# Keep It Fresh: Reducing the Age of Information in V2X Networks

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## ABSTRACT

The freshness of information is of the utmost importance in many contexts, including V2X networks and applications. One measure of this metric is the Age of Information (AoI), a notion recently introduced and explored by several authors, often with specific reference to vehicular networks. With this work, we explore the possibility of reducing the AoI of multi-hop information flooding in V2X networks exploiting the properties of the Eigenvector Centrality (EvC) of nodes in the topology, and the possibility that each node computes it exploiting only local information and very easy computations, so that each node can autonomously adapt its own networking parameters to redistribute information more efficiently. Starting from theoretical bounds and results, we explore how they hold in urban-constrained topologies and compare the AoI achieved exploiting EvC with the AoI achievable without this optimization of the nodes' behavior. Simulation results show a meaningful improvement without using additional resources and without the need of any global coordination.

## CCS CONCEPTS

• **Networks → Network performance analysis**; *Routing protocols*; *Packet scheduling*;

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## 1 INTRODUCTION

The concept of Age of Information (AoI), different from delay and latency, was introduced in the early '2010s as a measure of the efficiency of information distribution, especially for applications that require periodic updates in mesh networks [8]. A recent survey [9] provides the background necessary on this novel concept, while some recent works [6, 7, 12, 13] explore optimization and minimization techniques on single channel and multi-channels environments. As noted in [7], AoI "captures the freshness of the information from the *perspective of the destination*". Needless to say, in V2X networks periodic updates like Cooperative Awareness Message (CAM) messages are of paramount importance and their fast delivery to many vehicles, e.g., for cooperative driving, is fundamental [4], and the performance is driven by the *perspective of the destination*.

Recently we have proposed and developed a methodology to optimize the streaming of information in generic mesh networks [1], and we have also successfully applied it to sporadic flooding of messages in low duty-cycle networks [2]. The optimization takes, as the metric AoI, the perspective of the destination, imposing a "*receiver equal*" policy, which means that it tries to equalize the amount of information that destinations periodically receive. We call this policy Receiver Equal flooding ($RE_f$). The technique devised is based on the notion of *Eigenvector Centrality* [3], which, as we have shown in [1] can be computed very easily and locally at each node when the network is described by a stochastic adjacency matrix. We also recall that the eigenvector centrality is the base of the PageRank algorithm initially used by Google, albeit this has no relation with the properties we use here.

The contribution of this work is showing that the receiver equal policy leads to a reduction of the AoI in generic graphs. To show this property we derive a generic stochastic bound for the expectation of the AoI mediated on every source and destination of the network, and we show that in realistic urban topologies not only the mean of the AoI measured in simulations is below this bound, but also the 90th percentile is below this bound. Furthermore, the Empirical Cumulative

Density Function (ECDF) measured with our policy is a stochastic inferior of the ECDF measured without the use of the receiver equal policy.

## 2 BACKGROUND AND MODEL

We briefly recall here key results and notation from the literature, defining AoI and $\mathrm{RE}_f$.

### 2.1 Age of Information on Networks

We mainly refer to [8] for the definitions, and we consider a flow of generated packets labeled $1, 2 \ldots, z, \ldots$. Without loss of generality, but differently from [8], we consider a discrete time system[1] with time index $k$, and we focus on the case of periodic information generation with inter-arrival time $D$, leaving the analysis of stochastic inter-arrivals for future work. The age of information at node $d$ at time $k$ with respect to a given source of information $s$ is:

$$\Delta_{sd}(k) = k - u_{sd}(k)$$

where $u_{sd}(k)$ is the generation time of the last packet received by $d$ from $s$. We call $k^z_{sd}$ the reception time of packet $z$ from node $s$ by node $d$, and we call $F_{sd}$ the random variable (RV) that describes the dissemination delay of a message from a source $s$ to node $d$, hence,

$$k^z_{sd} = zD + F_{sd}$$

and

$$u_{sd}(k) = \max_z \{zD, \forall\, z \mid k^z_{sd} \leq k\}$$

Interpreting $F_{sd}$ as the service time of a D/G/1/∞/FIFO queuing station, with the same reasoning of AoI [8], the steady state AoI between nodes $s$ and $d$ is

$$\bar{\Delta}_{sd} = \lim_{k\to\infty} \Delta_{sd}(k) = \frac{DE[F_{sd}] + E[D^2]/2}{D} \tag{1}$$

Given a source $s$, mediating over all destinations $d$ we get

$$\bar{\Delta}_s = \frac{1}{(N-1)} \sum_{d \neq s} \bar{\Delta}_{sd} \tag{2}$$

and mediating over all $s$

$$\bar{\Delta} = \frac{1}{N} \sum_s \bar{\Delta}_s = E[F_c] + \frac{D}{2} \tag{3}$$

where $N$ is the number of nodes in the network, and $F_c$ is the RV obtained by the superposition of all $F_{sd}$. Unfortunately $F_{sd}$ are not i.i.d RV so we cannot in principle make approximations based on the central limit theorem; however, it can be interesting in the future to explore how such an approximation remains close to measured results as a function of the network topology. In the derivation of Eq. (3), there is the implicit assumption that the network maintains the ordering of packets, which is not necessarily true in reality. Simulation results, where this assumption is not verified, show that the approximation in the model does not hamper its validation.

[1]The reason of the discrete time modeling is due to the mathematical framework that allows the derivation of $\mathrm{RE}_f$, but we are confident that results holds in continuous time too.

### 2.2 A Bound on Receiver Equal flooding

In [1] and [2] we have derived the conditions that guarantee an optimal performance in streaming/flooding given that the overall resources allocated to the process remains constant and minimal, i.e., the the total number of times a packet is propagated by any node is not changed from one flooding strategy to another. We briefly summarize here these results and a stochastic upper bound for the flooding delay that is valid independently from the network topology given some basic properties are guaranteed. A cycle $T$ in the following can be interpreted as the elementary time step of a discrete time model.

Let $A'$ be a stochastic transition matrix for an undirected graph $G(V, E)$, $|V| = N$, so that the element $A'_{ij} \in [0, 1] \iff (i, j) \in E$. $A'_{ij}$ represents the probability for node $j$ to send a packet to node $i$ during a cycle $T$ and $\vec{1}^T A' = \vec{1}^T$. Let $\Theta_i$ be the throughput (in terms of packets sent per cycle) that node $j$ sustains on average in a cycle and $\Theta$ the resulting column vector. We start from a condition in which flooding in a network is obtained by having each node sending one packet per cycle ($\Theta = \vec{1}$) to one of its neighbors at random (represented by $A'$). We can call this strategy Sender Equal flooding ($\mathrm{SE}_f$), and we improve it introducing $\Theta$ and $A$ as follows, (from Theorem 1 in [1]):

$$\Theta_j = x_j \sum_{l=1}^{N} \frac{A'_{lj}}{x_l},\ A_{ij} = \frac{\frac{A'_{ij}}{x_i}}{\sum_{l=1}^{N} \frac{A'_{lj}}{x_l}} \tag{4}$$

such that:

$$\vec{1} = A\Theta \tag{5}$$

$$|\Theta| = |\vec{1}| = N \tag{6}$$

$$\vec{1}^T A = \vec{1}^T \tag{7}$$

$$A'_{ij} = 0 \iff A_{ij} = 0 \tag{8}$$

where $x_i \in \mathbb{R}$ is the PageRank centrality of node $i$. The theorem states that the new stochastic transition matrix $A$ describes the same links as $A'$ but with different probabilistic weights (Eqs. (7) and (8)), and $\Theta_j$ represents the number of packets node $j$ sends during a cycle $T$. In other words starting from a condition in which flooding in a network is obtained by having each node sending one packet to one of its neighbors at random we obtain a condition where nodes send more or less packets per cycle depending on their centrality, and they send them to neighbors with a

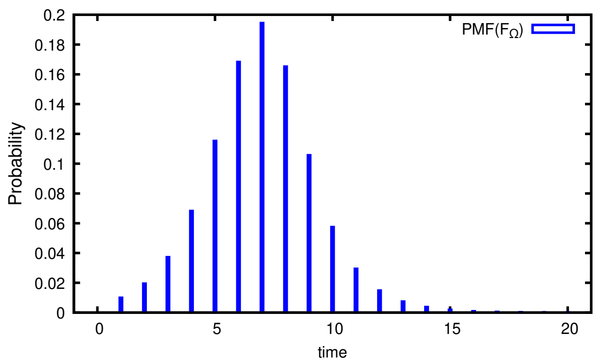


**Figure 1: Distribution of flooding delay according to the upper bound with 100 nodes.**

probability that depends, again, on centrality. As a result we equalize the probability of reception while the overall amount of resources used remains the same. It is important to stress that this optimization can be performed locally, through neighbour gossiping [1].

As reported in [2], it is possible to compute a stochastic upper bound $\Omega(k)$ for the probability of reception under $\mathrm{RE}_f$ that holds independently from the network topology, namely:

$$\begin{cases} \Omega(k+1) &= 2\Omega(k) - \frac{3}{2}\Omega^2(k) + \frac{\Omega^3(k)}{2} \\ \Omega(0) &= \frac{1}{N} \end{cases} \tag{9}$$

Eq. (9) express the Cumulative Density Function (CDF) of the upper bound of the flooding delay. As we work in discrete time this is a step function, and its derivative is a Probability Mass Function (PMF). By way of example, Fig. 1 reports the PMF of this upper bound for any network with 100 nodes.

Let $F_\Omega$ be the RV that describes the stochastic bound in Eq. (9), then by substituting $F_c = F_\Omega$ in Eq. (3) we obtain an upper bound $\gamma$ of the average AoI independent from the network topology:

$$\gamma = E[F_\Omega] + \frac{D}{2} \tag{10}$$

## 3 V2X NETWORK MODEL

The theoretical framework derived in Section 2 is valid for (almost) any topology, but clearly introduces approximations and assumption that need some form of validation. In particular, $\mathrm{RE}_f$ optimizes the average AoI, but does not guarantee that the average is not reduced penalizing marginal nodes, thus we need to verify distributions and different sources and topologies. Another interesting analysis regards the bound $\gamma$ defined in Eq. (10): again it is a bound on the average, so how often it is violated by outliers? Or, in other words, can we use this bound safely for dimensioning V2X multi-hop communication systems?

**Figure 2: Portion of the map of the city of Trento.**

Furthermore, as we already noted the theory assumes that packets are delivered in order, while in a network there might be mis-ordering due to packets that follow different routes. This probability may be minimized if $D >> 1$, however to test how much reordering may affect our results we set, in simulations, $D = 1$. Finally, we want to test our results in topologies that are somewhat realistic in terms of Vehicular Communications. Being our department based in Trento, Italy, we focus on the local street map, which can be easily obtained through OpenStreetMap[2] and is represented in Fig. 2.

The street map is centered at the GPS coordinate (46.0585, 11.1228) and has a radius of 1 km. On this map we randomly place 100 nodes (vehicles or road side units is irrelevant) uniformly with respect the street lengths and the number of street lanes in an area of radius 500 m. Different placements results in different topologies, all characterized by the same "urban" constraint. With 100 nodes and $D = 1$ Eq. (10) yields $\gamma \simeq 6.93 + \frac{1}{2} = 7.43$, and this will be our base reference for analysis.

To fix ideas we can imagine that this number refers to some standard message inter-arrival time, like the 100 ms of CAMs, and the multi-hop distribution system piggy-backs information to be disseminated on the same periodic message[3]. Other scenarios include TDMA-based technologies, 5G CV2X [5] where resources are allocated to nodes (vehicles) by the base station, or networks of fixed V2X nodes (Road

[2]https://www.openstreetmap.org

[3]We are aware that sticking to standards CAMs do not work like described, but these are just examples to help mapping the theoretic framework on real scenarios.

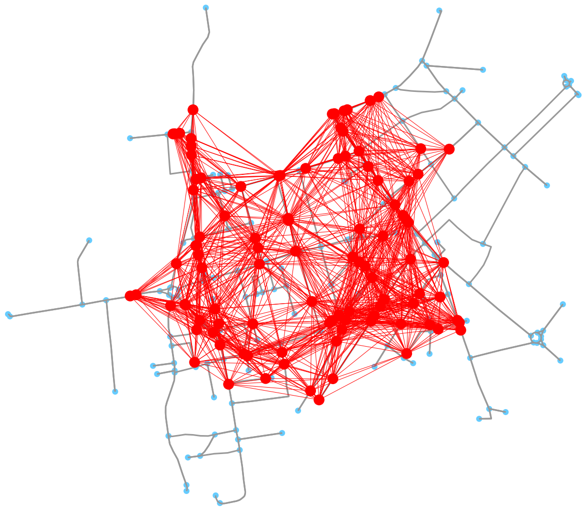

**Figure 3: Vehicular network randomly generated for the map of the city of Trento with 100 nodes.**

Side Unit (RSU), traffic lights, etc.). Also Visible Light Communications (VLC) networking, where clearly information need multi-hop to disseminate [10, 11].

To keep the scenario simple, once the vehicles or RSUs are placed randomly on the street topology respecting street lengths and width to modulate density, the simulator create bidirectional links among all nodes that are less than 300 m apart. An example of graph generated through our model is presented in Fig. 3. For the time being we do not consider buildings, so the network we derive is not representative of technolgies that require strict line of sight, an analysis left for future work.

During simulations, we consider each node as a data producer with rate $D = 1$, and all nodes are interested in receiving all information, thus requiring flooding in the network. Data multiplexing into aggregated packets and creation of node clusters with a backbone to orchestrate the distribution can be considered, but they can only improve the basic performance gains we discuss here, obviously reducing the bound in Eq. (10).

## 4 RESULTS

We use an event driven simulator[4] computing $\bar{\Delta}_{sd}$ for all the receiving vehicles $d \in V$ given a sender $s$ and we iterate over all nodes as senders as well as repeating the distribution for 100 messages, so that every simulation yields $9.9 \times 10^5$ message delivery delays. As already mentioned we set $D = 1$ which is the worst case scenario, sample simulations with different $D$ confirm the results.

[4]The same we already used in [1, 2] and that will be made available to the community as soon as it is stable and documented.

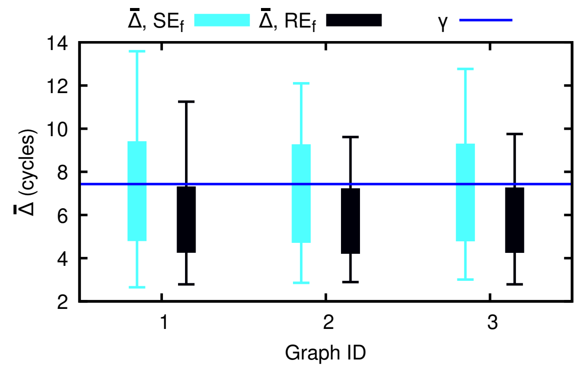


**Figure 4: Boxplots of the AoI $\bar{\Delta}_s$ simulated using three different graphs.**

We report data with boxplots, with minimum and maximum at the whiskers and 10th and 90th percentiles for the boxes. We are interested to compare the $RE_f$ flooding strategy we have proposed with the theoretical bound $\gamma$ that we have found and with the "traditional" flooding strategy, where every node sends the same amount of information and that we call $SE_f$. The two strategies use, for the entire network, exactly the same amount of transmission resources, so that the comparison is fair, and they also use similarly "blind" scheduling policies based only on a weighted random selection of the neighbors based on the stochastic adjacency matrix. Heuristic scheduling optimizations are easy for both schemes (e.g., do not send the message to the node that has sent you the information and blacklist nodes that you have already sent the message to), but would make the results not coherent with the bound $\gamma$. For this reason we do not explore heuristics here, though we are confident that they leave the relative performance of $RE_f$ and $SE_f$ unaltered, or even improve the relative $RE_f$ performance because of the additional knowledge on the topology that is inherent to the Receiver Equal strategy.

Out goal is to answer these questions:

(1) How do $RE_f$ and $SE_f$ strategies perform in terms of mean AoI?
(2) What are the advantages of the $RE_f$?
(3) How does the performance of $RE_f$ compare with the stochastic bound of Eq. (10)?

For the same map area of Trento, we consider three possible vehicular networks, one of them is represented in Fig. 3. Fig. 4 reports AoI $\bar{\Delta}_s$ mediated over all destinations given a sender $s$. Simulations iterate over all the vehicles as senders generating 100 different messages per sender, so each boxplot includes 9900 points.

As can be easily noted, $RE_f$ performs consistently better than $SE_f$. In fact, the $RE_f$ mean AoI $\bar{\Delta}_s$ is reduced both in terms of the absolute maxima and in terms of distribution mass, while the absolute minima remains comparable as expected. These results show that, keeping constant the overall amount of allocated resources, $\mathrm{RE}_f$ grants a distribution boost and a consequent improvement in the AoI. Indeed, these initial measures hints to the possibility that $\mathrm{RE}_f$ stochastically dominates $\mathrm{SE}_f$, an interesting possibility that might be proven in the future.

The stochastic bound of Eq. (10) states that, on average, the AoI $\bar{\Delta}$ achieved using $\mathrm{RE}_f$ on a network of 100 nodes is lower than 7.43. The results of Fig. 4 not only corroborates this theoretical result, but indicate that, at least for these networks, more than 90% of the values of $\bar{\Delta}_s$ using $\mathrm{RE}_f$ remain below the threshold, indicating that bound $\gamma$ in Eq. (10) is an extremely powerful means to dimension with great simplicity complex dynamic distribution systems.

In other words, these results indicates that not only $\mathrm{RE}_f$ performs consistently better than $\mathrm{SE}_f$, but it also comes with a theoretical framework that yields a stochastic bound that is not available for $\mathrm{SE}_f$ and that can be of paramount importance for designing and realizing real-time soft-constrained flooding systems in vehicular networks.

Although the aggregated mean AoI $\bar{\Delta}_s$ allows a good insight in the overall performance on the entire network, we are also interested in studying if any receiver or any sender may be penalized by $\mathrm{RE}_f$. To do this we aggregate the simulation measures for one of the scenarios in sender or receiver specific boxplots. Namely, we collect $\bar{\Delta}_{sd}$ (see Eq. (1)) so as to build a boxplot of all $\bar{\Delta}_s$ (see Eq. (2)) as a function of the receiver, or all $\bar{\Delta}_d$ as defined in Eq. (11).

$$\bar{\Delta}_d = \frac{1}{(N-1)} \sum_{s \neq d} \bar{\Delta}_{sd} \tag{11}$$

We start analyzing $\bar{\Delta}_s$. Figure 5 reports the boxplots of the AoI $\bar{\Delta}_s$ as a function of the receiver vehicle. The $x$ axis reports 50 out of 100 vehicles ordered by increasing AoI to improve readability, results for the other vehicles are stochastically identical to those reported, and we were careful to avoid "cutting" possible outliers. Again $\mathrm{RE}_f$ performs consistently better than $\mathrm{SE}_f$ and we can see that the stochastic bound $\gamma$ of Eq. (10) is valid for all vehicles, and for most vehicles the 90th percentile is below $\gamma$. This result is due to the Reception-Equal property which optimizes the network resources so to grant a propagation of data across the network as uniform as possible. This results are fundamentally the same presented in Fig. 4, but here it is possible to appreciate that no receiver is penalized in any way, while in Fig. 4 there is no way to see if all the outliers of the boxplot belong to the same vehicle or not.

Now we want to analyze if $\mathrm{RE}_f$ penalizes any sender. To this end Fig. 6 reports the boxplots of the AoI $\bar{\Delta}_d$ as a function of the sender vehicle. Also in this case $\mathrm{RE}_f$ performs consistently better than $\mathrm{SE}_f$ both in terms of mean AoI maxima and mass. The stochastic bound of Eq. (10) still holds for all the nodes, although for the nodes with worst performance, probably located in a peripheral fringe of the network, the 90th percentile is above $\gamma$, which is perfectly consistent with the theory, albeit maybe a bit annoying from a dimensioning point of view. Recall, however, that no optimization heuristic is applied here, and we deem that a properly crafted heuristic will not only reduce $\bar{\Delta}_{sd}$ on average, but also "compact" the distribution, improving the performance for outliers (topologically peripheral nodes) more than that of central nodes.

## 5 DISCUSSION AND FUTURE WORK

AoI has been introduced to capture the concept of information *freshness* from the receiver point of view. In the context of vehicular networks this metric can have significant importance due to the existing communication applications that require periodic updates. Our proposed flooding strategy, called Receiver Equal flooding, optimizes the network resources for data flooding and it can grant performance improvements on the AoI for vehicular networks compared to traditional strategies that do not exploit topological properties of the network. We remark that $\mathrm{RE}_f$ achieves this with zero signalling and without building a specific distribution overlay (e.g., a tree) on top of the network, so it is perfectly suited for a highly dynamic and time-varying environment as V2X communications. In this work, we derived and validated through simulations a stochastic bound $\gamma$ on the mean AoI $\bar{\Delta}$, a bound that depends only on the number of nodes in the network and is entirely independent from the topology. Moreover, we have shown experimentally that $\mathrm{RE}_f$ is superior to the more wide-spread $\mathrm{SE}_f$ in terms of performance.

This contribution is just a first step in exploiting the Eigenvector Centrality in the management of V2X communications, and much work lies ahead to improve the bound, possibly finding ways of fine-tuning it either to some network properties (e.g., average number of links per node) or to scheduling heuristics, for instance finding a deterministic worst-case bound that can be used for hard real-time applications and not a stochastic one that discounts the lack of a worst case dissemination delay inherent to a blind random choice of the nodes' neighbors. We stress that this limitation is due to the theoretical analysis to obtain the bound and is by no way inherent to $\mathrm{RE}_f$ strategy, which can be computed and used with any scheduling strategy.

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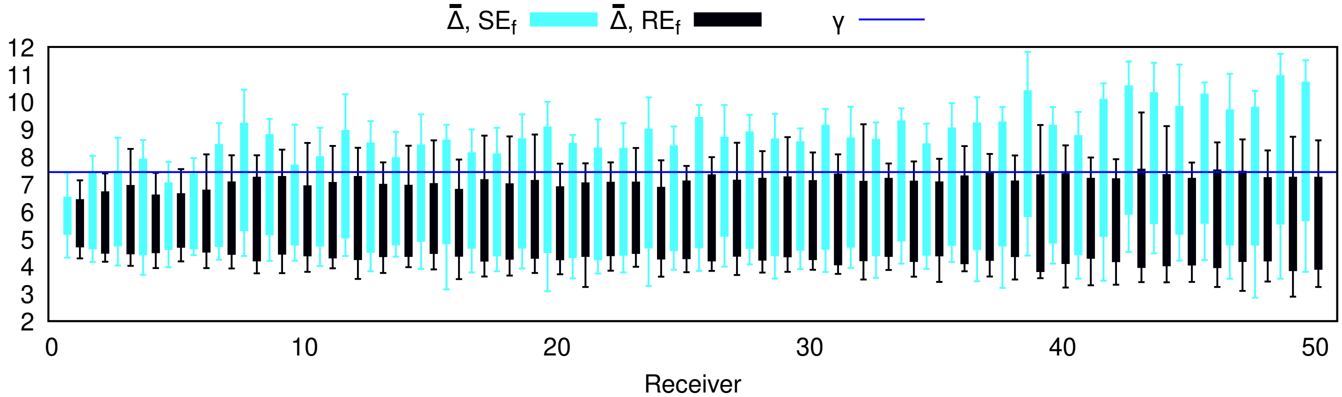


**Figure 5: Boxplots of $\bar{\Delta}_s$ as a function of the receiver vehicle.**

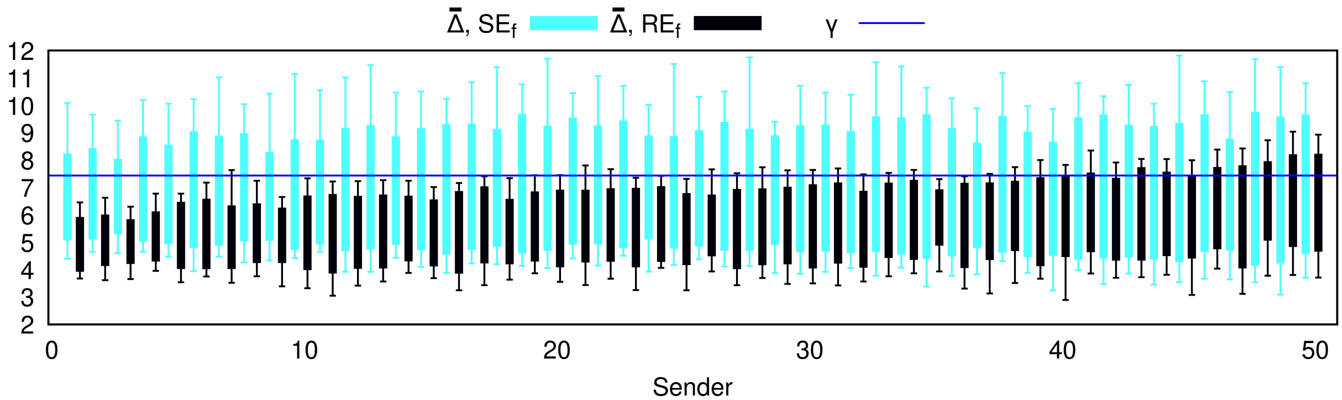


**Figure 6: Boxplots of $\bar{\Delta}_d$ distribution as a function of sender vehicle.**


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