VANET Mobility Modeling Challenged by Feedback Loops

(Invited Paper)

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***Abstract*—VANET applications are often providing street traffic information to vehicles and drivers, regarding, for instance, traffic conditions and parking space availability. This information influences in turn the driving behavior in real-world settings. Mobility models used in current VANET simulations are mostly ignoring this feedback entirely. In cases the feedback is included, it is mainly based on ad-hoc approaches with lack of generality.**

With this paper, we contribute to the investigation of such feedback loops within VANETs by describing the levels at which feedback loops can be introduced, i.e., on strategic, tactical, and operational levels of mobility. We further describe how feedback loops can be introduced in arbitrary mobility models and in particular in elementary mobility models. We exemplify our approach by introducing two types of feedback loops for the Manhattan Mobility model, the Random Trip model, and the Constrained Random Trip model. One feedback loop represents points of interest attracting vehicles, such as free parking spaces attracting vehicles searching for parking. The other feedback loop focuses on repelling vehicles, such as a traffic jam.

We discuss the impacts of the feedback in terms of the mobility metrics: vehicle density per area, number of direction changes, and intensity of direction changes. Furthermore, we discuss the effects in terms of information availability and delays of transmission in an opportunistic vehicular network.

I. Introduction

Vehicular Ad-hoc Networks (VANETs) provide data dissemination directly between mobile vehicles. This makes the mobility part of the system and the need to model mobility is at the center of investigations. Besides traditional data communication, dissemination of traffic-system information is a major application field of VANETs and it includes parking space management, traffic jam avoidance, rerouting of vehicles in case of emergency, and more. Hereby, the mobility of single vehicles is constrained by the underlying topography, by the movement of other vehicles, and by route changes due to received information and to driver decisions.

In related modeling approaches, a set of primitives for movement changes is introduced in [1], such as changing lanes, driving slower, etc. While these primitives allow control of micro-mobility behavior, other models incorporate the adaptation of driving behavior based on the movement of other vehicles [2]. Higher level influences to mobility behavior are challenging new research issues in VANET research. We focus in particular on discussing the feedback loop introduced by information-based decision taking on vehicular movement. In contrast to the implicit inclusion of this feedback loop, we introduce a structured way of modeling which allows separation of concerns of basic mobility behavior as expressed by the mobility model used and the alteration of mobility behavior based on a *navigation policy*.

In the remaining sections of the paper, we detail our approach: In Section II, we give a summary of feedback loop modeling approaches in recent VANET simulators accomplished by a discussion about the impacts experienced with respect to data dissemination performance. After introducing the framework for including a navigation feedback loop into mobility modeling in Section III, we discuss feedback loops in mobility models relevant for VANETs with a particular focus on elementary mobility models (Section IV). We start the discussion about the expected impacts by including such a navigation feedback loop by introducing two common city-area use cases for vehicular traffic management: parking space management and congestion management (Section V). Along with these use cases, we discuss the impacts on the elementary mobility models *Manhattan Mobility Model*, *Random Trip*, and *Constrained Random Trip* in terms of the mobility characteristics: density of nodes dwelling in an area over the observation time, number of direction changes of nodes, and intensity of direction changes (Section VI). The results are derived from a simulation of these scenarios and use cases assuming an out-of-band channel for street traffic information dissemination. Additionally, we present first results demonstrating the potential impact on data dissemination in terms of the ratio of nodes that obtained an information item (infected or informed nodes) and the dissemination delay. We conclude with a discussion about the findings and an outlook on future research directions.

II. Related Work

To approach the state-of-the-art in mobility modeling challenged by feedback loops, we give *(i)* an overview of state-of-the-art VANET simulators and outline mobility models used as well as feedback loops potentially supported, and *(ii)* discuss how related work deals with the impact of feedback loops.

In [3], [4], currently available vehicular traffic simulators and mobility models are surveyed and the importance of

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adapting mobility behavior to system events is emphasized, while in [5] it is further argued that bidirectional coupling of simulators is an important step toward realistic mobility modeling in VANET research. However, many simulations of vehicular ad hoc networks are still based on network simulations processing externally generated mobility traces. Beyond that, a number of frameworks enabling interaction between network and mobility by coupling both types of simulators have been proposed. The framework presented in [6] combines the SUMO[1] mobility generator and OMNeT++[2] network simulator by extending both with communication modules. The mobility generated by SUMO [7] is based on road networks (e.g., street maps supplemented by positions and semantics of traffic signs) where movements between source and destination roads are determined by a shortest path algorithm or, for example, traffic counting data. TraNS (Traffic and Network Simulation Environment) [8] incorporates an interface (TraCI [1]) to realize feedback communication between the traffic simulator (also SUMO) and a driver behavior model implemented in the ns-2 network simulator[3] to enable applications such as traffic congestion warning. Mobility patterns caused by traffic warnings are represented by compositions of mobility primitives, such as 'change speed', 'change target', or 'stop'.

Integrated VANET simulators basically support the implementation of feedback by integrating both traffic and network components. Although feedback possibilities are realized within such frameworks, the feedback loops required are still not fully investigated. A vehicular mobility model that incorporates a simple feedback loop is, for example, the STRAW (STreet RAndom Waypoint) model [2] prompting cars to, e.g., slow down due to traffic control.

Apart from the goal of realistic simulation, the effects of navigation are important for data dissemination. In particular VANET routing protocols that use navigation knowledge to improve packet delivery in delay-tolerant networks, such as GeoDTN+Nav [9], are potentially affected by navigation feedback loops. In [10], the authors present an approach that goes one step further by even taking the drivers' reactions to traffic information messages into account.

The impact of mobility models with respect to data dissemination metrics in vehicular ad hoc networks has been targeted, for example, in [11] with respect to contact metrics when using simple models as well as GIS based mobility models. A use case similar to those presented in this work is evaluated in [12] where the effect of route re-planning after traffic incidents on mean travel time is investigated.

III. Introducing the Navigation Feedback Loop

The change of mobility behavior due to information received by the vehicle can be integrated in a model. Our proposal is to make a clear separation of modeling basic mobility and including a *navigation policy* as depicted in Figure 1. The navigation policy depends on the VANET application and on the considered reactions of the vehicle; two use cases are described in Section V.

The navigation policy can be related to the purpose of a trip, optimization of the trip (fastest route, environment-aware route, etc.), or only related to basic changes of movement properties, such as velocity, direction, and mobility range. Therefore, we use the levels of abstraction introduced for human mobility in [13]. These levels of abstraction consist of three different levels: At the *strategic level*, humans decide on the activities they would like to perform and when to depart for an activity which leads to their daily movements, such as going to work, shopping, or taking a walk in the park. The *tactical level* considers the implementation of a strategic decision, such as choosing a mode of transport, taking into consideration which is the shortest or fastest path as given by environmental factors such as obstacles and congestion. At the *operational level*, the physical process of human movement is considered, including walking or driving speed, physical size of nodes or interaction with other traffic due to queuing or collision avoidance.

While vehicular traffic simulators often incorporate feedback on the operational level, e.g., slowing down when approaching a red traffic light, they are not as capable of including impacts introduced on the tactical and strategic level.

On tactical level, the change of routes according to available information is a major benefit envisioned for future VANET applications, for instance, to change routes according to current traffic situations by avoiding specific areas and to reach cooperative driving decisions for minimization of overall travel times.

On strategic level, the navigation policy may target aspects relevant for groups of individuals in an area. Traffic information might lead people to postpone or to change destinations for activities. Road tolls are, for instance, aimed at changing travel behaviors among drivers on the strategic level.

On all levels, the *navigation logic* (Figure 1) has to define the concrete adaptation of the mobility model including parameters such as when to alter, how to alter, and how to continue after the navigation driven movement ends. This adaptation depends also on the characteristics of the mobility model in use. The mobility and navigation system is modeled with a feedback loop.

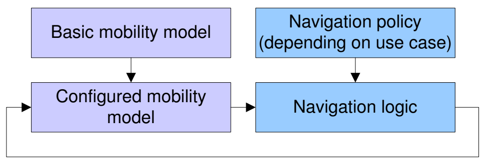

Fig. 1. Mobility modeling with navigation feedback loop.

IV. Feedback loops in Mobility Models

In order to establish the impact of external feedback loops on a VANET mobility model, we will initially introduce a

[1] http://sumo.sourceforge.net/
[2] http://www.omnetpp.org/
[3] http://www.isi.edu/nsnam/ns/

coarse classification. We will refer to mobility models as *elementary*, when they only capture movements of vehicles as if they were immaterial and uncoordinated with each other. In an elementary model setting, a node occupies a geometrical zero-dimensional point, and the presence of another, nearby node does not affect its behavior. We will refer to mobility models as *complex*, if they also account for node interactions with the environment they move in, whether it is other nodes, road signs, or traffic lights. These models can thus encompass node movement alterations such as lane changes when passing, or slowing down at junctions.

Mobility models used in VANET research are primarily derived from the broader scope of Mobile Ad-hoc Network (MANET) mobility. In the latter area, the most commonly used elementary models are *(i)* the Random Walk (RW), a movement pattern where direction and speed are set according to the output of a continuous, memoryless random process, and *(ii)* the Random Waypoint (RWP), where direction and speed are still random, but they are maintained between two – random or zero – pause times. Movements usually occur on a region represented by a convex domain, without any obstacles to node mobility. Variants of these models (such as the Probabilistic Random Walk [14], the Random Direction [15], and the Gauss-Markov model [16]) have added various degrees of realism to their original versions. However, the VANET research community agrees that neither the RW and RWP models, nor the above variants, succeed in capturing the specific nature of vehicle movements, especially their collective interactions. The most evident limitation of the above models is the lack of common constraints for the node movements (beside sharing the same region boundaries). This is a consequence of the memoryless properties of the direction/speed decision processes. The mobility they model is thus limited to the strategic level. Hence, we will not discuss them further.

A family of mobility models that, though originally designed for MANETs, arguably represents a step towards actual VANET behaviors are the so-called Group Mobility models, where nodes, though oblivious of each other, still show some coordination in their movements. In the Reference Point Group Mobility [17], which is the most general of group models, clustered nodes randomly move around a logical cluster reference point whose motion is randomly determined. Although a constraint binding each node to its reference point is introduced, it still amounts to just having region boundaries around each node. The presence of a feedback loop should primarily affect the reference point and then affect each node as a consequence. The reference point motion model can be as simplistic as a RW or a RWP, or as complicated as a fully-fledged realistic vehicular model. As the reference point model is again a model of independent points, we can refer our conclusions to the discussion on such models.

A constraint that is crucial for introducing a degree of realism in node movements, and is needed by tactical-level modeling, is the non-convexity of the domain where movement occurs. This domain can either be quite simple, such as a cross section where movement is only allowed inside the cross (often referred to as a "Swiss Flag" model [18]). Alternatively, it can be more complex and consist of a collection of segments of a graph upon which the node is forced to move (often referred to as a "City Section" model [19]). Such a graph can be shaped according to a road topology and its layout can be user-defined, map-based or random (as in the Voronoi [20] or Manhattan Street [21] models). The latter models are also referred to as *Stochastic Mobility models* in [22].

The possible effects of a feedback loop are not apparent on the road layout but, rather, on how nodes travel on such a layout. For example, the City Section model provides for nodes choosing their (random) destination on the road layout and then cruising along the shortest path to the destination, possibly with per-segment speed limits. In such a case, a feedback loop could be imposed on a segment speed limit by adding a dependence on the number of nodes on that segment. It is thus clear, based on the definitions in the previous section, that such an addition to the City Section model would raise it to the operational level. More advanced models such as the Restricted Random Waypoint model (RRWP) [18] offer additional leverage and provide even closer adherence to operational-level modeling. In RRWP, the waypoints are set as the vertices of the City Section graph and a probability can be associated to determine which waypoint is chosen next, upon reaching a vertex. The probability could be manipulated on a node-basis to reflect external conditions, such as the use of navigational aids that suggest less crowded, or faster routes that do not necessarily coincide with the shortest one.

As outlined above, complex vehicular mobility models [3] include a more detailed layout of streets as well as road factors such as traffic control signals, interaction with other vehicles, smooth acceleration and deceleration, or passing vehicles. As a further classification, we recall the one introduced by Fiore [22], which divides synthetic mobility models into five categories: beside the already mentioned *Stochastic Mobility models*, he also includes *Traffic Stream models*, *Car Following models*, *Queue models*, and *Behavioral models*.

Traffic Stream models treat vehicles at tactical level, relating vehicle velocity, vehicle density, and vehicle flow. These macroscopic models do not model individual vehicle behavior and thus have low applicability in the networking area. Queue models treat roads as queues in which vehicles leave the queue according to a scheduler. These schemes are good to model large road topologies with high vehicles densities, at the cost of some realism. Vehicle behavior in Car Following models is modeled according to the state of the surrounding vehicles in terms of position, speed, acceleration, etc. [23], thus adding operational-level characteristics to the tactical level. Examples range from the Nagel and Schreckemberg model [24] to the Intelligent Driver Model (IDM) [25]. Some of these models include lane changing schemes and intersection management. Finally, vehicles move according to social rules in Behavioral models. Social influences are reflected at all levels – strategic, tactical, and operational.

The first parameters that will be impacted by navigation tools and feedback loops are the trip generation (strategic level) and the path computation (tactical level). Users with navigators can obtain real-time information on events organization that can change a planned trip. Furthermore, pre-established computed paths from source to destination can be altered as long as real-time road conditions data is obtained. For example, data on a traffic jam can alter the pre-established path to avoid the jammed area. This effect can produce changes in vehicle densities, a parameter used in some of the aforementioned mobility models.

Interaction between vehicles, intersection management, speed and lane changing are operational-level parameters that will be impacted by feedback loops. As far as the vehicle density changes, the time spent at traffic lights and stops, and vehicle speed can vary. An interesting point is whether this effect has local or wider impact. As an example, information regarding free parking space will affect few number of vehicles in the surrounding of the parking space. This feedback loop will have increasing importance depending on how near interested vehicles are with respect to the parking space. However, information about an accident or traffic jam can impact large amounts of vehicles.

V. Use Cases

Among typical vehicular traffic scenarios in city areas, we select two scenarios where a navigation logic can help to optimize driving behavior. The use cases address not only the *tactical level*, by introducing the change of route, but also the *operational level* by adding new movement behavior.

A. Use Case 1: Parking Space Navigation

The distributed management of open parking spaces (not slotted, by road-side, and not centrally managed) is still a challenge, primary due to sensing inaccuracies and unsolved data dissemination trade-offs between connectivity, low costs, and low latencies.

Parking space navigation influences the movement behavior of vehicles by a feedback loop attracting vehicles within a Region of Interest (ROI), e.g., a driver will usually take the shortest path (optimizing time or distance metrics) toward an available parking space. If multiple drivers are heading toward the same region (or even same parking space), this can have significant influence on the mobility characteristics, e.g., occurrence of congestions, change of regional distribution of number of free parking spaces, longer cruising times because the parking space is already taken upon arrival, etc.

B. Use Case 2: Traffic Jam Avoidance

Like in the first use case, vehicles change their mobility behavior depending on their current position with respect to a traffic jam, which might lead to alternating routes. This use case is an example of situations where vehicle movements are affected by areas they want to bypass. Different navigation algorithms can be implemented to find any alternative route as long as the congested area is avoided.

One example of navigation alterations is a simple reflection of the move such as used in closed mobile systems where nodes are assumed to be reflected at the area borders. Alternatively, nodes may also drive along the boundary of the area or at a specific distance to the boundary of the area.

In more complex navigation logic approaches, the system might also consider the behavior of other vehicles to utilize cooperation in order to avoid new congestions on the alternative route. Furthermore, realistic approaches will have to consider the policies of city authorities who usually like to avoid re-routing of traffic to certain areas, for example, residential areas, and inner-city districts.

VI. Experiments

Here, we present the first results of simulation experiments for selected elementary mobility models. The aim of the experiments is to show the impact of the feedback loop on mobility characteristics of nodes and their effects on opportunistic data dissemination. Mobility models used in the simulations are:

- **Manhattan (MAN).** The Manhattan mobility model [21] allows nodes to move on a grid of horizontal and vertical streets. When reaching an intersection, a node moves either further on the same street (probability $p = 0.5$), turns left ($p = 0.25$), or turns right ($p = 0.25$). If a node reaches the simulation border its movement direction is inverted (reflected).
- **Random Trip (RT).** The Random Trip mobility model [18] is implemented as a Random Waypoint model where movement is limited to an underlying graph, i.e., a Manhattan grid. Start and endpoints of trips can lie on arbitrary positions on the graph. The start point of each trip lies on the end point of the last trip or on a random position for the first step.
- **Constrained Random Trip (CONST RT).** The Constrained Random Trip mobility model [18] is an extension of the random trip model where the start and end points of a trip have to be located on the graph vertices.

We evaluate the differences of the mobility models along three selected mobility metrics that are important for opportunistic data dissemination. The details about the mobility metrics used are as follows:

- **Density (in an area).** The node density gives the number of nodes within an area over the whole simulation period.
- **Number of directional changes.** Every change of the current direction of a node is counted; in our setting, the direction can be changed only along three different angles, i.e., $90°$,$180°$, or $270°$.
- **Direction change intensity.** The direction change intensity is the angle of a directional change. In our setting, the intensity is restricted to the three possible angles mentioned above.

The metrics show differences in the space-based dwelling behavior of nodes which is important for node contacts (density in an area) and efficient opportunistic forwarding (directional changes). In order to see the impact of feedback on data dissemination, the following metrics are used:

- **Ratio of infected nodes.** This metric gives the ratio of nodes that obtained a copy of the data object during the simulation.
- **Dissemination delay.** This delay is defined as the time from the generation of a data object to its delivery.

A. Mobility Characteristics with/without Navigation

We performed a first simulation study using the OMNeT++ simulator implementing the Manhattan (MAN), Random Trip (RT), and Constrained Random Trip (CONST RT) mobility models with and without the two basic feedback loops described in Section V. We discuss the differences by describing the empirical probability functions of the mobility characteristics in terms of their Empirical Cumulated Density Functions (ECDFs) and by using the Kullback-Leibler (KL) divergence to quantify the difference of the alterations to the basic mobility model in a single divergence value (Table II; using the implementation of the statistics tool R [26]). The higher the divergence values, the more the empirical PDFs differ. The simulation parameters are summarized in Table I.

Parameter	Value
Number of nodes	36
Simulation area	2x2km
Number of parking spaces	36
ROI parking space	500m
Node speed	50km/h
Pause time	0s
Manhattan grid size	200m
Simulation time	3600s
Analysis grid	50m

TABLE I
SIMULATION PARAMETERS.

In the first scenario (NAV), vehicles are attracted by positions (overall, 36 parking spaces). When a vehicle moves close to a free parking space it halts the underlying mobility model and navigates to the parking space following the shortest path. Here, the information about parking space availability forms the feedback loop. When leaving the parking space, the underlying mobility model is resumed until the node comes close to another free parking space.

In the second scenario (REP), four repulsion areas simulating congested regions are placed on the simulation area (here, circles of equal radius). When a node comes close to a repulsion area following the MAN model, it will be reflected at the border. If the node is following the RT or CONST RT models, the shortest path will be calculated so that the repulsion areas are circumvented. In the RT model, this also means that the node will be first reflected if the destination point is in between two crossings, then it circumvents the area.

Density: Density results show that the distribution of nodes is most uniform for MAN with a slight increase toward the center, while RT and CONST RT show higher densities in some regions due to traveling along (similar) shortest paths. For the NAV based models, densities near parking spaces increase while the repulsion scenario produces the expected repulsion areas. The distribution of densities outside the repulsion areas for all REP models is very similar to the original models with peaks on intersections. To give details about the alteration of densities, the cumulative density functions of node density are given in Figure 2 (NAV) and 3 (REP).

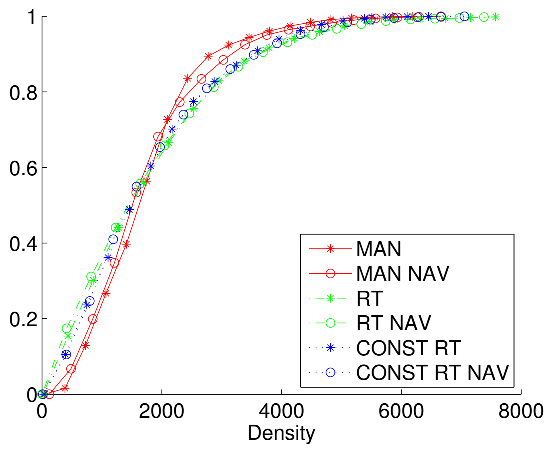

Fig. 2. ECDF Density of mobility models with and without navigation.

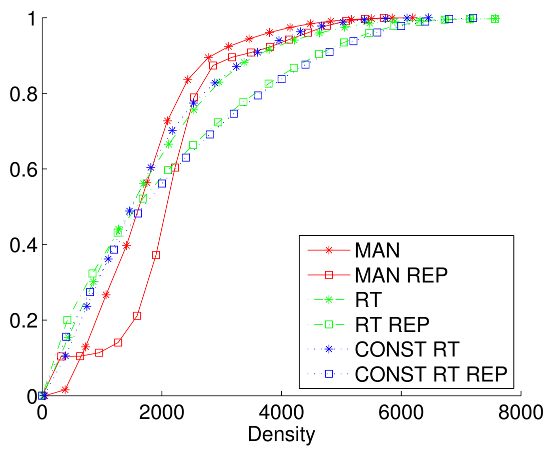

Fig. 3. ECDF Density of mobility models with and without repulsion areas.

It can be seen that the different models have similar density ECDFs in the NAV use case as for the original model. Here, only for MAN NAV, slightly lower and higher densities occur more often than for MAN. Higher densities occur more often in the REP use case for RT and CONST RT (as well as slightly lower densities), due to the factual shrinking of the dwelling area, whereas the number of vehicles on the area remains constant. The densities of MAN REP are influenced by the reflection at borders of the repulsion areas and simulation area. The density on streets located on the simulation area boundary is low while the density on the remaining streets is high and relative uniform which is reflected by a small number of low densities in the ECDF. The low density on these boundary streets is caused by the fact that the majority of nodes coming close to a boundary are reflected between a simulation and a repulsion area boundary and only a small number of nodes moves directly to an intersection located on a boundary. This phenomenon shows that feedback loops may force elementary mobility models to show concentrations in areas leading to lower relative frequencies of medium-large densities and more in the extreme cases. The KL divergence given in Table II confirms this observation by giving only small divergence numbers with slightly higher values for the REP model when compared to the NAV model for each elementary mobility model and slightly higher divergence values for MAN models.

Number of Directional Changes: In Figure 4, the ECDF of the number of directional changes is shown. When comparing the basic elementary models against each other, it can be seen that the MAN mobility model shows the highest number of directional changes. On each crossing there is a 50% chance to change the movement direction. RT based models follow the shortest path, which involves mostly straight movements with a low number of directional changes along the edges of the Manhattan grid. The number of directional changes for RT is higher than for CONST RT because path endpoints are not limited to intersections but can be located on arbitrary positions on the grid resulting in more directional changes.

Applying now NAV and REP navigation strategies, the number of directional changes increases which leads to a visual shift of the ECDFs in all the REP models when compared to their original models. The navigation logic of NAV and REP perturbs the movements of CONST RT and RT along straight paths which generates additional directional changes. This indicates that the main effect on the change of the number of directional changes is caused by the break-down of the mostly-straight shortest paths. In particular for the model with lowest number of directional changes, i.e., CONST RT and RT, the NAV and REP strategy yields remarkably higher frequencies at higher numbers of directional changes. In case of MAN NAV, the frequency of lower and higher number of directional changes increases. For MAN REP there is a drastic increase of directional changes caused by less and shorter available movement paths. The smaller number of available connected paths increases the chance that a movement leads to reflection. The observations are also confirmed by the KL divergence values given in Table II. First, these values show that there is divergence and, second, they confirm that the REP models impact the behavior of the elementary models more than the NAV models (most significantly in the MAN case).

Direction Change Intensity: Figure 5 shows the mean number of relative directional changes for the three possible turns. As seen by investigating number of directional changes, the occurrences of directional changes increases for RT and CONST RT with REP and NAV. The number of left and right turns is very similar within each model and increases slightly for RT REP and CONST RT REP because shortest paths have to circumvent repulsion areas which leads to more

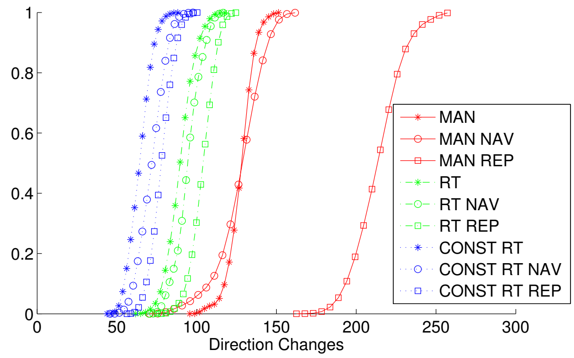

Fig. 4. ECDF Number of directional changes.

turn left and rights. For MAN NAV, there is hardly any change in the total number of directional changes, but there is a change in the ratio between different angles. In MAN, turnarounds (180°) occur only when a node is reflected on the simulation border. For MAN NAV, the number of turnarounds increases because during navigation now all three directional changes are allowed. For MAN REP, reflection also happens on repulsion areas and the number of available connected paths is lower which leads to additional turnarounds. The KL divergence value confirms this observation yielding low divergence values in the RT based models both for NAV and REP, while in the MAN case, the KL divergence values are slightly higher, in particular for the REP case when compared to the NAV case (see Table II).

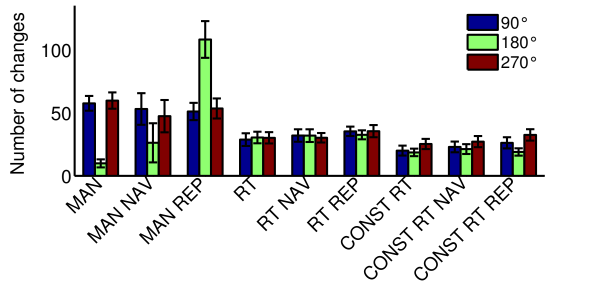

Fig. 5. Direction change intensity (average and standard deviation).

B. Data Dissemination Impacts

We now consider the dissemination of a message in the grid area using opportunistic networking which has been studied in the context of *epidemic modeling*. A node with a copy of the message is called an infected node. Every time an infected vehicle meets another vehicle, it copies the message and infects the new vehicle. Dissemination is then studied as how the infection is propagated in the area.

In Figures 6 and 7, the ratio of infected nodes as a function of the *Dissemination Delay* is drawn for the considered mobility models. We may first observe that the different models produce different dissemination delays. MAN models produce

TABLE II
KULLBACK-LEIBLER (KL) DIVERGENCE: THIS VALUE SHOWS THE DIVERGENCE OF THE NAV AND REP MODEL VARIANTS OF THE ORIGINAL ELEMENTARY MOBILITY MODELS MAN, RT, AND CONST RT RELATED TO THE CORRESPONDING ORIGINAL ELEMENTARY MOBILITY MODEL.

	MAN		RT		CONST RT	
Metric	**MAN NAV**	**MAN REP**	**RT NAV**	**RT REP**	**CONST RT NAV**	**CONST RT REP**
Density	0.0425	0.7669	0.0041	0.0646	0.0067	0.0946
Number of dir. ch.	0.1790	8.2773	0.1642	1.2550	0.3292	1.6145
Intensity of dir. ch.	0.0658	0.4348	0.0009	0.0016	0.0005	0.0057

higher dissemination delays than RT models. The explanation is due to the fact that in the Manhattan mobility model, a vehicle arriving to a cross-road chooses randomly a direction. This effect can be seen as a kind of random walk. However, in the RT and CONST RT, vehicles follow a trip selection rule. Thus, in the MAN model spreading is slower than in RT and CONST RT. The difference between RT and CONST RT is due to the underlying mobility model, e.g., CONST RT yields less directional changes than RT, producing thus different dissemination delays.

Navigation rules impact the way nodes meet in the grid and therefore how dissemination is spread, Figures 6, 7 (with confidence intervals) and Table III. For example, let us take the MAN mobility model with parking space navigation. The vehicles stop moving randomly and move toward the parking area. This effect changes the way vehicles meet in the grid with respect to a random walk-like mobility model: vehicles travel toward an attraction point in which they will surely contact. For RT and CONST RT, contacts depend on how end points are chosen since vehicles move toward the previously chosen end destinations. For example, in the CONST RT mobility model, nodes moving toward the same end points tend to chose similar paths. Besides, some vehicles near parking spaces change their original direction, and finally they meet in the surroundings of the parking space. RT behaves similarly as CONST RT in this case.

In the use case navigation with repulsion areas, we observe again impacts on data dissemination (Figure 7). MAN REP obtains higher dissemination delays than pure MAN without repulsion. The reason is again how the mobility model behaves. When a node collides with the repulsion area, it reflects. Direction changes are randomly chosen, thus, circumvention of the area depends on these random directions. Hence, the infection wave moves slower than without repulsion: every time node moving along the chosen direction collides with the repulsion area, the node moves backwards, increasing the traveling distance for the infection to arrive nearby the opposite side of the repulsion area. For RT and CONST RT, however, when a node reaches the repulsion area, it looks for an alternative path circumventing the area. Any node that wants to cross the repulsion area also has to circumvent the area, thus increasing the probability of meeting other nodes that avoid the repulsion area.

In both cases of, first, navigation to an attracting point and, second, repulsion, we observe how navigation increases

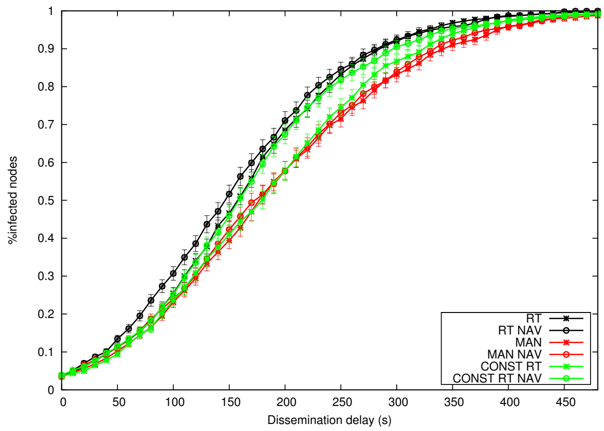

Fig. 6. Ratio of infected nodes as a function of Dissemination Delay, MAN, RT, CONST RT versus MAN NAV, RT NAV, CONST RT NAV.

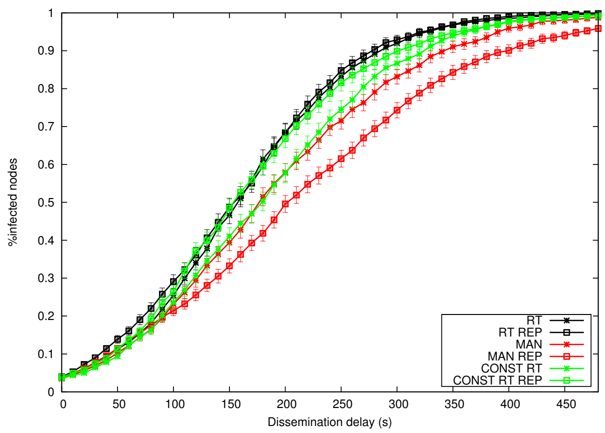

Fig. 7. Ratio of infected nodes as a function of Dissemination Delay, MAN, RT, CONST RT versus MAN REP, RT REP, CONST RT REP.

or decreases delay with respect to those models without navigation as summarized in terms of average dissemination delays in Table III. As a conclusion, we can deduce that navigation changes the way vehicles meet, impacting how fast the dissemination spreads in a given area.

VII. CONCLUSIONS AND FUTURE WORK

We presented a structured way of including navigation policies by using a feedback loop in mobility modeling. We focused on two typical traffic scenarios in city areas, i.e., navigation to free parking spaces and repulsion from

TABLE III
AVERAGE DISSEMINATION DELAYS (IN SECONDS).

MAN	**MAN NAV**	**MAN REP**
190.68	185.83	217.60
RT	**RT NAV**	**RT REP**
163.49	155.59	158.23
CONST RT	**CONST RT NAV**	**CONST RT REP**
183.08	167.90	166.94

congested areas. Two feedback loops have been introduced to three elementary mobility models: Manhattan mobility model, Random Trip model, and Constrained Random Trip model.

By means of simulation, we observed that the node density per area and the directional changes were impacted by the feedback loops. The distribution of node density changed, showing now higher relative frequencies of high node densities while the frequencies of medium-scale densities decreased. In terms of directional changes, the feedback loops caused in most cases an increase of the number of directional changes; in the Manhattan mobility model, the frequencies of specific turns changed. When applied to opportunistic data dissemination, we observed that average dissemination delays and the number of informed nodes are affected by the navigation feedback loops. By adding attraction points and repulsion areas, new contact options are generated that are beneficial for data dissemination, but the feedback loops also make contact options disappear when changing the navigation.

As a consequence of these first results, we conclude that feedback loops cannot be ignored in VANET models that target realistic mobility behavior in which navigation information is spread to vehicles. However, in our investigation we still have reduced the system complexity by assuming that the information about the areas of interest (attracting and repelling areas) is instantly available at all nodes distributed via an out-of-band channel. By lifting this simplification, the opportunistic data dissemination will itself impact the promptness of the information spread in a complex cycle. The required investigations are a subject of future work.

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