Procedia Computer Science
Volume 80, 2016, Pages 2086–2097
ICCS 2016. The International Conference on Computational Science

Urgent information spreading multi-layer model for simulation in mobile networks

Alexander A. Visheratin, Tamara B. Trofimenko, Ksenia D. Mukhina, Denis Nasonov, Alexander V. Boukhanovsky
ITMO University, Saint-Petersburg, Russia.
alexvish91@gmail.com, tamaratrofimenko@gmail.com, mukhinaks@gmail.com, denis.nasonov@gmail.com, boukhanovsky@mail.ifmo.ru

Abstract
Information spreading simulation is an important problem in scientific community and is widely studied nowadays using different techniques. Efficient users' activity simulation for urgent scenarios is even more important, because fast and accurate reaction in such situations can save human lives. In this paper we present multi-layer agent-based network model for information spreading simulation in urgent scenarios, which allows to investigate agents' behavior in a variety of situations. This model can be used for live city simulation in integration with other agent-based human interaction models. Experimental results demonstrate logical consistency of the proposed approach and show different cases of information spreading in the network with different social aspect.

Keywords: Information spreading, mobile networks, agent-based modelling, call detail record.

1 Introduction

Nowadays it is hard to imagine our life without cell phones. People make calls every day all around the world. Despite the fact that every person can call anyone whose phone number he or she knows or has in his contact list, people often have one certain social circle – relatively small group of people whom they call regularly. Members of this group may differ by their roles and count from one person type to another: family members and some friends for ordinary people; a lot of friends and colleagues for very communicative people; business partners and clients for businessmen, etc. If we know the social circle of a concrete person, we might assume that we can quite accurately predict whom this person will call in a particular situation. However there are several factors that should be taking into consideration: cell network and mobile device may have their own impact from the part of accessibility; social circle of the caller is also changing, reflecting on caller's life state (family, work, education, etc.). Taking all this together, the main goal of our research can be defined as: to create a model of information spreading in the mobile network using the developed multi-level agent-based model of calls that are making in the network with several types of agents. Using our model, we conduct a number of experiments to

Selection and peer-review under responsibility of the Scientific Programme Committee of ICCS 2016

doi:10.1016/j.procs.2016.05.528

investigate the applicability of the proposed approach for reconstruction of information spreading, which cannot be measured experimentally due to the very complex nature of the process.

2 Related works

Nowadays large number of articles are devoted to investigation of different properties of mobile networks as collections of nodes, which communicate with each other over wireless channel – ad hoc mobile networks [1], [2]. In these networks agents are moving in space, where their availability and transfer ability are strongly depend on position of the agent relative to other agents. Authors of [3] investigate applicability of epidemic model – Susceptible-Infected (SI) – for simulation of information diffusion in mobile ad hoc networks – MANETs.). The model was used to find out how density of the mobile devices affects infection rate and how to maximize infection rate. Despite the fact, that proposed method cannot be directly used for our problem in mobile networks, it shows that epidemiological models can be efficiently used for information spreading simulation in mobile networks.

Mobile network in another way can be understood as a social network, and that is why it is important to understand similarities and differences between these networks. In [4] authors investigated processes of information dissemination in two social networks – Digg and Twitter. Despite the fact, that the main principles of these two sites are different, functional patterns are quite similar for users interaction and information spreading dynamics. Social networks' characteristics highlighted in this paper give us good ideas for analysis of calls and contacts graphs, generated by our model.

Real-life call networks data studies showed [5] that amount of Incoming and outgoing calls for mobile users follows a power-law distribution, when a small group of users shows high calling activity, while majority of users make small number of calls. Our experimental investigation on a real-world data presented in section 4.1 also confirms these conclusions.

Many scientists have developed different approaches for simulation various communication networks. In [6] authors proposed an approach for simulation of growing complex network representing small social circle where all agents are connected. Calling process for new agents is based on power-law distribution – the more calls the number made or received the higher calling priority it has. This approach gives basic idea of prioritizing agents for calling probability distribution, but cannot be directly used in our model, because the network itself is created on startup as well as relations between agents.

In [7] authors evaluated a different approach to simulation of the information spreading network – they were investigating the influence of the new ideas appeared in the blogosphere environment. Authors used two widely common approaches for modeling of information spreading – Linear Threshold Model and Independent Cascade Model. Threshold approach does not fully correspond to our model because agents in the call network become aware immediately after receiving information and not when they reach a certain threshold. However, the threshold idea can be potentially implemented as acceptance parameter, where agent does not accept (e.g. believe) the information until a number of contacts try to transfer the information to the agent.

Completely different way to simulate the information spreading was used in [8]. Authors draw a parallel between the spread of information and the spread of infection. Authors use well known SIR (susceptible, infected, recovered) epidemiological model to represent different user states in idea spreading process. The model assumes that the idea has a certain period of relevance. Our model uses very close approach of information spreading, but, since we use quite small simulation periods, our model does not have recovered state for users.

In [9] authors developed an agent-based model with the aim to investigate the information spreading process. The network is presented as a graph, where agents may be informed an uninformed. The paper presents several ways to establish contacts between nodes, most of which is based on preferential attachment. But, since agents in mobile networks do not have information about calling activity of other agents and calling process in our model is defined by inner state of agents, we cannot apply this approach in our model.

In [10] authors propose theoretical epidemic model for information spreading with limited number of hops, which information can make. Authors conclude, that limiting the number of hops can crucially impact the efficiency of spreading process, no matter what model have been used. Also Wu et al. investigated users' behavioral patterns like selfishness, which can slow down spreading process by refusing to transfer information.

3 Problem statement

The background of information spreading simulation is really complex and has a lot of layers to be analyzed. In Fig. 1 the multi-layer structure describes common aspects of the all simulation. First layer represents cellular network with cell towers. Cellular towers cover almost the whole city territory by the mobile network signal, however there are locations like subway where cell towers are presented with the low density and mobile phone often can't access the network (on the picture red tower linked with red person). On the other hand mobile phone also are not stationary available: phone accumulator can discharge or financial blocking may occur due to negative balance (black phones connected with persons). Contact network forms third layer and the last in the quasi-stationary processes block. Contact between people are changing too low as well as cell towers and phone devices to be considered in the call network simulation process. That way for basic simplicity we assume all three level static and are concentrating on call network and information spreading.

According to generated contact network the process of calling can be simulated, however one of the most interesting part of call research is analyzing of information spreading.

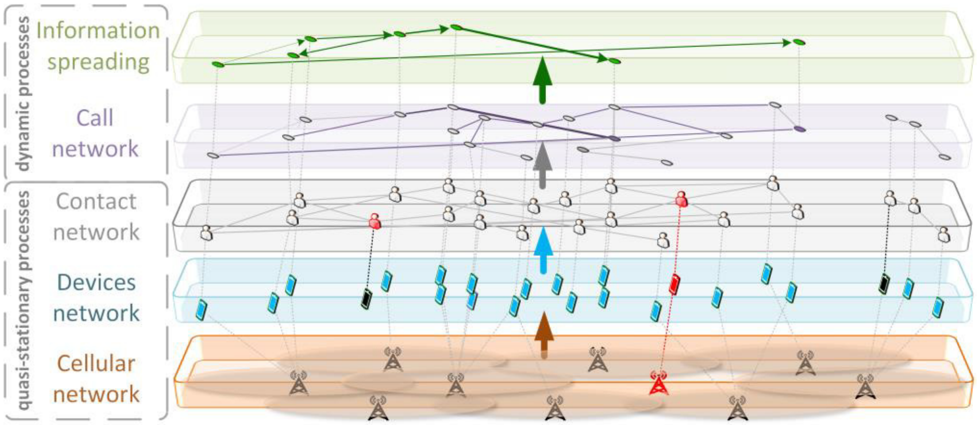

Figure 1 – Multi-layer structure of information spreading among phone cell network.

The details of developed call network model and information spreading model are presented in the section 4 as well as urgent scenario is described in section 5.

4 Model description

In our work for the processes of making calls and information transfer we used multi-agent simulation, due to its flexibility and ability to accurately represent complex systems [9], [11], [12]. The core of this approach is a set of agent types, their characteristics and rules of agents' interaction. Thus to create a proper multi-agent model we need to describe agents' parameters, identify several types of agents, define rules of their behavior and specify a number of global model restrictions, which help to control the integrity of the model.

Each agent of the model represents a person, who periodically makes calls. Every agent has its own contacts list, where call probability is distributed between contacts, which can be strongly or weakly connected with the agent. Strong connections represent members of agent's social circle, while weak connections stand for acquaintances. Connection type dramatically affects probability of the call, sometimes making a call between two agents almost impossible, what though quite well represents some situations in the real life. For every agent type we define part of call probability – strong connections fraction – which will be distributed between strong connections, while the rest part will be split across weak connections. As a result, for contacts list of the agent we defined following parameters: *contacts number*, *strong connections number* and *strong connections fraction*. Calling activity of agents can be described using two parameters: *activity interval*, which is an amount of time, after which agent makes a call, and *call length*.

4.1 Agent types identification

In order to identify types of agents for the model and obtain values for parameters described above, we analyzed two datasets containing real data about calls. The first dataset [5] contains information about 13035 mobile phone calls that were made by 27 high-school students during the period from September 2010 to February 2011. From this data for each of users we were able to obtain average values of call duration and activity interval. Since dataset contains large periods of inactivity and incorrect timestamps, activity interval was calculated as an interval between calls not exceeding approximately two days. We decided to use k-means clustering method for identifying users groups. For right number of clusters selection clusterings with $k = [2..10]$ were made. Their quality was verified with the use of Dunn index [13], which is internal metric for identifying compactness of clusters (small variance between cluster members) and their separation (relatively large distance between means of different clusters). The higher value of Dunn index identifies better clustering. Result of described verification can be found in Fig. 2a. As it can be seen from the figure, the optimal number of clusters for the dataset is 3 and the result of k-means clustering with $k = 3$ based on users' average activity interval and average call duration is presented in Fig.2b.

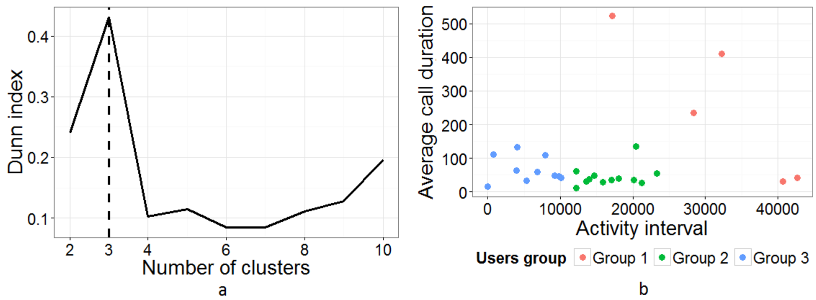

Figure 2 – Dunn index for different number of clusters and clustering result for calls dataset

At the plot we can see two groups of agents with relatively small call durations and one group with high activity intervals and call durations. Call behavior parameters calculated for each group of users are presented in Table 1.

Table 1 – Call behavior parameters for 3 groups of users

Parameter	Group 1, 5 agents	Group 2, 12 agents	Group 3, 10 agents
Calls duration mean, seconds	248.44	45.56	66.42
Activity interval mean, seconds	32220	16890	5791
Activity interval standard deviation, seconds	10271	3741	3606

The second dataset under investigations was collected by ourselves through social networks. We interviewed 127 people about the number of contacts they have in their phones, number of people they call more frequently than others and average number of calls they do every day. For clustering we selected number of contacts and number of calls as the most important parameters describing users' behavior. The steps for finding the optimal number of clusters were quite the same as for the first dataset.

Result of Dunn index verification are presented in Fig. 3a. The most appropriate number of clusters is 3, because it provides better compliance with previous dataset and its Dunn index is almost the same as for 4 clusters. The result of k-means clustering with $k = 3$ is presented in Fig.3b.

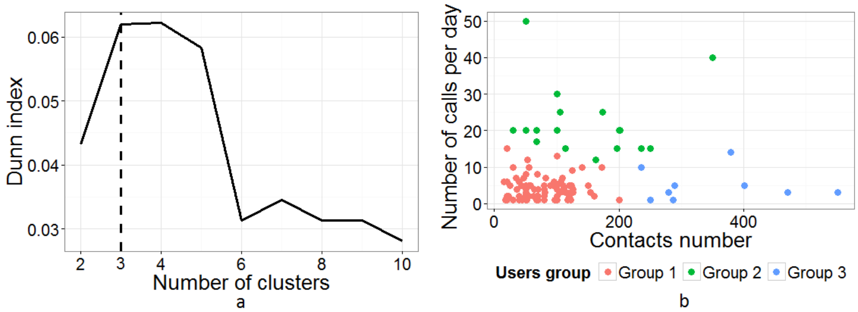

Figure 3 – Dunn index for different number of clusters and clustering result for interview dataset

At the plot we can clearly see three groups of agents: one with small both contacts number and number of calls per day, another with small number of contacts, but large number of calls and the third with high contacts number, but low number of calls. Call behavior parameters calculated for each group of users are presented in Table 2. Activity interval was calculated by dividing the number of seconds in a day by the value of calls per day parameter.

Table 2 – Call behavior parameters for 3 groups of interviewed people

Parameter	Group 1, 90 agents	Group 2, 19 agents	Group 3, 9 agents
Contacts number mean	80.55	142.21	348.88
Contacts number standard deviation	41.24	85.92	108.57
Strong contacts number mean	8.45	16.1	14.22
Activity interval mean, seconds	23206	2932	22857

To match users' classes of two clusterings we used activity interval parameter as only one present in both datasets. We can easily relate group 3 from Table 1 to group 2 from Table 2, as they both have the lowest activity interval. To identify other two groups we made an assumption, that group 1 from Table 2 represents regular people, who make calls not very often and have relatively small contacts list and social circle, but when they call someone, they want to discuss things important to them, though call length for such people should be high. According to this we relate group 1 from Table 2 to group 1 from Table 1. And finally group 2 from Table 1 is related to group 3 from Table 2.

As a result of clustering analysis of two datasets we were able to identify 3 types of agents for our model. Their parameters can be found in Table 3. Part of total agents number was calculated from the number of users in different groups in the second clustering.

For the future references gave following names to agent types: "Regular people", who have not very big contacts list, make calls not so often, but these calls are quite long, "Organizers", who have larger contacts list and make relatively short calls very often, and "Busy people", who have a lot of people in the contacts list and their calls are very short in comparison with "Regular people".

Table 3 – Overall parameters for different types of agents

Parameter	Type 1, "Organizers"	Type 2, "Regular people"	Type 3, "Busy people"
Contacts number mean	142.21	80.55	348.88
Contacts number standard deviation	41.24	85.92	108.57
Strong contacts number mean	16.1	8.45	14.22
Calls duration mean, seconds	66.42	248.44	45.56
Activity interval mean, seconds	5791	32220	16890
Activity interval standard deviation, seconds	3606	10271	3741
Part of total agents number, %	16	76	8

4.2 Contacts network simulation

For performing simulation of calling process within agents network the first step is to initialize the contacts network. There are four basic types of network models: regular, random, small-world and preferential attachment. All these model types have their pros and cons, but two of them basically fit our needs more than others – random model and small-world model. Random model, unlike regular lattice, allows to reproduce diversity and heterogeneity of real networks, but it was analytically shown that assortativity index of such graphs is zero [14] and in general random networks represent only limited number of social network features [15]. Mechanism of preferential attachment differs a lot with the way how people make contacts in mobile networks – they do not know who has many contacts and even if they do, they would not necessarily want to connect to such people [16]. On the other hand, small-world model was proven to be a good representation of social networks in general [17]. To make a small-world model better reproduce characteristics of real-world mobile networks we made an adjustment to the network initialization process. Usually people are connected with each other mutually – if Person 1 has Person 2 in the contact list, then Person 2 also has Person 1 in the contacts list. Assuming this we assigned 70% probability of new agent's connection to cause mutual connection, if there were not any.

To select the most appropriate model of contacts network initialization we conducted a set of experiments, where for different types of models and different number of agents graph quality characteristics were obtained. We considered three models – random (Erdős–Rényi model [18]), small-world (Watts-Strogatz model [19]) and our improved small-world model. Each experiment was repeated 50 times to make results statistically significant. Results of experiments are presented in Table 4.

Table 4 – Experimental results of network models investigation

	Erdős–Rényi model			Watts-Strogatz model			Our model		
Number of agents	500	1000	5000	500	1000	5000	500	1000	5000
Average clustering coefficient	0.4413	0.2475	0.056	0.5137	0.3506	0.2033	0.5095	0.3559	0.2182
Global clustering coefficient	0.4166	0.2334	0.0525	0.4776	0.3459	0.2273	0.468	0.3511	0.24445
Average path length	1.7937	1.9043	2.1485	1.7893	1.9237	2.2981	1.7902	1.9251	2.2998
Assortativity	-0.027	-0.02	-0.015	0.046	0.236	0.484	0.066	0.264	0.483

A global clustering coefficient measures connectivity of the whole network and average clustering coefficient is based on local clustering: if coefficient is equal to 1 it means that sub-graph of neighbors for specific node is fully-connected. Random network for small number of agents shows high clustering, but with the growth of network's size both its clustering coefficients drop sharp at 8 times, which does not correctly represent real-world behavior. Small-world networks, on the other hand, demonstrate gradual decrease of clustering coefficients with agents' number increase and our model shows slightly better results. Average path length measures the average number of steps between each pair of nodes, for real network this number is sufficiently small [20]. For all three models the average path length increases with network size and is no longer than 2.3. Assortativity coefficient indicates existence of tendency for nodes with similar degree to be connected. It is worth mentioning, that real-world social networks are predominantly assortative [14]. As expected random model shows assortativity close to zero, when for both small-world models this parameters grows with the network growth. Since our model shows good results in comparison with other models and is adjusted to our subject field, we use it for contacts network simulation.

The process of contacts list initialization for every agent looks as follows. During experimental investigation the most suitable value of rewire probability was found to be $\beta = 0.7$. Mean degree K is set as closest even number to the mean contacts number for agent's type (see Table 3). We create regular ring lattice with K contacts. After that for each contact edge we rewire it to some random agent with probability β. Then if there are any contacts left be created we connect target agent whether to someone from contacts list of its contacts or to some random agent with probability $\gamma = 0.7$. And on every contact initialization model tries to create mutual contact with probability $\delta = 0.5$.

4.3 Call network simulation

At the beginning of the simulation network is initialized with a defined number agents of different types based on their parts (last row of Table 3). After that for every agent we set up its parameters according to the type – initial activity interval, contacts number, strong connections number and strong connections fraction. Values of these parameters for each agent are distributed according to mean and deviation parameters from Table 3. The only exception is strong connections fraction, values of which are set based on a number of logical assumptions – for regular people their social circle is a very significant part of their calling activity (0.85), organizers due to the kind of their activity treat relatives and other contacts equally (0.5), and busy people make more calls related to business than to personal life (0.4). A number of works show good applicability of Poisson distribution for representing social processes – social network activity [21] or crowd formation and movement [22]. But for parameters with high mean and deviation values Poisson distribution would fail to reproduce variability of agents' characteristics. Due to this for activity interval and contacts number we used normal distribution and Poisson distribution for strong connections number.

On the next step each agent creates its contacts list according to the model described in previous section. After that call probability is distributed between contacts. Firstly agent proceeds strongly connected contacts, giving them calling probability according to strong connections number and strong connections fraction. Then the rest of probability is distributed across weakly connected contacts.

Every agent has two internal parameters – *activation time* and *call finish time*. Activation time indicates the moment, when the agent must make an attempt to call some agent from the contacts list. Call finish time represents the moment, after which current call ends and agent becomes free to make or receive calls. At each iteration every agent checks whether it should finish current call (simulation time reached call finish time) or initiate new call (simulation time reached activation time). On new call initiation agent selects another agent from its contacts list, whom it will try to call, based on call probability distribution between contacts. In case when selected contact is busy, model does nothing. If selected contact is free to call, model calculates call length according to agents' types and creates call, making both agents busy and updating their call finish times. Then model updates current agent's activity interval and sets new activation time with respect to call finish time and activity interval. On finishing current call model just sets both caller and receiver free to call. After simulation finishes, model returns calls graph.

4.4 Information spreading

In order to implement information spreading simulation in the model described in previous section, we need to select a general spreading simulation approach, which we will use as a basis for our model, identify key properties of information and develop rules, according to which it will be distributed.

One of the most widespread approaches for simulation of information spreading in social networks are epidemiological models [23][3]. Descriptions of agents states (susceptible, infected, recovered) quite well represent states of users in the social networks, when someone can be or be not aware of the information and can forget it. For our purposes we chose Susceptible-Infected (SI) model, because in our simulations we operate relatively small amounts of time (about two days) and assume that users cannot forget information is such short time. Detailed description and thoughtful analysis of SI model were given in [24]. To make use of this model we need to define infection probability, which in our case is called information transfer probability. For doing this we need to identify key characteristics of information, which can affect whether information will be transferred from one agent to another or not. These characteristics are *importance* and *relevance*. The first parameter shows relative importance of the information and we make logical assumption that important information spreads faster than unimportant. Relevance is a decreasing function representing change in the information relevance over time. It is calculated using formula:

$$Relevance = \frac{1}{1 + e^{\left(time - \frac{simTime}{2}\right)/(\alpha \cdot simTime)}}$$

where $time$ represents the current iteration number, $simTime$ stands for total simulation length and α is relevance coefficient, which defines how long the information keeps relevant. Since basically our model simulates normal (not extremal) information spreading, where information remains relevant for a long time, we used $\alpha = 0.06$.

To reproduce possible behavioral patterns of agents we introduce two additional parameters, which also influence information transfer probability. The first is *interest degree* – individual user parameter showing aptitude for information transferring. For different agent types value of this parameter distributed equally in different ranges – $[0..1]$ for regular agents, $[0.7..1]$ for organizers, because due to their type we assume them to be very interested in information, and $[0.3..1]$ for busy people, because in general they are more interested than regular people. Another parameter is *relative importance*, which defines how important is call receiver compared to others in the caller's contacts list. It makes information transfer more likely for closely related agents.

Thus we identified four parameters affecting information transfer. Since in our model all these parameters are in range $[0..1]$ the most basic formula for calculation transfer probability looks as follows:

$$P = \frac{R + I + ID + RI}{4}$$

where R is information relevance, I is information importance, ID is caller's interest degree and RI is relative importance of call recipient.

At the beginning of simulation depending on the aim of experiment we make some agents aware of the information. In the process of initiating call between two agents if caller is aware of the information model calculates P, generates random number in range $[0..1]$ and, if it exceeds standard threshold of 0.5 information is transferred to the receiver. But, since it always takes some time to tell something, we introduce the third parameter of information – complexity. It defines how long it takes to transfer the information from one agent to another, thus increasing the length of the call.

To give visual demonstration of the process of information spreading we conducted following experiment. Call graph was generated for 1000 agents in the modeling period of 48 hours. The simulation starts with all organizers aware of the information with importance equal to 1 and complexity equal to 20, which means that, if agents transfer the information, they spend 20 additional seconds of the call to tell it. The visualization of information spreading graph, created using framework for advanced scientific visualization FUSION [25], is presented in Fig. 4.

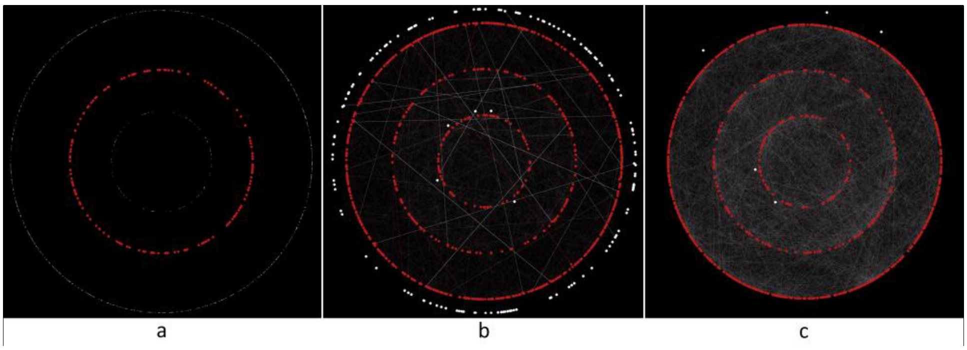

Figure 4 – Information spreading visualization. a – start of simulation, b – after 17 hours, c – end of simulation

In Fig. 4 nodes stand for agents and edges represent calls. Each agent have two states – unaware (white) and aware (red) of the information. Color of the edge shows whether information was or was not transferred during the call. As it can be seen from the picture, in the end of simulation (Fig.4c) almost all agents become informed.

5 Urgent situation scenario

To investigate information spreading process in developed model for urgent situations, like information about floods or terroristic attacks, we made significant changes into parameters of agents and the simulation process itself. Adjustments in agents' parameters are shown in table 5. Organizers, who in the context of emergency situations can represent operators in call-center of rescue service, make very short calls within very small time intervals, since their task is to inform as much people as possible as soon as possible. Regular people also make short calls, but their activity interval is higher than for organizers, because they aim not only to inform people, but also to take some actions regarding the situation, e.g. move from the dangerous place. Call length for busy people is higher, than for other agent types, because they might want to clarify some details about their business.

Table 5 – Overall parameters for different types of agents for urgent scenario

Parameter	"Organizers"	"Regular people"	"Busy people"
Calls duration mean, seconds	10	15	30
Activity interval mean, seconds	20	60	100
Activity interval standard deviation, seconds	10	50	50

Calls making process was also changed to comply better with real processes. On the step of selection the person from contacts list to call agents now select contacts by their call probability, which means, that agents now call people, who are important for them, in the first place. Also agents remember contacts they already called and do not call them again in the process of simulation. If agent they are trying to reach is busy, they will call next person in the contacts list and will try to reach targeted agent on the next try. Interest degree parameter for all types of agents was highly increased, because urgent situations usually affect a lot of people within the city thus making them more interested in spreading of information about the situation.

6 Experiments

To investigate the applicability of described model for reconstruction of information spreading we conducted a series of experiments where we changed different parameters of the simulation process and checked how well model responds to these changes. Every type of experiment was conducted 100 times to make results statistically significant.

The first experiment was devoted to investigation of model behavior for different agent types and different percentage of initially informed agents. Initially informed agents part varied from 5% to 95% with the step of 5%. Since during experiment the part of informed agents can be more than it originally is in table 3, the fraction of these agents was increased, which was obtained through proportionally decreasing fractions of other agent types. Results of the experiment are presented in Fig. 5. From the picture we can see that for nearly all cases awareness eventually reaches almost 100%, but the dynamics of awareness differs dramatically. Organizers spread information much faster than other agent types, especially for low numbers of initially informed agents (5-20%). And for all cases spreading curves for organizers are much steeper than for talkers and regular agents. High period of almost inactivity for regular agents is related to their high activity interval and relatively small contacts list with small number of strong connections, leading to very slow spreading. But after information transfers to agents of other types, process becomes much faster, because organizers and busy people, as we can see from Fig. 5a and 5b, spread information a lot faster.

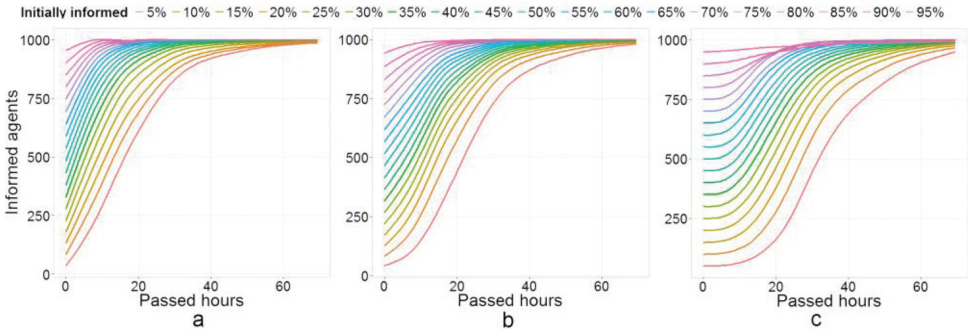

Figure 5 – Information spreading for different agent types and initially informed agents a – organizers, b – busy people, c – regular agents.

After that we investigated, how fast agents in described above conditions can inform the vast majority of the network. By vast majority here we mean 97.5% of all agents. Fig. 6 shows results of this experiment. From the plot it can be seen that organizers much easier reach the targeted fraction of people, than for regular agents and busy people. The main advantage of organizers over busy people is very short activity interval, which, despite much smaller contacts list, allows them to spread information much faster (6 hours on average). And the problem of regular people is relatively small contacts list, which makes it very hard for them to find agent for transferring information in case, when almost all of them are informed and there are few agents of other types (cases 80-95%).

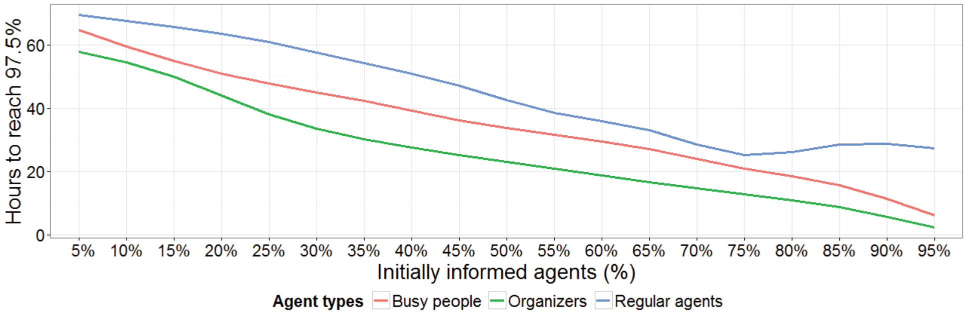

Figure 6 – Time to inform 97.5 % of the network depending on the initial amount of aware agents

To compare awareness dynamics in different scenarios we made two sets of experiments for different number of agents in two cases – standard and urgent situations. In all experiments only 10 organizers were initially informed. Simulation time for urgent experiments was 20 modeling minutes. Results of experiments are presented in Fig. 7. As we can see, general behavior in both cases is similar, whereas awareness change becomes steeper with agents number increase due to the much higher agents activity in urgent scenario.

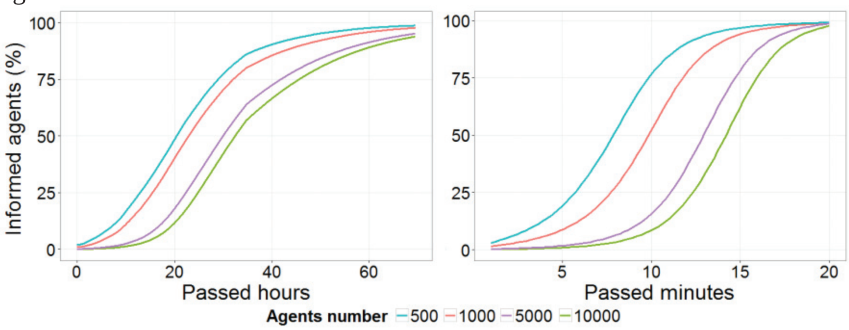

Figure 7 – Spreading dynamics for standard (left) and urgent (right) scenarios

In the next experiment we investigated, how different parameters – agents' interest degree, importance and complexity – can affect information distribution in urgent situations. For interest degree we set minimum value m for the parameter for all agents and its value are equally distributed in range $[m..1]$. Results of the experiment are presented in Fig. 8. We can see, that interest degree due to its stochastic nature does not significantly affect spreading, but information complexity increase dramatically slows the process, because on every call agents spend more time on telling the information.

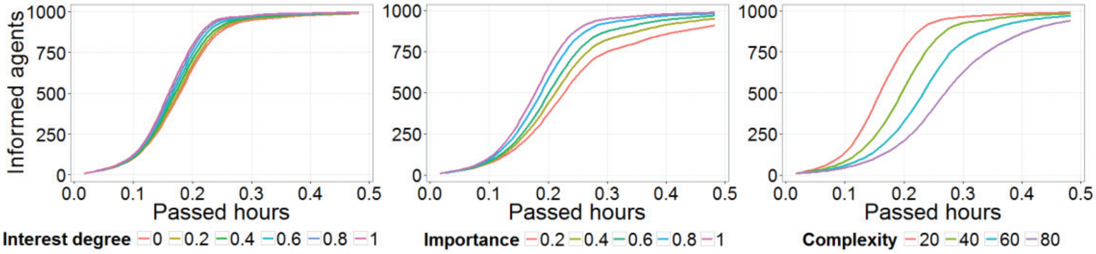

Figure 8 – Information spreading for different parameters

7 Conclusion and future works

In this work we presented the multi-layer agent-based model for information spreading within the mobile network in urgent situations. This model parameters were identified using statistical data obtained from different sources. We conducted a set of experiments with a range of initial parameters to check the correctness of developed model and investigate its behavior in different situations. Results of experiments show that the model behaves correct and does not contradict with logical assumptions about real-world processes.

Currently we are in process of tuning formulas for information spreading model in order to achieve even better and more sensible results. Our future research will be devoted to agents' network reconstruction using calls graph with help of machine learning techniques and information spreading simulation in extreme situations.

This paper is financially supported by The Russian Scientific Foundation, Agreement #14-11-00823 (15.07.2014)

References

[1] E. M. Royer, "An Analysis of the Optimum Node Density for Ad hoc Mobile Networks," *IEEE Int. Conf. Commun.*, pp. 857–861, 2001.

[2] S. Zeadally, R. Hunt, Y.-S. Chen, A. Irwin, and A. Hassan, "Vehicular ad hoc networks (VANETS): status, results, and challenges," *Telecommun. Syst.*, 2010.

[3] A. Khelil, C. Becker, J. Tian, and K. Rothermel, "An epidemic model for information diffusion in MANETs," *Proc. 5th ACM Int. Work. Model. Anal. Simul. Wirel. Mob. Syst. - MSWiM '02*, p. 54, 2002.

[4] K. Lerman and R. Ghosh, "Information Contagion: an Empirical Study of the Spread of News on Digg and Twitter Social Networks," *Proc. Fourth Int. AAAI Conf. Weblogs Soc. Media*, pp. 90–97, 2010.

[5] A. McDiarmid, S. Bell, J. Irvine, and J. Banford, "Nodobo: Detailed Mobile Phone Usage Dataset," pp. 1–9.

[6] W. Aiello, F. Chung, and L. Lu, "A random graph model for massive graphs," *Proc. thirty-second Annu. ACM Symp. Theory Comput. - STOC '00*, pp. 171–180, 2000.

[7] W. M. Tam, F. C. M. Lau, and C. K. Tse, "Complex-network modeling of a call network," *IEEE Trans. Circuits Syst. I Regul. Pap.*, vol. 56, no. 2, pp. 416–429, 2009.

[8] L. M. Bettencourt, A. Cintrón-Arias, D. I. Kaiser, and C. Castillo-Chávez, “The power of a good idea: Quantitative modeling of the spread of ideas from epidemiological models,” *Phys. A Stat. Mech. its Appl.*, vol. 364, pp. 513–536, 2006.

[9] L. Gulyás and G. Kampis, “Spreading processes on dynamically changing contact networks,” *Eur. Phys. J. Spec. Top.*, vol. 222, no. 6, pp. 1359–1376, 2013.

[10] Y. Wu, S. Deng, and H. Huang, “Hop limited epidemic-like information spreading in mobile social networks with selfish nodes,” *J. Phys. A Math. Theor.*, vol. 46, no. 26, p. 265101, 2013.

[11] E. Bonabeau, “Agent-based modeling: methods and techniques for simulating human systems.,” *Proc. Natl. Acad. Sci.*, vol. 99, no. suppl. 3, pp. 7280–7287, 2002.

[12] D. Voloshin, D. Rybokonenko, and V. Karbovskii, *Optimization-based Calibration for Micro-level Agent-based Simulation of Pedestrian Behavior in Public Spaces*, vol. 66. Elsevier Masson SAS, 2015.

[13] J. C. Dunn, “A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters,” *J. Cybern.*, vol. 3, no. 3, pp. 32–57, 1974.

[14] M. E. J. Newman, “Assortative Mixing in Networks,” *Phys. Rev. Lett.*, vol. 89, no. 20, p. 208701, 2002.

[15] S. N. Dorogovtsev and J. F. F. Mendes, “Evolution of Networks: From Biological Nets to the Internet and WWW,” *Booksgooglecom*, vol. 57, p. 280, 2003.

[16] P. S. Dodds, R. Muhamad, D. J. Watts, P. S. Dodds, R. Muhamad, and D. J. Watts, “An Experimental Study of Search in Global Social Networks,” *Science (80-.).*, vol. 301, no. 5634, pp. 827–829, 2003.

[17] M. E. Newman and D. J. Watts, “Scaling and percolation in the small-world network model.,” *Phys. Rev. E. Stat. Phys. Plasmas. Fluids. Relat. Interdiscip. Topics*, vol. 60, no. 6 Pt B, pp. 7332–7342, 1999.

[18] P. Erdös and a Rényi, “On random graphs,” *Publ. Math.*, vol. 6, pp. 290–297, 1959.

[19] D. J. Watts and S. H. Strogatz, “Collective dynamics of ‘small-world’ networks.,” *Nature*, vol. 393, no. 6684, pp. 440–2, 1998.

[20] X. F. Wang and G. Chen, “Complex Networks : Scale-Free and Beyond,” *Ieee Circuits Syst. Mag.*, vol. 116, no. 1, pp. 6–20, 2003.

[21] M. Trusov, A. V Bodapati, and R. E. Bucklin, “Determining Influential Users in Internet Social Networks,” *J. Mark. Res.*, vol. 47, no. 4, pp. 643–658, 2010.

[22] M. Moussaïd, N. Perozo, S. Garnier, D. Helbing, and G. Theraulaz, “The walking behaviour of pedestrian social groups and its impact on crowd dynamics,” *PLoS One*, vol. 5, no. 4, 2010.

[23] C. Liu and Z. K. Zhang, “Information spreading on dynamic social networks,” *Commun. Nonlinear Sci. Numer. Simul.*, vol. 19, no. 4, pp. 896–904, 2014.

[24] M. E. J. NEWMAN, *Networks. An introduction*. 2010.

[25] D. Egorov and A. Bezgodov, *Improved Force-Directed Method of Graph Layout Generation with Adaptive Step Length*, vol. 66. Elsevier Masson SAS, 2015.