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A Probability-Based Multimetric Routing Protocol for Vehicular Ad Hoc Networks in Urban Scenarios

LETICIA LEMUS CÁRDENAS[1], **AHMAD MOHAMAD MEZHER**[2],
PABLO ANDRÉS BARBECHO BAUTISTA[1], **AND MÓNICA AGUILAR IGARTUA**[1]
[1]Department of Network Engineering. Universitat Politècnica de Catalunya (UPC), 08034 Barcelona, Spain
[2]Electrical and Computer Engineering Department, University of New Brunswick (UNB), Fredericton, NB E3B 5A3, Canada

Corresponding author: Leticia Lemus Cárdenas (leticia.lemus@upc.edu)

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ABSTRACT Vehicular Ad hoc Networks have received considerable attention in recent years and are considered as one of the most promising ad-hoc network technologies for intelligent transport systems. Vehicular Ad hoc Networks have special requirements and unique characteristics (e.g., special mobility patterns, short life links, rapid topology changes) which make the design of suitable routing protocols, a challenge. Consequently, an efficient routing protocol that fits with VANETs' requirements and characteristics is a crucial task to obtain a good performance in terms of average percentage of packet losses and average end-to-end packet delay. To attain this goal, we propose a novel probabilistic multimetric routing protocol (ProMRP) that is specially designed for VANETs. ProMRP estimates the probability for each neighbor of the node currently carrying the packet, to successfully deliver a packet to destination. This probability is computed based on four designed metrics: distance to destination, node's position, available bandwidth and nodes' density. Furthermore, an improved version of ProMRP called EProMRP is also proposed. EProMRP includes an algorithm that accurately estimates the current position of nodes in the moment of sending the packet instead of using the last updated position obtained from the previous beacon message. Simulations are carried out in a realistic urban scenario using OMNeT++/VEINS/SUMO, including real maps from the OpenStreetMaps platform. Simulation results show a better performance of ProMRP and EProMRP compared to recent similar proposals found in the literature in terms of packet losses and end-to-end packet delay, for different vehicles' densities.

INDEX TERMS Probabilistic multimetric routing protocol, realistic urban scenarios, vehicular ad hoc networks.

I. INTRODUCTION

Vehicular Ad hoc Networks (VANETs) are a special type of mobile ad hoc network that enable communication between only vehicles as well as between vehicles and road-side units (RSUs). On the one hand, Vehicle-to-vehicle communications (V2V) allow vehicles to share messages among them using temporary links between vehicles.We are considering that vehicles send traffic reports to the nearest RSU using multi-hop communications. That is, vehicles forward messages hop-by-hop until the message reaches the closest RSU. Vehicles periodically interchange beacons (hello messages) among themselves and also with the infrastructure (i.e., the RSU). The vehicular network topology is organized and managed by the nodes themselves using those beacon messages that are periodically (once a second) interchanged. Using that information, vehicles update their neighbors' tables, which are used to choose the best next forwarding node for the packet. This kind of communication is efficient to provide information services related to road safety. On the other hand, vehicle-to-infrastructure communication (V2I) deals with exchanging information between vehicles

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and the fixed road infrastructure. V2I can provide vehicles with information about traffic conditions or weather forecast, as well as to grant access to Internet services [1]. Moreover, VANET vehicles have also the capacity to communicate with other entities (i.e., pedestrians, wireless devices, the Internet, the smart grid), which is known as vehicle-to-everything communication (V2X) [2]. Initially, the main motivation of VANETs was to provide safety to citizens (both drivers and pedestrians) by quickly sharing warning information about situations such as accidents. Also, VANETs can be used to report the state of the traffic to a traffic management center in the city, seeking to improve mobility in cities [3]. This kind of network has particular features, mainly the potentially high speed of nodes (i.e., vehicles) and the heterogeneous distribution of nodes, being too sparse in some areas or in specific periods. In addition, VANETs must cope with the effects of urban environment, where nodes might find infrastructure obstacles such as traffic lights, buildings or road junctions, which decrease the channel quality and connectivity. All these inherent characteristics cause persistent changes in the network topology. Thus, the design of proper routing protocols for VANETs becomes a challenging goal. Routing on VANETs has to deal with mobility and scalability issues, while also a satisfactory network performance should be provided. In this sense, during the last decade, the research community has been working hard to design routing proposals that can improve QoS parameters over VANETs.

VANET routing protocols can be classified according to specific characteristics, such as (i) topology, (ii) data diffusion, and (iii) nodes' position knowledge [4].

(i) Topology based routing protocols use the link state information available in the nodes to send data from source to destination, making it proactively (each node maintains a neighbors' table that is periodically updated to detect topology changes) or reactively (a route is established on demand).

(ii) Data diffusion is used to disseminate specific information, e.g., warning messages alerting about an accident. The information can be disseminated from a single node to all member nodes (multicast mode) or to all nodes in the network (broadcast mode). Furthermore, other smart dissemination alternatives can be found in the literature [5].

(iii) Position-based routing protocols (also known as geographic routing protocols) consider the physical position of the nodes in the network by using services such as the global position system (GPS) or a beacon interchange process. Geographic routing protocols have shown to be suitable for VANETs since nodes do not maintain end-to-end paths. Thereby, those protocols are robust and flexible to operate in networks where the high nodes' speeds cause constant changes in the network topology [1]. Normally, geographic routing protocols take forwarding decisions based on designed metrics and on a specific forwarding algorithm. This way, nodes forward packets hop-by-hop from source to destination. Distance to destination is the basic metric commonly used, e.g., GPSR which chooses the closest node to destination [6]. Nonetheless, many alternative approaches have been proposed to improve the network performance taking into account other metrics besides distance, such as trajectory, available bandwidth and vehicles' density, among others. Routing information in urban scenarios is more complex than in other environments, since it is necessary to consider multiple factors to evaluate the candidate nodes that could potentially participate in the hop-by-hop forwarding path to destination. Therefore, it seems necessary to design a multi-hop (i.e., able to take local forwarding decisions instead of establishing end-to-end forwarding paths) and multi-metric (i.e., that considers several metrics to take forwarding decisions) routing protocol able to adapt to the dynamic VANET conditions. In this spirit, we focus our work on urban scenarios (see Fig. 1) where the presence of buildings, intersections and traffic lights make communications specially challenging. We define our contribution in two parts:

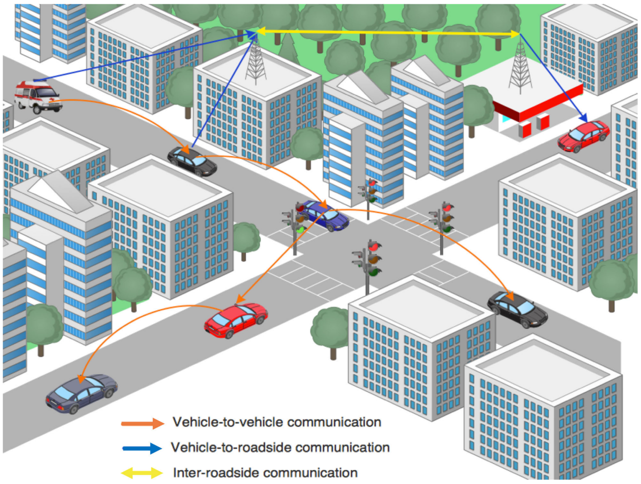

FIGURE 1. Types of VANET communications in urban scenarios.

1) Our forwarding algorithm includes four metrics which are: distance to destination, node's position, available bandwidth and nodes' density. Each metric is modeled with a probability density function based on a large number of representative simulations with a wide variety of configuration parameters. After designing the probabilistic distribution for each metric, we can estimate the probability for each candidate node to successfully forward a message to its destination. Our novel proposal is named probabilistic multimetric routing protocol (ProMRP).
2) Furthermore, we have improved ProMRP with an accurate node's position estimation at the specific moment of forwarding the packet. This way, distances from each candidate node to destination, which are considered by the forwarding algorithm, are estimated with the current accurate positions instead of with those positions taken from the last beacon received. We named this new version as enhanced ProMRP (EProMRP). Our proposal performs this mechanism at each forwarding node in a hop-by-hop scheme until the packet reaches its destination.

The rest of the work is outlined as follows. Section 2 presents relevant related works. Our proposal is explained in Section 3. Simulation results are analysed in Section 4. Finally, Section 5 concludes this article and points out some future work.

II. RELATED WORK

Recent works proved that the most efficient routing protocols for VANETs are those which consider several metrics to take forwarding decisions at intermediate nodes. Our research interest falls within proposals that consider multiple routing metrics to evaluate neighbor nodes and choose the best candidate node to forward packets. Accordingly, we highlight in this section some recent interesting proposals concerning (i) geographic routing protocols, (ii) multimetric routing algorithms, (iii) probability-based estimation measures, and (iv) estimation of the node's position.

(i) One of the first geographical routing protocols designed for VANETs and usually used as a reference, is the greedy perimeter stateless routing (GPSR) [6]. This protocol considers the distance to destination as the only metric to forward packets. However, it includes a perimeter forwarding mode that produces large delays, making this protocol not suitable for urban scenarios where a lot of disruptions take place. For that reason, diverse research works have proposed several enhancements over GPSR in urban scenarios. For instance, Stable Connected dominating set-based Routing Protocol (SCRP) uses the link lifetime between neighbor nodes as main strategy to select the next forwarding node, seeking to decrease the average end-to-end packet delay [7]. Besides, SCRP maintains a routing table on each node to forward packets through a path from source to destination. Finally, SCRP uses nodes located on junction roads as bridges to connect nodes along the forwarding path.

(ii) Among the different proposals of multimetric routing protocols available in the literature, we highlight a few ones that are related to our approach. The main goal of multimetric routing protocols is to consider several metrics to score neighbor nodes. Using that information, nodes decide which one is the best candidate to forward a packet towards its destination, making the routing process more efficient. Max duration-Min angle GPSR (MM-GPSR) proposes two techniques to improve the GPSR forwarding based on the distance metric [8]. For the greedy forwarding mode, MM-GPSR selects all those nodes that have a maximum estimation of the time T that a node will be in a specific communication area Q. In the perimeter forwarding mode, they calculate the angles formed by the neighboring nodes in the communication area Q with respect to the source to destination line. Then, they select the neighbor node with the lowest angle value, which is the closest one to destination. In a similar way, Path Aware GPSR (PA-GPSR) improves GPSR by extending the neighbors table (NT) with two additional tables [9]. These two tables are called Deny Table (DT), which records those nodes that already forwarded the packet; and Recent Send Table (RST), which records not only those nodes that already forwarded the packet but also the mode used for it. Using this extra information provided by the two NT extended tables, the routing protocol is able to manage efficiently the packet forwarding, and to avoid inappropriate routes to destination and packet loops. The proposal presented as Multi-metric Geographic Routing (M-GEDIR) selects one of the neighbors as the next forwarding node based on nodes' position, future position, speed, distance to destination, signal strength and moving direction [10]. In [11], authors propose a multimetric routing protocol considering link lifetime, nodes' density, nodes' mobility and nodes' load (i.e., buffer queue length). They implement a hierarchical mechanism to combine multiple decision criteria such as the relative importance that each metric has with respect to the others. They use a weighted function to assign a weight to each one of the candidate nodes. Finally, the candidate node with the minimum weight is the most favorable to forward the packet. Their results improve the basic distance-based GPSR in terms of delay and packet delivery ratio. Another multimetric proposal which considers a cluster-based forwarding approach using metrics such as throughput, vehicle's speed and available bandwidth, to decide which neighbor node is the best candidate to forward each packet is described in [12]. On the other hand, the multimedia multimetric map-aware routing protocol (3MRP), which is one of the latest efficient proposals is presented in [13]. This approach uses weighted metrics to select the next forwarding node. The metrics considered to score each candidate node are: available bandwidth in the link formed with each neighbor, nodes' density, trajectory, distance to destination and percentage of MAC packet losses.

(iii) Finally, we have identified three studies which show some relation to our probability-based approach, but with essential differences. In [14] authors propose two probability-based predictors to select the best forwarding node among the candidates in the list of neighbors. The first parameter refers to the probability that the signal to interference plus noise ratio (SINR) in a receiver node is larger than the receiving threshold during a period of time. The second parameter defines the probability of packet queue length (PQL) to be smaller than a maximum allowed value after an interval of time. Also, they propose a weighting function to calculate the utility value of each node. This utility consists in using the SINR and PQL variances as weights, and then averaging the total value for each node. Finally, the best candidate node is the one with the largest utility value. The [15] proposal considers two types of probabilities: (a) The forwarding probability measures the probability to access the channel; and (b) the successful forwarding probability, which refers to the probability that a node actually transmits. In the forwarding probability, the source nodes assigns values to its neighbors nodes so that the farthest node (from the source) has the highest forwarding probability. The probability of successful forwarding is the probability of exactly one node (within the transmission range of the source) transmitting at the beginning of an empty slot. In [16] authors propose a method to select relaying vehicles using additional information shared by the nodes in their hello messages. This information includes link quality, link stability and node's direction. Two probabilities are considered: (a) link quality probability and (b) successful packet reception probability. (a) The link quality probability is calculated according to the viability of the link, considering the distance from source to each neighbor in transmission range, a link attenuation factor and the link lifetime. (b) Successful reception probability, or availability of a communication link between two nodes. This probability is computed from the vehicle's speed, distance to destination, packet transmission time and sender's transmission range. Finally, a weighted score is assigned to each candidate node, computed from relative distance, link lifetime, link quality probability and successful packet reception probability.

(iv) Taking the estimation of the node's position into account, VANET routing protocols can take more accurate forwarding decisions when they use metrics based on the node's position. For instance, in [17] authors estimate the future position of a node (after a time interval t) using the current node's location (x, y), the node's velocity (v_x, v_y), and the moving direction of the node θ. Every time a node receives a hello message, it calculates the new position of its neighboring nodes, keeping a list of those nodes that approximate towards destination. In this way, they choose the next-hop forwarding node with the best future position (the shortest distance towards destination). A similar proposal that uses the same parameters to estimate the node's position is explained in [18]. Also, instead of arranging nodes based on their estimated future position, a weight is calculated for every new node's position. Such weight is based on the sum of three factors: P (relative distance to destination), q_1 and q_2 (angles formed with each neighbor and with destination). In the forwarding decision, the neighbor with the highest weight will be the next-hop node. Authors in [19], propose an algorithm to estimate the vehicle's movement in the near future and then selects the best neighbor. First, each node calculates its velocity (V_0) and the heading direction using previous position (x_0, y_0) and current speed at initial moment t_0. After that, the future position of a node is estimated adding the product of velocity and time interval Δt (time between two hello messages) to the current position. Unlike the two previous proposals, this future position is shared into the hello messages. In this way, all network nodes receive and save in their corresponding list the future position of all its neighbors. The next-hop forwarding node will be the one with the shortest estimated distance to destination in the near future. In [20] a system model to organise nodes in transmission zones (clusters) interconnected by headers nodes (HN) is proposed. Authors compare the positions of each intermediate node N_i (Ni_x, Ni_y) and destination node N_d (Nd_x, Nd_y), with their new positions $Pos_t(Ni)$ and $Pos_t(Nd)$ after a time (t). With this strategy, they configure end paths from a source node (S) to final destination node (D) through different zones and intermediate nodes. Again, the parameters used to calculate the node's position are: (x, y) coordinates, movement direction (θ) and velocity (v_x, v_y) in a time interval (t). Network nodes share and update this information via hello messages.

To summarize, in the literature there are several geographic routing protocols proposed for VANETs that consider some additional metrics to evaluate the best node to be selected as next-hop forwarding node. Examples of those metrics are distance to destination, available bandwidth, trajectory, vehicle's speed and nodes' density. Nonetheless, none of those proposals evaluates the probability that candidate nodes successfully deliver packets at destination as a function of the metrics' values.

In this work, we propose a novel probabilistic routing protocol named probabilistic multimetric routing protocol (ProMRP) based on a probability-based forwarding algorithm to choose the best next forwarding node among the neighboring candidates of the node currently carrying the packet. We focus our analysis on a realistic urban scenario using real maps. To the best of our knowledge, there is no proposal yet about a multimetric routing protocol for VANETs that bases its forwarding decision on the successful delivery probability of the packet at destination. Besides, our proposal includes an estimation of future position of the nodes to further improve the forwarding decision. Finally, we have compared our work with the well-known GPSR and also with one of the most recent proposed routing protocol for VANETs named 3MRP [13].

III. PROPOSED WORK

In this section we describe our proposal of a probabilistic forwarding routing algorithm for VANETs. This algorithm evaluates all candidate nodes and chooses the best candidate to forward the current packet. The selection is done based on the estimation of the probability of successful packet delivery at destination.

A. MOTIVATION

After analyzing several proposals described in section II, we observed that most of those that show a good performance in terms of packet losses and delay use several metrics to select intermediate nodes to forward packets, instead of just using the basic metric of the distance to destination. Certainly, it is crucial to consider several metrics in the packet forwarding to be able to address properly the special characteristics of VANETs.

Nevertheless, as far as we know none of the proposals consider the probability of packet successfully delivered as a metric in the forwarding algorithm. In this work we have designed a probabilistic multimetric forwarding algorithm using several metrics to take forwarding decisions. Our proposals outperform other routing protocols in terms of average percentage of packet losses and average end-to-end packet delay. We have compared our proposals to the well-known GPSR [6] routing protocol as reference, and to a recent proposal called 3MRP [13].

We claim that the sequence of events that represent the packet receptions in a hop-by-hop scheme in VANETs, can be represented as a probability distribution. This probability distribution describes the path that each packet will follow from source to destination. This way, the best next forwarding node to forward a packet will be chosen hop-by-hop towards destination. First, we have carried out an off-line analysis over a representative data set taken from a large number of simulations under different representative scenarios. Then, the probability distribution of packet successfully delivered is obtained. Afterwards, we have implemented our probability-based routing proposal and, as section IV depicts, the performance evaluation shows good results that outperform other proposals described in the literature [6], [13].

B. MODELING THE PROBABILISTIC DISTRIBUTION OF METRICS

The strategy employed by our algorithm is based on the probability distribution of the considered metrics. This requires a previous data organization and analysis to identify the categorical variables; that is, which variables have an impact on the subject of study.

Our aim is to find out the probability that a candidate forwarding node has to successfully deliver the packet to its destination given some environmental parameters. The parameters that we have considered are: percentage of time the channel is idle (used to estimate the amount of available bandwidth); nodes' density; and distance to destination.

In order to provide a general description of our approach we will use an example, depicted in Fig. 2. Let us consider an output variable named Y which can take two values (0, 1) representing the occurrence of an event. In other words, the event is referred to whether a node will successfully deliver a message or not. Also, let us consider an input variable M with different environmental metric values that will influence in Y [21].

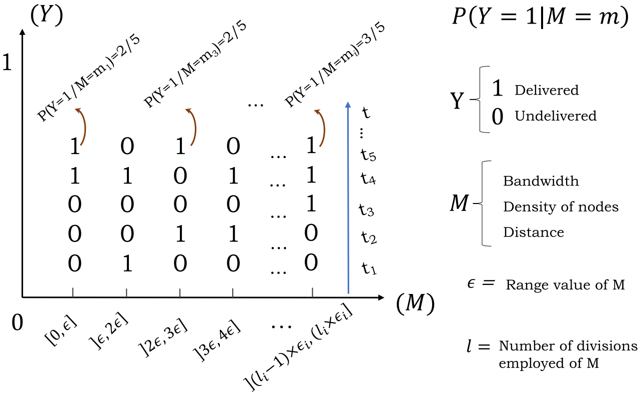

FIGURE 2. Estimation of the probability to successfully deliver a packet at destination given that the considered metric M equals m_i.

Fig. 2 shows a theoretical representation of an output sequence of random events throughout time. Let us suppose that we have n values of a metric M (e.g., distance to destination, available bandwidth, density of nodes) over time t. Then, we estimate the probability $P(Y = 1|M = m_i)$ of a candidate node to successfully deliver the packet to its destination $(Y = 1)$ given a specific value m_i of the considered metric M at a given time t_j, where $1 \leq i \leq n$ and $1 \leq j \leq t$. Notice that it is quite hard that two or more values for the same metric at different time slot match. For the sake of simplicity, we divided the whole set of possible values for each specific metric into ranges in the form of $[0, \epsilon_i]$, $]\epsilon_i, 2\epsilon_i]$ until $](l_i-1)\times\epsilon_i, l_i\times\epsilon_i]$ where ϵ_i is previously defined and l_i is the number of divisions employed between the minimum and the maximum value for each metric which is equal to $max(M)/\epsilon_i$. For instance, as the nominal bandwidth is 6Mbps, this means that the possible values of bandwidth for any node will be between 0 and 6 Mbps. So, having $\epsilon = 0.2$ means that the number of divisions will be 30 and the equal ranges will be as follows $[0, 0.2]$, $]0.2, 0.4]$ until $]5.8, 6]$. Let us suppose that within the range of $[0, 0.2]$, our dataset has three values equal to 0.1 Mbps, 0.12 Mbps, 0.05 Mbps, with corresponding output Y values equal to 0, 1, 0, respectively. Thus, we can conclude that if we have any input value of bandwidth for a candidate node in the range of [0 0.2], the probability that this candidate node successfully delivers the packet to its destination will be 1/3.

In Fig. 2, when the analyzed metric M takes the value m_1 between zero and $\epsilon = 0.2$ two packets (out of five) where successfully delivered. Therefore, the probability to successfully deliver a packet at destination given a specific value between zero and 0.2 $P(Y = 1|M = m_1) = 2/5$.

In this work we take three metrics into account to estimate (for each candidate forwarding node) the probability of successfully deliver a packet at destination. The node with the highest probability will be chosen as next forwarding node. This process is repeated hop-by-hop till the packet reaches its destination. In this way, the selection of the successive forwarding nodes is made adapting to the current network conditions.

C. PROTOCOL IMPLEMENTATION

To analyse the behavior of the different metrics considered in this work, a previous offline study over a real data set was done. We carried out a large number of representative simulations to prepare a data set. The goal was to derive the probability density function (PDF) for each one of this metrics: distance to destination, nodes' density and available bandwidth. To obtain our data set, we have considered an urban scenario where vehicles move with speeds in the range from 30 to 50 km/h. We have also considered different vehicles' densities and different types of streets.

Once the statistical model to represent each metric was obtained, we included those models in the forwarding algorithm of our proposed routing protocol. This way, vehicles can take their forwarding decisions according to estimations of the probability to deliver the packet to destination. The modeling of the PDF for each metric is described below. Notations are introduced in Table 1.

1) EXPONENTIAL DISTRIBUTION TO MODEL THE DISTANCE METRIC

We have analyzed the probability to successfully deliver a packet at destination for each possible next-hop forwarding

TABLE 1. List of variables used in the system.

Parameter	Definition
N_{gh}	Neighbor node
D	Destination
$d(N_{gh}, D)$	Distance between a candidate N_{gh} and D
P_{dst}	Probability of packet successfully delivered at D for a given distance d
$BW_{N_{gh}}$	Available bandwidth BW in the link formed with N_{gh}
P_{BW}	Probability estimation of packet successfully delivered at the next-hop given BW
$NV_{N_{gh}}$	Vehicles' density of the candidate N_{gh}
P_{dns}	Probability of packet successfully delivered at D given $NV_{N_{gh}}$
$\overline{P}_{N_{gh}}$	Score value of each candidate node N_{gh}
T_b	Beacon period

node. This probability is obtained as a function of the distance from that node to destination. We claim that knowing in advance this probability can help to take better forwarding decisions.

We have obtained a data set for the probability (Y) of packet successfully delivered at destination for a given distance ($d(N_{gh}, D)$) (d in short) from the candidate node to destination. This data set was generated from many simulations with different vehicles' speeds (30, 60, 80 and 100 km/h). To have a wide range of distances in our urban scenarios, we set either highway-like roads, normal roads, and narrow streets.

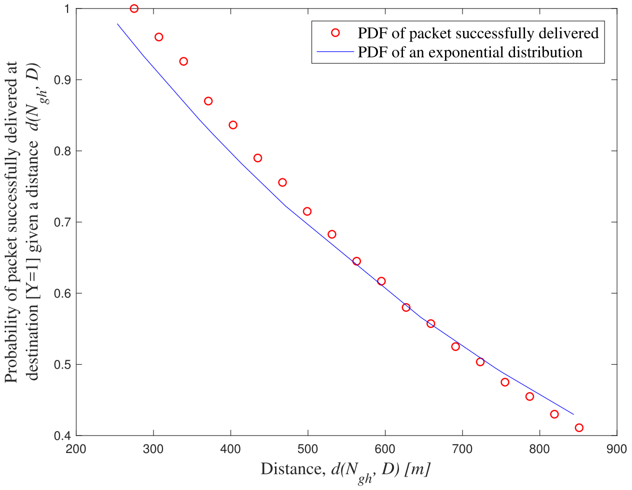

FIGURE 3. Probability density function (PDF) of the success in the packet delivery at destination, as a function of the distance $d(N_{gh}, D)$ between candidate node N_{gh} and destination D (red values taken from the data set). It fits well with the PDF of an exponential distribution (blue line).

We have organized the data set results in a graph, see Figure 3. In this figure, we show the PDF of the success in the packet delivery at destination, as a function of the distance between the candidate node and destination. The values taken from the data set (red line) are organized from the minimum distance (between a candidate node and destination) to the maximum one present in the data set. We can see that the PDF of packet successfully delivered (red line) fits well with an exponential distribution function expressed in Eq. (1) (see blue line). We have considered a sequence of random distances in the range from 200 to 850 meters, which are the minimum and maximum distance values obtained in the simulations. Notice that the probability to deliver a packet at destination tends to zero as the distance between a candidate node and destination grows.

$P(Y = 1 \mid d)$ (P_{dst} in short) is the probability estimation of packet successfully delivered at destination, for a distance d between candidate node N_{gh} and destination D. Let λ be the parameter of the exponential distribution function.

$$P(Y = 1 \mid d) = \lambda \cdot e^{-\lambda \cdot \frac{1}{d}}, \quad 0 \leq d < \infty \qquad (1)$$

Using the *fitdist* function [22] to adjust the values in our data set with Eq. (1), we got that the exponential distribution parameter λ equals $1.39 \cdot 10^{-3}$.

Once the neighbors' distances to destination d are obtained, the probability of succeed in the packet delivery at destination as a function of that distance d from each candidate neighbor N_{gh} to destination D, is calculated using Eq. (1).

2) NORMAL OR GAUSSIAN DISTRIBUTION TO MODEL THE NODES' DENSITY METRIC

We generated another data set to analyse the effect of the neighbors' density in the PDF of the success in the packet delivery at destination. This data set was generated from a large number of simulations with different nodes' densities (50, 100, 150, 200, 250 and 300 vehicles/km^2) in an urban scenario. Following the same methodology as in the previous section, we represent the PDF of the packet successfully delivered from the values taken from the data set, as a function of the nodes' density, see the red points in Fig. 4. We can see that those points adjust very well with a normal distribution, see the blue line in Fig. 4.

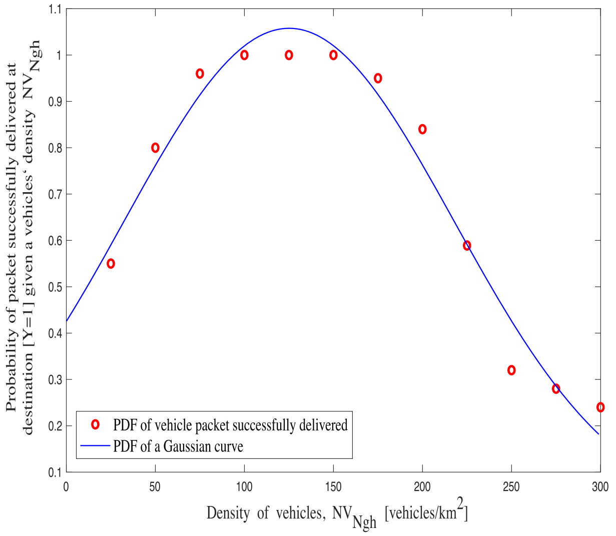

FIGURE 4. Probability density function (PDF) of the success in the packet delivery at destination (red values, taken from the data set), as a function of the vehicles' density of the candidates to forward the packet. It suits very well with the PDF of a normal distribution (blue line).

Accordingly, we obtained the parameters of a Gaussian curve $N(\mu, \sigma) = (175, 93)$ to fit with the data set values. The Gaussian curve (blue line) and the data set simulation values (red points), are shown in Fig. 4. Notice that the probability to deliver a packet at destination grows with the vehicles' density of the candidate nodes, since a higher network connectivity is preferred to success in forwarding the packet towards destination. This is true until a threshold (around 120 vehicles/km^2) in Fig. 4 upon which the number of collisions grows so much that hinders the forwarding of the packet.

$P(Y = 1 \mid NV_{N_{gh}})$ (P_{dns} in short) is the probability that the packet arrives at destination by choosing a next-hop candidate N_{gh} given a vehicles' density that equals $NV_{N_{gh}}$.

$$P(Y = 1 \mid NV_{N_{gh}}) = \frac{1}{\sigma \cdot \sqrt{2\pi}} \cdot e^{-\frac{(NV_{N_{gh}} - \mu)^2}{2 \cdot \sigma^2}} \qquad (2)$$
$$0 \leq NV_{N_{gh}} < \infty$$

Finally, the PDF of the packet successfully delivered at destination, as a function of the vehicles' density can be described using Eq. (2).

3) MULTINOMIAL LOGISTIC REGRESSION TO MODEL THE AVAILABLE BANDWIDTH METRIC

In this section we assess the PDF of the success in the one-hop packet delivery at the next-hop forwarding node, as a function of the available bandwidth in the link formed by the node currently carrying the packet and each candidate neighbor to be next forwarding node. Ad-hoc networks typically rely on hop-by-hop forwarding, where nodes use only local information to take forwarding decisions until the message reaches its destination. This strategy is simple and scalable. Besides, results are good enough while keeping a good trade-off among quality, overhead and simplicity [23].

Let us consider all those available bandwidth (BW) values that produce an output Y = 1 (delivered) or 0 (not delivered), according to the general scheme shown in Fig. 2. Results are represented in the red circles of Fig. 5. We can see that the results follow a distribution that fits with a logistic regression (LR), which can be described using Eq. (3). Once we observed this behavior, we applied a multinomial regression to find the coefficient estimates β_i. We found the categorical variable equal $\beta_0 = 0$ and $\beta_1 = -8.6707$. Adapting the LR model equation, we obtain:

$$P(Y = 1 \mid BW_{N_{gh}}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot BW_{N_{gh}})}} \qquad (3)$$
$$0 \leq BW_{N_{gh}} < \infty$$

$P(Y = 1 \mid BW_{N_{gh}})$ (P_{BW} in short) is the probability estimation of packet successfully delivered at the next-hop node given an available bandwidth BW in the link formed with neighbor node N_{gh}.

We plot the LR model and the data set results into the range of bandwidth values taken from simulations (0 to $6 \cdot 10^6$ bits/sec). In Fig. 5 we observe that the values taken from the data set simulation (red circles) fit well with the LR distribution model (blue line). Notice that the probability to deliver a packet at the next hop remains null until a threshold upon which the packet is successfully forwarded to the next hop.

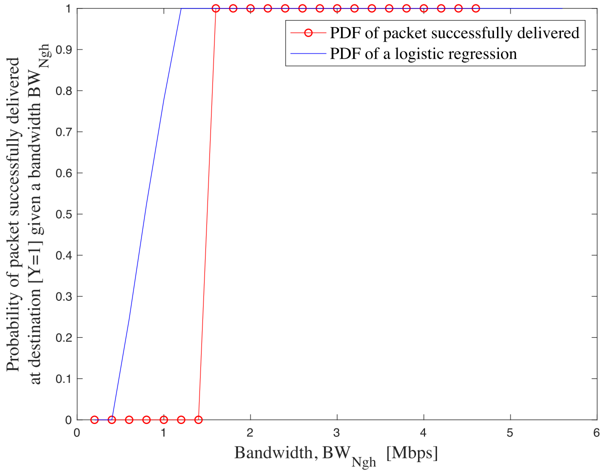

FIGURE 5. Probability density function (PDF) of the success in the packet delivery at the next-hop node, as a function of the available bandwidth in the link between the node currently carrying the packet and each candidate node to be next hop. Red circle values obtained from the data set. Blue line values obtained from the multinomial logistic regression (see Eq. (3)).

To estimate the available bandwidth in a link formed by two nodes, each node can measure its percentage of idle time in that link by sensing the common wireless medium. Each node includes this value in the next beacon message. We apply the available bandwidth estimator (ABE) according to [24]. Each node can estimate the bandwidth in the link formed with each one of its neighbors' upon the reception of their beacon messages (BMs). Finally, using Eq. (3) we can estimate the probability of packet delivery at the next-hop node as a function of the available bandwidth in the link formed by the node currently carrying the packet and each candidate node N_{gh}.

D. PROBABILITY FORWARDING DECISION

Each vehicle currently carrying a packet, will select a next-hop neighbor node to forward that packet towards its destination. To do so, nodes will use the three probability values described in the previous section.

Fig. 6 shows the three probability values (P_{dst}, P_{dns}, P_{BW}) calculated with Eqs. (1), (2) and (3), respectively. Those values are computed at each neighbor N_{gh} within the vehicle's transmission range. In this example, the destination is an access point (AP) used to communicate with the city's infrastructure.

The probability-based forwarding decision is taken hop-by-hop based on the neighbors' table information. Vehicles follow our routing algorithm to choose the optimal next forwarding node. In the example depicted in Fig. 6, we can see a sender node S that receives beacon messages from its neighbors in transmission range, (C_1, C_2 and C_3). Node S updates the table with the information received from its neighbor

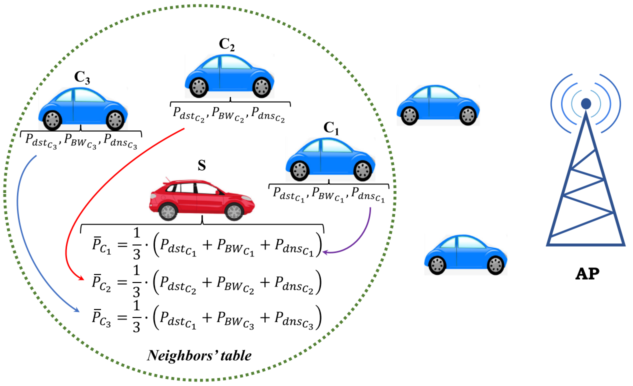

FIGURE 6. Updating the neighbors' list for vehicle *S*. An access point (AP) is the destination node of the packets.

nodes. After that, the sender node evaluates its neighbor nodes and calculates the probabilities of successfully deliver the packet at destination through each one of the available candidates.

First, the node currently carrying the packet (sender or intermediate forwarding node) calculates the probability of success in the delivery of the packet at destination, by applying Eqs. (1) and (2); and the probability of success in the delivery of the packet to the next-hop node using Eq. (3). Second, we apply an arithmetic mean on the three probabilities obtained in the previous step as follows:

$$\overline{P}_{N_{gh}} = \frac{1}{3} \cdot \sum_{i=0}^{3} P_i = \frac{1}{3} \cdot (P_{dst_i} + P_{BW_i} + P_{dns_i}) \tag{4}$$

Finally, the score value $\overline{P}_{N_{gh}}$ for each candidate node N_{gh} is obtained using Eq. (4) and the node with the highest score will be chosen to forward the packet.

1) UPDATING THE NEIGHBORS' TABLE

Each node updates its neighbors' table every time a beacon message (BM) is received. The sending period of BMs is set to be one second. The neighbors' table is sorted according to the probability score $\overline{P}_{N_{gh}}$. To update the neighbors' table, we follow the process described in algorithm 1. Then, nodes are arranged according to the probability-based score value described in algorithm 2.

When a source node S needs to send a message to the AP (e.g., a warning message concerning an accident), it will first check in its neighbors' table if the destination node (i.e., the AP) was previously registered in the last beacon reception. If positive, the message will be sent to destination ID. Otherwise, the neighbor node with the highest probability to success in the packet delivery will be chosen. This process will be repeated hop-by-hop until the packet reaches its destination.

E. ACCURATE ESTIMATION OF THE CURRENT NODE'S POSITION

Estimating the nodes' position is a strategy included in routing algorithms as a key parameter to improve the selection of forwarding nodes, looking to deliver the packet to destination.

Algorithm 1 Updating the neighbors' table

```
Require: A New Beacon Message Received With
         Parameters: ID of the $N_{gh}$, Location $(x, y)$
Start: $i = 1$
while $i <=$ # list of neighbors do
    review the neighbor Id;
    if neighbor (ID) is in the neighbors' list then
        Update the information;
    else
        Add the neighbor in the neighbors' list;
    end
    $i{+}{+}$;
end
```

Algorithm 2 Sorting the Neighbors' List According to the Probability-Based Score

```
Require: A new beacon message received with these
         parameters: ID of the $N_{gh}$, location $(x, y)$,
         $BW_{Ngh}$ and $NV_{N_{gh}}$
Start: $i = 1$ $curr = head$ # initial position
while $i <=$ # list of neighbors do
    $tmp = curr$;
    $curr = curr \rightarrow next$;
    read current;
    if $(curr! = NULL)$ then
        Calculate: $curr(Probability_{metric})$;
        $tmp(Probability_{metric})$; Score1 = mean
        $(curr(Probability))$; Score2 = mean
        $(tmp(Probability))$;
        if $(Score1 > Score2)$ then
            $head = tmp$;
            $tmp = curr$;
            $curr = head$;
        end;
    end;
    $i{+}{+}$;
end;
```

In that sense, there is already a work where related works were identified and a comparison was made with some of these to see if the new proposal improves the performance of the routing protocol [25]. In this section we describe an improvement to accurately estimate the position of nodes at the precise moment of sending a message in a VANET.

Routing protocols, such as the ones described in Section II, use information exchanged by nodes through the beacon process. This information will be used to take forwarding decisions. Specifically, nodes can calculate or estimate the positions of the neighboring nodes. Nevertheless, nodes only update their neighbors' table upon the reception of a beacon message. This means that this information used to take the forwarding decision to send the current packet corresponds to the moment when the last beacon message was received, which might lead not to take the best forwarding decision. This is the key point of our algorithms that make it different than other previous proposals. Besides, we attain better results at the cost of insignificant computational cost.

Let us consider a moment $t_1 + \Delta t$ when a source node S needs to send a message. Let us assume that the last BM was received at moment t_1. The S node will look for the packet's destination in its neighbors' list. If the destination is not in the neighborhood, S looks for a proper neighboring node to forward the message. Considering a beacon period $T_b = t_2 - t_1$ (set to one second in our simulations), let Δt *be* $0 \leq \Delta t \leq T_b$, as it is shown in Fig. 7.

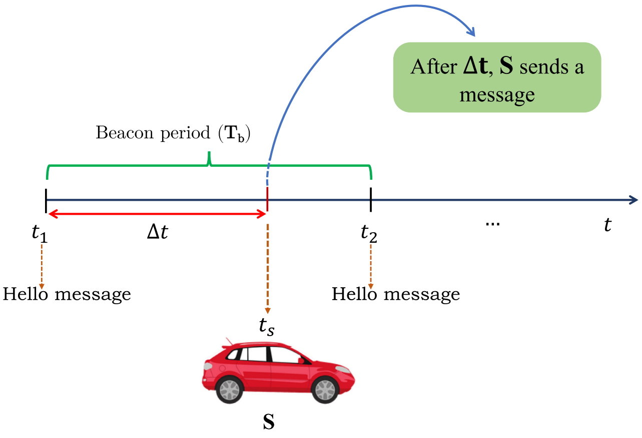

FIGURE 7. Time line representation of the beacon interval $T_b = (t_2 - t_1)$ and the event of sending the message at moment $t_s = t_1 + \Delta t$.

The information concerning the positions for each candidate node is taken from the last beacon received from each candidate node at moment t_1. This information will not be updated until the reception of the next beacon message at time t_2. Hence, the current node uses the previous known position information of each candidate node at time t_1 to select the next forwarding node to which it will send the message at moment $t_s = t_1 + \Delta t$. We claim that it is possible to accurately estimate the real position of the candidate nodes at moment t_s (current forwarding moment). The goal is to potentially select a better candidate node. We have included this new feature in our proposal ProMRP, resulting in a new improved version named enhanced ProMRP (EProMRP).

It is well-known that in the Euclidean space $\mathbb{R}^2$, the distance d between two points (x_1, y_1) and (x_2, y_2) is given by:

$$d = \left(\sum_{i=1}^{2} |(x_i - y_i)|^2 \right)^{\frac{1}{2}} \tag{5}$$

Let us suppose a sender node S located at position $(0, 0)$ needs to send a packet at moment $t_s = t_1 + \Delta t = t_1 + 0.7s$ to an access point A located at position $(1000, 1000)$. Let us consider that S has two candidate nodes C_1 and C_2 to forward the packet. Let us assume that the last beacon messages from both candidate nodes C_1 and C_2 were received by S in a certain moment within the last beacon period at moment t_1 $=1$ s. Then, at moment t_1 our proposal ProMRP would compute the probabilities $P_{(A-C_1)}$ and $P_{(A-C_2)}$ for distance metric of successful delivery the packet at destination using Eq. (1). In this equation, the distances between each candidate node and the access point A are computed using the nodes' positions (x_1, y_1) and (x_2, y_2) reported in their last beacon messages, as shown in Table 2. In this example $P_{(A-C_2)} > P_{(A-C_1)}$, so ProMRP chooses C_2 as the next forwarding node to send the packet at moment $t_s = 1.7$ s (see Fig. 8 (a)).

TABLE 2. Parameters of two candidate nodes reported in their last beacon messages.

Candidate node	x (m)	y (m)	v_x (m/s)	v_y (m/s)
C_1	x_1=500	y_1=500	v_{x_1}=20	v_{y_1}=20
C_2	x_2=510	y_2=510	v_{x_2}=2	v_{y_2}=20

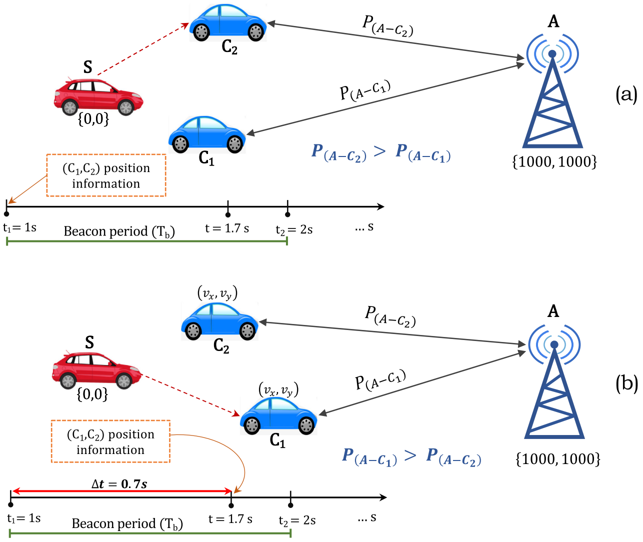

FIGURE 8. Selection of a candidate node according to (a) ProMRP or (b) EProMRP.

Nevertheless, if we take into account the v_x and v_y speeds of each one of the candidates to more accurately estimate their current positions at the exact forwarding moment ($t = 1.7$ s) when the packet is intended to be sent, we would be able to take a better forwarding decision. Probabilities $P_{(A-C_1)}$ and $P_{(A-C_2)}$ of packet successfully delivered at destination as a function of the distances till destination, will be thus computed using Eq. (1) by applying the estimated current positions of C_1 and C_2. Those actual estimated positions will be used instead of the last reported ones via beacon messages (see Table 2). Notice that the reported positions could be far from the current estimated positions at the sending moment $t_1 + 0.7s$. Thus, the reported positions could lead to a wrong selection for the best forwarding node. According to the example depicted in Fig. 8 (b), EProMRP would detect that at t $=$ 1.7 s, $P_{(A-C_1)} > P_{(A-C_2)}$. Therefore, C_1 would be selected as the best forwarding node instead of C_2.

Notice that at time $t_1 + \Delta t$, P_{dns} and P_{BW} remain with the same previous value for both C_1 and C_2 candidates. Therefore, the only term that changes is the one based on the distance (P_{dst}) by using the estimated current positions in Eq. (1). Hence, the final probability score ($\overline{P}_{N_{gh}}$) in Eq. (4) will be different from the previous one obtained using the last beacon received at t_1.

The benefits of our EProMRP proposal have the cost of a slight additional overhead. To perform the EProMRP operation, we need to add two more fields in the beacon message to allocate the speed's coordinates (v_x, v_y) of the forwarding candidate (see Table 2), together with the node's position (x_1, x_2) computed in the last BM sent. This way, the source node S will be able to accurately estimate the current candidates' positions in the forwarding decision moment, see Fig. 8 (b).

For high mobility scenarios, an estimation on the current position will improve the performance of any routing protocol in which its decision to choose the best forwarding node depends completely or partially on the distance to destination metric [6], [24]. When node S needs to forward a packet, it must estimate the current position of the forwarding candidate nodes according to the equations described below, expressed for candidate node C_1 in Fig. 8:

$$x_{est_1}(\Delta t) = x_1 + v_{x_1} \cdot \Delta t, \quad 0 < \Delta t < T_b \tag{6}$$

$$y_{est_1}(\Delta t) = y_1 + v_{y_1} \cdot \Delta t, \quad 0 < \Delta t < T_b \tag{7}$$

where (x_{est_1}, y_{est_1}) is the estimation of the current position of candidate node C_1 at the sending moment used by the node currently carrying the packet (node S in Fig. 8). The node's speed is represented by (v_{x_1}, v_{y_1}); Δt refers to the interval time elapsed since the last beacon from that candidate node was received; T_b is the beacon period.

To select the next forwarding node for a packet, our algorithm arranges the neighboring vehicles of the node currently carrying the packet in a list, according to the score value $\overline{P}_{N_{gh}}$ for each candidate node N_{gh} obtained with Eq. (4). In that equation, our proposal EProMRP outperforms the computation of the term P_{dst}, i.e. the probability of successful delivery at destination as a function of the distance, for each candidate node. Those probabilities are computed with the estimated current positions of each candidate node.

The estimation of the node's position will be activated at the moment when a node needs to send or forward a warning message (see Algorithm 2). Each current distance position of the neighbor list is estimated and added to the distance probability computation. Now, the distance probability values of the nodes correspond to their updated positions. Therefore, the probability score could be more precise.

As it is shown in Fig. 9, every time a message is sent (or forwarded), the node's position estimation will be done in those nodes that hop-by-hop forward the packet through the network until reaching destination. Thus, with EProMRP, all forwarding decisions are taken with a more accurate estimation of current neighbors' positions in the forwarding decision moment (see Fig. 7).

IV. SIMULATION RESULTS

In this section, we describe the simulation scenario and discuss the results. Table 3 describes the main simulation settings of the urban scenario considered. All figures show confidence intervals (CI) of 95% obtained from five simulation per point, with each simulation having an independent mobility scenario. Simulations were conducted over VEINS [26], an open source inter-vehicular communication simulation framework, together with an event-based network simulator (OMNeT++) [27] and a road traffic simulator (SUMO) [28]. We implemented 3MRP [13] and GPSR [6] routing protocols for VANETs in the VEINS framework, in order to compare their performance with our proposals ProMRP and EProMRP. To carry out the simulations in a realistic scenario, we used a real city area obtained from the Eixample/Gracia districts of Barcelona and we imported the real map from the OpenStreetMap [29] platform.

We analyzed the performance of our probability-based routing protocols compared to 3MRP and GPSR. The

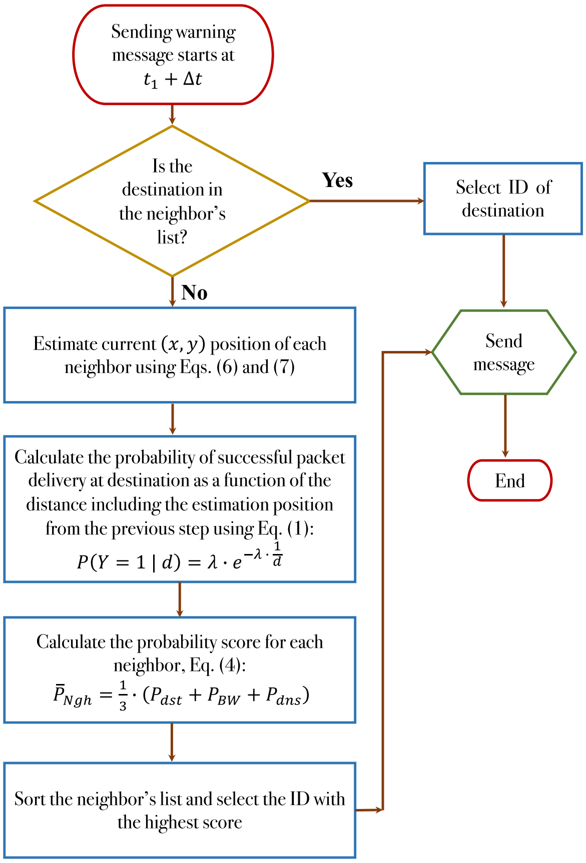

FIGURE 9. Flow chart that shows the node selection sequence at moment $t_1 + \Delta t$.

TABLE 3. Simulation settings of the VANET scenario.

Map Zone	Eixample/Gracia Distric of Barcelona
Area	2300 m x 2100 m
Density of vehicles	50 and 100 vehicles/km^2
Transmission range	340 m
Mobility generator	SUMO v.25 [28]
MAC specification	IEEE 802.11p
Nominal bandwidth	6 Mbps
Source bit rate	CBR (2 pkts/s)
Beacon interval	1 s
Simulation time	100 s
Routing protocols	GPSR [6], 3MRP [13], ProMRP, EProMRP
Vehicles' speed	20 km/h to 50 km/h
Metrics	distance to destination, vehicles' density and bandwidth
Simulation tool	VEINS [26] / OMNeT++ [27]

simulation area was 2300 × 2100 m. We have considered two vehicles' densities of 50 and 100 vehicles/km^2 with vehicles randomly positioned in the map. The vehicles' speeds are between 20 km/h and 50 km/h. Vehicles send packets to a fixed destination (an access point, AP), through which vehicles are able to report traffic information. Messages are forwarded using vehicle-to-vehicle communications in a multi-hop way until the message reaches the infrastructure (i.e. the AP). In our particular case we consider a warning message alerting on the existence of a traffic accident. We assume a crashed source vehicle (its sensors detected the accident) that sends a warning message concerning the accident in the scenario (see Fig. 10).

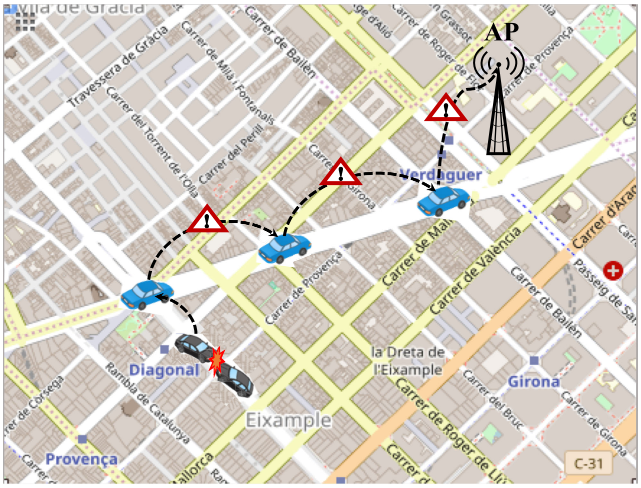

FIGURE 10. **Simulation scenario of Barcelona. It includes an access point (AP) located in a principal avenue of the city, Av. Diagonal. Eixample/Gracia district map of Barcelona imported from the OpenStreetMap [29].**

A. AVERAGE PACKET LOSSES

Fig. 11 shows the average packet losses for our proposals ProMRP and EProMRP compared to GPSR and 3MRP, for different vehicles' densities. When the vehicles' density is low, their distribution is sparse and finding next forwarding nodes is not an easy task. For the higher considered vehicles' density (100 vehicles/km^2), the average packet losses decreases, since network connectivity improves compared to the sparser case (50 vehicles/km^2). This is true upon a maximum vehicles' density above which collisions increase overmuch and affect the packet transmission process. This threshold is around 120 vehicles/km^2 as it was shown in Fig. 4. We can see that the worst performance is shown by GPSR. Additionally, we can see that considering various metrics (3MRP, ProMRP and EProMRP) packet losses decrease in a considerable way compared to GPSR. Besides, by including our probabilistic distribution model for each considered metric in order to score each candidate node using Eq. (4) and take the corresponding forwarding decisions (ProMRP), losses decrease 50% with respect to 3MRP in the high density scenario. The reason is that ProMRP achieves a more accurate selection of the best next-hop nodes. Consequently, the performance of ProMRP clearly outperforms 3MRP and GPSR in terms of packet losses.

Furthermore, our proposal EProMRP is able to accurately correct the position of the candidate neighbors at the moment of sending the message. We can clearly see in Fig. 11 the benefits of including the estimation of candidates' positions on the obtained results, specifically in terms of lower packet losses. This improvement is important in those critical situations when the density of nodes is low.

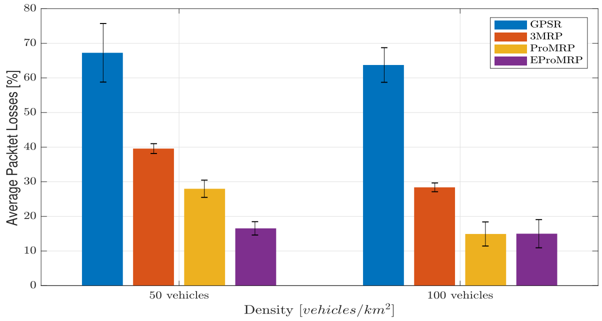

FIGURE 11. **Average packet losses. Our proposals ProMRP and EProMRP clearly improve GPSR and 3MRP.**

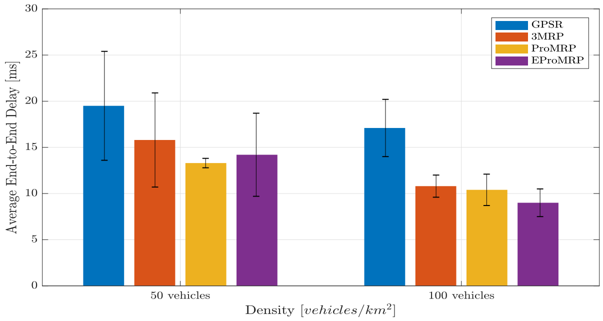

FIGURE 12. **Average end-to-end delay. Our proposals ProMRP and EProMRP show similar delays than 3MRP.**

B. AVERAGE END-TO-END PACKET DELAY

Fig. 12 shows the average end-to-end packet delay for the evaluated routing protocols (i.e., GPSR, 3MRP, ProMRP, and EProMRP) under both considered vehicles' densities. For a low density scenario, the node currently carrying the packet has a low number of neighbor nodes so the routing paths are unstable and unreliable producing higher losses. Nonetheless, considering more metrics than just the basic distance to destination (as the basic GPSR) we are able to guarantee a higher percentage of messages reception as shown in Fig. 11, while also keeping low the average end-to-end packet delay as Fig. 12 shows. However, although our both proposals ProMRP and EProMRP get similar results with respect to GPRS and 3MRP in terms of average packet delay, their percentage of packet losses is notably lower.

On the other hand, including in EProMRP the correction in the node's position at the moment of sending a packet, shows that the choice of forwarding nodes is more efficient, specially in the high vehicles' density case. The delay in the low vehicles' density case also keeps a similar average delay compared to ProMRP.

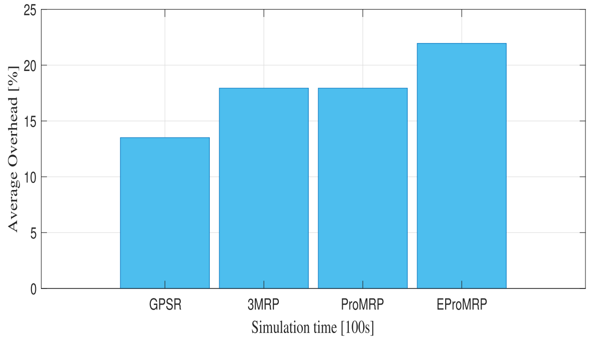

FIGURE 13. **Routing protocol overhead of our proposals ProMRP and EProMRP compared to 3MRP and GPSR.**

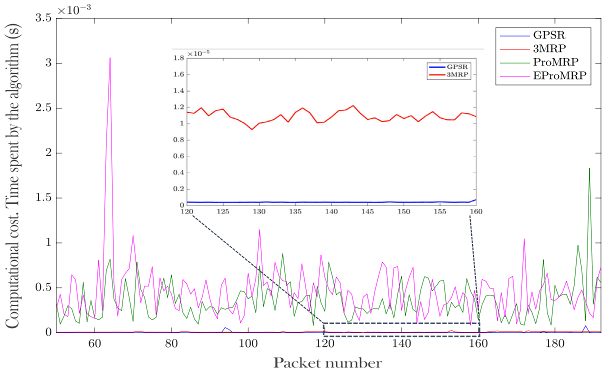

FIGURE 14. **The computational cost squence of the routing protocols: GPSR, 3MRP, ProMRP and EProMRP.**

C. OVERHEAD

Fig. 13 shows the overhead incurred by each one of the routing protocols analyzed in this work. GPSR is the protocol with the lowest overhead (13%), although it produces the highest percentage of packet losses (around 65%) and highest average packet delay (around 18 ms), according to figures 11 and 12, respectively. Both 3MRP and ProMRP increase the overhead until 17% since they use two additional fields (16 bytes each field) in the hello messages to carry the three additional metric values (node's position, available bandwidth and nodes' density) used in the forwarding algorithm together with the distance to destination metric (already included in GPSR). Nevertheless, the benefits in packet losses and packet delay are notable as figures 11 and 12 show. Our proposal ProMRP shows packet losses around 15-25% and packet delays around 15-17 ms. Finally, our proposal EProMRP achieves the best performance in terms of packet losses (around 15%) and packet delay (around 10-15 ms), with a slightly higher amount of overhead around 21%.

D. COMPUTATIONAL COST

Fig. 14 depicts the computational cost incurred by our proposals ProMRP and EProMRP, compared to GPSR and 3MRP. To compute the computational cost of each routing protocol, we made an analysis of the number of operations and time incurred by the forwarding algorithms used by the four routing protocols. The computational cost of the forwarding algorithms used in GPSR and 3MRP is under 0.01 milliseconds, as it is shown in the zoom box of Fig. 14. Instead, our proposed routing protocols increase this computational cost in the ranges of 0.1 to 1 milliseconds, with a peak that reached 3 ms for a few packets. The slightly higher delay is the cost of the additional operations included in the forwarding algorithms. Nevertheless, that extra delay is still very low and it pays-off the benefits of our proposed routing protocols ProMRP and EProMRP.

V. CONCLUSION AND FUTURE WORK

In this paper, we present a new routing protocol named probabilistic multimetric routing protocol (ProMRP) for VANETs specially designed for urban scenarios. ProMRP includes three metrics (vehicles' density, distance to destination and available bandwidth) to take forwarding decisions based on a probabilistic scheme.

The probabilistic models to evaluate the three metrics have been derived previously offline. After that, our proposals use the obtained models to asses the three considered metrics in order to arrange the candidate nodes in the neighborhood of the node currently carrying the packet. In this way, the protocol chooses as next forwarding node the best one that ensures the delivery of the packet with the highest probability, while keeping low the average packet delay. Besides, an algorithm to accurately estimate the current node position in the forwarding moment was included in the version named EProMRP. This new proposal further improves the performance in terms of lower losses, while keeping similar average end-to-end packet delays.

The modeling of the probability density functions of the three considered metrics was done based on a previous offline analysis from a significant number of representative simulations in urban scenarios. Thus, our proposal takes better forwarding decisions that guarantee the packet delivery at destination with higher probability than the other proposals evaluated.

Our algorithm could be adapted and implemented in any VANET routing protocol that uses a multimetric algorithm to select the best next-hop node to forward information. Our EProMRP proposal not only corrects the node's current position when sending the packet, but also takes the best forwarding decision to successfully guarantee the delivery of the packet.

As future work, we seek to take a flexible smart selection of forwarding nodes according to the current network conditions at any moment. To attain this goal, we plan to design a machine learning (ML) mechanism to predict the network behavior, and then include that prediction in the forwarding decision algorithm of the routing protocol.

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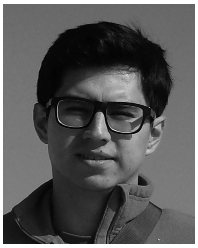
LETICIA LEMUS CÁRDENAS received the degree in telecommunication engineering from the University of Guadalajara (UdeG), México, in 2007, and the M.Sc. degree in telecommunication engineering from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in 2011, where she is currently pursuing the Ph.D. degree with the Department of Network Engineering (ENTEL). Her research interests include vehicular ad hoc networks, machine learning, and electric cars and autonomous vehicles in urban environments.

AHMAD MOHAMAD MEZHER received the M.S. degree in signals and systems from the Central University of Las Villas, Santa Clara, Cuba, in 2011, and the Ph.D. degree in network engineering from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in 2016. He currently holds a Postdoctoral Fellowship position with the Electrical and Computer Engineering Department, University of New Brunswick (UNB). His research interests include smart grid communications, vehicular ad hoc networks, data privacy, and machine learning. He was a recipient of a FI-AGAUR Fellowship from the Generalitat of Catalunya and the Social European Budget.



PABLO ANDRÉS BARBECHO BAUTISTA received the degree in electronic engineering from the University of Azuay, Cuenca, Ecuador, in 2012, the M.Sc. degree in communication networks from the Pontificia Universidad Católica del Ecuador, in 2017, and the M.Sc. degree in telecommunication engineering from the Universitat Politècnica de Catalunya, Barcelona, Spain, where he is currently pursuing the Ph.D. degree in network engineering. His research interests include design and performance evaluation of routing protocols for vehicular ad hoc networks (VANETs). His research activity focuses on the integration of electric vehicles in VANETs and their interaction with smart grids and smart cities.

MÓNICA AGUILAR IGARTUA received the M.Sc. and Ph.D. degrees in telecommunication engineering from the Universitat Politècnica de Catalunya, Barcelona, Spain, in 1995 and 2000, respectively. She is author of more than 20 journal articles. Her research interest includes design and performance evaluation of routing protocols to distribute multimedia services over vehicular ad hoc networks (VANETs). Later, her research activity focuses on the integration of electric vehicles and autonomous vehicles in VANETs and their interaction with smart grids and smart cities. She is a member of the Editorial Board of *Ad Hoc Networks* journal. She has chaired several conferences.

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