Impact of Mobility and Topology on Information Diffusion in MANETs

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***Abstract*—In some delay-tolerant communication systems such as vehicular ad-hoc networks, information flow can be represented as an infectious process, where each entity having already received the information will try to share it with its neighbours. The random walk and random waypoint models are popular analysis tools for these epidemic broadcasts, and represent two types of random mobility. In this paper, we introduce a simulation framework investigating the impact of a gradual increase of bias in path selection (i.e. reduction of randomness), when moving from the former to the latter. Randomness in path selection can significantly alter the system performances, in both regular and irregular network structures. The implications of these results for real systems are discussed in details.**

I. Introduction

In order to efficiently control large-scale structures such as sensor networks (see e.g. [1]) and ad-hoc networks, it is necessary to understand their dynamics, especially in terms of information diffusion. Experiment analysis is essential in this process [2], but often challenging. This paper is an example of computer-based modelling used as an aid and complement in this investigation.

In most of these systems, the information flow can be modelled as an infectious process: as soon as one entity of the system receives information, it starts sharing it with its neighbours. Information diffusion can therefore be represented as an epidemic spread on a complex network.

This representation is valid for several systems in the context of information networking. This includes message dissemination in mobile ad-hoc networks, computer virus spreading in the Internet and word-of-mouth communication in online community.

In this paper, we introduce a modelling framework for computer-based analysis of such epidemic broadcasts. In particular, we look at the impact of bias in path selection for a number of network configurations. Implications for practical applications in communication networks are also discussed.

II. Experimental framework

A. Motivation

Epidemic broadcast is an approach dedicated to specific contexts where a centralised information dissemination is either impossible or not cost-efficient. It can be seen as an opportunity-based flooding for message broadcasting, where an originating entity has a message that needs to be delivered to all others in the system.

As there is no centralised control, performance may be affected by a number of factors, in particular node mobility, (through characteristics such as velocity, destination, path selection, interference with other nodes, etc.) and network topology, (e.g. network size, average degree, degree distribution, clustering coefficient, spectral radius).

While some of these characteristics has previously been investigated, (see e.g. [3]–[5]), we focus here on the specific impact of randomness. Is randomness in path selection an advantage, or does decelerate information diffusion? Does increasing randomness in the network structures have any impact on the optimal path selection strategy?

These questions are crucial to designing efficient communication systems. This type of randomness is largely uncontrollable, and difficult to manage in communication systems. It is therefore essential, in the context of network design, that it is understood in details.

B. Broadcast simulation platform

The computer-based modelling framework used in this paper relies on an agent-based structure. Each communicating entity is modeled as an independent agent, which can move on the network as well as share information with other agents co-located on the same node of this network.

Such an approach is particularly suited to the context of epidemic broadcasts, as it permits reciprocity between agents and the counterpart communicating entities, and reflects interactions of the real system as exchanges between agents.

Naturally, epidemic broadcasts are closely related to epidemic disease outbreaks. These biomedical systems have proved suited for agent-based analysis on numerous occasions, (see e.g. [6]–[8]), thus guaranteeing the validity of our approach for their communication network counterparts.

C. Agent mobility

Even though more refined mobility models exist, the random walk and random waypoint models are still widely used in communication network research because of their simplicity

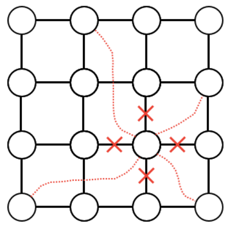

Fig. 1. One node is disconnected, and linked to random nodes

and analytical tractability. Clarifying the impact of randomness on these two models, and the intermediate strategies between these two, is therefore crucial, and an objective of this paper.

In the former configuration, an agent chooses a destination on the network, and moves towards this node using the shortest path available from its current location. Once the destination is reached, it randomly selects its next target. This represents an extension to discrete graphs of the classical random waypoint model, that was developed on a continuous space. In the latter configuration, the agent does not use any specific path. At every time step, it randomly selects one node from the neighbours of its current location, and moves to this node.

In our simulation platform, we focus on randomness in path selection, (agent velocity is fixed), and extend these two mobility models by introducing a parameter β, which represents a bias towards the shortest path. At the start of the simulation, each agent is initially given a random position and a random destination on the network (and single agent is given the information that needs to be shared). Then, at each time step, the agent moves by exactly one node. With a probability β, it moves using the shortest path from its current location to this destination. The probability to move to a random neighbouring node is therefore $1-\beta$. Once the destination is reached, a new one is randomly selected.

Clearly, if $\beta = 0$, the destination is never taken into account when deciding the next step, and this mobility model is then equivalent to the standard random walk. Conversely, when $\beta = 1$, the agent always chooses the shortest path to its destination, (a lower degree of randomness), and is therefore restricted to the random waypoint model. Intermediate values of β represent hybrid mobility patterns with various degrees of randomness.

D. Network topology

Network topology must also be taken into account, and mobility models must be tested on several structures. To this end, we introduce a parameter ρ, which represents a level of distortion added to the network.

$\rho = 0$ corresponds to a regular $n \times n$ 2D grid. Increasing values of ρ lead to the destruction of grid-type network links, which are replaced by an equal number of randomly-generated links, as shown in Figure 1. At $\rho = 0.1$, 10% of nodes are detached from the network and re-connected in this manner. The average degree remains constant, but the grid structure is gradually lost. At $\rho = 1$, we obtain a random network.

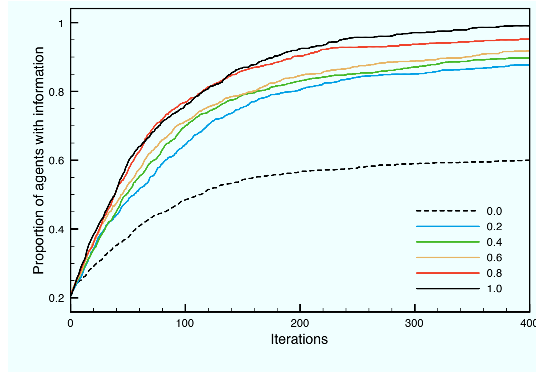

Fig. 2. Influence of β for a 2D 10×10 grid with 5 agents

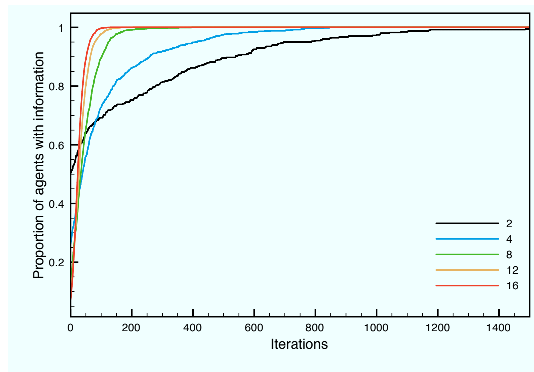

Fig. 3. Influence of the number of agents for a 2D 10×10 grid with $\beta = 1$

III. Result analysis

A. Path selection on regular networks

Simulations on the 2D $n \times n$ grid show that more structured mobility models spread the information faster. This is shown in Figure 2 for $n = 10$ and a population of 5 agents. Increasing the number of agents has a positive impact on information diffusion, as shown in Figure 3. Effects of the network size are discussed in Section III-E.

Interestingly, adding even a limited amount of structure to the mobility model significantly improves performance. The speed-up when moving from $\beta = 0$ to $\beta = 0.2$ is larger than when going from $\beta = 0.2$ to $\beta = 1$, even though each increase resulted in an improvement.

The positive impact of structured mobility results from a better network coverage. In a purely-random walk ($\beta = 0$), an agent may remain trapped in the subset of neighbours for long periods. When β is increased, such oscillations and cycles are gradually removed, as the agent more frequently choses the shortest path. The agent therefore visits a larger region of the network. Interact with not previously-encountered counterparts thus becomes more likely.

This is confirmed by looking at how the average ratio of visited nodes evolves over time, as shown in Figure 4 for the random walk (RW) and random waypoint (RWP) models on a 10×10 grid with 5 agents. For both models, each agent eventually visits all nodes. However, it clearly appears that, at

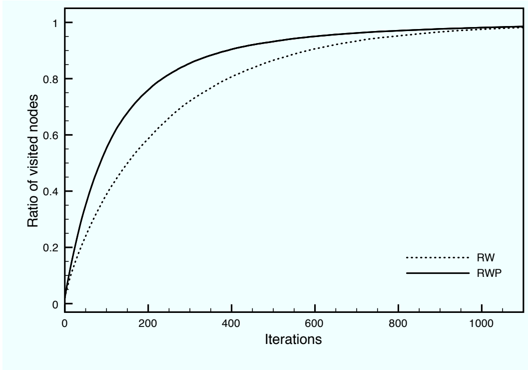

Fig. 4. Visited nodes in the random walk and random waypoint models

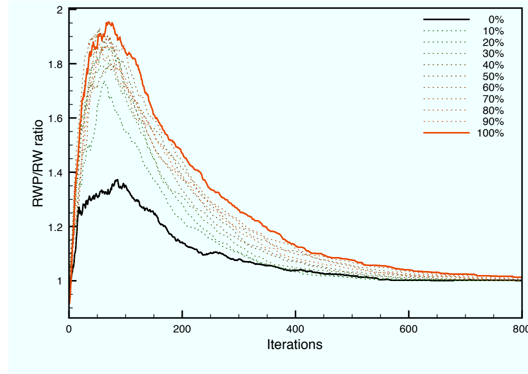

Fig. 5. Influence of ρ for 5 agents and 10×10 grid

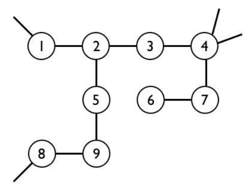

Fig. 6. Example subnetwork

any given time point, an agent has on average visited more nodes using the random waypoint model than when using random walk. This improved coverage is responsible for the accelerated information diffusion.

B. *Influence of network topology*

Tests have shown that larger values of β (i.e. more structured mobility patterns) are more effective at information diffusion in the context of a 2D grid. In this subsection, we investigated whether this bias in path selection remains efficient for higher values of ρ, and focus on the two extreme mobility models: RW ($\beta = 0$) and RWP ($\beta = 1$). Of particular interest is the ratio between the number of agents who have received the information in both models. In what follows, this is referred to as the "RWP/RW ratio".

Figure 5 shows the evolution of this ratio for increasing values of ρ, with $n = 10$ and population of 5 agents. All simulations start with a single agent given the information, so the ratio is initially equal to 1. Similarly, all agents eventually receive this information, and the ratio tends to 1 as the simulations progresses. More interestingly, this ratio is never smaller than 1. This means that the random waypoint model is always more efficient than random walks.

It should also be noted that the ratio is increasing with ρ. The less structured the network becomes, the greater the advantage of the random waypoint model gets. As was observed for β, even small changes have a significant impact: the difference between $\rho = 0$ and $\rho = 0.1$ is greater than to between $\rho = 0.1$ and $\rho = 1$.

This increasing ratio can be explained by opposite reactions to the grid perturbation level ρ. Looking at each mobility model individually, it appears that, as ρ increases, the random waypoint model performs better, while information diffusion is degraded in the random walk model.

This results from distinct responses to a less regular network structures. Let us consider the subnetwork shown in Figure 6. When $\beta = 0$, an agent located on node 7 has a 50% chance of reaching node 6. If this occurs, it returns to node 7 at the following time step, where it has a 50% chance of moving back to node 6. These oscillations means that, on average, agents take longer to visit the whole network. We have seen earlier that this leads to degraded performances. When β is increased, the shortest path is chosen more frequently, and oscillations within a subset of nodes become less likely.

In Figure 6, two paths (1-2-3-4 and 2-5-9-8) are essential to linking the distant regions of the network , and are therefore included in a large number of shortest paths. As β increases, these paths are used with a greater frequency, and the likelihood of agent interactions on these nodes is increased. This, in turn, speeds up information diffusion.

It should also be noted that, even though some paths have a greater frequency of visits, this does not mean that some regions of the network are completely "abandoned" when β increases. Complete coverage of the network is ensured by randomly choosing the destinations. At any point in the simulation, and for all values of ρ, agents in the random waypoint model have visited more nodes than those limited to random walks.

Overall, greater values of β are always associated with faster information diffusion. The gap is increases with ρ.

C. *Time to complete diffusion: delay and stability*

For some communication systems, the stability of information diffusion can be almost as important as its average speed. To investigate this, it is useful to look at the time to complete information diffusion, which correspond to the number of iterations it took for all agents to obtain the information.

In previous sections, we have seen that, on average, at any time point during a simulation, the proportion of agents who have received the information is higher for greater values of β, irrespective of the perturbation level ρ. In systems information may change over time, or loses its value very quickly, this becomes crucial, as it is more important to share

ρ	Average	Median	Standard deviation
0.0	154.8	112	140.4
0.2	67.2	62	33.9
0.4	62.5	56	32.1
0.6	78.7	67	48.0
0.8	73.2	64	42.6
1.0	65.2	58	34.9

TABLE I
INFLUENCE OF ρ ON THE COMPLETE DIFFUSION TIME (RWP)

ρ	Average	Median	Standard deviation
0.0	243.2	197	146.9
0.2	265.8	236	145.8
0.4	277.7	249	152.3
0.6	335.2	300	203.0
0.8	321.1	279	200.4
1.0	369.5	315	257.8

TABLE II
INFLUENCE OF ρ ON THE COMPLETE DIFFUSION TIME (RW)

the information with as many agents as possible over a short time, than to reach all agents.

Conversely, there are systems where the emphasis is on complete information diffusion. It is investigated here by looking at the average and median time to complete diffusion, as well as the standard deviation.

When gradually increasing β for simulations on 2D grids, the median time is monotonously reduced. This pattern is also observed for the average time and standard deviation for high values of β. For intermediate values, however, there is some instability: even though the median times is improved, the average and standard deviation are not.

As expected, altering the grid perturbation level, ρ, improves the performances of the random waypoint model, and degrades those of the random walk. It does not result in any instability. This is summarised in Tables I and II for RWP and RW, respectively.

D. Communication redundancy and efficiency

To investigate the efficiency of each mobility model, we first focus on the number of messages sent between the agents. Unsurprisingly, for a given mobility model, the number of messages increases quadratically with the number of agents, as a result of the greater number of interactions.

More interestingly, the mobility model also has an impact on the number of messages. The random waypoint model leads to an increased number of messages, both during the initial stages (information diffusion is faster, so more agents start sending the information) and for whole simulation (due to more frequent encounters between the agents). This begs the question of the efficiency of the various strategies.

In a perfectly efficient system, messages would be sent only to agents which are yet to receive the information, and the ratio between the number of agents who have received the information, and the number of messages that are exchanged, would be equal to 1.

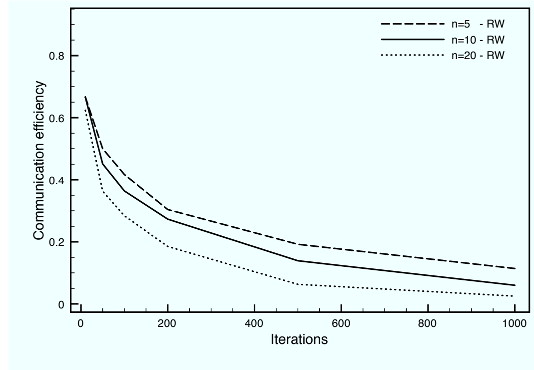

Fig. 7. Influence of the number of agents on efficiency (random walk model)

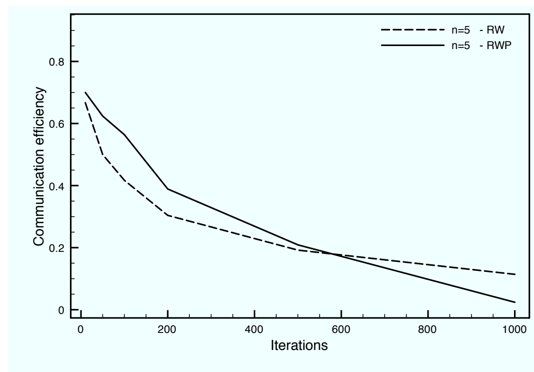

Fig. 8. Influence of the mobility model on efficiency (5 agents)

Here, there are no mechanisms for the agents to know whether their counterparts already have the information, so we know that the ratio will always be smaller than 1, and that it will tend to 0 as the simulation progresses. Of particular interest, therefore, is the early progression of the ratio.

The influence of the number of agents on efficiency is shown in Figure 7 for random walks. Performances are largely similar during the early stages, but degrade faster for larger populations of agents. The faster spread does not balance the quadratic increase in exchanged messages.

Figure 8 highlights the importance of the mobility model. Despite a larger number of messages sent at any given time during the simulations, RWP is confirmed to be the most efficient choice. Only after all agents have received the information does it become more wasteful than random walks. This is a crucial result, as this mobility model was also associated with both the largest proportion of agents with information and the smallest time to complete information diffusion.

As the number of agents increases, complete diffusion is obtained faster, and the point where RWP becomes wasteful is reached earlier. Despite this, this mobility model can be considered the most efficient communication strategy.

E. A note on network size

The figures above correspond to networks with 100 nodes. Similar simulations were performed with network sizes ranging from 16 to 2500 nodes.

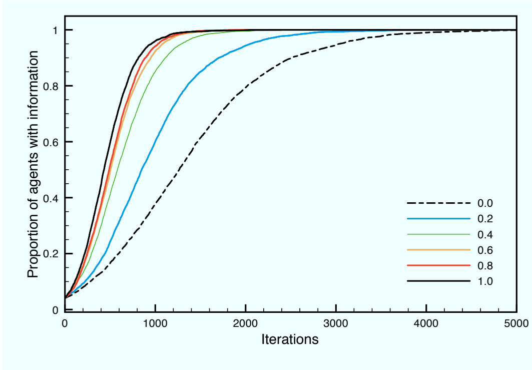

Fig. 9. Influence of β for a 2D 50×50 grid with 25 agents

For a fixed agent population, increasing the network size results in slower information diffusion. This is a direct consequence of a drop in the likelihood of two agents being located on the same node of the network, and does not affect the overall diffusion pattern. The results above on the influence of β and ρ are therefore valid for all tested sizes. For illustrative purposes, Figure 9 shows the influence of β for a grid network with 2500 nodes.

Network size may have a greater impact for dynamic network topologies, (where edges are added or removed as the simulation progresses), and for mobility models including congestion avoidance. These, however, are not in the scope of this paper, and will be covered in a future study.

IV. Implications for practical applications

As we have discussed in Section II-A, this paper focuses on *uncontrollable* randomness. Agent mobility is generally difficult to control, (VANETs being a typical example).

First, our findings therefore clarify applicable areas of an epidemic broadcast. Our simulation results help us to predict and understand the performance of an epidemic broadcast for a given node mobility and network topology. If we know the node mobility and network topology of a target system, we can predict how effectively and stably an epidemic broadcast works. Second, our findings give us a design guideline for an epidemic broadcast system. Although randomness in agent mobility and network topology are generally not easy to control, there are several systems in which those random features are controllable.

Our findings clearly indicate that randomness in agent mobility and network topology has a significant impact on the performance of an epidemic broadcast.

Small bias greatly improves the information dissemination speed: This implies that an epidemic broadcast works quite effectively if agent mobility has bias in terms of path selection. Since agent mobility in a real system generally has a certain level of bias, this implies favorable characteristics of an epidemic broadcast.

Small randomness in agent mobility in terms of path selection might make the system less stable: This implies that there is a trade-offs among efficiency and stability. Namely, too much randomness in node mobility makes the system less efficient while too much bias in node mobility makes the system less stable. Note that an epidemic broadcast is one of opportunistic-based communications, stability should not be one of the most important design goals for a real system.

Larger number of agents multiplicatively increases the information dissemination speed: This implies a desirable property of an epidemic broadcast. Even though the impact of agent density on the performance of an epidemic broadcast is non-linear, it is still easy to predict. In particular, if one knows the performance of an epidemic broadcast for a given agent density, its performance with other agent densities can be easily predicted. Thus, one can easily choose an appropriate agent density according to the desired performance goals.

Larger topological dimension causes higher trapping effect: This implies that in real systems, which generally have a two-dimensional network topology, bias in agent mobility is particularly important. Most communication systems used for epidemic broadcast are geographically sparse; i.e. nodes are geographically dispersed on a field. The network topology can be seen as one of planar graphs. This indicates that understanding (and sometimes controlling) randomness in node mobility is the key for realising an efficient epidemic broadcast.

V. Conclusion

This study investigated the impact of randomness on information diffusion, in particular in terms of node mobility, and produced a number of important results. Simulation results showed that bias in agent mobility (towards the shortest path) significantly improves the information dissemination speed. Interestingly, mobility models with a higher bias are also more suited to deal with randomness in network topology: their performances are improved when a structured grid is gradually distorted, while those of purely-random mobility models are degraded.

These results have significant implications for the development of future communication networks. Further work will investigate dynamic network topologies, additional aspects of mobility (e.g. velocity, congestion avoidance) and more advanced mobility models.

Acknowledgments

Financial support from the Irish Research Council for Science, Engineering and Technology (IRCSET), co-funded by Marie Curie Actions under FP7, is warmly acknowledged.

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