffic reports. When there is small elapsed time between two requests and same information is needed, the collectors wouldn't interact twice, therefore minimizing the communication and processing overhead.
  - The matching module is in charge of identifying the most suitable list of data collectors located in the consumer area of interest. The geographic location of the users is obtained from the cell towers by dealing with their providers. The algorithm of the matching module and how the participants are selected is provided section III.
  - The traffic estimation module is in charge of estimating and classifying the traffic condition into one of the three phases: Traffic Jam, Moderate Congestion and Free Flowing. The algorithm deployed for the estimation relies on a density and a mean speed characteristics. The mathematical formulations and the thresholds used for classification are presented in section IV.
  - The analysis and reporting module is in charge of inferring the final traffic condition to be sent as response to the consumer. When the density and mean speed in the traffic estimation module predict different traffic condition, this module uses inference rules based on deductive logic to resolve the conflict. Otherwise, the initial traffic status agreed on is directly sent to the requester. In section V, we propose in this paper a new strategy for the conflicting problem and elaborate the used inference rules.

TABLE 1. Formulas notations.

Variable	Description
ST	Set of Tower
SS	Set of Sensor
R	The desired road from which the traffic condition is requested
R'	An adjacent road heading from R
$S_{id}^{T_i}$	Sensor S with ID = id collected from Tower T_i
$pos_{t_i}^{S_j}$	Position of S_j at t_i
$S_j.sType$	Origin of S_j's sensed data
$S_j.avail$	The availability of S
$S_j.batLevel$	The battery level of S
$S_j.rep$	The reputation of S
$S_j.capab$	The capability of S
$S_j.dataAcc$	The data accuracy of S
v_{max}	Maximum speed that could be reached on a road

III. MATCHING MODEL THROUGH MOBILE CELL TOWERS

When a data consumer requests the traffic condition on a road, the first module in our platform to interact with is the matching module. All the notations presented in our model equations are described in Table 1. Initially, the server matches the received request with the cell towers located in the specified area in order to collect all nodes connected to them. A first sensing request is then sent to each node from the matched set requesting its specific location. All sensed data coming from in-vehicles sensors and found on the targeted road are selected to form the most suitable set of collectors. Since the traffic estimation model requires two sensed data from each sensor on road to predict the traffic condition, a second sensing request is therefore sent after 10 seconds [29] to the elected set of nodes.

The proposed matching model relies on several criteria to match the consumer request with the appropriate list of collectors in order to get the data of their geographic locations. Once the data consumer sends sensing request to the platform requesting the traffic condition on a specific road, the server launches the matching module. The model supports fully on-demand approach, without requiring any continuous or

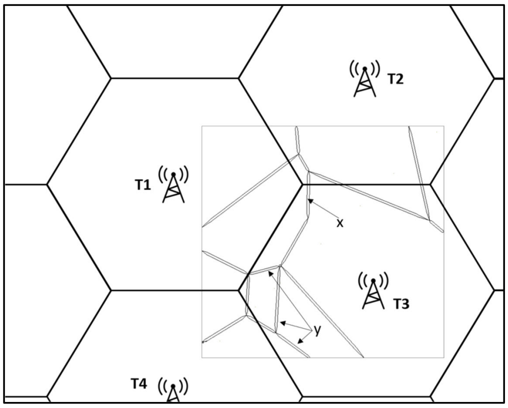

FIGURE 2. Representation of the road topology and cellular towers locations on the case study area.

previous sensed data from the nodes. The first criterion to take into consideration is the geographic location of the nodes, which is defined as follows: First, the cell towers that cover the entire road, from which the traffic condition is requested, are identified based on a map topology and predefined towers locations. The number of towers chosen is defined by:

$$ST : \sum_{i=1}^{n} T_i | T_i \ covers \ R \tag{1}$$

where ST contains the set of all the towers T_i surrounding the road R through their coverage area.

The cell towers have different sizes. The large ones, which are usually found on highways, are called macrocells and offer wide area coverage. Over a smaller area, microcells are used to cover urban and suburban cells. Moreover, picocells are employed for even smaller coverage area such as buildings, campuses, and airports [28]. In the proposed approach, we deal with microcells that cover around one mile in diameter since our study addresses the urban roads. Figure 2 illustrates the road topology used in the simulated scenarios including the cell towers with hexagonal shape covering the case study area. If a data consumer requests the status of the road x presented in the figure, towers T2 and T3 are picked to capture the vehicles movement. Then, all the nodes IDs connected to the chosen towers are requested from the mobile providers. The collected set of nodes is defined by:

$$SS_{init} : \bigcup_{i=1}^{n} S_{id}^{T_i} \tag{2}$$

where SS_{init} stands for the initial set of sensors that includes the union of their IDs gathered from the different requested Towers.

Afterwards, sensing request is sent to each node in the SS_{init} participating in the sensing activities to get its geographic location at the request time t_1, along with the origin of the data sent (i.e. pedestrian or vehicle). The current mobile devices provide a new feature to recognize whether sensed data comes from a pedestrian or in-vehicle device. Therefore, we filter the obtained set to keep only the on-road vehicular sensors, after eliminating the pedestrians' nodes. Hence, the filtered set of sensors after receiving the nodes responses at t_1 becomes as follows:

$$SS_{filtered.t_1} : \textstyle\sum_{j=1}^{m} (pos_{t_1}^{S_j} \in R) \wedge (S_j.sType == Veh) \tag{3}$$

where $SS_{filtered.t_1}$ holds all the nodes located on the road R at t_1, and having vehicular (Veh) sensor type.

Besides the geographic location of the nodes, the matching module relies on the following criteria: user availability, node battery level, user reputation, node sensing capability, and the accuracy of the sent data. The user has the choice to indicate whether he intends to participate in the sensing activities or not. When a user updates his status to *not-available*, the server will not contact him for any sensing request even though he appears in the area of interest. The battery level is also considered in the matching criteria: When the phone battery is below 20%, then we assume that the device is not able to send or receive any sensing request. This criterion is considered in order not to drain the battery of the user and not to interrupt the communication between the server and the user in case the device goes off. The user reputation is used to enhance the performance of the platform. In some cases, a user might misbehave and send wrong data to the server, therefore affecting the accuracy of the estimated traffic. To prevent such occurrence, we keep track of the data sent from the users and compare it with the actual traffic condition to categorize the users with good or bad reputation. After each on-demand request process, the server compares the predicted traffic condition with the data sent from the participating collectors. If there is a major difference between one or more data collectors' responses and the predicted result, then bad reputation will be assigned to this/those collectors. Thus, users having bad reputation will not be contacted for future sensing requests. In order to motivate the user to properly behave, we prevent him from requesting any traffic condition from the server whenever he behaves badly in the sensing activities. Another criterion in the matching module is the sensing capabilities of the user. Different type of information such as the geographic location, some photos captured for the street, etc. might be requested to be sent to the platform. Using this criterion in the matching process allows to know whether the participating sensor-enabled devices are able to sense the requested data. The last criterion to consider is the accuracy of the data collected. The accuracy of the location differs when obtained from WiFi, GPS or cellular network and this should be taking into consideration when requesting sensed data from the users. The updated set of sensors after adding all the criteria is defined as follows:

$$\begin{aligned} SS_{updated} : \sum_{j=1}^{k} & (pos_{t_1}^{S_j} \in R) \wedge (S_j.sType == Veh) \\ & \wedge (S_j.avail == true) \wedge (S_j.batLevel > 20) \\ & \wedge (S_j.rep == good) \wedge (S_j.capab == true) \\ & \wedge (S_j.dataAcc == high) \end{aligned} \tag{4}$$

where $SS_{updated}$ holds the filtered nodes that are available, with battery level more than 20%, having good reputation, and are capable of sensing the needed data with high accuracy.

To obtain the two required sensed data from the collectors to estimate the road condition, a second sensing request is sent to the set $SS_{updated}$ after 10 seconds of t_1 to get the new nodes positions as responses. The final set of sensors SS_{final} identified after receiving $SS_{updated}$ responses is represented as follows:

$$\begin{aligned} SS_{final} : \sum_{j=1}^{p} &(pos_{t_1}^{S_j} \in R) \wedge (S_j.sType == Veh) \\ &\wedge \left[pos_{t_2}^{S_j} \in R \vee pos_{t_2}^{S_j} \in R'\right] \wedge (S_j.avail == true) \\ &\wedge (S_j.batLevel > 20) \wedge (S_j.rep == good) \\ &\wedge (S_j.capab == true) \wedge (S_j.dataAcc == high) \end{aligned} \tag{5}$$

where SS_{final} holds all the nodes located on R or R' (the adjacent road heading from R) at t_2.

We developed the algorithm of the aforementioned model within the matching module of the sensing platform. Algorithm 1 illustrates all the steps of the matching including the interactions with the other modules of the platform.

Algorithm 1 - Matching Algorithm Through Cellular Tower

Input: Map Topology + Towers locations
Output: Set of targeted cars SS_{final} located in the specified destination
t_1 = time of consumer request
Get the set of towers ST covering the targeted road R
Construct a list S_{init} : Ø for the initial set of sensors
for each T_i in ST **do**
    send request to T_i's provider, and get its nodes IDs S_{id}
    $SS_{init} = SS_{init} \bigcup S_{id}^{T_i}$
end for
for each sensor S_j in SS_{init} **do**
    send sensing request to S_j, and get its position pos^{S_j} at t_1
end for
Construct a list $S_{filtered.t_1}$: Ø for the set of sensors
for each sensor S_j in SS_{init} **do**
    if $pos_{t_i}^{S_j}$ == onRoad && S_j in Veh **then**
        add S_j to $SS_{filtered.t_1}$
    end if
end for
Construct a list $S_{updated}$: Ø for the set of sensors
for each sensor S_j in $SS_{filtered.t_1}$ **do**
    if $(S_j.avail == true)$ && $(S_j.batLevel > 20)$ && $(S_j.rep == good)$ && $(S_j.capab == true)$ && $(S_j.dataAcc == high)$ **then**
        add S_j to $SS_{filtered}$
    end if
end for
$t_2 = t_1$ + 10 secs. / t_1 = time of consumer request
for each sensor S_j in $SS_{filtered}$ **do**
    send sensing request to S_j, and get its position pos^{S_j} at t_2
end for
Construct a list S_{final} : Ø for the set of sensors
for each sensor S_j in $SS_{filtered}$ **do**
    if S_j == available **then**
        if $pos_{t_i}^{S_j}$ == onRoad R ‖ $pos_{t_i}^{S_j}$ == onRoad R' **then** && S_j in V
            add S_j to SS_{final}
        end if
    end if
end for

IV. CLASSIFICATION-BASED TRAFFIC ESTIMATION MODEL

Once the matching model identifies the final set of collectors to participate in the sensing request, the server runs the algorithm implementing the traffic estimation model. Our proposed model combines the density and mean speed characteristics to best reflect the road status.

In this section, we present our proposed model for traffic estimation that aims to classify the different traffic flow conditions based on Kerner's theory [23]. Density, mean speed and flow [36] are the three main characteristics used to evaluate the traffic stream in macroscopic traffic flow model. Some proposed approaches [54], [42] focus on two characteristics to estimate the traffic condition, while others [17], [29] use only one. In our proposed model, we base our estimation on an approach combining both density and mean speed. Moreover, we adopt Kerner's theory that divides the traffic into three categories: 1) Traffic Jam describing a wide traffic, 2) Moderate congestion, also known as Synchronized Flow, showing no significant stoppage of vehicles, and 3) Free Flow reflecting continuous traffic flow with no congestion. Each of the density and mean speed classifies the traffic status into one of these categories. In case of conflicting results, an analysis and reporting models identify the final decision of traffic, using a percentage-based resolution strategy. In the sequel, we present how the density and mean speed predict the traffic.

A. DENSITY BASED ESTIMATION

The density based estimation represents the number of vehicles occupying the segment of the requested road as denoted in the following:

$$k = \frac{N}{L} \tag{6}$$

where N is equal to the number of vehicles on R, and L is the length of R (in miles).

N is obtained from equation (6) when the set of $SS_{filtered}$ shares their location at t_1. We use the number of vehicles in the set $SS_{filtered}$ and base our density estimation on it for the following reason: $SS_{filtered}$ holds all the vehicles that are

TABLE 2. Relations between traffic condition and density.

Traffic Condition	k (vehicles/mile)	k (vehicles/305 meters)
Free Flowing	$0 \leq k \leq 30$	$0 \leq k \leq 5$
Moderate Congestion	$30 < k \leq 160$	$5 < k \leq 30$
Traffic Jam	$160 < k \leq 233$	$30 < k \leq 44$

TABLE 3. Relations between traffic condition and mean speed.

Traffic Condition	v_{mean} (km/h)
Free Flowing	$13 \leq v_{mean} \leq v_{max}$
Moderate Congestion	$7 \leq v_{max} < 13$
Traffic Jam	$0 \leq v_{max} < 7$

located on road R at time t_1. Some of these vehicles might not be selected for further communication with the server and participation in the traffic estimation prediction due to their (1) non-availability, (2) low devices' battery level, (3) bad reputation, (4) inadequate devices' sensing capabilities, and (5) inaccurate accuracy in the sensed data. Although these vehicles are filtered out from the sets $SS_{updated}$ and SS_{final}, their presence on the road and their total number are vital for the density-based estimation.

Table 2 shows how the different traffic conditions are deduced when k varies between zero and the maximum number of vehicles over one mile [26].

By analyzing the flow condition on road x in Figure 2, we can find that the length of the road is 305 meters, and therefore the relation between the traffic condition and the number of vehicles is calculated and provided in Table 2.

B. MEAN SPEED BASED ESTIMATION

To calculate the mean speed at a given time, we need to obtain the data collected from a set of sensors located in a specific area of interest. More precisely, a pair of latitude and longitude coordinates data consecutively sampled from each sensor is needed. Consequently, the nodes geographic locations in the set SS_{final} (equation 5) are used to estimate the real mean speed. To start with, we measure r_j, the distance of road traveled by each sensor S_j in SS_{final} between t_1 and t_2. r_j is characterized by

$$r_j = \left(pos_{t_1}^{S_j}, pos_{t_2}^{'S_j}\right) \tag{7}$$

where the position of S_j at t_1, which is $pos_{t_1}^{S_j}$, is always on R, however $pos_{t_2}^{S_j}$ could be either on R or R'. R' represents any adjacent road heading from R. Therefore, we adopt $pos_{t_2}^{'S_j}$ for the position of S_j at t_2. If $pos_{t_2}^{S_j}$ is on R, then $pos_{t_2}^{'S_j} = pos_{t_2}^{S_j}$. Otherwise, $pos_{t_2}^{'S_j}$ is the intersection of the end/exist road R.

Next, we calculate the average speed v_j of each sensor in the same set SS_{final} as follows:

$$v_j = \frac{r_j}{(t_1, t_2)} \tag{8}$$

The formula used for the mean speed is calculated based on equations 7 and 8 and can be defined as

$$v_{mean} = \frac{\sum_{s_j \in SS_{final}} \left[v_j \times \left(pos_{t_1}^{S_j}, pos_{t_2}^{'S_j}\right)\right]}{\sum_{s_j \in SS_{final}} \left(pos_{t_1}^{S_j}, pos_{t_2}^{'S_j}\right)} \tag{9}$$

The classification of the mean speed v_{mean} into the three levels is estimated based on the thresholds [38] illustrated in Table 3, where v_{max} represents the maximum allowed speed on a specified road.

V. ANALYSIS AND REPORTING MODEL: RULE-BASED TRAFFIC CONDITION

The analysis and reporting model provides the estimated traffic condition symbolized either by red for Jam, yellow for synchronized, or green for free flowing. As previously mentioned, the final traffic condition category is deduced from both density and mean speed models after combining their estimated results. If the two resulting conditions match, then a straightforward decision is inferred and sent to the consumer. In this context, the final congestion level is red, yellow or green when both density and mean speed show traffic jam, moderate congestion, or free flowing condition respectively. Otherwise, it may happen that each model classifies the road condition into different congestion level. When such a conflict occurs, the estimated levels could not be averaged out since we adopt only two criteria. To address the conflicting problem between the two models, we propose the following strategy which ensures the validity of the final result:

"The further the value of a criteria is away from its decision boundaries, the more accurate its classification estimation will be"

For instance, let's take the example where k is equal to 35 vehicles/mile and v_{mean} is equal to 4 km/h. Therefore, the density-based model estimates a Moderate Congestion condition, while the mean speed based model reports a Traffic Jam. Thereby, we calculate how each variable is away from the boundary of the conflicting level, and hence we consider the final classification of the one having higher value. In this case, between k that falls between 30 and 160 and how close from 30 is and v_{mean} that falls between 0 and 7 and how close from 7 is, we can say that k is closer to the considered boundary and the final traffic condition is hence the one of the mean speed.

To realize formally the semantics in case of conflicting, we elaborated inference rules based on deductive logic to decide on the final road status and classify it as Free Flow (FF), Moderate Congestion (MC), and Traffic Jam (TJ). Inference rules usually have standard structure, where the conclusion is presented below a horizontal line and a list of premises listed above the line [45].

TABLE 4. Boundaries notations for the density and mean speeds.

Traffic Condition	k (vehicles/mile)	v_{mean} (km/h)
Free Flowing	$Bk1 \leq k \leq Bk2$	$Bv1 \leq k \leq Bv2$
Moderate Congestion	$Bk2 < k \leq Bk3$	$Bv2 \leq k < Bv3$
Traffic Jam	$Bk3 < k \leq Bk4$	$Bv3 \leq k < Bv4$

The final traffic condition (TC) is represented as follows:

$$\frac{(premise_1)op(\text{premise}_2)op...op\ (\text{premise}_n)}{<\text{TC, Final}> \xrightarrow[\text{classify}]{} \text{FF/MC/TJ}}$$

where op is either ∨ to represent the logical operator "and", or ∧ to represent the logical operator "or".

Premises 1 and 2 denote the traffic conditions (TC) estimated from density and mean speed models respectively.

$$<\text{TC, Density}> \xrightarrow[\text{classify}]{} \text{FF/MC/TJ} \quad (\text{premise 1})$$
$$<\text{TC, Mean Speed}> \xrightarrow[\text{classify}]{} \text{FF/MC/TJ} \quad (\text{premise 2})$$

where TC is classified to FF, MC or TJ

The other premises are combinations of rules-based of the calculated ranges (v_{range} and k_{range}) needed in case of conflict in premise 1 and premise 2 classification.

In the sequel, we present the details of calculating v_{range} and k_{range}, in addition to the inference rules for conflicting classification.

A. MEAN SPEED AND DENSITY RANGE CALCULATION

This strategy: **"The further the value of a criteria is away from its decision boundaries, the more accurate its classification estimation will be"** is yet opted since we have confidence in the classification of the variable (density/mean speed) that has a value close to the middle of its boundaries. To realize the proposed strategy, we first adopt the boundaries notations presented in Table 4.

Second, we get the two boundaries Bk_i and Bk_j where the density goes between, and the two corresponding ones Bv_i and Bv_x for the mean speed. Then, for the density k (computed in equation 6) and mean speed v (computed in equation 9), we calculate how far away from their boundaries are as percentage value following equations 9 and 10 respectively

$$k_{range} = \frac{|k - Bk_i|}{|Bk_j - Bk_i|} \times 100 \tag{10}$$

$$v_{range} = \frac{|v - Bv_i|}{|Bv_x - Bv_i|} \times 100 \tag{11}$$

Eventually, the final traffic condition tends to consider the classification of the variable that has higher range. Consider the following cases in Table 5 which summarize all combinations of the density and mean speed leading to conflicting problem:

TABLE 5. Mean speed and density conflicting problems.

Traffic Condition	k (vehicles/mile)	v_{mean} (km/h)
Free Flowing	$0 \leq k \leq 30$	$7 \leq v_{max} < 13$
Moderate Congestion	$30 < k \leq 160$	$13 \leq v_{mean} \leq v_{max}$
Traffic Jam	$160 < k \leq 233$	$0 \leq v_{max} < 7$

- **Case 1:** when density estimates free flowing condition, while mean speed estimates moderate congestion. The conflicting levels are Free Flowing (FF) and Moderate Congestion (MC). Thus, the density range is represented by:

$$k_{\text{range: MC}\rightarrow\text{FF}} = \frac{|K - Bk_2|}{|Bk_1 - Bk_2|} \times 100$$

where density tends to change the traffic status from MC to FF by calculating the distance from k value to Bk_2 And the mean speed range is represented by:

$$v_{\text{range: FF}\rightarrow\text{MC}} = \frac{|v - Bv_2|}{|Bv_3 - Bv_2|} \times 100$$

where mean speed tends to change the traffic status from FF to MC by calculating the distance from v_{mean} to Bv_2

- **Case 2:** when density estimates moderate congestion condition, while mean speed estimates free flowing congestion. The conflicting levels are Moderate Congestion and Free Flowing. Thus, the density range is represented by:

$$k_{\text{range: FF}\rightarrow\text{MC}} = \frac{|K - Bk_2|}{|Bk_3 - Bk_2|} \times 100$$

where density tends to change the traffic status from FF to MC by calculating the distance from k value to Bk_2 And the mean speed range is represented by:

$$v_{\text{range: MC}\rightarrow\text{FF}} = \frac{|v - Bv_2|}{|Bv_1 - Bv_2|} \times 100$$

where mean speed tends to change the traffic status from MC to FF by calculating the distance from v_{mean} to Bv_2

- **Case 3:** when density estimates moderate congestion condition, while mean speed estimates traffic jam congestion. The conflicting levels are Moderate Congestion and Traffic Jam (TJ). Thus, the density range is represented by:

$$k_{\text{range: TJ}\rightarrow\text{MC}} = \frac{|K - Bk_3|}{|Bk_2 - Bk_3|} \times 100$$

where density tends to change the traffic status from TJ to MC by calculating the distance from k value to Bk_3 And the mean speed range is represented by:

$$v_{\text{range: MC}\rightarrow\text{TJ}} = \frac{|v - Bv_3|}{|Bv_4 - Bv_3|} \times 100$$

where mean speed tends to change the traffic status from MC to TJ by calculating the distance from v_{mean} to Bv_3

$$\frac{\begin{array}{c} \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{FF}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{FF}\right)\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{FF}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(\mathrm{k}_{\text{range: MC}\rightarrow\text{FF}} > v_{\text{range: FF}\rightarrow\text{MC}}\right)\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{FF}\right) \wedge \left(v_{\text{range: MC}\rightarrow\text{FF}} > \mathrm{k}_{\text{range: FF}\rightarrow\text{MC}}\right)\right) \end{array}}{< \text{TC, final} > \xrightarrow[\text{classify}]{} \text{FF}}$$

FIGURE 3. Semantics based Rules for the final traffic condition classified as FF.

$$\frac{\begin{array}{c} \left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{MC}\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{FF}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(v_{\text{range: FF}\rightarrow\text{MC}} > \mathrm{k}_{\text{range: MC}\rightarrow\text{FF}}\right)\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{FF}\right) \wedge \left(\mathrm{k}_{\text{range: FF}\rightarrow\text{MC}} > v_{\text{range: MC}\rightarrow\text{FF}}\right)\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{TJ}\right) \wedge \left(\mathrm{k}_{\text{range: TJ}\rightarrow\text{MC}} > v_{\text{range: MC}\rightarrow\text{TJ}}\right)\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{TJ}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(v_{\text{range: TJ}\rightarrow\text{MC}} > \mathrm{k}_{\text{range: MC}\rightarrow\text{TJ}}\right)\right) \end{array}}{< \text{TC, final} > \xrightarrow[\text{classify}]{} \text{MC}}$$

FIGURE 4. Semantics based Rules for the final traffic condition classified as MC.

- **Case 4:** when density estimates traffic jam condition, while mean speed estimates moderate congestion. The conflicting levels are Traffic Jam and Moderate Congestion. Thus, the density range is represented by:

$$\mathrm{k}_{\text{range: MC}\rightarrow\text{TJ}} = \frac{|\mathrm{K} - \mathrm{Bk}_3|}{|\mathrm{Bk}_4 - \mathrm{Bk}_3|} \times 100$$

  where density tends to change the traffic status from MC to TJ by calculating the distance from k value to Bk_3 And the mean speed range is represented by:

$$v_{\text{range: TJ}\rightarrow\text{MC}} = \frac{|v - \mathrm{B}v_3|}{|\mathrm{B}v_2 - \mathrm{B}v_3|} \times 100$$

  where mean speed tends to change the traffic status from TJ to MC by calculating the distance from v_{mean} to $\mathrm{B}v_3$

B. INFERENCE RULES FOR TRAFFIC CONDITION CLASSIFICATION

In this section, we present the inference rules of the final traffic condition classifications illustrated in Figures 3, 4 and 5.

In Figure 3, the final TC is classified to FF if the TC inferred from both density and mean speed is FF, or the density-based TC estimation is FF while the mean speed estimation is MC and k_{range} is greater than v_{range}, or the density estimation is MC while the mean speed estimation is FF and v_{range} is greater than k_{range}.

In Figure 4, the final TC is classified to MC if one of the following five cases occurs:

- Both density and mean speed estimate the TC as MC
- Density based estimation is FF, while mean speed based estimation is MC and $v_{range} > \mathrm{k}_{range}$
- Density based estimation is MC, while mean speed based estimation is FF and $\mathrm{k}_{range} > v_{range}$

$$\frac{\begin{array}{c} \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{TJ}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{TJ}\right)\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{TJ}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(\mathrm{k}_{\text{range: MC}\rightarrow\text{TJ}} > v_{\text{range: TJ}\rightarrow\text{MC}}\right)\right) \\ \vee \left(\left(< \text{TC, density} > \xrightarrow[\text{classify}]{} \text{MC}\right) \wedge \left(< \text{TC, MeanSpeed} > \xrightarrow[\text{classify}]{} \text{TJ}\right) \wedge \left(v_{\text{range: MC}\rightarrow\text{TJ}} > \mathrm{k}_{\text{range: TJ}\rightarrow\text{MC}}\right)\right) \end{array}}{< \text{TC, final} > \xrightarrow[\text{classify}]{} \text{TJ}}$$

FIGURE 5. Semantics based Rules for the final traffic condition classified as TJ.

- Density based estimation is MC, while mean speed based estimation is TJ and $\mathrm{k}_{range} > v_{range}$
- Density based estimation is TJ, while mean speed based estimation is MC and $v_{range} > \mathrm{k}_{range}$

In Figure 5, the final TC is classified to TJ if the TC inferred from both density and mean speed is TJ, or the density-based TC estimation is TJ while the mean speed estimation is MC and k_{range} is greater than v_{range}, or the density estimation is MC while the mean speed estimation is TJ and v_{range} is greater than k_{range}.

VI. SOLUTION VALIDATION AND EXPERIMENTAL RESULTS

In this section, we present how we validated our solution through the conducted experiments, using some test scenarios and performance metrics.

A. TESTING SCENARIO

Figure 6 illustrates our proposed sensing scenario used through our experiments. The data consumer first interacts with the platform by sending sensing request (msg 1) asking for traffic condition on specific road. The platform therefore searches for all towers that surround the requested road (msg 2), sends them requests (msg 3) and waits for their replies (msg 4). Once done (msg 5), sensing request is sent to each sensor in the set gathered from the towers to get their current locations (msg 6). The data collectors perform sensing operation (msg 7) to send the sensed data back to the platform (msg 8). Since many collectors are not located on the desired road and some of them are not even in vehicles, the platform filters the set (msg 9) and sends another request only to the filtered nodes (msg 10). When the data collectors operate sensing activity (msg 11) and all responses are received (msg 12), the platform runs both density and mean speed estimation algorithms (msgs 13 & 14) to predict the real-time traffic status of the road and sends it to the consumer (msg 15).

B. EXPERIMENTAL SETUP

To carry out the experiments, we implemented our vehicular sensing framework on a machine equipped with Intel core i7, 2.4 GHz processor and 12 GB of RAM. The dataset is based on a scenario where, on a specific or random road topology and for a certain period of time, a number of cars move all along the roads, providing simultaneously their longitude and

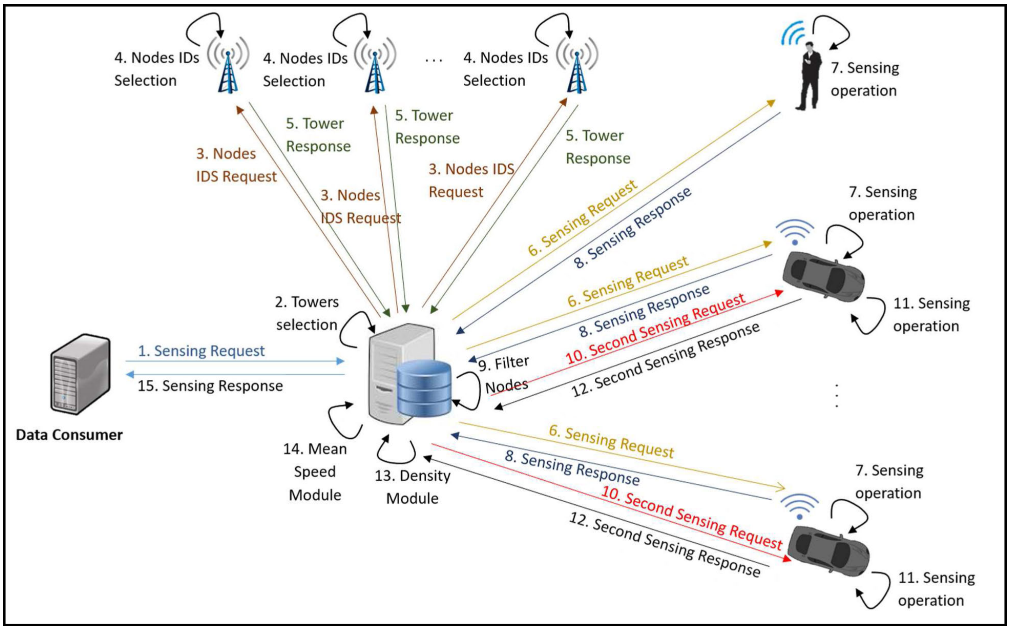

FIGURE 6. Full on-demand sensing scenario.

latitude in addition to their speed throughout the simulation. The simulator adopted to generate such movement traces is VanetMobiSim [16], which is widely used and could replace the need of collecting real sensory data from mobile phones. We used in our experiments the road topology of Figure 2 generated from VanetMobiSim and simulated four cell towers to cover the entire region. Each tower has 1 mile of diameter that covers the area shown in hexagonal shape. The simulated scenario is tested for the three traffic conditions where the real TC is observed visually from the demo showing the simulation traces.

C. PROTOTYPE SOFTWARE ARCHITECTURE

Our prototype, which is implemented in JAVA, includes the following three main components nodes, achieving communication using REST APIs:

- A node, which represents the data consumer, has (1) a module responsible of launching the requests and handling their responses, (2) a manager module for the generated sessions responsible of tracking them and setting their statuses, and (3) a local repository to store the sessions statuses and the corresponding data.
- A large number of nodes representing the data collectors are generated on one machine using VanetMobiSim. The latter is first used for simulating the scenarios to be studied, and reflecting and controlling different traffic flows. Each scenario generates a file holding information related to all simulated vehicles. Thus, each node accesses the generated file to store in a local database its assigned data of movement traces. This combination of prototyping and simulated traffic traces substitutes for the use of real mobile devices, which their usage makes it hard to control the traffic parameters. Each implemented data collector node has the following: (1) a module responsible of receiving the request and sending the sensed data, (2) a manager module for the generated sessions responsible of tracking them and setting their statuses, (3) a module responsible of scheduling the multiple requests sent by the platform, (4) a module responsible of retrieving the needed data (i.e. the position of the car at a specific time) from the node's local database, (5) a module responsible of processing the exchanged messages via REST API between the node and the platform, and (6) a local repository to store the traffic related data generated from VanetMobiSim.
- A vehicular sensing platform that has the following: (1) a module responsible of handling and processing the received requests and responses, (2) a matching module responsible of finding the suitable set of data collectors, (3) a traffic estimation module responsible of predicted the traffic by implementing its algorithm, (4) an analysis and reporting module responsible of reporting the final traffic condition, (5) a module responsible of queuing requests to the matched data collectors, (6) a module responsible of assigning IDs to the users and sessions, and (7) a repository to store information about the users, sensing sessions, and their generated reports.

D. EXPERIMENTAL RESULTS

The objectives of the conducted experiments are the following:

1) Evaluate our proposed approach and indicate how accurate is the final inferred TC in diversity of scenarios when using the vehicles selection model through mobile cell towers and our rule-based classification model for traffic condition.

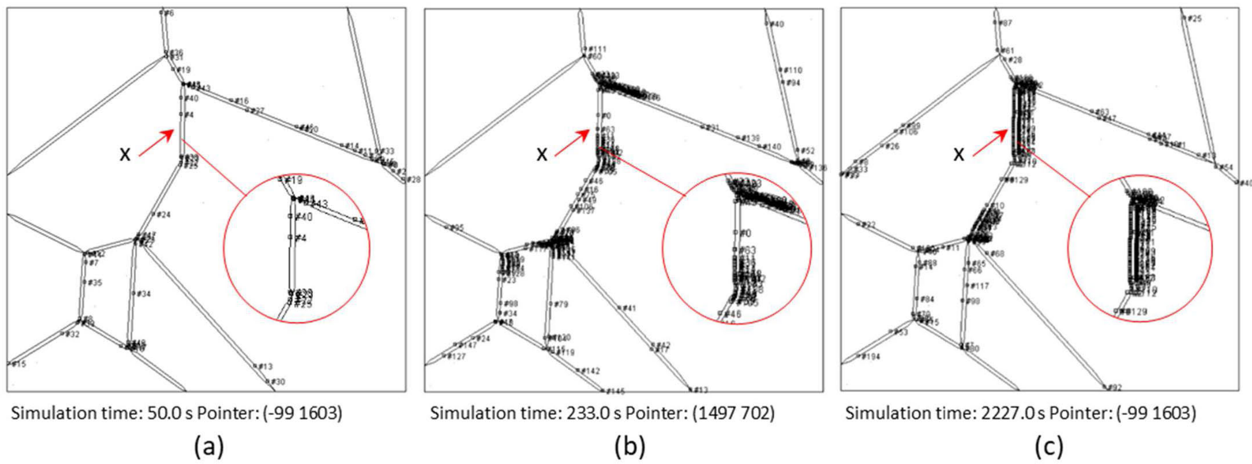

FIGURE 7. Three different scenarios reflecting the FF, MC, and TJ conditions on road x.

2) Compare the performance of our approach with the infrastructure-less on-demand model [41], which estimates the traffic condition through the mean speed metric only and without relying on cell towers. In order to predict the location of the collectors, the approach in [41] assumes that each collector periodically publishes a sensed data to the platform about its position.
3) Evaluate the overall system's performance included all the communications and processing overhead along with the response time while comparing it to the infrastructure-less on-demand [41] and the traditional continuous approaches [22], [35].
4) Evaluate the performance of the six selection criteria used in the matching module in terms of traffic estimation error and response time.

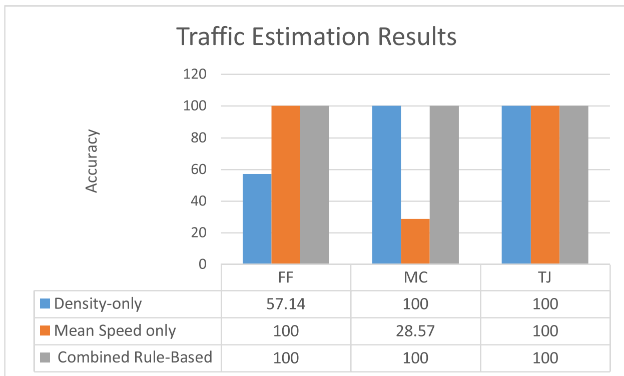

FIGURE 8. Traffic estimation results.

1) TRAFFIC ESTIMATION ACCURACY FOR DIFFERENT SIMULATED SCENARIOS

Various scenarios have been simulated to study the traffic flow at different time frame during the day, and Figure 7 reflects the flow when free, moderate, and congested. Figure 7 (a) shows clearly the free flow condition, where only 3 cars were located at road x after 50.0 seconds of the simulation. The moderate congestion is reflected in Figure 7 (b) with 16 cars on the road at 233.0 sec. As for Figure 7 (c), it displays the traffic jam condition, which represents the peak-hour traffic simulated at 2227.0 sec.

Besides the three scenarios presented in Figure 7, each of the FF, MC, and TJ conditions was studied at least at 7 different points in time, and the results are shown in Figure 8. The latter shows the performance of the traffic estimation module while considering the TC deduced from the density estimation only (equation 6), the mean speed estimation only (equation 9), and the TC inferred from the combined estimation based on our rule-based classification. The accuracy presented in this figure is calculated as (the number of experiments where the final TC was correctly classified as FF, MC, or TJ) / (the total number of experiments conducted) * 100.

In case of free flowing (FF), the density-based estimation shows 57.14% accuracy where the misleading experiments estimated the TC as MC. In the latter experiments, the number of cars found on the road were varying between 6 and 7, which exceeds the density thresholds presented in Table 2 for the FF condition. Accordingly, the density module estimates the traffic as moderate congestion, which is not the case. As for the mean speed estimation, all conducted experiments were properly classified and hence achieving an accuracy of 100%. By combining both the density and mean speed modules based on our rule-based classification, we were able to correct the density estimation and reflect 100% accuracy for the final TC inferred.

In case of Moderate Congestion (MC), the density based estimation shows 100% accuracy while the mean speed estimation shows only 28.57%. Among the 71% of the non-accurate experiments, some estimated a FF condition while others estimated a TJ. In such experiments, it was noticed that when the cars are scattered on the road, they could have somehow high speed and hence a FF condition is predicted. However, when they are located close to each other, a low speed is sensed; Therefore traffic jam is inferred. Regarding the TC inferred from the proposed combined rule-based

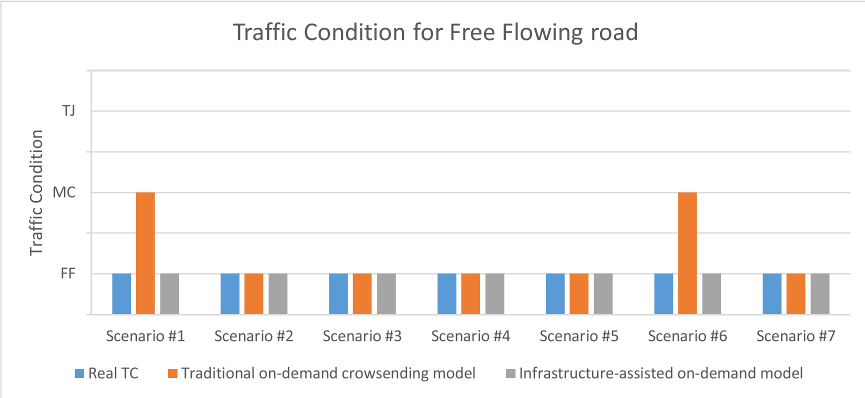

FIGURE 9. Accuracy comparison of the mean speed and the combined classification approaches in FF traffic condition.

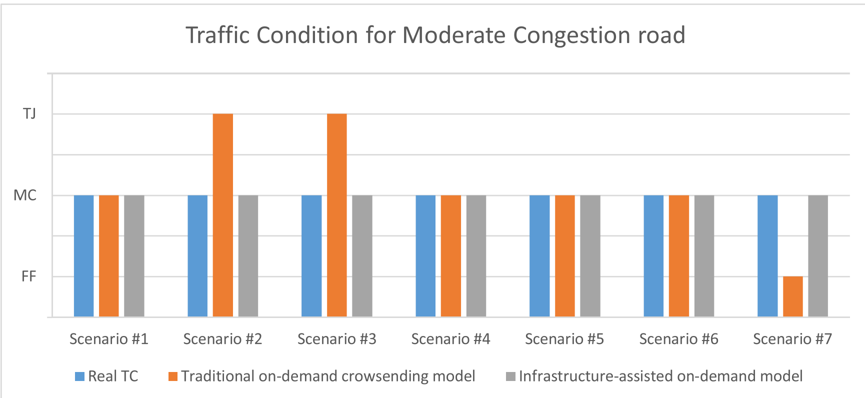

FIGURE 10. Accuracy comparison of the mean speed and the combined classification approaches in MC traffic condition.

estimation, the results show 100% accuracy in all the cases studied.

Finally, by analyzing the results in case of TJ classification, we can find that all the experiments show accurate results since the number of cars on the road is big and the speeds are low along the entire road. In such context, both mean speed and density approaches provide accurate estimations.

2) ACCURACY COMPARISON OF OUR COMBINED CLASSIFICATION APPROACH TO THE TRADITIONAL ON-DEMAND MODEL

We compare in this section the accuracy of our approach to the traditional on-demand crowdsensing model implemented in [41]. The latter estimates the traffic condition by purely relying on mobile devices and without using mobile infrastructures. The proposed approach engages the participating nodes to periodically (every two minutes) share their location, which allows the platform to use their last saved records for the traffic prediction, in addition to a new sensed data requested at the request time of a data consumer. However, since the elapsed time between the last record shared and the request time is enough to change the status of the cars and whether they are still located on the targeted road, the accuracy of the estimation might be affected. Moreover, the traffic condition refers to the mean speed estimation used in equation 9 in terms of km/h. To compare our infrastructure-assisted on-demand approach to the work in [41], we classify the traffic condition as FF, MC, and TJ based on the thresholds of the mean speed in Table 3. The classifications of both approaches are shown in Figures 9 and 10.

Figure 9 illustrates what each of the approaches estimates as traffic condition when studying a FF scenario. In the traditional on-demand approach, 2 out of 7 scenarios were improperly classified while our approach correctly predicts the classifications for all the studied scenarios. In case of MC condition, Figure 10 shows that 3 out of 7 scenarios in the traditional on-demand approach were improperly classified, while our approach classifies the 7 scenarios as MC.

It was noticed that the traditional on-demand approach was incorrectly classifying the traffic condition in some cases due to the following: First, the matching module picks the set of data collectors on the targeted road based on the last location shared with the platform. As the interval of time between receiving a request from a consumer and sharing the last sensed data with the platform before that request could vary between zero and two minutes, some nodes might move into and/or out of the targeted road without being detecting by the platform. This affects the selection of the collectors and

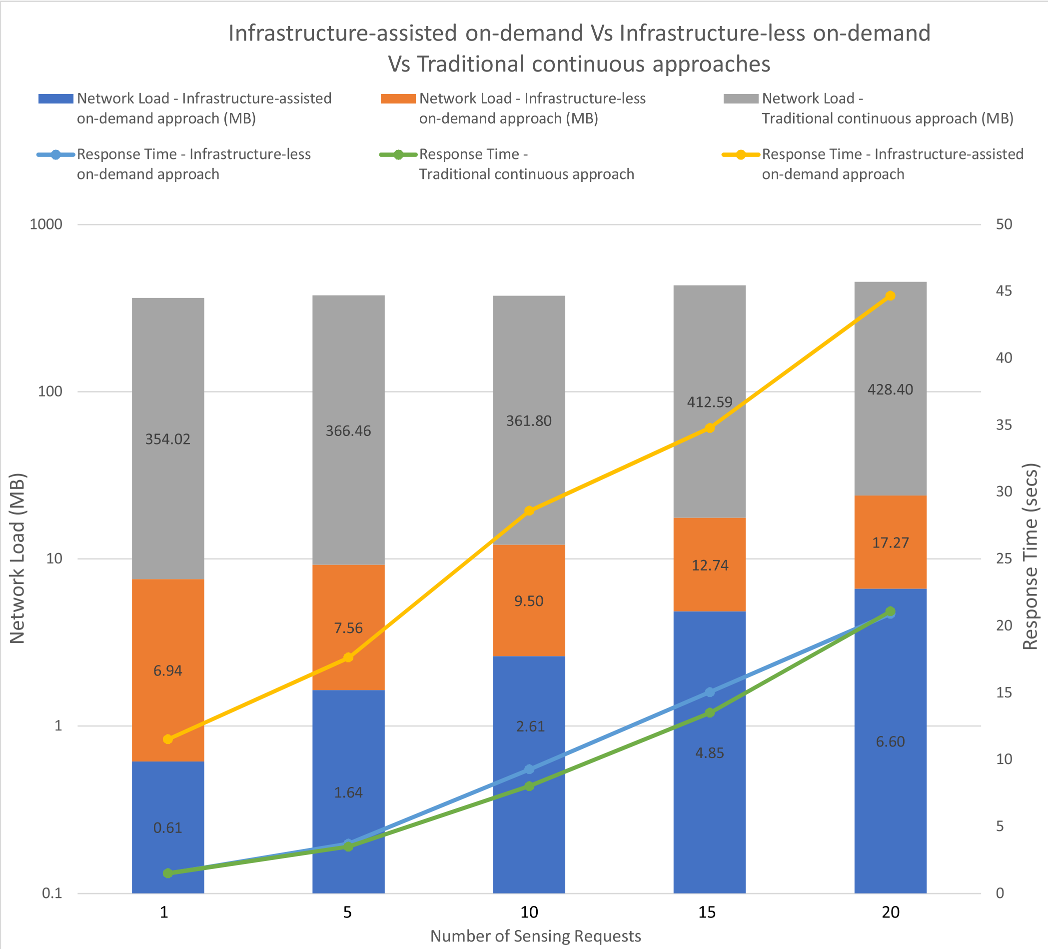

FIGURE 11. Performance comparison of our Infrastructure-assisted on-demand approach to the traditional on-demand and the Traditional continuous approaches.

produces non-accurate mean speed values. Second, only the mean speed metric is taking into consideration in the traditional on-demand approach, which is not enough to reflect the real traffic condition. This was correctly classified in our proposed approach while using two metrics along with a rule-based classification for the traffic prediction.

3) PERFORMANCE COMPARISON OF OUR ON-DEMAND TO THE TRADITIONAL ON-DEMAND AND THE TRADITIONAL CONTINUOUS MODELS

Some load tests in terms of network load and response time have been conducted to evaluate the overall system performance and compare it to the traditional on-demand approach [41] and the traditional continuous one [22], [35]. The latter requires the data collectors to continuously sense data to the server every 2 seconds, while the former requests sensed data from the users every 2 minutes to keep track of their locations. As for our approach, the collectors sense location-based data only on-demand. Figure 11 shows the obtained load testing results during five minutes of simulation, where the network load represents the size of the packets exchanged between the vehicular network platform and the data consumers and collectors, and the response time is the elapsed time between sending a request and receiving its response. Both the system network load and response time are measured when the number of requests simultaneously sent from the consumers varies from 1 to 20 requests. In the simulation area, the micro-cell towers that are adopted in our infrastructure-assisted approach could support up to 200 concurrent active users. We suppose that the 200 users connected to their associated towers are subscribed to our platform, and all of them participate in the sensing activities and publish their sensed data whenever requested. 20 towers are covered in our simulation, which involves 4000 users contacted in case of 20 requests for our approach and the 4000 users continuously publish their sensed data in the other two approaches.

In some scenarios, the targeted roads could be covered by two towers (i.e. road x in Figure 2) or even more. In the conducted experiments, we consider the case where the targeted roads (roads y in Figure 2) are fully located in the coverage area of only one tower.

As shown in Figure 11, the size of the exchanged packets for 1 to 20 sensing requests ranges from 0.61 MB to 6.6, from 6.94 MB to 17.27, and from 354.02 to 428.4 MB in the infrastructure-assisted on-demand, the infrastructure-less on-demand, and the traditional continuous approaches respectively. The network load's growth pattern in the three models can be explained by the fact that the more sensing requests are received, the more data collectors are targeted, which increases the number of messages exchanged through the system. In the other two approaches, the collectors have to sense location-based data and continuously send it to the platform depending on the frequency, which requires significant network load compared to our approach.

Regarding the response time Figure 11, the maximum response time that our infrastructure-assisted on-demand model reaches is 44.68 seconds for 20 sensing requests received by the platform at the same time. However, such big number of sensing requests received simultaneously by the platform is a worst-case scenario. It is worth to mention that when one sensing request is received at a time, which is the typical scenario, the response time is only 11.52 seconds. The response time in the other two models is less, which ranges from almost 1.5 seconds for 1 request to 20 seconds for 20 requests. This difference is caused by the 10 seconds waiting time on the server side to send the second request to the collectors in the infrastructure-assisted on-demand model since the platform has no knowledge about the collectors location as in the infrastructure-less and continuous model. Moreover, whenever the number of requests increases, more data collectors will be contacted by our infrastructure-assisted on-demand approach. This is because all users connected to the cell towers in the studied area will be asked for their locations, whereas in the other two approaches, persistent updates from the consumers are published, which engages contacting only the relevant set of users matching our six criteria. In other words, the messages 2 to 9 exchanged between the components in Figure 6 are required in our infrastructure-assisted model in order to locate the data collectors. This engages more response time than the other two approaches, which do not perform such communication. Hence, we can state that our proposed model outperforms the others in terms the network load yet involves longer response time. However, the difference in time in our approach is somehow negligible compared to the gain achieved in the decrease of the network load and the on-device computation overhead caused by the infrastructure-less on-demand and the traditional continuous approaches.

In the conducted experiments, we consider that each sensing request falls into different towers in the studied area (e.g. in Figure 2, one request for a road covered by cell #3, while another covered by cell #1, and so on). We also consider that these requests are sent in parallel, so the platform will be performing the whole communication and data processing simultaneously. When the number of requests reaches 20, then the platform will be establishing communication with 4000 data collectors at once. Therefore, in a scenario where a new data consumer asks for the traffic condition at a time close to an existing request, messages 2 till 5 in Figure 6 will not be established to process the request. This is explained by the fact that the server has already defined from a previous request the set of collectors in each tower, which requires contacting only 200 nodes out of 4000 for the new request. Thus, the traffic decision will be generated in few milliseconds.

4) MATCHING ALGORITHM PERFORMANCE EVALUATION

We studied in this section the performance of the matching module in our sensing platform while varying the six criteria used (1. User geographic location, 2. User availability, 3. Node battery level, 4. User reputation, 5. Node sensing capability, 6. Node data transfer accuracy). Figures 12 and 13 show respectively the matching error and response time of 2, 3, 4 and 6 selected criteria.

The matching error in Figure 12 is calculated as: [1 - (the number of cars selected by the matching algorithm) / (the actual number of cars found on the targeted road)] * 100. We use the simulation traces of VanetMobiSim visualization to acquire the actual number of cars at the time studying the traffic condition. In these experiments, 50 to 1000 nodes have been processed, and whenever the number increases, more nodes will be on road matching the requirements. For the 6 selection criteria, the matching error is zero for a total number of cars equals to 50 and 100. This error increases slightly until reaching approximately 13% only when 1000 cars are processed. As fewer criteria are considered (4, 3 then 2), an increase in the matching error arises. In case of 2 selected criteria, the matching error starts with 22.79% for 50 processing cars until reaching 30.18% for 1000 cars. Consequently, we can see how the criteria used in the sensing platform affects the vehicles selection algorithm and yields very low matching error when all criteria are considered.

The response time measured in Figure 13 is the elapsed time between the sending point of a request from a data consumer to the vehicular platform (message 1 in Figure 6) and the receiving point of its response (message 15 in Figure 6). It encompasses the following: the execution time of the different platform algorithms, the communication time with the data consumers and collectors, and the 10 seconds waiting time on the server side to send second requests to the targeted collectors for the sake of accomplishing the traffic estimation algorithm. For 50 processed cars, the response time varies between 10.25 secs when 2 criteria are selected and 10.38 secs when 6 are selected. When processing 1000 cars, the response time becomes 10.63 secs for 2 criteria and 10.7 secs for 6 criteria. The response time is slightly affected when varying the number of criteria and therefore using all the criteria implemented by the matching algorithm won't affect the system performance. Hence, it is recommended to increase the number of matching criteria in order to reduce the matching error.

VII. RELATED WORK

Many studies on the traffic data collection have been carried out. The approaches proposed to generate the different traffic

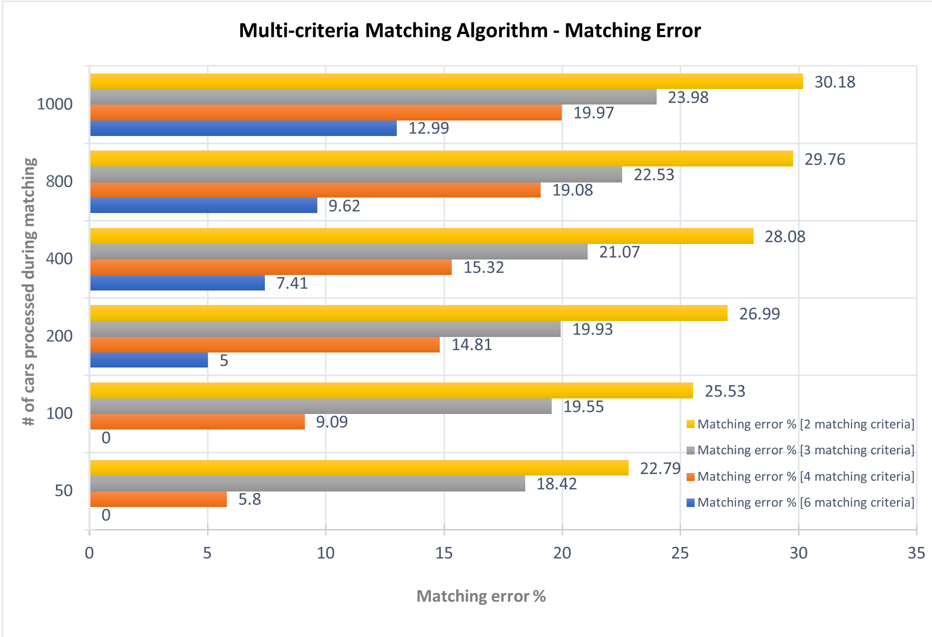

FIGURE 12. Matching error for two/three/four/six criteria in the matching algorithm.

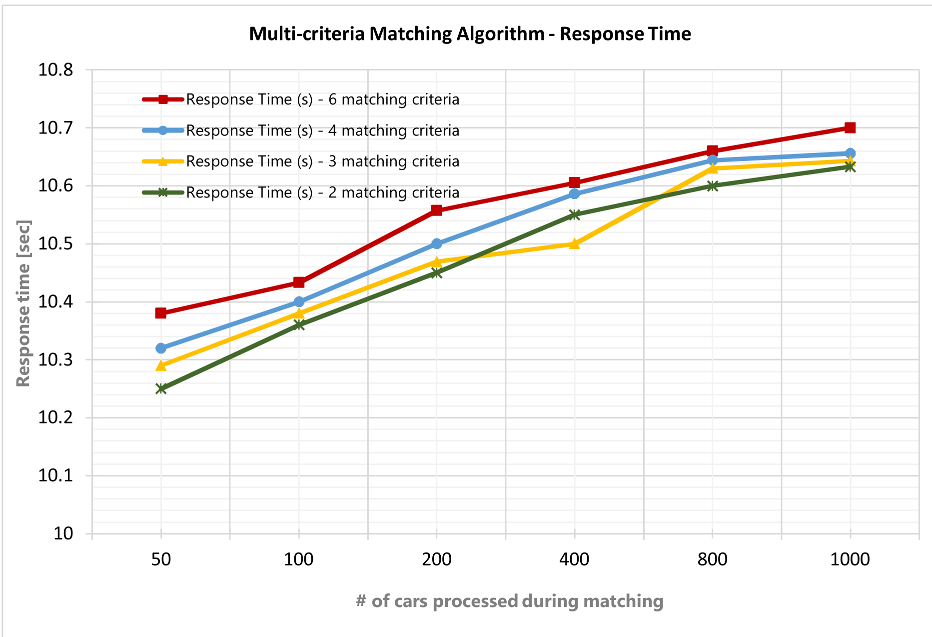

FIGURE 13. Response time for two/three/four/six criteria in the matching algorithm.

conditions are divided into many categories: In section VII-A, we present the approaches where roads are covered by dedicated sensing infrastructure, in addition to the approaches where probe vehicles exist. In section VII-B, we discuss the works in which a group of users having devices equipped with sensors (e.g. GPS readers, mobile phones) collaborate to sense and share relevant data for the estimation of traffic status in an area of interest. In section VII-C, we elaborate the main related approaches focusing on the Mobile Sensing as a service devices. We summarize the related work in section VII-D, where we show the limitations of the existing approaches.

A. TRAFFIC ESTIMATION BASED ON SENSING INFRASTRUCTURE AND PROBE VEHICLES

There exist some traffic estimation approaches designed for roads covered by dedicated sensing infrastructures and others focusing on arterials in which the only available data source is the one coming from probe vehicles. [8], [55] are example of works related to the first category of solutions. Those approaches rely on the availability of abundant data about traffic (collected using the dedicated sensing infrastructures) and use this data to deduce the macroscopic traffic flow state at a fine spatio-temporal scale. [21], [27], [46] are examples of the second category of solutions. Those approaches address the problem of traffic estimation in arterials (the secondary network) and highways not embedded with dedicated sensing infrastructures. In such cases, the data source used is the one sensed form probe vehicles. This type of data poses some challenges due to its lack of ubiquity and reliability, the variety of the data types and specifications, and the randomness of its spatio-temporal coverage. This makes it insufficient to directly deduce the traffic state at a fine spatial-temporal scale. The authors in [46] studied how to analyze the high frequency data gathered (one measurement every 20 sec. or less) to infer traffic state. Other approaches based on optimization [4], regression [33], pattern matching and neural networks algorithms [10] have also been proposed. The authors in [19] propose an approach to analyze probe vehicle data for arterial traffic estimation, by modeling a Coupled Hidden Markov Model to track the traffic states evolution. Although this approach addresses the sparse probe noisy data, it is not appropriate for our on-demand sensing setting. In fact, it relies on the collective state data collected from some of the vehicles in a large geographic area to model the states of the system and predict the travel distribution time on all streets.

B. TRAFFIC ESTIMATION BASED ON SENSOR-ENABLED DEVICES

The traffic condition estimated based on a number of users having sensors-embedded devices can be summarized in the following approaches: The authors in [3] targeted the detection of different traffic statuses, potholes, and abnormalities on roads using GPS and accelerometer. In the proposed approach, five components have been considered: a database, mobile devices, a server with a central database, open wireless networks, and roads map. A heuristic algorithm receives the sensed data to analyze it and estimate the road traffic status. In [20], the authors proposed a solution which mainly focuses on highways for traffic conditions. The model encompasses GPS as a physical component in addition to the following three cyber elements: a mobile network operator, an aggregator for the sensed data, and an algorithm for the traffic prediction. In this approach, mobile phones are used to gather data on specified routes named virtual trip lines. The server receives the data sent, and forwards it to the algorithm for the prediction after being aggregated. The authors in [46] proposed a model to address the energy consumption problem as well as the imprecise position sampling provided. They used Hidden Markov Model (HMM) to identify the traversed route of a car over an area selected from the map, then the traveling time of the targeted roads travesered has been calculated using a map matching. NeriCell solution in [35] has been proposed by focusing on two components: An intelligent system that requires to have on roads some dedicated sensors, and a component encompassing the sensing devices such as GPS, microphone, and accelerometer. NeriCell consists of a system that tracks the roads and uses the cars' acceleration data generated by the phones to predict the traffic. In [18], the authors proposed a spatial and temporal gathering techniques of data. The spatial sampling infers vehicles to share their information such as the velocity and location at some time points no matter where they are located, while the temporal technique infers the vehicles to sense and send their data as they traverse some predefined spatial sampling. In this approach, a rich history of data was formed by collecting from Nokia N95 devices data every 3 seconds with the corresponding instantaneous velocity. The authors in this paper were able to solve the privacy aspect regarding the users' ID. In [17], a peer-to-peer solution for traffic prediction has been proposed. In this solution, vehicles rely on V2V communication to gather from surrounding cars data related to position and velocity. Sparse data is gathered as floating car data snapshots and a density-based model is applied in the traffic prediction algorithm.

C. TRAFFIC ESTIMATION BASED ON SENSING AS A SERVICE

The proposed solutions in [7], [9], [40], [53] were shedding light upon the interest of Mobile Sensing as a Service: In [7], the authors targeted two important aspects. One regarding a very precise extraction of urban traffic, and another about the privacy protection. In this study, a comparison has been made between collecting traffic related information from fixed-sensors and from mobile devices. It was clearly revealed that, due to the significant benefits of data extracted from mobile devices, fixed-sensors are not efficient sensors to be considered. The authors in [53] surveyed different domains for mobile sensing such as environment, health, traffic estimation, social, ecommerce, prediction of human behavior, and many more. The conducted survey differentiates between the participatory and opportunistic urban sensing types. In both approaches, the public, personal, and social components were used in the provided solutions. In [9], Das et al. focused on the community sensing (participatory and opportunistic) instead of solving the traffic estimation problem. The main contributions of this paper are to guarantee (1) generality through the support of a variety of applications, (2) security by keeping the sensitive data extracted from the devices private and not misused by the applications, and (3) scalability by encompassing a big number of devices without needless charges on the infrastructure. To control the roads traffic, the authors in [40] studied how to limit the massive data shared in the Vehicular Sensor Network. This was achieved by determining some time points, in which the data should be communicated. However, the defined timing does not depend on the evolution of the traffic conditions, which requires new traffic related data.

D. ANALYSIS OF THE EXISTING WORK

The existing models are suitable for continuous sensing in which the data is sampled continuously from cars, and are not applicable to the case of fully on-demand sensing which relies on sparse probe data. Furthermore, the real-time nature of on-demand sensing requires a simple and fast solution for the inference of traffic status, rather than a complex statistical approach such as the Hidden Markov Model that some approaches use. In addition, the idea of collective state in a large geographic area that is also adopted is not suitable for the case of on-demand sensing which targets a specific road segment at a time. In this regard and to the best of our knowledge, none of the existing approaches addressed the limitations of the traffic related data collected from either the sensing infrastructures or the continuous sensing, which was achieved in our infrastructure-assisted on demand approach.

VIII. CONCLUSION

In this paper, we addressed the limitations of continuous and infrastructure-less on-demand sensing approaches for ITS by proposing an infrastructure-assisted on-demand vehicular sensing framework with the collaboration of mobile cell towers to minimize the communication with the participants in the sensing activities. Moreover, we elaborated a novel deductive rule-based model for classifying traffic condition while resolving conflicts between mean speed and density estimations. The support of mobile infrastructure helps detecting the users that are located in the consumer area of interest to collect the sensory data required for estimating the traffic condition through the mean speed and density. Thorough experiments were conducted using the simulation traces of VanetMobiSim and the communication between the platform and the users is achieved through RESTful APIs. The obtained results show that the platform successfully responds to all the consumers requests by inferring the right traffic condition varying from free flow to moderate congestion and traffic jam. Moreover, our approach outperforms the current works in the literature that consider only the mean speed in the traffic estimation in case of free flowing and moderate congestion. It is also worth to mention that our approach outperforms the infrastructure-less on-demand and the continuous approaches by showing a significant decrease in the network load and the on-device computation overhead. Finally, the results show that our six selection criteria matching the needed data collectors help reducing the matching error with a negligible increase in the response time.

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