TRUSTed: A Distributed System for Information Management and Knowledge Distribution in VANETs

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***Abstract*—The constant sharing of information among vehicles is of vital importance to provide different types of service in Intelligent Transportation Systems (ITS). Typically, ITS apply the sharing benefit to carrying out tasks such as extracting knowledge of vehicle traffic conditions and its distribution. The ITS that use this approach are able to perform the knowledge distribution, however, they lack of mechanisms to select the most appropriate vehicles to do so. It is common, in these systems, such tasks are performed by all vehicles. Consequently, it could easily cause a network overhead because of the highly redundant knowledge about the traffic that is being transmitted. With this in mind, we propose a system for information management and knowledge distribution named TRUSTed. The proposed system applies the egocentric betweenness measure to select the most relevant vehicle to carry out such tasks. Simulation results have shown that TRUSTed outperforms other systems found in the literature in several requirements.**

I. Introduction

One of the promising technologies for Intelligent Transport Systems (ITS) applications is Vehicular ad hoc Networks (VANETs). It enables vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, with the help of Road Side Units (RSUs) [1], [2]. In order to deal with the highly dynamic topology of VANETs, a new stack of protocols was created. The IEEE 1609 Wireless Access in Vehicular Environments (WAVE) offers support for inter-vehicular communications and was also necessary to meet a set of VANETs requirements such as short communication time and frequent network partition [3]. In addition to that, the standard IEEE 802.11p DSRC (Dedicated Short-Range Communication) has assigned multiple inter-vehicular communication channels such as control channel (CCH) and service channels (SCHs) [3].

For many ITS applications, the constant sharing of local information, with one-hop communication neighbors, is essential to create an awareness about vehicle traffic conditions [4], [5], [6]. This type of sharing is well-known as beaconing, and most often the exchanges occur in the control channel with a transmission frequency generally between 1Hz and 10Hz [7]. The default information contained in the beacon package include the vehicle identification, current vehicle position, average speed, direction of travel, among others [3]. On the other hand, the service channels are used to share all other data needed by the applications.

Several ITS that deal with local information management and knowledge distribution about vehicle traffic conditions, have been proposed [4], [5], [6]. This type of system extracts knowledge, for instance, about the traffic condition of a given road, by processing the aggregated local information received from the neighbor vehicles. However, many proposed systems have the same shortcoming, the absence of a vehicle selection mechanism to carry out the tasks of information aggregation and knowledge generation. Without the selection mechanism, all vehicles would perform such tasks resulting in a highly redundant traffic of knowledge. In addition, other systems [4], [5] do not apply any broadcast suppression mechanism during knowledge distribution, increasing even further the network overhead.

In order to overcome the above-cited limitation, we propose the TRUSTed, a distributed system for information management and knowledge distribution. By means of beaconing, TRUSTed collects the local information needed to apply the egocentric betweenness measure. The result is the selection, within a subset of vehicles, of the most relevant one in a given moment to carry out the tasks of information aggregation and knowledge generation. The *relevance* is defined as the importance of a vehicle in relation to the information flows that pass through it. In other words, it defines how important is the intermediate vehicle for the information flow continuity in the network. One of the advantages of the egocentric measure is the use of the local information, which is available to perform the necessary calculation. Beyond this advantage, the work of [8] confirmed that the egocentric betweenness measure, in a highly dynamic topology, has a high correlation with the sociocentric betweenness measure. Last but not least, a broadcast suppression mechanism was applied to avoid the redundant traffic of knowledge.

The main objective of this work is to reduce the network overhead. Extensive simulations have been conducted comparing our system with systems found in the literature [4], [5], [6] according to several requirements. The performance assessment was done from two perspectives: (i) performance of the systems in relation to knowledge distribution and (ii) performance of the control channel.

The remainder of this paper is organized as follows. Section II shows a brief overview of some related works, while our system is presented in Section III. Some numerical results and analysis are given in Section IV. Finally, Section V concludes the paper and presents the future work.

II. Related Work

In this section, all proposals presented here employ a periodic exchange of local information, between one-hop communication neighbors, this allows them to create the local knowledge base. In addition, they were designed to operate only with vehicle-to-vehicle communication technology.

The authors in [4] proposed a probabilistic aggregation system for knowledge distribution. The system applies a hierarchical aggregation technique for the local information called soft-state sketches. This technique is based on an extension of Flajolet-Martin sketches [9]. The key characteristic of this technique lies in the fact that it aggregates information that does not have specific values of the monitored place, for instance, number of vehicles from a determined road. The aggregated information has, instead, a probabilistic value. The main advantage of this technique is the ability to combine multiple aggregated values, of the same information content, for the generation of knowledge. However, the main disadvantage of this system is that it does not have any vehicle selection mechanism to perform its tasks of information aggregation and knowledge generation. Therefore, all vehicles are candidates to perform such tasks, this way generating highly redundant traffic of knowledge. Furthermore, there is no broadcast suppression mechanism during the knowledge distribution phase.

An adaptive forwarding delay control system, named Catch-up, has been proposed by Yu et al. in [5]. Its main objective is to gather aggregated local information from different sources for the knowledge generation. To this end, the forwarding speed of nearby information is dynamically changed. In doing that, they have a better chance to meet each other and, as a result, be aggregated together. Each aggregate information can have one of the two types of adaptive delays, *RUN* (short) or *WALK* (long). The system was designed based on a distributed learning algorithm, which means that, each vehicle learns by means of local information and computes a delay based on the results of the learning. The advantages of Catch-up are the use of an adaptive forwarding delay for the knowledge generation as well as probabilistic aggregation. However, it falls short by not having a broadcast suppression mechanism during the knowledge distribution. Another disadvantage is that all vehicles can act as an information aggregator and knowledge generator, which can incur in network overhead, as mentioned before.

Yuan et al. in [6] propose the DARF (Data Aggregation Algorithm by Restricting Forwarders). The DARF focuses mainly on the selection of the vehicles that will continue the knowledge forwarding process, which was generated in the aggregation step. In order to do that, each vehicle receives one of the two labels (forwarder or non-forwarder) according to the neighborhood labels. This label, as the name says, determines whether the vehicles will forwarder, or not, the knowledge. The vehicles will be non-forwarder if there is a forwarding vehicle immediately in front of and behind it. The labeling of the vehicles is based on periodic exchange of local information. One of the advantages of DARF is the broadcast suppression mechanism, which is applied during the knowledge distribution process. However, it is possible to notice that there is no vehicle selection mechanism to aggregate local information and generate the knowledge. In this way, all vehicle can contribute to the knowledge generation, thus, generating a highly redundant traffic of knowledge in the network.

All the above-mentioned proposals have presented some limitations. For instance, the systems proposed by [4], [5], only take into account the information aggregation technique. Another proposal, [6], apply some type of the information aggregation technique together with the broadcast suppression mechanism. Nevertheless, none of these systems adopted a vehicle selection mechanism to perform the tasks of information aggregation and knowledge generation. Taking into account this limitation, a system for information management and knowledge distribution, so-called TRUSTed, was proposed. TRUSTed applies the egocentric betweenness measure, in order to perform the selection of the most relevant vehicle to carry out above-mentioned tasks. In addition to that, the proposed system also uses a broadcast suppression mechanism to avoid the traffic of redundant knowledge.

III. TRUSTed

TRUSTed is a distributed system for information management and knowledge distribution related to vehicle traffic conditions in VANETs. One of the main challenges of this type of system, due to the highly dynamic topology, is the selection of the most relevant vehicle, within a subset of vehicles, to perform the tasks of information aggregation and/or knowledge generation. If a vehicle is not selected, all of them could carry out such tasks, this can overload the network with highly redundant traffic of knowledge. With this in mind, the egocentric betweenness measure was applied to select the vehicle that will carry out above-mentioned tasks. The egocentric measure was chosen because it requires only the available local information (one-hop neighbors) to find the most relevance vehicle. This relevance is based on the information flow passing through it. It also allows connecting two distinct vehicles by means of the shortest path.

A. Egocentric Betweenness Measure

The egocentric betweenness measure (EBM) is computed over ego-network topologies. By definition, an ego-network is a subgraph formed by a single node (so-called *ego*) together with the nodes to which they are connected to (so-called *alters*), and all links the *alters* themselves [10], [11]. Figure 1(a) highlights a subgraph where n represents the *ego* and the one-hop neighbors (1, 2, 3, 4, and 5) represent the *alters*. The EBM formal definition and the mathematical calculation is given next.

Egocentric betweenness *is computed using an ego-network representation. Let N_n^r be the set of nodes that is r-hop away from n (ego), i.e., $N_n^r = \{v' \in V | v' \neq n \wedge 1 \leq d(n, v') \leq r\}$, where $d(n, v')$ denotes a one-hop between n and v' (alters). Thereby, 1^{th}-order of node n consists of undirected graph $G = (V_n^1, E_n^1)$, where the set of nodes corresponds $V_n^1 = \{N_n^1 \cup \{n\}\}$ and the set of edges corresponds $E_n^1 = \{(i,j) \in E_n^1 | i, j \in V_n^1\}$.*

Mathematically, node-to-node links can be represented by a symmetric adjacency matrix A ($k \times k$), where k is the number of one-hop neighbor nodes. Thereby, each A element, $a_{i,j}$, can be given by:

$$a_{ij} = \begin{cases} 1 & \text{if there is a direct link between } i \text{ and } j \\ 0 & \text{otherwise} \end{cases}$$

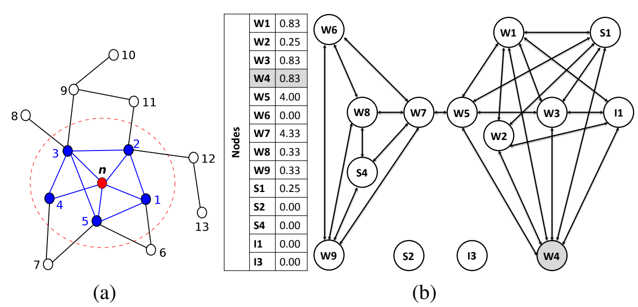


Fig. 1: (a) highlights an ego-network topology. (b) example taken from study case [10].

Figure 1(b) depicts the classical example employed to demonstrate the calculation of the EBM [10]. EBM is computed by counting nodes that are connected through the ego node [12]. Represented by the mathematical expression, $A^2[1 - A]_{i,j}$, the EBM is the sum of reciprocals of the mathematical expression [12], where 1 is a matrix of all 1's. As an example, we compute EBM from the perspective of the node $W4$ of the Figure 1(b). The following adjacency matrix describes a view of all connection links between the $W4$ and its alters, and also the links between the alter's pairs.

$$W4 = \begin{array}{c} \\ W4 \\ I1 \\ S1 \\ W3 \\ W1 \\ W2 \\ W5 \end{array} \begin{array}{c} \begin{array}{ccccccc} W4 & I1 & S1 & W3 & W1 & W2 & W5 \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 0 & 0 \end{bmatrix} \end{array}$$

Since the $W4$ matrix is symmetric, only non-zero values above the main diagonal should be considered. In this case, the remaining elements of $W4^2[1 - W4]$ are 4, 3, and 4, as can be seen in the following matrix.

$$W4^2[1 - W4] = \begin{array}{c} \\ W4 \\ I1 \\ S1 \\ W3 \\ W1 \\ W2 \\ W5 \end{array} \begin{array}{c} \begin{array}{ccccccc} W4 & I1 & S1 & W3 & W1 & W2 & W5 \end{array} \\ \begin{bmatrix} * & * & * & * & * & * & * \\ * & * & 4 & * & * & * & 3 \\ * & * & * & * & * & * & * \\ * & * & * & * & * & * & * \\ * & * & * & * & * & * & * \\ * & * & * & * & * & * & 4 \\ * & * & * & * & * & * & * \end{bmatrix} \end{array}$$

Thereby, the EBM value of the node $W4$ ($1/4 + 1/3 + 1/4$) is 0.83. Therefore, all the nodes are able to compute they EBM value using only local information. In VANETs, the EBM value should be calculated whenever the adjacency matrix is updated. Each matrix element is collected by means of beacon packets periodically broadcasted.

There is evidence that the betweenness centrality measure in egocentric and sociocentric networks have the highest correlation in a static network [10]. However, new research indicates that the highest correlation can also happens in a highly dynamic network [8], such as VANETs.

As mentioned before, the EBM is applied to select the most relevant vehicles to perform the tasks of information aggregation and/or knowledge generation. As shown in Figure 1(b) it is possible to have nodes with the same EBM value. In this particular case, three nodes have an EBM value of 0.83, two nodes have 0.25, and two nodes have 0.33. Assuming that the graph depicted in Figure 1(b) describes the inter-vehicular communication links at a given time. If the node $I1$ needs to forward its aggregate local information it, beforehand, have to select the next alter, with highest EBM value, to carry out such tasks. As shown, the $I1$ has three alters ($W1$, $W3$ and $W4$) with an EBM value of 0.83. In this case, the Two-Ray Interference model (Equation 1) [13] is applied as the tie-breaking criterion.

$$L_{TRI}[dB] = 20log(4\pi\frac{d}{\lambda}|1 + \Gamma \exp^{\varphi}|^{-1}) \qquad (1)$$

where λ is the wavelength, d is the Euclidean distance between two vehicles, Γ is the reflection coefficient, and φ is the interfering rays.

Following the previous example, once selected the next alter, assuming the $W3$ was elected, it performs the aggregation of its information with the received ones. At the same time, the remaining alters discard the aggregated information received. The information aggregation process will be carried out until reaching the node $W7$, because it has the highest EBM value in the network in this example. Once all information received has been aggregated, the $W7$ node is responsible for generating and distributing the knowledge. The data aggregation technique, the procedure for the knowledge generation, and the broadcast suppression mechanism will be detailed in the next section.

B. Information Aggregation and Knowledge Generation

The TRUSTed system, periodically shares the local information, among its one-hop communication neighbors. This is performed using beacon packets through the control channel, and it is used to create the local knowledge base. In addition to the information already contained in the beacon package, two more information fields were added: the current EBM value and the aggregated information.

The local knowledge base is created by aggregating the local information received from the one-hop neighbor, as well as the calculation the weight of roads. The next step, once the local knowledge base was created, is to share it with the most relevant neighbor vehicle, following to the selection criterion presented in the Subsection III-A.

The Fusion of two aggregated values may be represented as follows: $A_r := \partial(A_1, A_2)$, where ∂ is the aggregation function that has two input values (A_1 and A_2). These values are combined, generating a new aggregated value (A_r). As the main goal of the proposed work is on information management and knowledge distribution about the vehicle traffic condition, the aggregation function is given as follows:

$$v^{avg}_{agg_i} = \frac{v_1 c_1 + v_2 c_2}{c_1 + c_2} \qquad (2)$$

where $v^{avg}_{agg_i}$ represents the aggregate average speed of a given road i. The parameters v_1 and v_2 are the two input values of the road i, which are going to be aggregated. c_i indicates the amount of information that contributed to the generation of the new aggregated value. Thereby, the weight of the road i (w_i) is calculated as follows:

$$w_i = \frac{v^{avg}_{agg_i}}{v^{max}_{spe_i}}, \begin{cases} w_i : \text{weight of road } i \\ v^{avg}_{agg_i} : \text{aggregate average speed of road } i \\ v^{max}_{spe_i} : \text{maximum speed of road } i \end{cases} \qquad (3)$$

After aggregating all the local information, the vehicle that has the highest EBM value classifies the weight of the roads according to the Table I. The levels of service and traffic classification were based on the Highway Capacity Manual (HCM) [14].

TABLE I: Level of service and traffic classification [14].

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	$(0.33 \sim 0.0]$

As soon as the classification step is over, if an event is identified (in our case, levels D, E or F of the Table I), a message (also known as knowledge), containing the identification of the roads in question is generated. This procedure initiates the knowledge distribution process in the service channel. The sender's neighboring vehicles that received the knowledge will schedule a retransmission to continue the knowledge distribution process. Every time that a vehicle receives a knowledge to be distributed, it checks if it is within the zone of preference [2], if so, it transmits first. Due to the broadcast suppression mechanism implemented (zone of preference), as soon as the neighboring vehicles outside the zone of preference receive the same scheduled knowledge, they cancel the retransmission, thereby avoiding the traffic of redundant knowledge in the network.

Figure 2 illustrates the operation flowchart of the TRUSTed. When TRUSTed receives the local information, it either inserts or aggregates this local information into the local knowledge base (Block 1). After this step, it calculates the weight of roads according to the Equation 3 (Legend (a)). In addition, if the vehicle has the highest EBM value (Legend (b)), it also classifies the weight of roads according to the Table I (Legend (c)). In this process, if the selected vehicle finds out that there is some congested traffic flow, a knowledge is generated and distributed in the network (Legend (d)). On the other hand, if the vehicle does not have the highest EBM value, it selects the next most relevant vehicle, according to the Subsection III-A and sends the aggregated local information to it (Legend (e)).

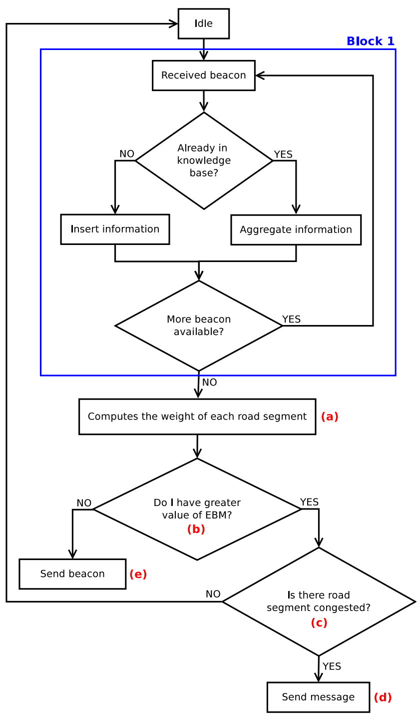


Fig. 2: Operation flowchart of TRUSTed system.

IV. Performance Evaluation

In order to assess the performance of TRUSTed, the system was designed, implemented, and simulated with the aid of the following tools: Omnet++ 5.0 - Network Simulation Framework[1], SUMO 0.29.0 - Simulation of Urban Mobility[2], and Veins 4.5 - Vehicular Network Simulations[3]. First of all, the parameters of the experimental scenario are explained. After that, it is provided the analysis of the experimental results.

A. Experimental Settings

In order to produce realistic mobility traces, a real map clipping of the city of Erlangen/Germany was imported from OSM (OpenStreetMap[4]), as shown in Figure 3. In addition, five distinct traffic densities (100, 150, 200, 250 and 300 vehicles/km^2) were used during the simulations. Furthermore, the *Krauss* car following mobility model [15] was also adopted.

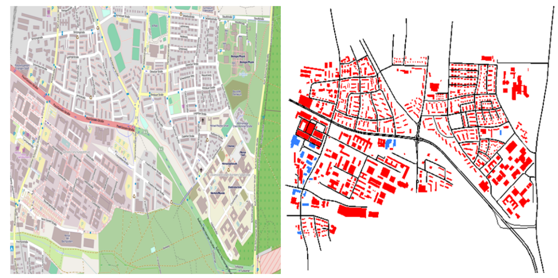


Fig. 3: Map segment from Erlangen/Germany.

The bitrate was set to 6 Mbps in the MAC layer and a transmission range of approximately 200 m under a two-ray ground propagation model [13] was applied. Following the same idea, the transmission power was set to 0.98 mW.

Finally, all the experimental results of this work were gather by conducting thirty three times on different traffic conditions with a confidence interval of 95%. Table II summarizes the parameters used in the simulation.

TABLE II: Simulation parameters.

Parameter	Value
Density of vehicles	100 to 300 vehicles/km^2
MAC layer	802.11p
Transmission power	0.98 mW
Bitrate	6 Mbps
Transmission range	200 m
Beacon transmission frequency	1 Hz
Confidence interval	95 %

Seven metrics were applied in order to evaluate the performance of the TRUSTed system:

1) **Coverage**: percentage of messages delivered to the vehicles that are within the scenario;
2) **Overhead**: measures the total amount of transmitted messages by the vehicles in the network;
3) **Delay**: demonstrates the time spent in delivering the messages to vehicles that are within the scenario;
4) **Collision**: shows the total number of packet collisions during message transmission;
5) **Channel busy ratio**: measures the percentage of channel usage during the exchange of the information;
6) **Total beacons transmitted**: displays the total amount of beacons transmitted in the network;
7) **Beacons transmitted per vehicle**: exhibits the number of beacon packages transmitted per vehicle.

The analysis of results is divided into two subsections. First, it is analyzed the performance of the solutions in the knowledge distribution process, Subsection IV-B. Second, the Subsection IV-C assess the performance of the control channel during the exchange of local information.

B. Knowledge Distribution Process Assessment

Figure 4 depicts the results of the experiments from the point-of-view of the knowledge distribution, as a function of

[1]https://omnetpp.org/
[2]http://sumo.sourceforge.net/
[3]http://veins.car2x.org/
[4]https://www.openstreetmap.org/

vehicle densities. Particularly, Figure 4(a) presents the performance results of all solutions analyzed using the coverage metric. The Probabilistic solution displays the lowest coverage, reaching an average of 80 %, for all analyzed densities. These results can be justified due to the network overhead, which is caused because all vehicles perform the tasks of information aggregation, generation, and distribution of the knowledge (Figure 4(b) and Figure 4(d)). In addition, during the process of knowledge distribution none broadcast suppression mechanism is applied, thus, resulting in a highly redundant traffic of knowledge, as shown in Figure 4(b). Because of this, it is possible to observe a high rate of packet collisions in the network (Figure 4(d)). It is also evident the long delays in the delivery of knowledge, compared to the other systems considered (Figure 4(c)). We can see a slight drop in the coverage rate as the vehicle density increases. This is due to the fact of the high network overhead and the high collision rate.

The other solution analyzed is the Catch-up system. The main strategy of this system is the insertion of an adaptive delay in the message forwarding process. This allows increasing the probability of the meeting of the aggregated information. This approach was able to decrease the total number of messages transmitted and consequently, the collisions, as shown in the Figures 4(b) and 4(d). For this reason, Catch-up achieves better results when, compared to the Probabilistic system. It was able to reduce, on average, 10 % of both transmitted messages and packet collisions. In addition to that, it increased the coverage by 5 % (Figure 4(a)). In both, Probabilistic and Catch-up, there is a slight drop in the coverage rate as the vehicle density raises. In addition to this, the Catch-up system still has a higher knowledge transmission rate and packet collisions. It is known that both Probabilistic and Catch-up do not use any type of selection mechanism to chose the most relevant vehicle to perform the tasks of information aggregation, generation, and distribution of knowledge. The lack of such mechanism is translated in the delays for both systems when compared to DARF and TRUSTed. This situation is depicted in Figure 4(c).

The DA2RF system employs a broadcast suppression mechanism in the knowledge forwarding process.This approach, as shown in Figure 4(a), improves the coverage rate by 18 % and 15 % when compared to Probabilistic and Catch-up, respectively. By applying the suppression mechanism, it is possible to clearly see a decrease in the total number of the messages transmitted (Figure 4(b)). On average, was reached a reduction of 30 % in comparison to the Probabilistic system, and 20 % fewer messages when compared to Catch-up. The same tendency was observed in regards to the packet collisions rate (Figure 4(d)). On average there was a reduction of 30 % and 25 %, compared to Probabilistic and Catch-up, respectively. It is important to notice that DA2RF is implemented only with the broadcast suppression mechanism and does not have any selection mechanism. Because of this, it still introduces a delay very close to the other previously analyzed systems, as depicted in Figure 4(c).

Finally, the proposed TRUSTed system applies the egocentric betweenness measure to perform the selection of the most relevant vehicle to carry out the information aggregation and knowledge generation. In addition, it also applies the broadcast suppression mechanism in the knowledge distribution process. This combination enables it to outperform all other systems in all the metrics evaluated. TRUSTed significantly reduces the total number of messages transmitted in the network, with an average decrease of more than 85 % in comparison to Probabilistic, as well as 80 % and 70 % compared to Catch-up and DA2RF, respectively (Figure 4(b)). As a consequence of this reduction, the knowledge generated can reach a larger number of vehicles in all densities analyzed, resulting in a higher coverage rate, close to 98 %, on average, as shown in Figure 4(a). Furthermore, the broadcast suppression mechanism implemented has helped reduce the number of packet collisions (Figure 4(d)). The average reduction reached more than 75 %, 70 %, and 50 % compared to Probabilistic, Catch-up, and DA2RF, respectively. At the end, the TRUSTed system also presented the lowest average delay, among all systems analyzed, being around of 0.15 seconds (Figure 4(c)).

Two main lessons were learned from the analysis of results. The first one is that there is a need for a mechanism to select the most relevant vehicle in the network. Because by using this kind of mechanism it is possible to make the system scalable. The second one refers to the egocentric betweenness measure being a viable option for the selection mechanism in highly dynamic networks.

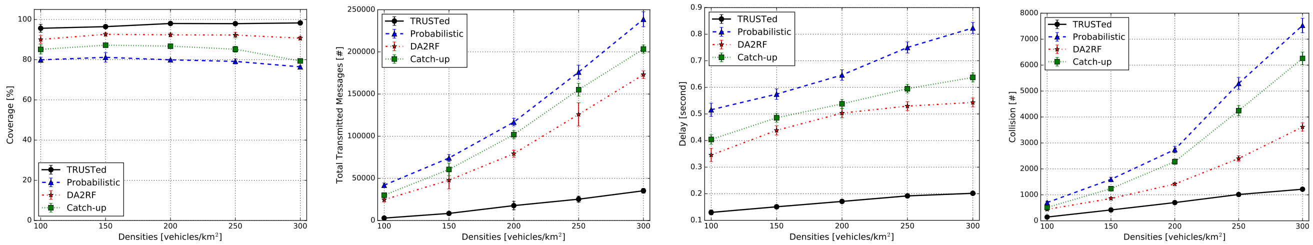
C. Control Channel Perspective Assessment

The periodic exchange of beacon packages was used, in all the analyzed systems, to create the local knowledge base (local information exchanged between one-hop neighbors). Moreover the transmission frequency of 1Hz was set to all systems [4], [5], [6], including TRUSTed. Because of that, the following results are consistent between all the systems assessed in this work.

Figure 5 depicts the performance results of the control channel in all the vehicle densities. A macroscopic view of the total number of beacon packets transmitted in the network, is presented in Figure 5(a). It is possible to notice that the number of transmitted packets increases linearly following the vehicle density expansion. This result is expected, because as the vehicle densities increase in the course of the simulations, the larger the number of beacons transmitted in the network. Note that the channel busy rate, shown in Figure 5(b), exhibits the same behavior, in average value, in relation to the total number of beacons transmitted, see Figure 5(a). The observed behavior of the results is also expected, because of the channel busy rate increases as the number of packets transmitted on the network increases. When the system is running with the highest densities evaluated, such as 200, 250 and 300 vehicles/km^2, the channel busy rate reached, on average, 28 %, 34 %, and 35 %, respectively (Figure 5(b)).

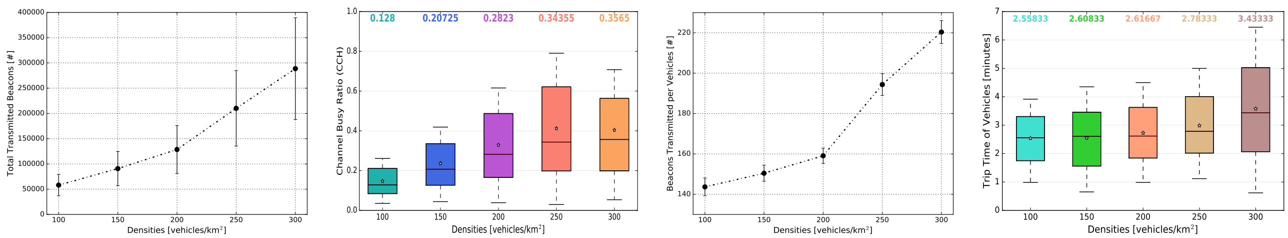
A microscopic view of the number of beacon packets transmitted in the network, can be seen in Figure 5(c). It shows the average number of beacons transmitted by each vehicle as a function of vehicle densities. It is known that the number of beacons transmitted by each vehicle is directly related to its travel time, which is the time that it remains in the simulation. With this in mind, the results of the travel time for each density was generated, see Figure 5(d). As the beacon transmission frequency is of 1 Hz, we can see that the number of packets transmitted, on average, by each vehicle is in accordance with the average time in each density.

As a results, a beacon transmission frequency rate of 1 Hz, may be considered adequate for this type of scenario when evaluated together with the adopted mobility model. Because the channel busy rate was around of 35 %, on average, at the maximum analyzed density (300 vehicles/km^2), as shown in Figure 5(b).



(a) Coverage. (b) Total of transmitted messages. (c) Delay. (d) Collision.

Fig. 4: Knowledge distribution results.



(a) Total of transmitted beacons. (b) Channel busy ratio. (c) Beacon transmitted per vehicle. (d) Trip time by each vehicle.

Fig. 5: Control channel results.

V. Conclusion

Several Intelligent Transport Systems have been proposed to deal with information management and knowledge distribution related to vehicle traffic conditions. In this type of system, the knowledge is generated from the processing of aggregated local information. However, in the systems found in the literature, all the vehicles perform the tasks of information aggregation and knowledge generation. This situation leads to overloading the network. In order to address this issue, the TRUSTed system was proposed. TRUSTed is a distributed system for information management and knowledge distribution, which employs the egocentric betweenness measure, in order to select the most relevant vehicle to perform above-mentioned tasks. In addition, it applies the broadcast suppression mechanism during the knowledge distribution process, reducing the network overhead.

The experimental results showed that TRUSTed outperforms all its competitors in all metrics. As future work, alternative route calculation will be added to the proposed system, enabling to alert the drivers to avoid congested areas. With this, it will be possible to address all the three phases of the system: (i) environment sensing, (ii) generation and distribution of knowledge, and (iii) consumption of the knowledge produced.

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