*i*MOB: An Intelligent Urban Mobility Management System Based on Vehicular Social Networks

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***Abstract*—The vehicular social networks (VSNs) paradigm is a special class of vehicular networks (VANETs), where features and social aspects are taken into account. Starting from this concept, two different approaches can be applied in VSNs, which are the social network analysis (SNA) measures and the social networking concepts (SNC). In the past few years, several systems have been proposed to deal with traffic congestion problems. They rely on integrating computational technologies such as VANETs, central server, and roadside units. A number of systems employ a hybrid approach, this means that they still need an infrastructure support (central server or roadside unit) to achieve the goals of the system. In order to surpass that, this work deals with the question of how to manage the urban mobility, when an en-route event is detected, in an infrastructure-less environment and scalable fashion. To achieve that, the main goal is to apply VSNs to investigate how SNA measures and SNC can help in the urban mobility management in a distributed fashion. To this end, it was proposed the *i*MOB system, which is an intelligent urban mobility management system. The system consists of the 3-tier: the *environment sensing* (bottom tier), the *vehicle ranking mechanism* (middle tier), and the *altruistic rerouting decision* (upper tier). The SNA egocentric betweenness measure is applied in the middle tier and SNCs such as social interactions and virtual community were utilized in the upper tier. *i*MOB was evaluated in simulation-based experiments being able to outperform all its competitors in all assessed metrics. The results obtained lead us to conclude that the application of concepts and analysis of social network, in a vehicular environment, have great potential to improve the reliability and efficiency of urban mobility management systems in a practical and cost-effective way.**

I. Introduction

The integration between wireless communication technology and social networking area, in vehicular ad hoc networks (VANETs), has emerged as a new paradigm of Vehicular Social Networks (VSNs) concept [1], [2], [3], [4]. VSN can be explored in two different approaches: *(i)* by applying the social network analysis (SNA) measures [2], [4] and/or *(ii)* by combining social networking concepts (SNC) [1], [4].

The former approach focuses on exploring the social properties of VSN nodes. The degree centrality, closeness centrality, and betweenness centrality are the three most used measures in VSNs [2], [4]. The details about the centrality measures can be used to analyze the social behavior of VSNs nodes. Calculating the centrality of a node in a VSN is a challenging task due to its highly dynamic topology. On the other hand, once identified, it can facilitate many applications such as the spread of the information flow through the network [2], just to give one example. Additionally, the SNC approach involves social interactions of commuters who have mutual interests in the virtual community of vehicles [4]. The VSN has the benefit of sharing social information, for example, the personal route. This enables it to deal with the specific issues of drivers on the road, *e.g.*, traffic congestion. In others words, it provides the opportunity for commuters to participate in a vehicular community and share information of mutual interest through social interactions [3], [4]. A social interaction is initiated when vehicles encounter and share their social information with each other. In VSNs the interactions between network entities are performed through wireless communication links in two basic ways: vehicle-to-vehicle (V2V) and/or vehicle-to-infrastructure (V2I) [5].

Inspired by the aforementioned approaches, a 3-tier system called *i*MOB, for ***i***ntelligent urban **MOB**ility management systems based on VSNs, was proposed. In the proposed 3-tier system, the bottom one represents the *environment sensing* which is responsible to acquire the local awareness through vehicles-crowdsensing. The middle tier, *vehicle ranking mechanism*, is applied to select the best-located vehicle in the network. The selected vehicle is responsible for information aggregation and knowledge-generating processes. In this tier, it is applied an egocentric centrality measure. Lastly, the top tier is the *altruistic rerouting decision*, in which the vehicle rerouting strategy is performed collaboratively. In this step, two concepts of social networks are applied, namely social interactions and virtual community. The main objective of the *i*MOB system is to apply the concepts and analysis of social networks to improve the urban mobility and to reduce the traffic congestions.

A set of simulations has been performed and the results were analyzed from two perspectives: *(i)* scalability assessment and *(ii)* urban mobility management assessment. The *i*MOB system outperformed its competitors in both of the analyzed perspectives. Thus, from the proposed system, a range of issues stemming from the inherent characteristics of VSNs, *e.g.*, highly dynamic topology and frequent disconnection in the network, can be well addressed as well as improving urban traffic management.

The main contributions of this work are:

- The design and implementation of an infrastructure-less system based on the real-life traffic condition to improve the urban mobility management. This is done in a practical and cost-effective way;
- The integration of an SNA measure and SNC into the vehicular environment. This provides both scalability of the system and the reduction of the level of traffic congestion.

The remainder of this paper is organized as follows. Section II shows an overview of the related works, while Section III describes the *i*MOB system in details. Section IV presents the experimental setup used to evaluate the performance of the proposed *i*MOB system. The numerical results and analysis are presented in Section V. Lastly, Section VI concludes the work and presents the future work.

II. Related Work

This section shows an overview of traffic management systems found in the literature.

Doolan et al. [6] proposed a traffic management system called EcoTrec. It is a VANETs application designed to decrease CO_2 emissions without significantly affecting the vehicle's travel times. This system is composed of three main components: Vehicle Model, Road Model, and Traffic Model. The Vehicle Model stores and updates each individual vehicle information, and also shares information periodically with the roadside unit through beacon packets. The information contained in this component comes from GPS sensors, speedometer, and accelerometer. The Road Model is maintained at the roadside unit and it is updated with information of the local roads. The Traffic Model is a central server that stores the road characteristics and updates vehicle traffic conditions of each individual road segment. Both components (Road Model and Traffic Model) receive all the necessary information from vehicles through V2I communication. The traffic condition of each road segment is computed in the central server. Each vehicle makes a constant request to the server about the traffic condition of the road it is on. If the road is congested the vehicle calculates an alternative route selfishly, *i.e.*, without taking into account the chosen routes from the surrounding vehicles. In this approach, there is a high network overhead during the information exchanges, especially in dense traffic conditions. In addition, it employs a selfish approach to alternative route calculation.

The authors in [7] proposed a hybrid vehicular rerouting for the traffic management system called DIVERT. The approach is hybrid because it requires a central server to determine an accurate global view of vehicle traffic conditions and the calculation of alternative routes is carried out by vehicles in a distributed fashion. The central server operates as a coordinator that receives location reports from vehicles through V2I communication, besides detecting traffic congestion spot and it sends rerouting notifications to the vehicles. The DIVERT system offloads the rerouting calculation at the vehicles making the rerouting process a real-time operation. During the rerouting calculation, the vehicle takes into account the alternative route from the surrounding vehicles to build a new route, *i.e.*, a collaborative rerouting decision or altruistic decision. The altruistic decision-making tends to be more efficient than selfish ones [7]. It is worth mentioning that, in this system, the broadcast suppression mechanism was not applied during the data dissemination process. In this way, it increases the consumption of the network bandwidth and compromise system scalability.

Wang et al. [8] propose a system called NRR (Next Road Rerouting). The main goal is to aid drivers in making the most suitable next road choice bypassing unexpected congestions spot. NRR acts in two-step traffic rerouting: *(i)* it calculates only the optimal next road for the vehicle to bypass the congested spot, and after that *(ii)* it uses the vehicle navigation system to complete the alternative route until it reaches its destination. The justification for this approach is that the optimal next-road calculation is much faster than recalculating the entire route. NRR also needs a central server, *i.e.*, Traffic Operation Center, to gather real-time traffic information from traffic lights beside identifying congestion spots. In this case, NRR assumes that there is a traffic light at each intersection and also loop detectors to collect such information. Once identified the congestion, the server notifies the closest traffic lights to the congestion spot. Thus, the traffic light broadcast the rerouting message to all vehicles that are inside its transmission range. The vehicles that are going towards the congestion send the rerouting request to the traffic lights. Lastly, traffic light computes the optimal next road and sends the message back to the requester. The remaining of the route is computed with the aid of the vehicle navigation system. It can be observed that, in this approach, there is a high message exchange rate in the network. In addition to that, there is no experimental evaluation regarding the system's scalability.

Incidentally, all the previously mentioned systems apply a hybrid approach for the urban mobility management. The use of infrastructure support lies in the difficulty of selecting the most appropriate vehicle, in a highly dynamic network, to identify traffic congestion. With this in mind, we designed and implemented a vehicle ranking mechanism based on an SNA measure, in particular, the egocentric betweenness measure [9]. In addition to that, we apply two SNCs namely the virtual social community and social interactions for the altruistic rerouting decision.

III. Intelligent Urban Mobility Management System

The *i*MOB system relies upon three main tiers as shown in Figure 1. In a bottom-up view, the first tier is the *Environment Sensing*, the middle tier is the *Vehicle Selection Mechanism*, and the top tier is the *Altruistic Rerouting Decision*. As previously stated, VSN can be exploited in two approaches: *(i)* applying the social network analysis techniques and/or *(ii)* using social networking concepts. In this work, both approaches are adopted. For example, an SNA technique is applied to rank the vehicles in the middle tier of the proposed *i*MOB system. While in the upper tier, an SNC was used to exchange information of common interest. A detailed description of each tier is given below.

A. Environment Sensing

Crowdsensing is a paradigm that allows the ubiquitous mobile devices with the ability to sense the environment and share local data towards a collective goal [10], [11]. Thus, by aggregating crowd-generated local data, it is possible to extract useful information according to the need of a specific application.

Following the same idea, vehicle-crowdsensing enables users of the VSN to solve problems in collaboration with each other participant. For example, the participants of the VSN can contribute to the improvement of urban mobility through the exchange of environmental sensing data about the road traffic conditions. By doing that, the crowdsensing capability of VSNs can offer details about the real-time road conditions, which will be transmitted to help in the decision process of the urban mobility management system.

Furthermore, crowdsensing can use smart vehicles to monitor the road traffic conditions by performing environmental

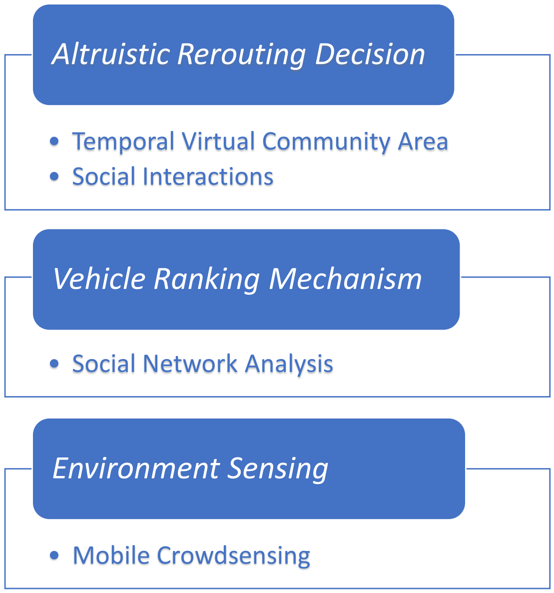


Fig. 1: The main tiers of the *i*MOB system.

sensing, collecting data, and sharing information. To this end, we apply the *beaconing* approach [12]. This means that each vehicle i periodically exchanges short status messages (b_i) to create an environmental awareness. Each of these message contains data about the vehicle such as current speed (s_i), location (p_i), time stamp (t_i), and vehicle rank score (v_{rank_i}), as described in the Equation 1. Each one of the parameters of the equation will be explained in the following sections.

$$b_i = ((p_i, t_i), s_i, \sigma(\cdot), v_{rank_i}) \tag{1}$$

B. Vehicle Ranking Mechanism

As mentioned before, the detection of the best-positioned vehicle in the network, according to the communication links between vehicles, is a very challenging task due to the highly dynamic topology of VSNs. On the other hand, once detected after each topology change, it may be useful for many systems such as the spread of data flow through the network [2].

The idea of the vehicle ranking mechanism is to assign the highest rank for the best-positioned vehicle in the network. This is performed by applying only the local topology knowledge. To this end, we use a measure based on SNA techniques, called the egocentric betweenness [13]. The measure was chosen because it is applied as a metric of the influence of a node on the spread of information flow in the network [14], [15]. Besides the egocentric betweenness measure, we also take into consideration the wireless communication link quality between vehicles as an additional parameter. The main goal of this parameter is to ensure that the messages will travel on a link with less interference. The model applied was the two-ray ground-reflection [16]. Thus, the vehicle ranking mechanism is presented in the Equation 2.

$$v_{rank_i} = \sum_{A_i(m,n)\neq 0, m<n} (A_i^2[1 - A_i]_{m,n})^{-1} + 20\log_{10}(4\pi d\lambda^{-1}|\frac{1}{1+\Gamma \exp^{\varphi}}|) \tag{2}$$

The first half of the equation refers to egocentric betweenness measure, where A_i represents the adjacency matrix of the vehicle i. It is worth noticing that, mathematically, vehicle-to-vehicle links can be described by a symmetric adjacency matrix. The matrix A_i^2 provides the number of the geodesic distances of length 2 (the maximum distance of the egocentric network) between node pairs m and n, and 1 is a matrix with all elements equal to 1. Briefly, the egocentric betweenness of a vehicle i can be computed by the sum of reciprocal values of the $A_i^2[1-A_i]_{m,n}$. For more details of the egocentric measure please refer to [14], [15].

The second half of the equation refers to the two-ray ground-reflection model, where d is the Euclidean distance between vehicles, λ is the wavelength, Γ is the reflection coefficient, and φ is the interfering rays [16]. All the vehicles compute its own rank score at each local topology change and attach (v_{rank}) in the subsequent beacons.

C. Knowledge Generation and Dissemination

The iMOB system sends beacon messages (b_i) periodically to its surrounding vehicles. The is performed by applying the crowdsensing paradigm, as described in Equation 1. This allows it to monitor the road traffic conditions. Before presenting the details of the aggregation functions used in this work, we need defining the road network.

Definition: *Let G = (V, E) be a graph that represents a road network, in which V denotes a set of vertices (or intersections) and E depicts a set of edges (or roads) E ⊆ V × V, i.e., an edge i,j ∈ E corresponds to a road connecting two intersections i,j, for i,j ∈ V.*

To create the environmental awareness, we aggregate the beacon data received from the neighborhood. For this, it is applied the following aggregation function:

$$A := ((E', \max_{1\leq i\leq n} t_i), \operatorname*{avg}_{1\leq i\leq n} s_i) \tag{3}$$

where $E' = \{e_1, \ldots, e_n\} \mid E' \in E(G)$. The parameters $\max_{1\leq i\leq n} t_i$ and $\operatorname*{avg}_{1\leq i\leq n} s_i$ represent current time and average speed of each element of E', respectively. Once the beacon data is aggregated into a single message, it is attached $\sigma_i(A)$ in the subsequent beacon. The next step is to share it with the highest-ranking neighbor vehicle, according to the Equation 2.

On the other hand, to merge two aggregates information, we apply the following aggregation function:

$$A_{u,v} := \sum_{1\leq u,v\leq n} \alpha A_u + (1-\alpha)A_v \ , \begin{cases} t_u > t_v \\ s_u \text{ and } s_v \neq 0 \end{cases} \tag{4}$$

where α is the weighting factor. The main goal of this factor is to assign a higher weight to the most current information ($t_u > t_v$). The aggregation continues until it reaches the vehicle with the highest-ranking score in the network at any given moment.

Once the highest-ranking vehicle in the network finishes the process of aggregating the information received, it computes the weight of each road (w_k), according to the Equation 5, and also classifies each one according to the Table I. The levels-of-service and traffic classification were based on the High Capacity Manual [17].

$$w_k = s_{agg_k}^{avg} \times (s_{e_k}^{max})^{-1} \mid \forall e_k \in E' \quad (5)$$

TABLE I: Traffic classification according to the weight of each road [17].

Level of Service	Traffic Classification	w_i
A	Free flow	$(1.0 \sim 0.9]$
B	Reasonably free flow	$(0.9 \sim 0.7]$
C	Stable flow	$(0.7 \sim 0.5]$
D	Approaching unstable flow	$(0.5 \sim 0.4]$
E	Unstable flow	$(0.4 \sim 0.33]$
F	Forced or breakdown flow	$(0.33 \sim 0.0]$

After the classification step, the vehicle checks if there are congested roads. It will look for roads with levels-of-service D, E, and F. Once identified the congested roads, the next step is to create and disseminate a message along with their respective identifications. As it is known, if the data dissemination scheme is not coordinated among its neighbors, it will lead to the broadcast storm problem. With this in mind, it was applied the zone of preference (ZoP) concept [18], [19] to deal with this problem. ZoP is a region inside the transmission range, in which the vehicles are best suited to continue the dissemination process. In other words, only the vehicles located within the ZoP are enough to continue the data dissemination efficiently [19]. The ZoP concept is decision-based on delay, *i.e.*, vehicles within it have a lower delay (or priority) than the vehicles outside of it. Thus, vehicles outside the ZoP receive redundant information and then cancel the scheduled transmission.

D. Altruistic Rerouting Decision

VSN is also known as a class of mobile social networks. One of its goals is to promote social interaction among commuters or interconnected vehicles that have mutual interests [4], [20]. In addition to that, assuming the vehicles are traveling along the same road and facing the heavy traffic conditions, they can participate in a temporal virtual community and share the alternative route chosen. This allows avoiding that most of the vehicles will choose the same alternative route. In other words, VSN involves the social interaction of commuters in the temporal virtual community of vehicles based on social interests and mutual objectives [21].

In this tier, we apply an altruistic rerouting decision. This means that the choice of an alternative route is made in a collaborative fashion to avoid the congestion spot. In order to do that, the chosen alternative route is shared among surrounding vehicles. The main goal is to divert the maximum number of vehicles from traffic congestions along their route. For this purpose, two social networking concepts were employed: temporal virtual community and social interactions, as shown in Figure 2. Therefore, all vehicles inside the temporal virtual community area are considered as participants in it. Besides that, the covered area by such community depends on the circumference radius that is defined by the application. On the other hand, the social interactions between the participants in the community are done through V2V communication links as the information of common interest exchanged is the personal alternative route.

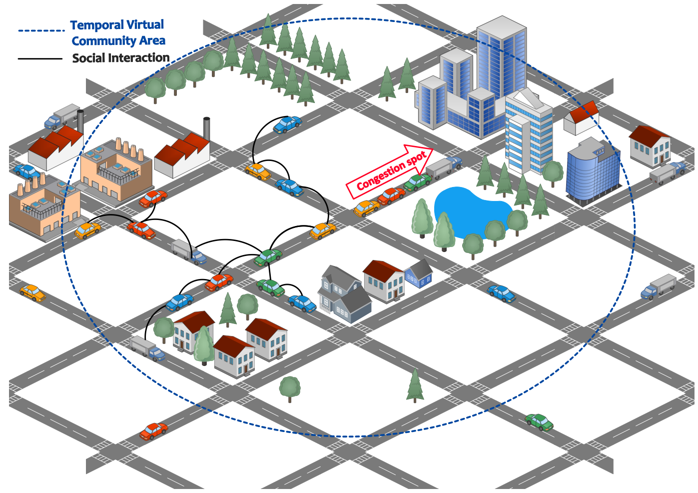


Fig. 2: An illustrative example of the temporal virtual community and social interactions in VSN.

During the altruistic rerouting decision phase, the vehicles closest to the congestion spot has the priority in choosing an alternative route. Therefore, the vehicles must be rerouted in a synchronized fashion. To this end, a short time delay was applied, which is directly proportional to the distance (d) between the vehicle's position and the congestion point. The calculation of such delay is done by multiplying the distance d by a constant k. This constant is the minimum value needed for the system to receive the alternative routes from surrounding vehicles and calculate a personal alternative route, as well as share it through social interaction. Note that the first vehicle calculates its alternative route individually. From the second onwards, the alternative routes of the neighboring vehicles are considered in the calculation.

Before calculating a personal alternative route, the vehicle updates the popularity of the road segment according to the alternate routes received from neighboring vehicles. The popularity of the road j is calculated according to the Equation 6.

$$\rho_j = n_j \times (\frac{length_j}{lanes_j}) \quad (6)$$

where the parameters n_j, $length_j$, and $lanes_j$ are the number of vehicles which pass by it, the length of the road, and the number of road lanes, respectively.

In this way, the vehicle computes an alternative route using the k-shortest path based on the road popularity. Lastly, the vehicle selects the least popular route among k possible routes and share it through social interaction. Thereby reducing the possibility of generating congestion in another spot soon.

IV. Experiments

The Veins [22] vehicular network simulator was used to conduct the performance evaluation. It integrates the network simulator OMNeT++ [23] with the road traffic simulator SUMO [24]. The Physical (PHY) and Medium Acess Control (MAC) layers are implemented in Veins and based on the IEEE 802.11p (WAVE) standard. In addition, the Handbook Emission Factors for Road Transport (HBEFA) model was used to measure the CO_2 emission and it is already coupled in the SUMO simulator.

A. Experimental Settings

In order to evaluate an urban mobility management system, a close to real life urban mobility environment should be considered. To this end, the TAPASCologne project[1] of the Institute of Transportation Systems at the German Aerospace Center (ITS-DLR) was used in our evaluation scenario. This project aims to reproduce, with the highest level of realism possible, vehicle traffic in a large-scale scenario of the city of Köln, Germany. It contains vehicle routes describing a real demand, for the entire map region, of one day. However, only a central submap of the city of Köln was picked for our simulation experiments, because it reveals a higher incidence of traffic congestion, as highlighted in the Figure 3. In addition, we have separated this new dataset into five different penetration rates, which are 20 %, 40 %, 60 %, 80 %, and 100 %. This means that, of the total of the new dataset, only 20 % of the vehicles are inserted in the scenario for our simulation experiments, and so on.

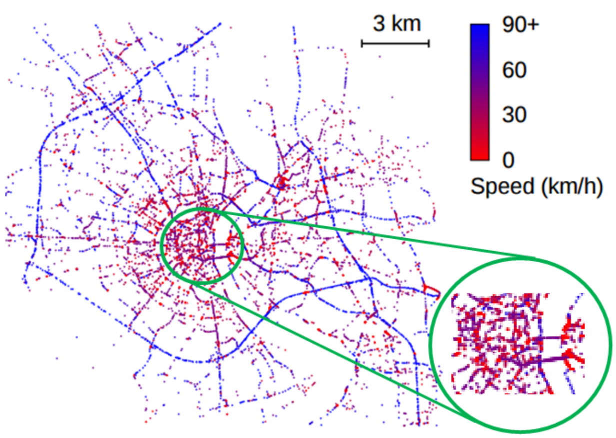


Fig. 3: A snapshot of the vehicular traffic conditions status of the city of Köln - adapted [25].

We set the NIC bitrate to 6 Mbps in the MAC layer, and the NIC sensitivity to -82 dBm as well as the transmission power to 20 mW. Thus achieving a transmission range of approximately 287 m under a two-ray ground propagation model [16]. Table II summarizes the simulation parameter settings.

B. Evaluation Metrics

Eight metrics were used to evaluate the performance of the proposed system. They were divided into two perspectives (or assessment) as described below in detail:

1) Scalability assessment:
   - **Transmitted messages**: shows the total number of transmitted messages by the vehicles in the network;
   - **Packet loss**: shows the total number of packets lost during message transmission. That occurs due to the busy communication channel as well as bit errors in received packets.

[1]http://sumo.dlr.de/wiki/Data/Scenarios/TAPASCologne

TABLE II: Simulation parameters.

Parameter	Value
Penetration rates of vehicles	20 % to 100 %
MAC layer	802.11p
NIC TX power	20 mW
NIC Bitrate	6 Mbps
NIC Sensitivity	-82 dBm
Transmission range	287 m
Temporal virtual community radius	1 Km
Beacon transmission frequency	1 Hz
Confidence interval	95 %
Constant k	10^{-2}

   - **Coverage**: displays the delivered message rate to vehicles for each one generated;
   - **Latency**: measures the time spent to transmit messages to the vehicles during the data dissemination process.

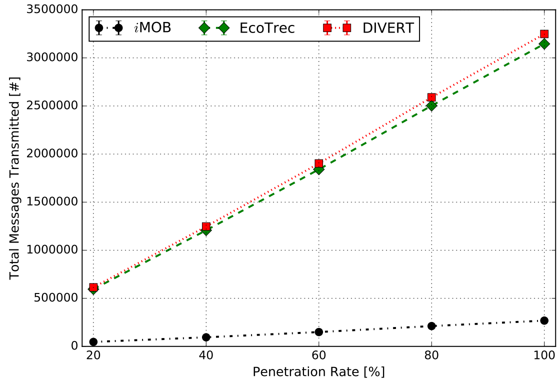
2) Urban mobility management assessment:
   - **Average travel time**: shows the average travel time of all vehicles' trips, *i.e.*, it indicates the overall traffic status for the entire observed road network;
   - **Congestion time loss**: describes the average congestion time loss of all vehicles;
   - **Travel time index**: measures the urban traffic congestion level [26]. It is computed as the ratio of the sum of the travel time to the sum of the free-flow travel time for all vehicles;
   - **CO_2 emission**: gives the average CO_2 emission of all vehicles.

V. Performance Analysis

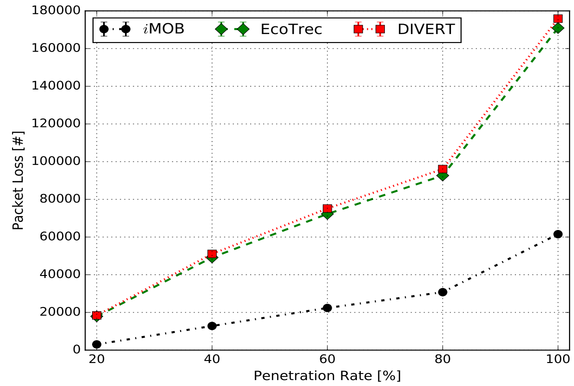
The main goal of our simulation-based evaluation is to assess the performance of the *i*MOB system against the EcoTrec [6] and DIVERT [7] systems. The baseline will be the original vehicular mobility trace of the Cologne (OVMT) and it is only used in the urban mobility management assessment. Because it does not apply any vehicle routing mechanism. For a better presentation of the results, we divided into two Subsections, namely scalability assessment (V-A) and urban mobility management assessment (V-B).

A. Scalability Assessment

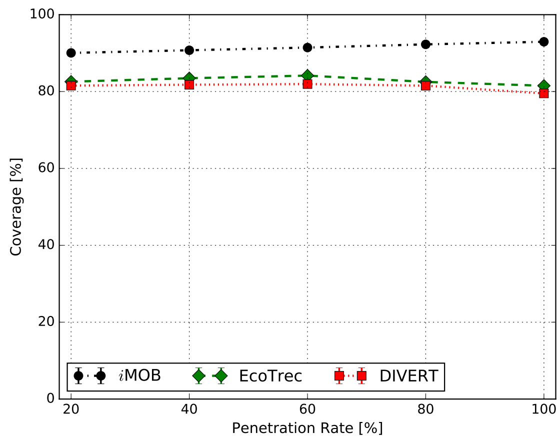
Figure 4 displays the numerical results of the scalability assessment comparing *i*MOB with the EcoTrec and DIVERT systems. The metrics displayed are the number of transmitted messages, packet loss, coverage, and latency at different penetration rates. It is worth noticing that, in the EcoTrec and DIVERT systems, the support of an architecture must be considered. As is known, in the EcoTrec system each vehicle sends its information periodically to the server and also makes periodic requests about the condition of the road in which it is. The consequence of this approach is the high exchange of messages between vehicles and the central server. This situation can be seen clearly in Figure 4(a). Another direct consequence is the high rate of packet loss in the network (Figure 4(b)). This aspect is even more expressive at high penetration rates (80 % and 100 %). Due to the high



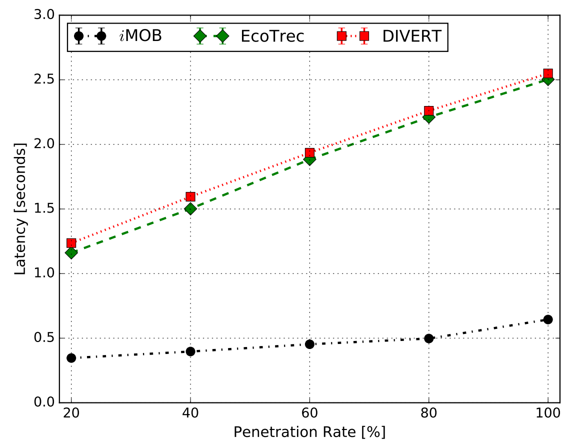
(a) Transmitted messages.



(b) Packet loss.



(c) Coverage.



(d) Latency.

Fig. 4: The scalability assessment results.

network overhead, EcoTrec has only a coverage of around 82 % (Figure 4(c)) and a long average latency of 1.88 seconds, compared to the *i*MOB system and taking into account all penetration rates (Figure 4(d)).

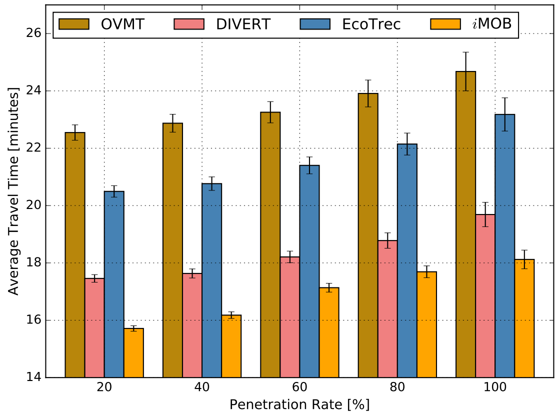
The Divert system follows the same approach of EcoTrec. In it, the vehicles also periodically communicate with the central server, however, they report local traffic density data and receive the road traffic conditions. In addition to that, DIVERT applies the altruistic routing decision to compute an alternative route when congestion is detected. Due to this, one can observe a slight increase in the number of messages transmitted and also in the loss of packets compared to the EcoTrec system, Figures 4(a) and 4(b), respectively. The advantage of such an altruistic decision will be explained in the next subsection. Both EcoTrec and DIVERT systems have a high network overhead due to messages exchanged between vehicles and the central server. Because of this, the performance in relation to the coverage and latency metrics is similar between them, as can be seen in Figures 4(c) and 4(d).

Finally, the proposed *i*MOB system which adopts an infrastructure-less system and applies information aggregation along with the vehicle ranking mechanism for the generation of knowledge. *i*MOB also has a mechanism to deal with the broadcast storm problem during the knowledge distribution process, as well as altruistic rerouting decision. Based on these strategies, it can be observed that the *i*MOB system reduces network overhead significantly (Figures 4(a) and 4(b)), compared to the EcoTrec and DIVERT systems. This happens because only the best-ranked vehicle, in the network, accomplishes the generation of knowledge. For transmitted messages, *i*MOB had a decrease of around 78 % (Figure 4(a)), in all the penetration rates analyzed. While for packet loss, approximately 63 % reduction is achieved (Figure 4(b)), compared to the other two systems. Due to the low network overhead, *i*MOB achieves greater coverage of approximately 91 % in all the penetration rates analyzed (Figure 4(c)), compared to the other systems considered. Lastly, a lower latency, among all systems, around 0.5 second is achieved by *i*MOB (Figure 4(d)).

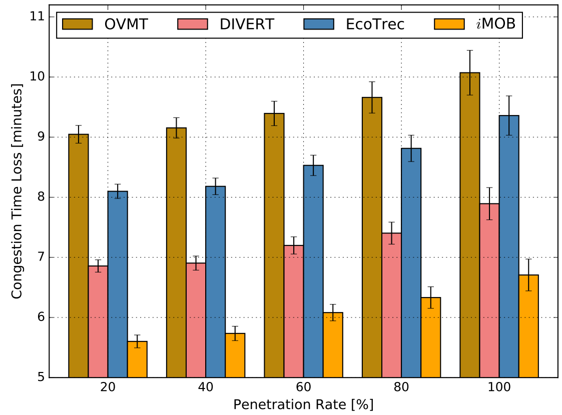
After analyzing the results obtained, it is possible to conclude that the high network overhead and also high latency, in both the EcoTrec and DIVERT systems, have significantly reduced their scalability potential. On the other hand, the *i*MOB system has shown a distributed approach that can be scalable in a practical and cost-effective way.

B. Urban Mobility Management Assessment

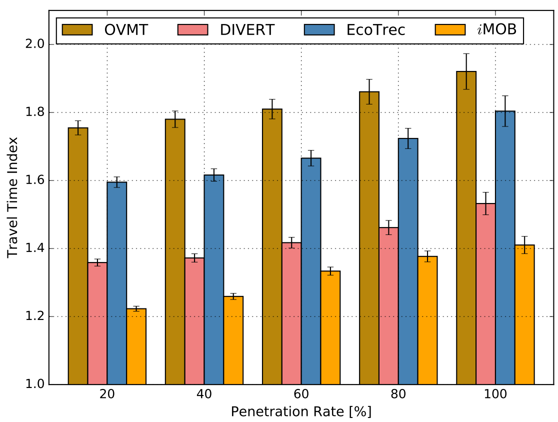
Figure 5 shows the results of the urban mobility management of the *i*MOB system against the DIVERT and EcoTrec systems. The assessed metrics were the average travel time, travel time index, congestion time loss, and CO_2 emission at different penetration rates. Specifically, Figure 5(a) presents



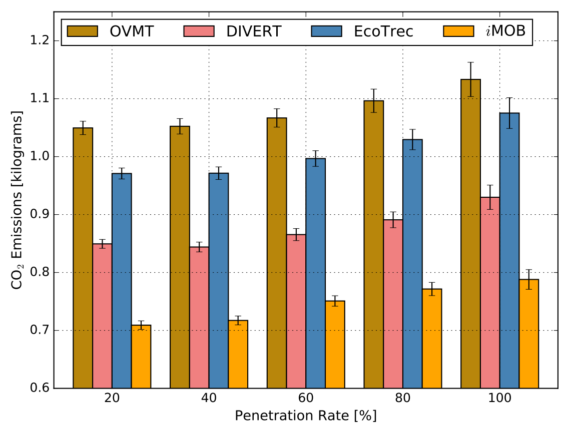
(a) Average travel time.



(b) Congestion time loss.



(c) Travel time index.



(d) CO_2 emissions.

Fig. 5: The urban mobility management assessment results.

the average travel time and, as expected, OVMT has the longest time, with an average of 23.6 minutes at all the penetration rates analyzed. This can be explained because it is the only one that does not perform vehicle routing when congestion is detected. Due to this approach, it will also have the longest time spent in the congestion, on average, 9.5 minutes (Figure 5(b)). The travel time index (Figure 5(c)) is, on average, 1.8. Based on these results it is also expected that OVMT will have the highest CO_2 emission of around 1.05 kilograms, as can be observed in Figure 5(d).

EcoTrec applies the selfish rerouting decision for the selection of an alternate route when the congestion is detected. Through this approach, it achieved a decrease of around 8 % on the average travel time, in relation to OVMT in all the penetration rates analyzed, Figure 5(a). Other consequences of this approach are the reduction of time lost in congestion (around of 10 %) and also in the travel time index (around of 7 %), as can be seen in Figures 5(b) and 5(c), respectively. As EcoTrec has the shortest time lost in congestion in comparison to the OVMT, the vehicles will spend less time in accelerations and decelerations. The direct consequence of this is the lower CO_2 emission in all penetration rates analyzed, Figure 5(d).

Unlike EcoTrec, DIVERT applies an altruistic routing decision, and such approach is known to outperform the selfish one. This is confirmed by Figures 5(a), 5(b), 5(c), and 5(d). Particularly, DIVERT has a reduction of around 22 % and 16 % in the average travel time (Figure 5(a)), compared to OVMT and EcoTrec, respectively. Still comparing DIVERT to OVMT and EcoTrec, other advantages can be mentioned such as a shorter congestion time loss (Figure 5(b)) and the reduction in the travel time index (Figure 5(c)). The two advantages aforementioned are directly related in the reduction of the CO_2 emissions (Figure 5(d)) of around 19 % and 16 %, in comparison to the OVMT and EcoTrec, respectively.

Following the same approach as DIVERT, the *i*MOB also applies the altruistic rerouting decision. Even so, the *i*MOB system is able to outperform the DIVERT system because of its low network overhead. As DIVERT has a high network overhead, many data packets arrive corrupted at the destination. Because of that, they cannot get accurate information for decision-makers. Due to the low overhead along with the altruistic rerouting decision, *i*MOB has the shortest average travel time (Figure 5(a)) of around 17 minutes, in all the penetration rates considered. This represents a reduction of 38 %, 26 %, and 7 %, compared to OVMT, EcoTrec, and DIVERT, respectively. The direct consequence of such reduction is reflected in the time lost in the congestion (Figure 5(b)) and in the travel time index (Figure 5(c)) as well as at the CO_2 emission (Figure 5(d)). For the congestion time loss metric, *i*MOB achieves an reduction rate around of 58 %, 43 %, and 28 % in comparison to OVMT, EcoTrec, and DIVERT, respectively. For the travel time index metric it achieves an reduction around of 42 %, 35 %, and 17 %, compared to OVMT, EcoTrec, and DIVERT, respectively. As the *i*MOB system has the shortest time spent in congestion, it will also have the lowest CO_2 emission compared to other systems considered, around of 0.746 kilogram as can be observed in Figure 5(d).

The assessment of the results leads to the conclusion that the use of social interactions and virtual community into the vehicular environment can help to improve the urban mobility management.

VI. Conclusion

This work proposes the *i*MOB system, an intelligent urban mobility management system. The main advantage of *i*MOB is the combined use of two approaches of VSNs such as social network analysis measure and social networking concepts. A social network analysis measure, in special, the egocentric betweenness measure is employed in the vehicle ranking mechanism. The advantage of this mechanism lies in only using the local knowledge of the network topology to carry out the calculation. In addition to that, two social networking concepts were employed to the vehicle rerouting strategy, namely the social interactions and virtual community. Simulation experiments were carried out following two perspectives: *(i)* scalability assessment and *(ii)* urban mobility management assessment. The proposed system was compared with two systems of literature, namely EcoTrec and DIVERT. The results reveal that the *i*MOB system outperformed its competitions in all the assessed metrics. This supports the conclusion that *i*MOB is a scalable, cost-effective, and efficient urban mobility management system.

In future works, we intend to incorporate the mobility patterns of drivers and user preference into the *i*MOB system. These parameters will be considered in the decision process of choosing an alternative route.

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