

---

## Social-based routing algorithm for energy preservation in mobile opportunistic networks

---

Cristian Chilipirea, Andreea-Cristina Petre and  
Ciprian Dobre\*

Faculty of Automatic Controls and Computers,  
University Politehnica of Bucharest,  
Spl. Independentei 313, 060042, Bucharest, Romania  
E-mail: cristian.chilipirea@cti.pub.ro  
E-mail: andreea.petre@cti.pub.ro  
E-mail: ciprian.dobre@cs.pub.ro  
\*Corresponding author

**Abstract:** In particular types of delay-tolerant networks (DTN) such as opportunistic mobile networks, node connectivity is transient. For this reason, traditional routing mechanisms are no longer suitable. New approaches use social relations between mobile users as a criterion for the routing process. We argue that in such an approach, nodes with high social popularity may quickly deplete their energy resources and, therefore, might be unwilling to participate in the routing process. We show that social-based routing algorithms such as BUBBLE Rap are prone to this behaviour, and introduce energy awareness as an important criterion in the routing decision. We present experimental results showing that our approach delivers performances similar to BUBBLE Rap, whilst balancing the energy consumption between nodes in the network.

**Keywords:** opportunistic networking; mobile devices; energy awareness.

**Reference** to this paper should be made as follows: Chilipirea, C., Petre, A-C. and Dobre, C. (2014) 'Social-based routing algorithm for energy preservation in mobile opportunistic networks', *Int. J. Embedded Systems*, Vol. 6, No. 1, pp.14–27.

**Biographical notes:** Cristian Chilipirea received his BSc in Computer Science at University Politehnica of Bucharest, Romania. Currently, he is in his second year in MSc in Parallel and Distributed Computer Systems at Vrije Universiteit of Amsterdam. His areas of interest is distributed network systems, cloud computing and internet of things.

Andreea-Cristina Petre received her BSc in Computer Science at University Politehnica of Bucharest, Romania. Currently, she is doing his MSc in Artificial Intelligence at University Politehnica of Bucharest, Romania. Her areas of interest are distributed systems, multi-agent systems, natural language processing and operating systems.

Ciprian Dobre received his PhD in Computer Science at the University Politehnica of Bucharest in 2008. He received his MSc in Computer Science in 2004 and Engineering degree in Computer Science in 2003, at the same university. His main research interests are grid computing, monitoring and control of distributed systems, modelling and simulation, advanced networking architectures, parallel and distributed algorithms. He is a member of the RoGrid consortium and is involved in a number of national and international projects. His research activities were awarded with the Innovations in Networking Award for Experimental Applications in 2008 by the Corporation for Education Network Initiatives (CENIC).

This paper is a revised and expanded version of a paper entitled 'Energy-aware social-based routing in opportunistic networks' presented at the 2013 27th International Conference on Advanced Information Networking and Applications Workshops (AINAW'13), Barcelona, Spain, 2013.

---

### 1 Introduction

Energy consumption is a major factor in the performance and deployment of modern computational and communication systems (Probst et al., 2007; Känel and Vecchiola, 2013). It is increasingly necessary to preserve

scarce resources and have such systems perform with the utmost energy efficiency. In order to achieve as minimal energy consumption as possible while maintaining extreme adaptability to environmental challenges and resources it is necessary to develop highly autonomous systems with the

capability to adapt dynamically to energy availability and usage.

The emergence and wide-spread of new-generation mobile devices together with the increased integration of wireless technologies such as Bluetooth and WiFi create the premises for new means of communication and interaction, challenge the traditional network architectures and are spawning an interest in alternative, ad hoc networks such as opportunistic mobile networks. An opportunistic mobile network (ON) (Pelusi et al., 2006b) is established in environments where human-carried mobile devices act as network nodes and are able to exchange data while in proximity. Whenever a destination is not directly accessible, a source would opportunistically forward data to its neighbours. The latter act as carriers and relay the data until the destination is reached or the messages expire. ONs do not rely on any kind of existing infrastructure, and commit solely to human mobility for data delivery. In this scenario, new challenges emerge: there is no a-priori known topology (as user mobility is highly unpredictable), end-to-end paths between communicating nodes may be absent (Zhang, 2006) (for several reasons: uneven node distribution in the environment, energy conserving policies, etc.), the computing and memory resources available for each node are limited. Unlike conventional networks, where faults are considered exceptions, in ONs it is assumed they are common. Therefore, traditional routing mechanisms such as those from the TCP/IP stack are an unsuitable solution for ad hoc networks such as ONs. The natural approach is to extend the store-and-forward routing to store-carry-forward (SCF) routing (Jain et al., 2004).

Routing algorithms for ONs are either mobility-aware or social-aware. The former (which includes protocols such as PROPHET (Lindgren et al., 2003a) takes routing decisions based on the number and duration of node encounters; the latter [which includes BUBBLE Rap (Hui et al., 2011)] relies on the knowledge that members (or nodes) of an ON are people carrying mobile devices. ONs involve routing decisions based on how people are organised into communities, according to places of living and work, common interests, leisure activities, etc. In this case social relations between people can be generally inferred from the user interactions in such networks. This is why in recent years researchers have started to show an interest in social-based routing algorithms for ONs. However, approaches such as Hui et al. (2011) can quickly deplete the energy of more popular ON members, which can become flooded by message forwarding requests.

Energy consumption is an important factor in the mobile devices we use every day. This factor can prove even more important in certain scenarios such as: disasters in which the electrical infrastructure is damaged, faults in the electrical grid, movement through remote areas like mountains or deserts where access to an electrical infrastructure can be rare or completely lacking.

In this paper, we present a novel social-driven solution which includes energy as an important element in selecting the routing decision. If energy consumption is considered, in

social-driven ON routing popular nodes can be cumbered and their resources drained. This may cause popular nodes to become unavailable and the benefits they bring to the network disappear. Such a scenario is unlikely in an environment where recharging points for the battery are widely available, especially with improvements in battery life, but in case of natural disasters or areas that do not benefit of the abundance of charging points, or when energy is scarce, extending the energy life of the network quickly becomes important priority.

The rest of this paper is structured as follows: Section 2 presents related work. In Section 3, we describe the proposed energy-aware routing algorithm. Section 4 presents simulation results and comparisons with other algorithms, and finally, in Section 5, we conclude and suggest future work.

## 2 Related work

Since opportunistic networks have become more and more popular over the past years, partly due to the ubiquitousness of mobile devices, several authors have treated this research area in great detail. A review of opportunistic networking can be found in Conti et al. (2010), where functions such as message forwarding, security, data dissemination and mobility models are analysed. Several opportunistic forwarding algorithms are also reviewed, among them being BUBBLE Rap (Hui et al., 2011), and PROPICMAN (Nguyen et al., 2007). We previously proposed a taxonomy for data dissemination algorithms in Ciobanu and Dobre (2012a), where we split such algorithms into four main categories. The first category refers to the infrastructure of the network, i.e., the way the network is organised into an overlay. The dissemination techniques are also split according to their node properties, such as state or interaction. The third category of the taxonomy is represented by content characteristics, i.e., the way content is organised and analysed, and finally the last category (and the most important one, in our opinion) is social awareness. We consider it to be the future of opportunistic networks, because the nodes in such a network are mobile devices carried by humans, which interact with each other according to social relationships. The addition of social network information to opportunistic routing has been studied in Bigwood et al. (2008), where the authors show that using Facebook information instead of community detection algorithms decreases the delivery cost and produces comparable delivery ratio.

BUBBLE Rap (Hui et al., 2011) is a social-based forwarding algorithm for use in delay tolerant networks. In BUBBLE Rap, a message is forwarded to the most popular node in the local community of the current node (bubbled up) by using the local rank, and sent between different communities by means of a global rank. Once the node with the greatest local rank has been reached, the routing continues at a global level (between different communities in the opportunistic network) until a community of a destination is reached. Then the message is locally

forwarded until it reaches the destination node. BUBBLE Rap shows significant improvements when compared to non-social routing algorithms applied on opportunistic networks.

There are a number of successful attempts of improving the performance of the BUBBLE Rap algorithm (Hui et al., 2011). Socially-aware prediction (SAP) (Ciobanu and Dobre, 2012c) is an algorithm created for opportunistic routing which forwards a message to a node that has a high probability of establishing a connection with the destination node. The algorithm accomplishes this by considering how recent the message is, the community to which the node belongs, the social distance between the source and the destination of the message, the number of hops the message has passed through, the total time spent by the next node in contact with the messages destination (Ciobanu and Dobre, 2012c) and the time of day when the next node frequently forms a connection with the destination.

Still, such social-aware routing protocols for ONs are energy-unaware. In contrast, protocols such as biased random algorithm for load balancing (BRALB) (Touray et al., 2012), assume a static network, and forward messages to neighbours with which a node had the smallest number of message transfers. This is done to improve the overall energy use of the system by constantly modifying the transmission path. Still, to the best of our knowledge, the addition of an energy-aware layer over the routing decision in social-driver ONs was never tackled before.

Also, in our experiment, we consider epidemic (Vahdat and Becker, 2000) to be an interesting theoretical algorithm that offers good comparison metrics when dealing with opportunistic mobile networks. Unfortunately, the way epidemic works, by sending a message to all the neighbouring nodes, presumes infinite storage capacity and infinite resources (such as battery, bandwidth, and processing power). As such epidemic does not have a real world use and it should only be used in comparison with other algorithms.

Reduction in energy consumption in MANET networks is also studied in Ghada et al. (2010). The article proposes the use of a utility function that considers both power and mobility parameters. This function is then used to determine a route for the packets. Unlike our work, the utility function only uses data from one hop neighbours. Because this provides only a local optima the transmission rate and latency for the whole network are heavily affected.

### 3 The energy problem

In case of a disaster scenario access to important resources such as communication or even electrical infrastructure can be drastically reduced. There are a number of events that can limit this, from a tree breaking the main electrical line going into a village to a government or a group limiting the access to resources in order to oppress a population.

A delay tolerant network is a strategic resource at the disposal of individual citizens that can offer assurances that communication is still possible even if the infrastructure is

no longer available. This type of network becomes even more useful in the case of a disaster when search and rescue teams really on communication to coordinate their efforts.

Even if mobile devices can function without a proper communications infrastructure each device still requires electrical power to work. If both communication and electrical infrastructure are down for a long period of time these devices will eventually stop working as their battery runs out. To add to this problem, a modern Smartphone or Tablet can only use Wi-Fi for a few hours before the battery is emptied. With the high amount of traffic required by a DTN this time can be even smaller.

We have run simulations on multiple traces in which devices would stop working after the battery has depleted. The battery is simulated by assuming every device can send or receive a limited number of messages before it stops working. We consider that every message uses one energy unit. We vary the amount of energy units a battery has available to determine the effect the amount of battery has on the network.

Multiple traces were chosen and used to see the effects in different scenarios. A network that is formed of sparse nodes that really communicate behaves differently from a network where the nodes are close to each other and most are in constant contact. It is important to observe the effects of the limited battery capacity has on all of these scenarios.

There are a number of routing algorithms that we have considered:

- *Epidemic* (Vahdat and Becker, 2000) is an algorithm that sends all the packets to all its neighbours, this way it is assured that a packet reaches its destination. However, epidemic assumes that all devices have unlimited resources and this is not true in a real scenario. We keep this algorithm for comparison purposes.
- *Wait* (Spyropoulos et al., 2004), also called direct delivery, sends a packet only if the receiver is the destination for that packet. This implies that for 2 nodes to communicate they need to be in range of each other. Wait is not fit for real life scenarios because of its extremely low hit rate but it is a useful comparison algorithm.
- *MCP* (Hui et al., 2011) is a more efficient epidemic algorithm, instead of sending an unlimited number of copies to all the neighbours it limits the number of copies and the number of receiving neighbours, hence the name multiple-copy-multiple-HoP.
- *dLife* (Moreira et al., 2012) and *PROPHET* (Lindgren et al., 2003b) use a probability to determine the direction in which to send the packet, what neighbour to choose, while PROPHET calculates the probability while the network is used, by determining how likely a node is to encounter the destination, dLife also uses outside data like a social graph.

- *PROPICMAN* (Nguyen et al., 2007) and *CiPRO* (Nguyen and Giordano, 2012) are algorithms that use personal data to make better routing decisions. This data can consist on house address, work place, schedule and others and it is used to determine the best path for the packets. Acquiring this data can prove difficult, most are not willing to share it and as such this algorithms are difficult to implement or test.
- *The Rank algorithm* (Hui et al., 2011) calculates the centrality of a node, its rank, by determining how many encounters that node had, a node with many encounters is more likely to deliver the messages. *Label* (Hui and Crowcroft, 2007), on the other hand, makes the assumption that people are grouped in communities and to deliver a message first the destination community needs to be reached.
- *BUBBLE Rap* (Hui et al., 2011) merges rank and label to form a stronger algorithm by sending packets towards both the destination community and the central, more popular nodes. We have chosen this algorithm to extend because as it is presented in Hui et al. (2011) and our personal research it is one of the most well performing algorithms. There are two versions of *BUBBLE Rap*, A and B, B is a small improvement that removes the packets once they are transmitted. In our simulations and in the development of the Energy Efficient *BUBBLE Rap* algorithm, we used version A of the original algorithm.

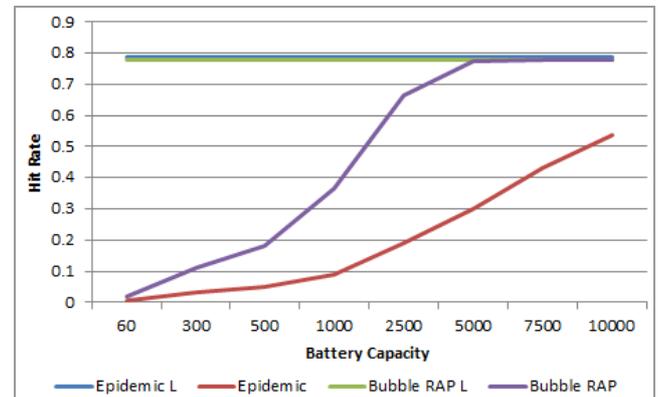
During our simulation we have chosen epidemic and *BUBBLE Rap* because one offers a comparison upper limit for performance while the other is the most well performing algorithm in the literature. We note *Epidemic L* and *BUBBLE Rap L* the cases. Next, we will present how these algorithms perform on our simulations on different traces. The traces we used are:

- *Reality* (Eagle and Sandy) was chosen because of the large number of nodes (100) and great time span of 9 months. It represents a sparse network spread in both space and time. The connections were detected using Bluetooth and 75 out of 100 users represent students or faculty stuff in the MIT Media Laboratory.

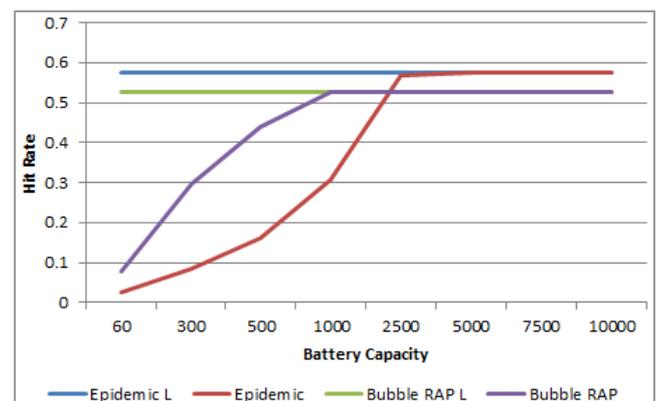
In Figure 1, we can see that epidemics performance grows at a far smaller rate than *BUBBLE Rap*, this is because epidemic, by sending a large number of packets, to all the neighbours it encounters it drains the battery of most devices earlier. Without these devices a large number of packets cannot reach their destination as possible paths between the source and the destination become unavailable. *BUBBLE Rap* does perform better but it is still heavily affected when there is a small amount of battery per device. We should note that in our simulation we used a relatively small number of messages and small battery capacity, but the 2 can scale proportionally to take into account a standard network with millions of packets.

- *St. Andrews* (Pelusi et al., 2006a) is a trace of a network of 25 mobile devices. The experiment lasted for 2 months, between the 15th of February to the 29th of April 2008. This represents the standard use behaviour, it is important to note that the devices have a longer range and manage to connect to each other even during the night time.

**Figure 1** Reality – hit rate/battery (see online version for colours)



**Figure 2** St. Andrews Sassy – hit rate/battery (see online version for colours)



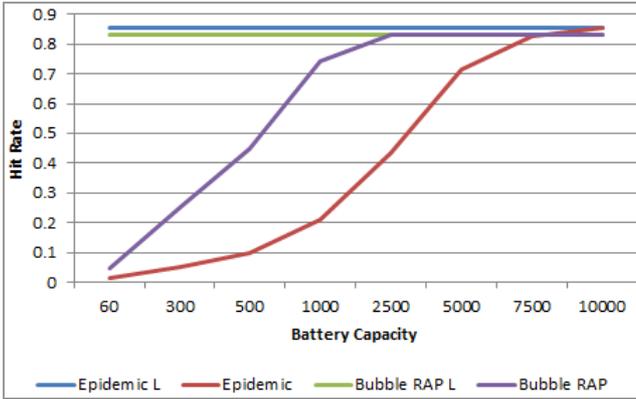
In the case of St Andrews, Figure 2, we can notice that the network is not as affected by the battery loss, both *BUBBLE Rap* and epidemic perform better. One of the main reasons this happens is because the number of packets or messages in the network is dependent on the number of nodes, and St. Andrews only has 25 nodes. Another reason for which epidemic performs so much better is that the nodes are more likely to have a connection and the packet is more likely to reach a destination. Also because of the small number of nodes there are fewer copies of the same package to be spread around.

- *Cambridge and Cambridge 06* (Scott et al., 2006) are two traces that include Bluetooth sightings by individuals carrying small devices called iMotes at 2 IEEE Infocom conferences in 2005 and 2006. These traces represent networks that have the nodes extremely close to each other and a lot of packets are sent in a small time frame. One should also note that these traces

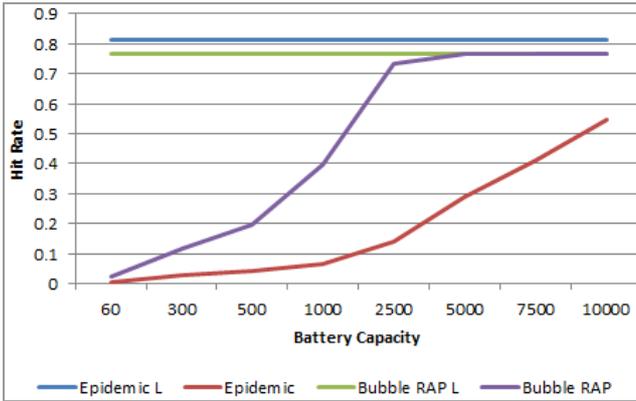
last for only three days but have as many connections as the reality trace.

- Figures 3 and 4 represent the Cambridge and Cambridge 06 traces. We can notice the same thing in this case, the one with more nodes, Cambridge 06 has the algorithms more strongly affected by the lack of battery, especially for epidemic.

**Figure 3** Cambridge – hit rate/battery (see online version for colours)



**Figure 4** Cambridge 06 – hit rate/battery (see online version for colours)



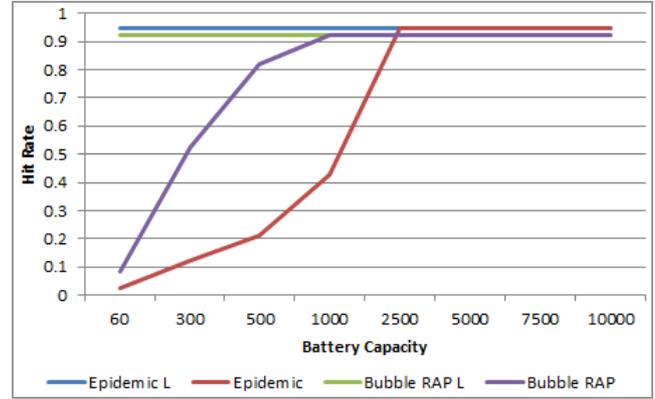
- *Random waypoint* is a simulated trace we developed similar to the one used in Petz et al. (2009). In this trace, we presume that the nodes are moving randomly and we consider connections only when they are close to each other, the distance between two nodes is smaller than a chosen limit Epsilon.

The results for random waypoint trace can be seen in Figure 5. These results are very similar to the ones obtained in the St. Andrews trace because the network is very similar, similar number of nodes and many connections between them. However, the connections are properly dispersed and this is why the hit rate is closer to 1.

- From all this simulations we can see that both BUBBLE Rap and epidemic are heavily affected by a limited battery capacity and that if an algorithm sends a smaller number of messages and better targeted it is not as affected by the limits induced by the battery. In

Table 1, we can see the performance of the algorithms in there is no battery limit. That represents the best they can perform. Table 2 represents the number of nodes and the messages transmitted, these values should explain the differences between the five graphs.

**Figure 5** Random waypoint – hit rate/battery (see online version for colours)



**Table 1** Maximum possible hit rates

	<i>BubbleRap L.</i>	<i>Epidemic L.</i>
Cambridge	0.83109754	0.85365856
Cambridge 06	0.76836735	0.8132653
Reality	0.7796875	0.78776044
St. Andrews Sassy	0.528	0.574
Random Waypoint	0.92083335	0.94666666

**Table 2** Trace summary: total node and message count

	<i>Node count</i>	<i>Message count</i>
Cambridge	41	1,640
Cambridge 06	98	3,920
Reality	96	3,840
St. Andrews Sassy	25	1,000
Random waypoint	30	1,200

#### 4 BUBBLE Rap functionality

We have run BUBBLE Rap on all the traces we have discussed earlier, Figures 2 to 5 and have counted the number of transmissions for each node. As expected because BUBBLE Rap uses some nodes excessively. These are the nodes that have a large number of connections are extremely popular, the longer these nodes are kept alive the longer the network can function correctly.

As we can see in the figures no matter what type of network we are discussing the results are similar, some nodes have very few transfers while others have a very large number of transfers. This limit is also a very clear indicator of what battery capacity is needed for the network to function properly.

Let us take for instance the case of Cambridge (Figures 6–8), we can see both from the graph that represents the hit rate and the graph that represents the number of transmissions per node that a battery capacity of over 1,800 would make the hole system function perfectly. However, if we lower the battery to 1,000, even if only few nodes should fail the decrease in hit rate is an important one.

This phenomenon is best noticed in the case of St. Andrews (Figure 9) where with a battery capacity of 300 10 out of 25 nodes fail and the hit rate drops from 0.6 to less than 0.3. This dramatic drop shows the importance of keeping these popular nodes alive for as long as possible. This is also the reason we built the Energy Efficient BUBBLE Rap algorithm that takes available battery into

account to be able to keep the popular nodes alive for as long as possible.

The problem extends if we are discussing a natural disaster. In this case a popular node can be represented by a search and rescue team that meets a lot of people. If this node is overused and fails it can even cause the network to permanently split in two or more sub-networks.

Another important fact that needs to be observed is that even in the case of the random waypoint trace, where nodes should be equally popular we can see huge discrepancies between the number of messages they have to handle. The discrepancies are not as clear as the other cases but they are there and because they are smaller this is directly translated in the steeper drop in hit rate which we saw in the previous graph.

Figure 6 Cambridge – messages/node (see online version for colours)

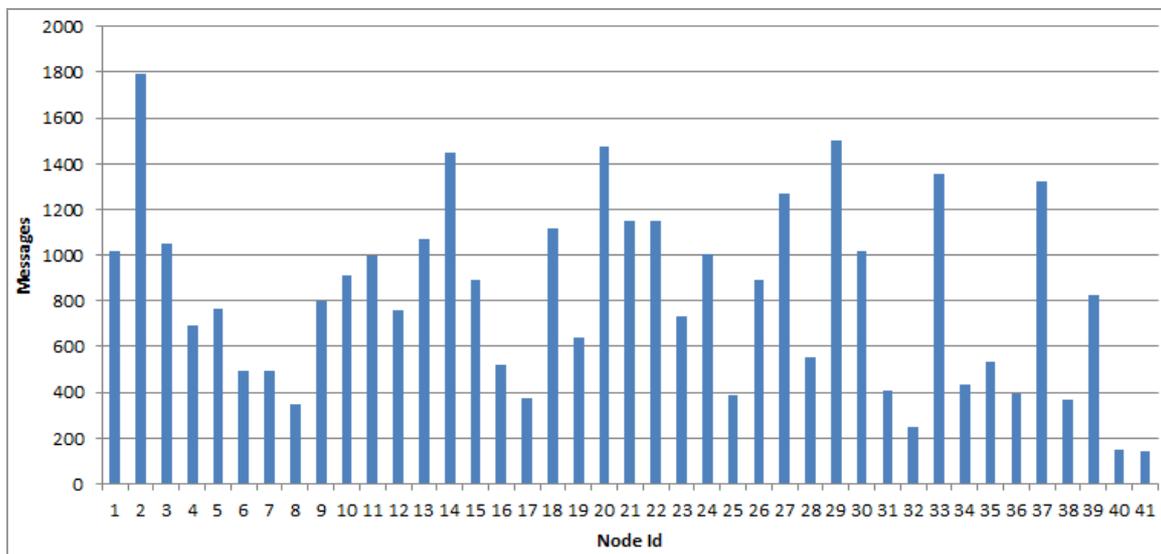
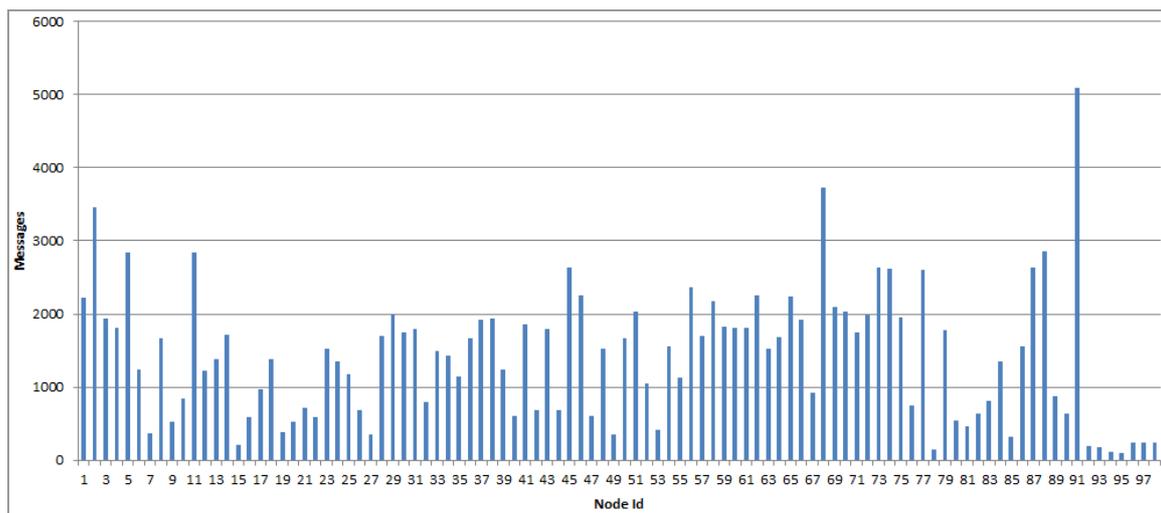
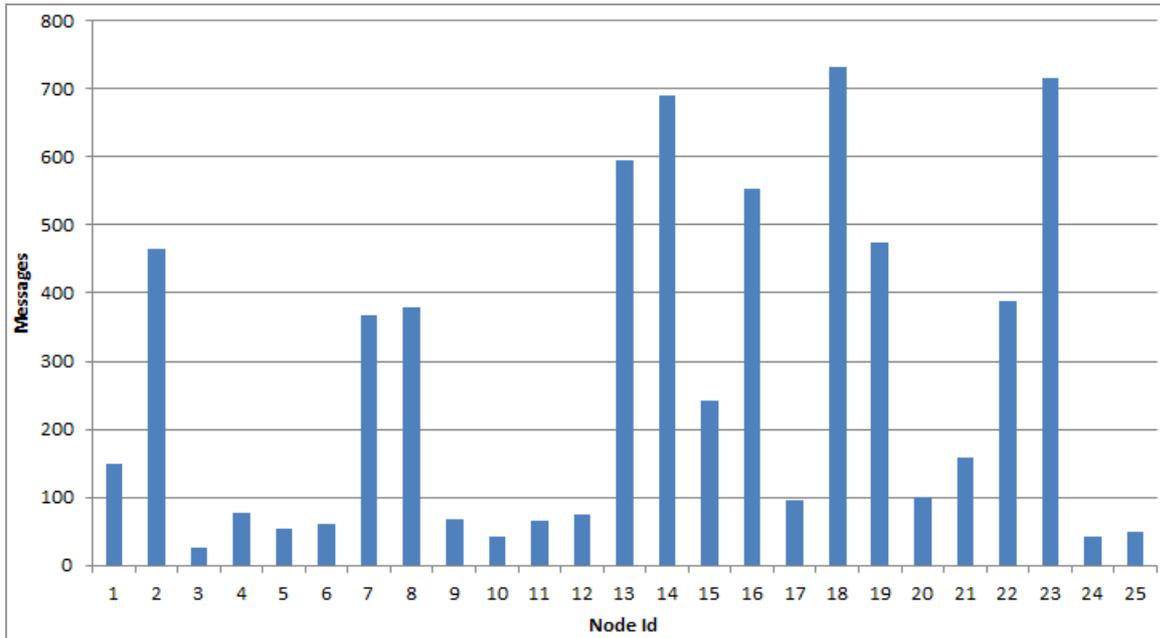


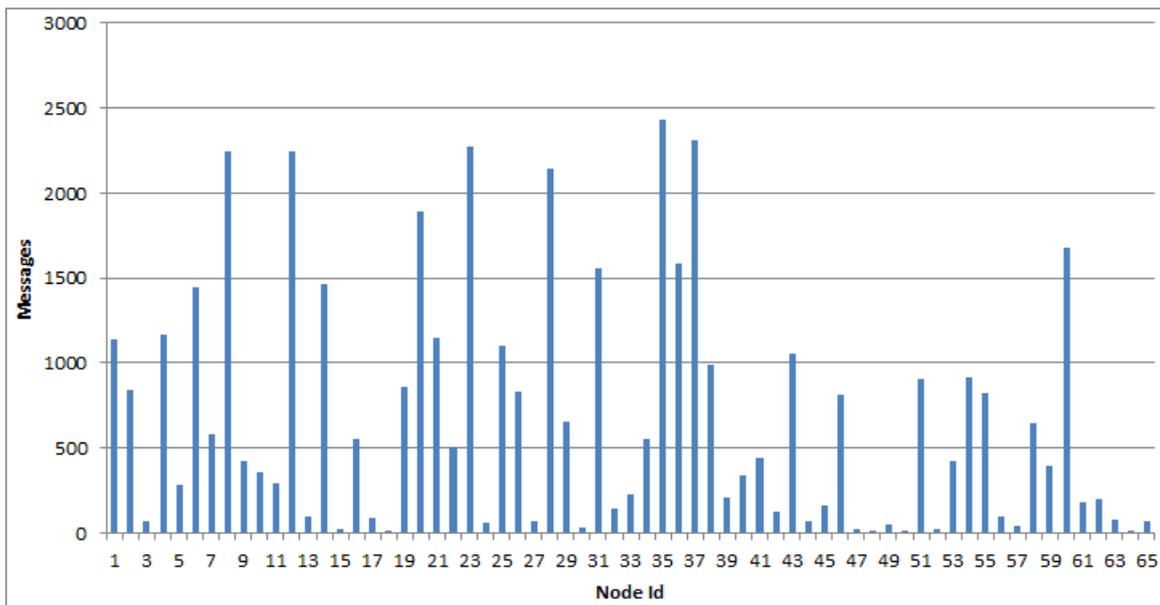
Figure 7 Cambridge – messages/node (see online version for colours)



**Figure 8** Cambridge 06 – messages/node (see online version for colours)



**Figure 9** St. Andrews Sassy – messages/node (see online version for colours)



In opposition to random waypoint (Figure 10), reality has the biggest difference between the number of messages transmitted to or from the popular nodes and the ones from the non-popular, standard nodes (Figure 11). This difference directly translates in the almost linear drop in hit rate that we presented for the reality case in the previous chapter.

Because of this big difference between the popular and unpopular nodes we present in the next section Energy

Efficient BUBBLE Rap, which is an algorithm that tries to limit this difference and as such obtain better results.

We have not presented the graphs for UPB2012 in this chapter or the previous one as they will be presented in more detail in the next chapter. The results that we obtained for UPB2012 are similar to the ones obtained for all the other traces.

Figure 10 Random waypoint – messages/node (see online version for colours)

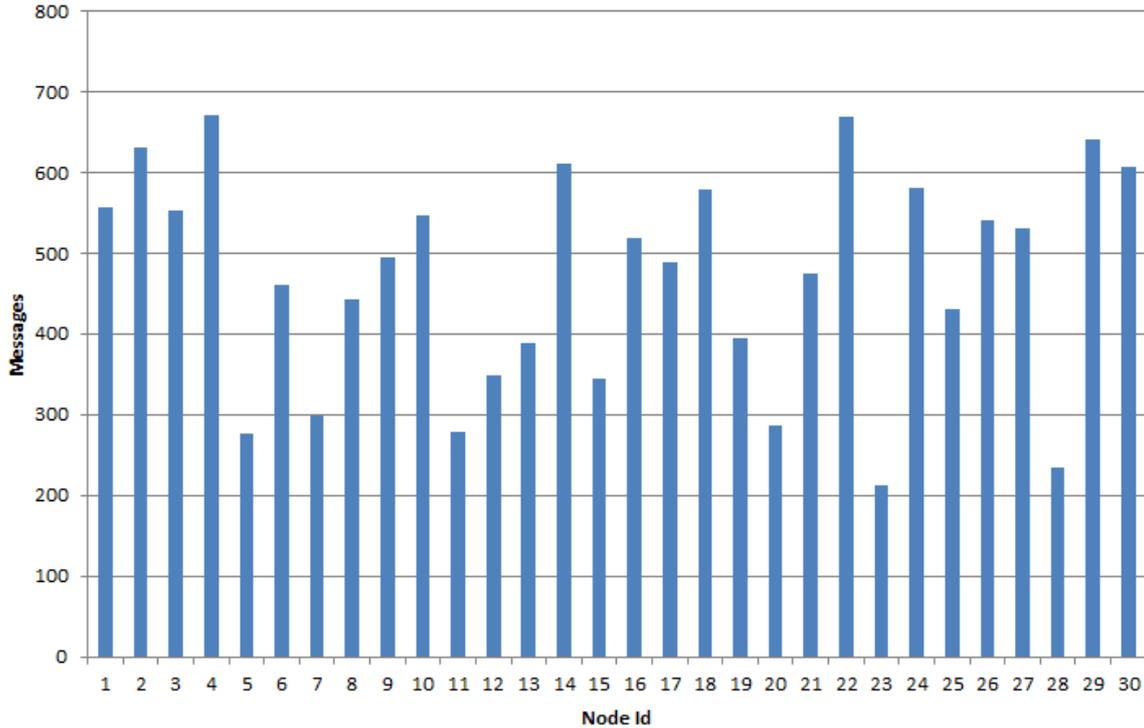
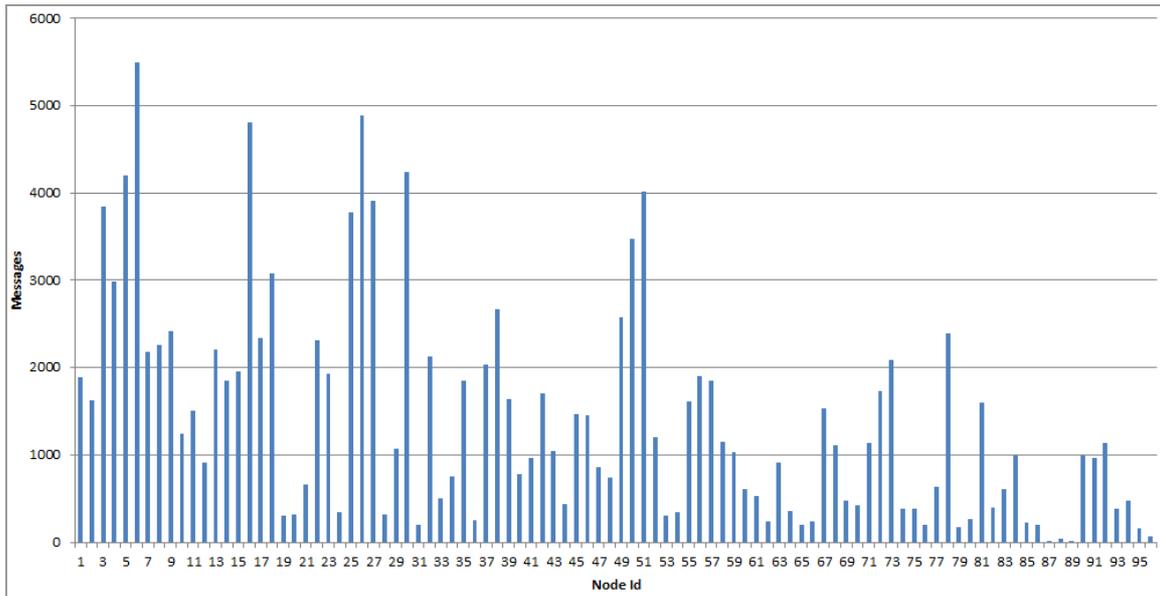


Figure 11 Reality – messages/node (see online version for colours)



### 5 Energy-aware BUBBLE Rap

As explained, Energy-Aware BUBBLE Rap (or EA BUBBLE Rap) combines socially-aware routing with energy consumption optimisation. The goal is to balance the energy consumption of the ON, making it uniform, whilst maintaining or even reducing the delivery cost and hop count. Thus, our objective is to increase the overall life of the network. In the original BUBBLE Rap algorithm, when two nodes meet they use a utility function to decide for each message to forward it through the neighbouring node. The decision includes the global and local ranks of the two

nodes that meet. If a node has a higher rank, the probability that it will receive more forward packages increases, since its centrality is higher.

In our approach, we extend the utility function to allow it to also decrease if the neighbouring node has insufficient energy resources to support the message transfer. As the energy decreases, the probability for that node to be a successful carrier also decreases.

To make the routing decision energy aware, we introduce the cost of using particular resources (such as battery), with the following properties:

- $\frac{\partial f}{\partial e} < 0$ , which means that the utility function  $f(e)$ , decreases with the increase of the energy consumption – so a node will not accept messages in transit if the battery is depleted for example.
- $\frac{\partial^2 f(e)}{\partial e^2} > 0$ , which means that the utility function decreases rapidly, considering the concavity of this function (the routing decision must be able to quickly react to possible changes in energy conditions).
- $0 < f(e) \leq K$ , which means that we have a threshold for this utility function.

Here,  $e$  is the energy level of a node. We also consider  $e_{\max}$  a maximum energy level (in a realist world Smartphones dispose of limited energy). Under this assumption, the energy-aware routing process can be modelled similar to an evolutionary process, in an electrical RLC circuit (where active and passive components have important roles in the evolution of the process). Thus, we apply a similar method to describe the evolution of the utility function for a particular Smartphone as:

$$\frac{\partial^2 f(e)}{\partial e^2} + \frac{\alpha}{2} \frac{\partial f(e)}{\partial e} - \frac{\alpha^2}{2} f(e) = 0$$

The equation has as solution:

$$f(e) = K \exp\{-\alpha e\},$$

where  $K$  is a constant that will be set as a threshold for the utility function, and  $\alpha$  is a quality factor for the utility function which depends on the maximum assumed energy (for a Smartphone, or for a particular route). So, considering a control point for the utility function of  $(e_{\max}, \varepsilon)$ , which means that for the maximum level of energy we reach the  $\varepsilon \cdot K$  threshold (a small fraction of the  $K$  threshold), we now have  $\alpha = -\ln \varepsilon / e_{\max}$ , thus:

$$f(e) = K \exp\{\ln \varepsilon \cdot e / e_{\max}\} \quad (1)$$

The constant  $\varepsilon$  in our experiments was considered to be  $10^{-3}$ , based on empirical observations, as a limit for practical measurements.

The logic implemented at the encounter of an arbitrary node from the ON is shown in Listing 1. Here, *NewLocalRankOf* and *NewGlobalRankOf* are obtained as sum between the original local and global functions defined by BUBBLE Rap, and the energy-aware utility function shown in equation (1).

From a computational point of view our proposed algorithm has the same complexity and the same number of transmitted messages as the original BUBBLE Rap algorithm. All the information that is needed to make the adjustment is provided by each individual device and represents information about the battery status. The battery status of the neighbour devices can be sent in the same packets that are used to calculate the local rank and global rank, thus not increasing the number of transmitted messages.

**Listing 1** The adjusted BUBBLE Rap procedure

---

```

begin EABubbleProcedure ( )
if ( LabelOf ( cur rentNode )==LabelOf (destination))
then
if (LabelOf (EncounteredNode i) ==
LabelOf (destination)) and (
NewLocalRankOf (EncounteredNode i)>
NewLocalRankOf (currentNode))
then
EncounteredNode i. addMessageToBuffer (message);
else
If (LabelOf(EncounteredNode i)==
LabelOf(destination)) or (
NewGlobalRankOf(EncounteredNode i)
> NewGlobalRankOf(currentNode))
Then
EncounteredNode i. addMessageToBuffer
(message);
end

```

---

## 6 Experimental setup and results

This section represents an experimental analysis of the Energy-Aware BUBBLE Rap algorithm.

### 6.1 Experimental setup

Evaluation experiments were first performed on the UPB 2012 trace (Ciobanu and Dobre, 2012b). The trace includes 66 participants from the University Politehnica of Bucharest. For 64 days the participants recorded their contacts on Bluetooth and Wi-Fi. We validated next our conclusions on another trace, from University of Cambridge, Cambridge-haggle-imote-content (Leguay et al., 2006). In this trace the data was collected with 36 mobile participants that used Intel iMote devices, small sensors that run ARM7 and can communicate through Bluetooth, and 18 fixed ones, in an area of 3 km<sup>2</sup>.

We assumed an energy model (i.e., battery life) where the energy decreases linear with the transmission of each message. Every time a message is exchanged between two nodes, one energy unit is consumed by each node (for send and receive). During the experiments, we varied the amount of energy available for each device/node. All devices start with the same amount of energy. Also, the number of messages sent through the network is of 580 for UPB2012, and 1001 for Cambridge-haggle-imote-content (because of different densities in nodes and contacts between the two traces). We considered only the energy depletion process, and we assume that when a node reaches the bottom level energy it will not be able to participate anymore in the communication (i.e., a Smartphone with no battery cannot forward messages).

Figure 12 UPB2012 – 5,000 maximum energy (see online version for colours)

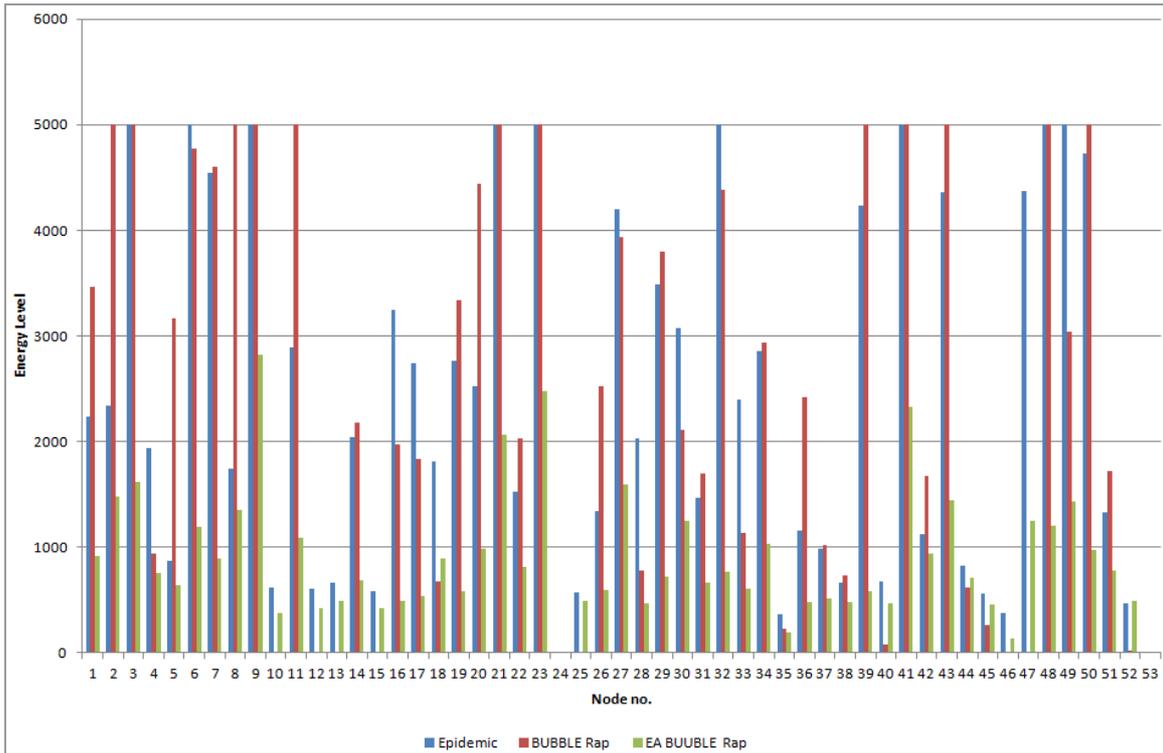
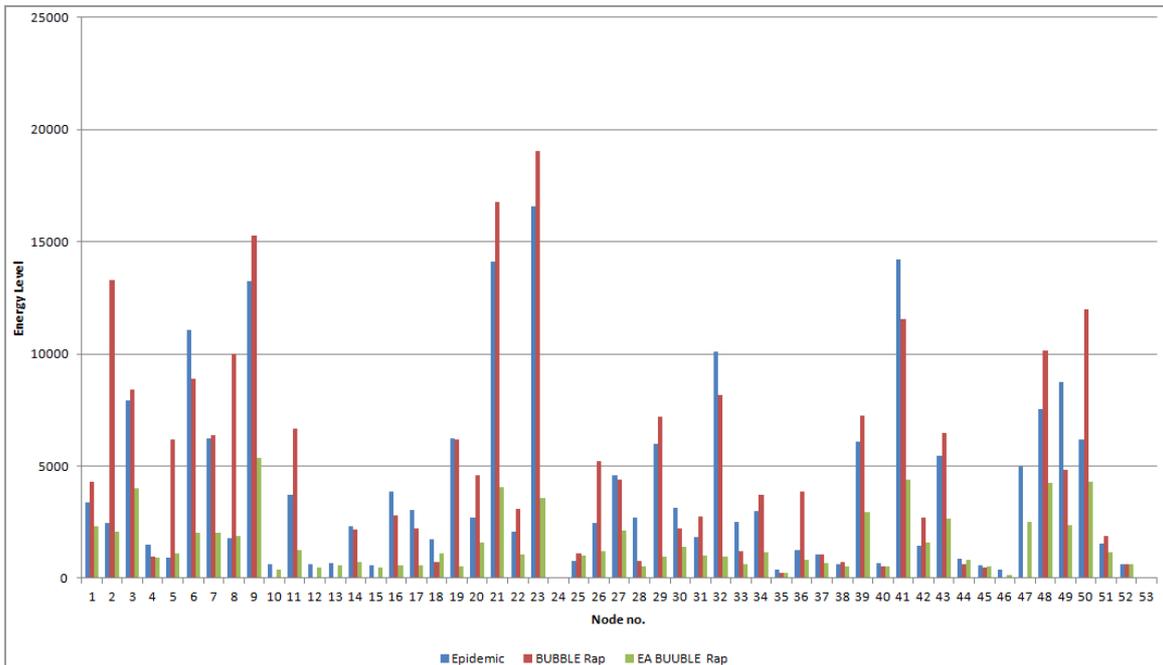
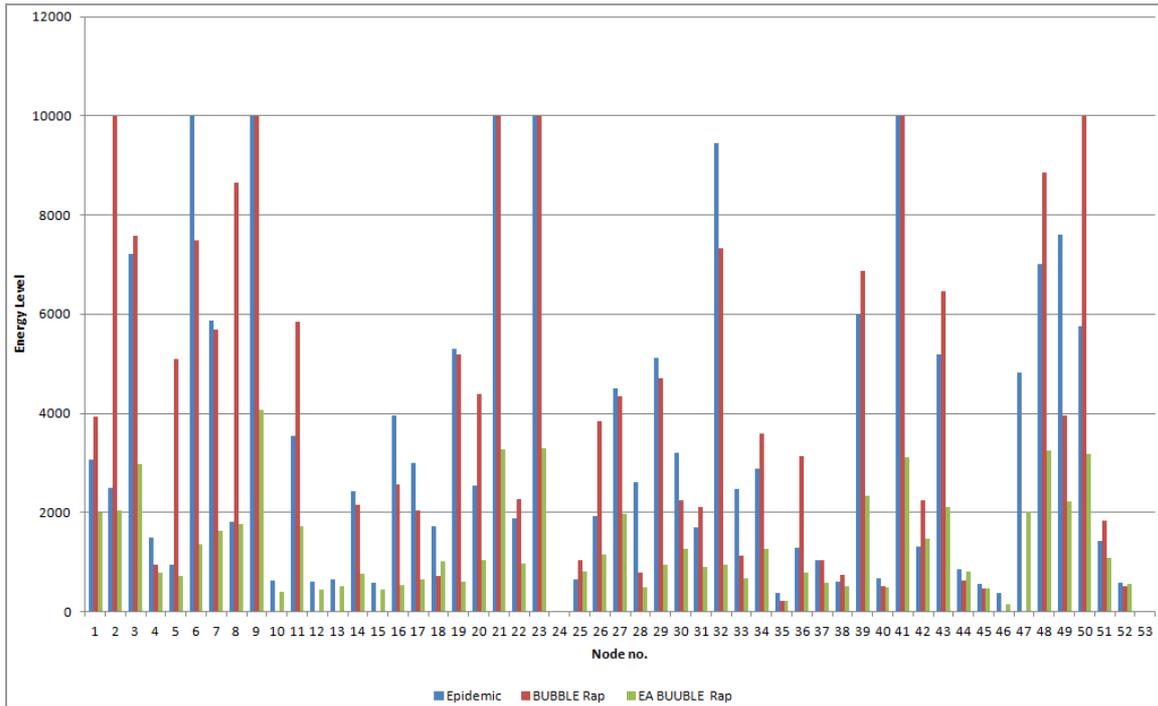
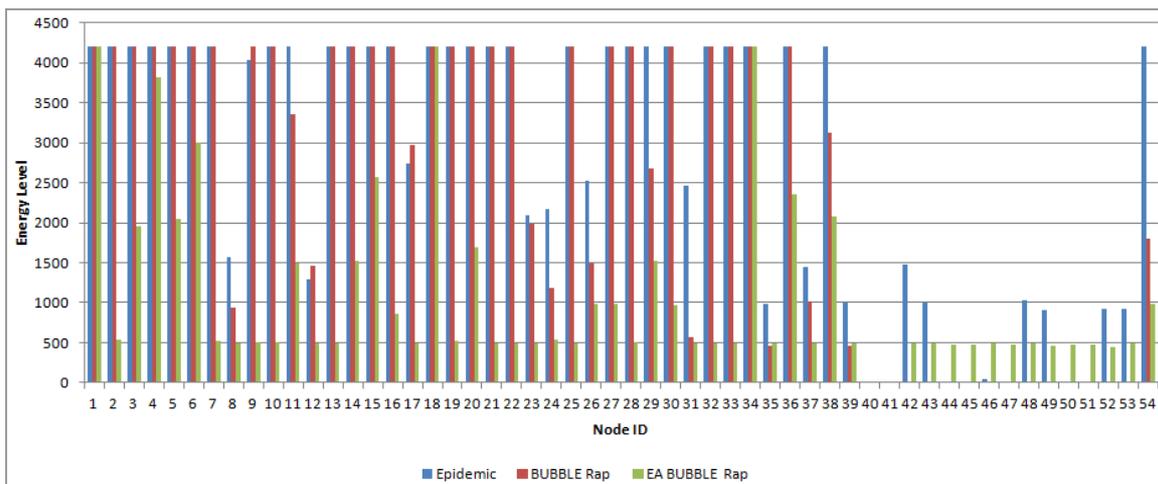


Figure 13 UPB2012 – 20,000 maximum energy (see online version for colours)



**Figure 14** UPB2012 – 10,000 maximum energy (see online version for colours)**Figure 15** Cambridge-iMote – 4,200 maximum energy (see online version for colours)

Finally, we compared our proposed algorithm with the original BUBBLE Rap, as well as with epidemic, under the same conditions.

## 6.2 Experimental results

There are several metrics that we use for analysing the simulation data. First of all, we look at hit rate, which is the ratio between data objects that have successfully arrived at requesting nodes and the total number of requests generated by all nodes. Although in this paper we treat the energy problem, hit rate still remains the main goal of opportunistic routing algorithms. Achieving a hit rate close to 100% means that ONs are plausible for implementation in real-life. Secondly, we consider the *delivery cost* as the ratio

between the total number of messages exchanged during the course of the experiment and the number of generated messages. This is a measure of network congestion, since fewer messages sent in the network leads to a less congested network. Another measure of congestion, but this time at the nodes, is the *hop count*. It is computed as the number of nodes that carried a message until it reached the destination on the shortest path.

Finally, for our experiments we looked at the *amount of energy consumed by each node* at the end of each round. Under different initial levels of energy existing in the network, we were interested how the routing decision balances the remaining energy of nodes.

Figure 16 UPB2012 – 2,500 maximum energy (see online version for colours)

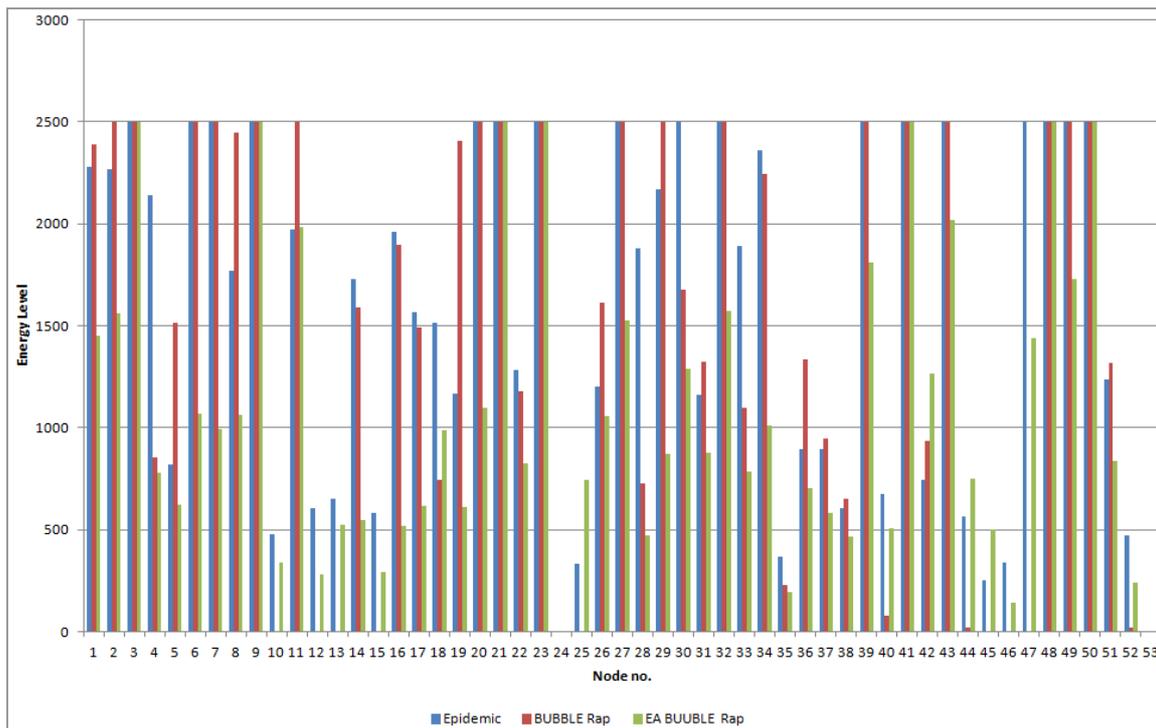
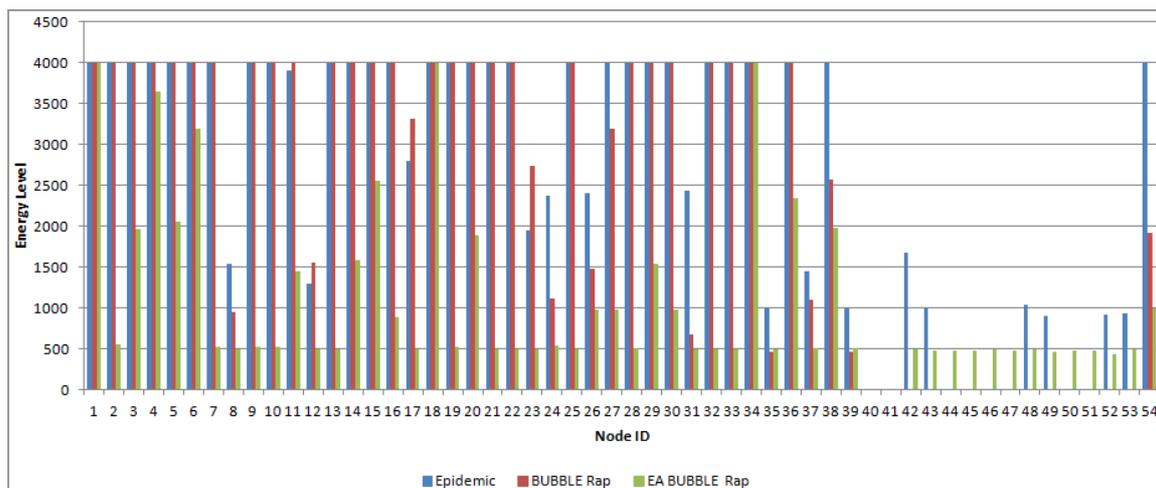


Figure 17 Cambridge-iMote – 4,000 maximum energy (see online version for colours)



A well-balanced result show that nodes are still able to preserve their energy for possibly other critical local services (such as making a phone call) and the overall life-time of the network is expanded. A non-balanced result show that some nodes lose their capability to participate in the communication (and, possibly, the energy for other services as well).

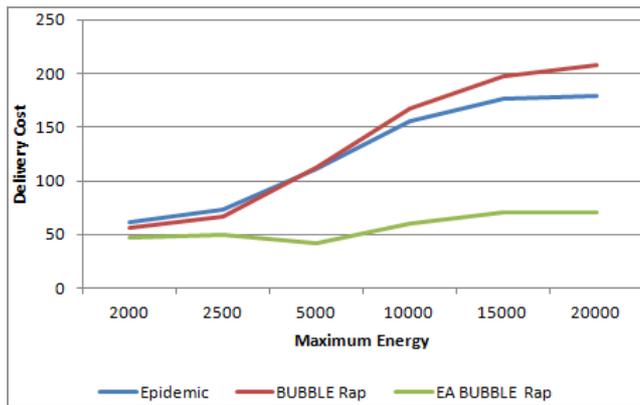
The results obtained for the energy consumption are presented in Figures 12 to 17. As seen, EA BUBBLE Rap manages to balance the energy consumption between more nodes inside the network. The algorithm manages to protect a higher number of devices from energy depletion. This also helps the network by decongesting the popular nodes, the ones that reach the maximum allowed consumed energy first. In a real life scenario other improvements may be

noticed, like lowering the bandwidth use of the popular nodes.

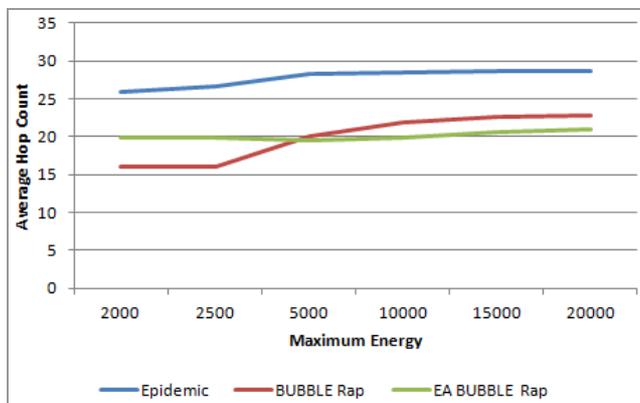
In terms of *delivery cost*, by decongesting the popular nodes messages actually need fewer transfers or hops to get to the destination, thus lowering the delivery cost (see Figure 18). This can also be seen in the average hop count (see Figure 19).

The average hop count can vary because by avoiding the popular nodes most messages need to find a longer path to get to their destination. But depending on the stability of the network, avoiding the popular nodes can prove to be an advantage. The differences in the following metrics are better seen if the devices have a smaller energy life (Figure 19).

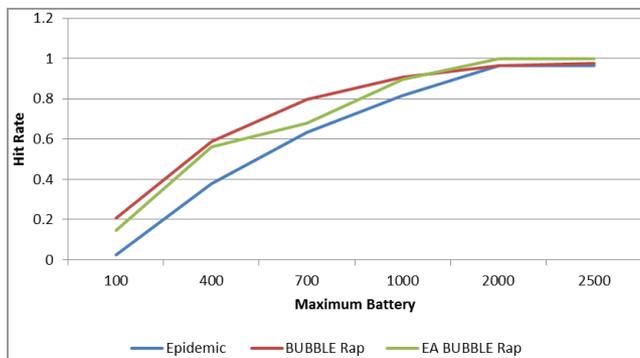
**Figure 18** UPB2012 – delivery cost (see online version for colours)



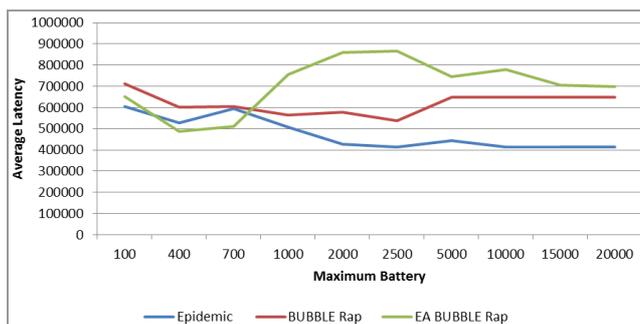
**Figure 19** UPB2012 – average hop count (see online version for colours)



**Figure 20** UPB2012 – hit rate (see online version for colours)



**Figure 21** UPB2012 – average latency (see online version for colours)



In terms of *hit rate* (Figure 20), EA BUBBLE Rap manages to deliver a similar or larger amount of messages. In the case of bigger battery life it actually manages to reach 100% message delivery and it does this with less maximum battery than the other two algorithms.

Because of the way EA BUBBLE Rap avoids the popular nodes it takes a larger amount of time to deliver the messages (Figure 21). Still, in case of a small amount of available energy, the algorithm manages to deliver better results than the other two algorithms.

## 7 Conclusions

In this paper, we presented a novel social-driven routing algorithm for ONs, which includes energy as an important element in selecting the routing decision. As demonstrated, when energy consumption is considered in social-driven ON routing, popular nodes can be saved from their resources being drained (we demonstrated such a behaviour for social-based routing algorithms such as BUBBLE Rap). After introducing energy awareness as an important criterion in the routing decision, we presented experimental results showing that our approach delivers performances similar to BUBBLE Rap, whilst balancing the energy consumption between nodes in the network. The results demonstrate that the total life span of the ON is increased, with minor or no modifications of hit rate and significant improvements to delivery cost.

The work presented in this paper can bring significant advantages to DTNs, especially in scenarios where battery life is a key factor and recharging points are scarce.

## References

- Bigwood, G., Rehunathan, D., Bateman, M., Henderson, T. and Bhatti, S. (2008) ‘Exploiting self-reported social networks for routing in ubiquitous computing environments’, in *Networking and Communications, 2008, WIMOB '08, IEEE International Conference on Wireless and Mobile Computing*, pp.484–489.
- Ciobanu, R.I. and Dobre, C. (2012a) ‘Data dissemination in opportunistic networks’, CoRR, abs/1202.2571.
- Ciobanu, R.I. and Dobre, C. (2012b) ‘Predicting encounters in opportunistic networks’, in *Proceedings of the 1st ACM Workshop on High Performance Mobile Opportunistic Systems, HP-MOSys '12*, ACM, New York, NY, USA, pp.9–14.
- Ciobanu, R.I. and Dobre, C. (2012c) *Routing in Opportunistic Networks using Contact Predictions and Social Connections*, Master’s thesis, University Politehnica of Bucharest, Romania.
- Conti, M., Giordano, S., May, M. and Passarella, A. (2010) ‘From opportunistic networks to opportunistic computing’, *Comm. Mag.*, Vol. 48, No. 9, pp.126–139.
- Ghada, K., Li, J. and Ji, Y. (2010) ‘Energy and mobility-aware topology control in heterogeneous mobile ad hoc networks’, in *International Journal of Computational Science and Engineering*, Vol. 5, No. 2, pp.147–153.

- Hui, P. and Crowcroft, J. (2007) 'How small labels create big improvements', in *Fifth Annual IEEE International Conference on Pervasive Computing and Communications Workshops, 2007, PerCom Workshops '07*, pp.65–70.
- Hui, P., Crowcroft, J. and Yoneki, E. (2011) 'BUBBLE Rap: social-based forwarding in delay-tolerant networks', *IEEE Transactions on Mobile Computing*, Vol. 10, No. 11, pp.1576–1589.
- Jain, S., Fall, K. and Patra, R. (2004) 'Routing in a delay tolerant network', in *Proceedings of the 2004 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications, SIGCOMM '04*, ACM, New York, NY, USA, pp.145–158.
- Känel, J.V. and Vecchiola, C. (2013) 'Global technology trends: perspectives from IBM research Australia on resilient systems', *International J. of Computational Science and Engineering*, Vol. 8, No. 3, pp.269–273.
- Leguay, J., Lindgren, A., Scott, J., Friedman, T. and Crowcroft, J. (2006) 'Opportunistic content distribution in an urban setting', in *Proceedings of the 2006 SIGCOMM Workshop on Challenged Networks, CHANTS '06*, ACM, New York, NY, USA, pp.205–212.
- Lindgren, A., Doria, A. and Schelén, O. (2003a) 'Probabilistic routing in intermittently connected networks', *SIGMOBILE Mob. Comput. Commun. Rev.*, Vol. 7, No. 3, pp.19–20.
- Lindgren, A., Doria, A. and Schelén, O. (2003b) 'Probabilistic routing in intermittently connected networks', *SIGMOBILE Mob. Comput. Commun. Rev.*, Vol. 7, No. 3, pp.19–20.
- Moreira, W., Mendes, P. and Sargento, S. (2012) 'Opportunistic routing based on daily routines', in *World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, pp.1–6.
- Nguyen, H.A. and Giordano, S. (2012) 'Context information prediction for social-based routing in opportunistic networks', *Ad Hoc Networks*, Vol. 10, No. 8, pp.1557–1569.
- Nguyen, H.A., Giordano, S. and Puiatti, A. (2007) 'Probabilistic routing protocol for intermittently connected mobile ad hoc network (propicman)', in *World of Wireless, Mobile and Multimedia Networks, 2007, WoWMoM 2007*, pp.1–6.
- Pelusi, L., Passarella, A. and Conti, M. (2006a) 'Beyond MANETs: dissertation on opportunistic networking', Technical report.
- Pelusi, L., Passarella, A. and Conti, M. (2006b) 'Opportunistic networking: data forwarding in disconnected mobile ad hoc networks', *Communications Magazine*, Vol. 44, No. 11, pp.134–141, IEEE.
- Petz, A., Enderle, J., Julien, C., Petz, A., Enderle, J. and Julien, C. (2009) 'A framework for evaluating DTN mobility models', in *SCENES Conference Proceedings*.
- Probst, C. et al. (2007) 'Power-aware computing systems', in *International Journal of Embedded Systems*, Vol. 3, No. 1, pp.3–7.
- Scott, J., Gass, R., Crowcroft, J., Hui, P., Diot, C. and Chaintreau, A. (2006) CRAWDAD trace cambridge/haggle/imote/infocom (v. 2006-01-31).
- Spyropoulos, T., Psounis, K. and Raghavendra, C. (2004) 'Single-copy routing in intermittently connected mobile networks', in *2004 First Annual IEEE Communications Society Conference on Sensor and Ad Hoc Communications and Networks, 2004, IEEE SECON 2004*, pp.235–244.
- Touray, B., Shim, J. and Johnson, P. (2012) 'Biased random algorithm for load balancing in wireless sensor networks (BRALB)', in *Power Electronics and Motion Control Conference (EPE/PEMC), 2012 15th International*, pp.LS4e.1-1–LS4e.1-5.
- Vahdat, A. and Becker, D. (2000) 'Epidemic routing for partially-connected ad hoc networks', Technical report.
- Zhang, Z. (2006) 'Routing in intermittently connected mobile ad hoc networks and delay tolerant networks: overview and challenges', *Communications Surveys Tutorials*, Vol. 8, No. 1, pp.24–37, IEEE.