Enhanced Lobby Influence: *Knowledge based content forwarding algorithm for opportunistic communication networks*

[4]Sardar Kashif Ashraf Khan, [1]Jonathan Loo, [1]Muhammad Awais Azam, [2]Humaira Sardar, [3]Muhammad Adeel, [3]Laurissa N Tokarchuk
[1]School of Science and Technology, Middlesex University, London, UK
[2]Department of Software Engineering, Fatima Jinnah Women University, Rawalpindi, Pakistan
[3]School of Electronic Engineering and Computer Science, Queen Mary University of London, UK
[4]Department of Electrical Engineering, Mirpur University of Science and Technology, Mirpur AK, Pakistan
ska.khan@must.edu.pk, {j.loo, m.azam}@mdx.ac.uk, {muhammad.adeel, laurissa.tokarchuk}@eecs.qmul.ac.uk

***Abstract*— Content transfer without any prior knowledge of the routes, always causes a challenge in opportunistic networks. Content forwarding in these networks have repercussions in the form of communication cost. Enhancement in content forwarding in opportunistic networks can be realized by targeting key nodes that show high degree of influence, popularity or knowledge inside the network. Based on these observations, this paper presents an improved version of Lobby Influence algorithm called Enhanced Lobby Influence. The forwarding decision of Enhanced Lobby Influence not only depends on the intermediate node selection criteria as defined in Lobby Influence but also based on the knowledge of previously direct content delivery of intended recipient. The experimental results have shown that the new algorithm performed extremely well against its predecessor Lobby Influence and illustrates that not only it reduces the communication cost but at the same time makes content delivery efficient for intended recipients.**

Keywords- Social Networks; Forwarding algorithm; Opportunistic routing; Ad hoc communication; Human relationships; Content forwarding

I. INTRODUCTION

It is common in opportunistic networks that there is no advance knowledge how to locate destination nodes in unknown paths. One way to address this issue is to flood the contents/messages throughout the network; this generates unnecessary traffic in the network and has adverse effect in terms of network resources. The resources of a node can deplete very quickly as receiving irrelevant contents and may force nodes to leave the network. Epidemic algorithm [1] has significantly reduced this problem by not allowing duplicate packets to be forwarded to the same nodes. Although, this concept stops duplicate packets, but nodes are still receiving irrelevant packets, which eats up precious resources.

Many social based algorithms [2, 3] based on three centrality measures: betweenness[4], degree[5] and closeness [6], proposed new ideas how to reduce the unnecessary resource consumptions in opportunistic networks. These ideas basically revolve around the concept of exploiting key nodes in the network, which can help delivering the information. For instance, key nodes may come across with other influential nodes; thus there is a good possibility that these nodes may meet with destination nodes or some other nodes that knows the destination node. Bubble Rap [2] is an algorithm that exploits popular nodes as efficient information carriers to reduce the unnecessary traffic in the network. Bubble Rap has significantly reduced the overutilization of network resources compare to Epidemic algorithm but pays off in the form of quick resource depletion in popular nodes. The Lobby Influence (LI) [3] is another social based algorithm that exploits key nodes as efficient content forwarders. The content forwarding decisions in LI is achieved by combining two important factors 1) popularity of node [2] 2) popularity of node's neighbours [7]. LI allows less popular nodes to transmit message to more popular nodes. Similarly, LI also allows more popular nodes to transmit messages to less popular nodes with condition of having more popular neighbours. This kind of content forwarding presented by LI has indeed improved the overall message delivery and reduced the delays in opportunistic communication. However, LI also poses a drawback in the form of an increase in overall network communication cost as compared to existing social forwarding algorithm such as Bubble Rap.

In this work we present an efficient knowledge based content forwarding algorithm, Enhanced Lobby Influence (ELI), which not only improves the overall message delivery but also reduces the communication cost as observed in its predecessor LI.ELI allows nodes to keep the record of those nodes which they have delivered messages directly as final recipient. Basically ELI made nodes aware that in future if any intermediate node finds a message for a recipient, which they know directly during previous course of content delivery, should stop forwarding the messages and keeps those messages to them until they find the final recipient. By doing so, a significant amount of message traffic in the network is reduced by not allowing to the irrelevant nodes. This new algorithm is tested against its predecessor Lobby Influence and Bubble Rap in working day model (WDM) scenario [8]. Simulation results have shown that ELI not only outperforms LI in terms of message delivery but also decreases a significant amount of communication cost compare to BR.

The paper organized as follows: Section II gives the related work. Section III details the concept of the Enhance Lobby Influence algorithm. Section IV provides the experimental results and discussion. Section V gives our conclusion with a discussion of future work.

II. RELATED WORK

The communication cost observed in simple flooding the opportunistic network is significantly reduced in Epidemic routing [1]. The Epidemic routing reduces the number of duplicate packets by not allowing packets tagged with same IDs twice to same node. Nevertheless, it does not stop sending irrelevant packets all over the network, and as a result the communication cost of this algorithm is still very high. To address this issue, a social based forwarding algorithm known as Bubble Rap (BR) [2] is proposed by Hui. BR is based on the concept of community and centrality, where nodes form communities to show their association with subset of nodes within the network. These nodes can be reached by exploiting betweenness centrality i.e. how many times a node come across as a message carrier during previous course of communication. The betweenness centrality in BR is taken from the analogy of person popularity in his social circle; the popular persons have more relations with other members of community, thus are ideal candidates to use as information forwarders. This message forwarding technique decreases the overall duplicate packets in the network and points the traffic to relevant destination nodes. However, drawback of this technique is an increase of load on popular nodes and buffer of these nodes can overflow very rapidly, as a result, packet loss can increase.

The BR highlighted the importance of social based algorithm, where content forwarding in opportunistic networks can improve by inferring analogies based on human relationships in a society. However, there are other algorithms that exploit human relationships analogies differently. For instance, a concept of exploiting individual with popular neighbours in a society is presented in the diplomat's dilemma [9], taken from the analogy that a diplomat has a high influence in a society, because his contacts are mainly with influential members of society. These individual can thus have more knowledge in the society, which give them more power with minimum effort of making personal relations. Based on diplomat's dilemma, Korn et al [7] presented a metric known as Lobby Index that defines "a node has high lobby index if its neighbours have at least equal or more neighbours than the node itself" [7].

Lobby Influence [3] is another social based algorithm that combines the characteristics of both the popularity of a node, as presented in [2], and the popularity of the node's neighbour, as presented in [7]. This algorithm is based on assumptions that apparently un-popular nodes might have popular neighbours and thus can be exploited for information transmission. By the help of these nodes, a high access or knowledge of other relevant nodes in the network can be gathered, which eventually help to deliver the messages to intended recipients. The LI has significantly improved the overall delivery ratios in opportunistic networks; however, it proved to be costly in terms of communication overhead.

The rest of the paper presents our enhanced version of Lobby influence algorithm, which inherits all the characteristics of its predecessor Lobby influence with addition of knowledge based content forwarding concept.

III. KNOWLEDGE BASED CONTENT FORWARDING

ELI uses the same concept as described in LI, with the addition of keeping record of previous direct encounter with destination nodes. Keeping previous record of direct encounters have following objectives:

- ELI is based on assumption that when a node directly deliver content to final destination node, this means that node is member of same community as the destination node or in case of human relationship analogy that node can be a close relative, friend or colleague. The probability of meeting with the same destination node in future is very high. Keeping this information in node's database may help not to transmit unnecessary traffic to irrelevant nodes, thus can decrease overall network communication cost.
- Keep the size of node's database small, because in opportunistic networks there is no prior knowledge of route to the destination node. No way can a node store information of every forwarding node used for previous communication, only most relevant information is allowed to store in node's database such as IDs of destination nodes.
- When a forwarding node receives a packet for a destination node whose information is available in node's database. Forwarding node simply keeps the packet of that particular destination until meets personally to deliver the content.

In order to understand the knowledge based content forwarding concept, consider figure 1, where ELI illustrates observations based on which it reduces the communication cost but at the same time makes content delivery efficient for intended recipients. When two nodes encounter each other, the current node forward content to the encountered node based on three criteria:

1) More popular: high centrality i.e. how many times a node takes part as a forwarding/intermediate node, defines its popularity, as presented in [2].
2) Popular neighbours: high lobby index i.e. seemingly un-popular nodes could have a high degree of popular neighbours and are thus, good candidates for information transmission, as presented in [7].
3) Knowledge based nodes: previously directly delivered content to same destination node.

As depicted in Figure 1, nodes only forward messages if the encountered node is either more popular or un-popular

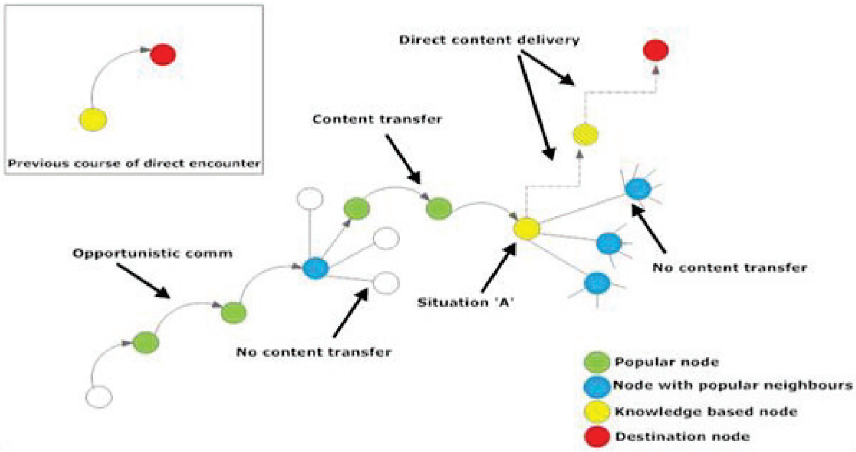

Figure 1. Enhanced Lobby Influence Concept

with high degree of popular neighbours, represented as green and blue nodes, respectively, this concept is inherited from Lobby Influence algorithm. Enhanced Lobby influence comes into play when situation 'A' arises, as shown in Figure 1. Node (represented in yellow) has popular neighbours, was previously engaged in delivering content to the intended destination node. This node does not transmit message any further to its neighbours, it keeps content until deliver it directly. Therefore, ELI restricts nodes not to send content further unnecessarily based on the previous knowledge of direct delivery to same destination node, as a result a significant amount of communication cost can be saved.

IV. RESULTS & DISCUSSION

A. *Simulation Setup*

The Enhanced Lobby Influence is the advance version of Lobby Influence algorithm. Therefore, all the concepts used in [3] are also considered in ELI algorithm. The same label scheme as describe in [10] is used for community association. The simulation setting used in this experiment is exactly the same as described in [3]; some key points are highlighted here. The word content and message has same meaning in this section and may use alternatively. To evaluate this algorithm, opportunistic networking environment (ONE) simulator [11] is used. This simulator is specifically designed to test the opportunistic concepts on different built in synthetic movement models, such as, in our case, Working Day movement model (WDM). The beauty of WDM model is that nodes activities are very close to the human daily life activities. In this movement model, nodes start off day from home, spend time in office, go for evening activities and finally come back home by the end of the day. During these movements, nodes have chance to meet with other nodes and nodes far apart from each other can be reached through intermediate nodes.

Devices considered in this experiment are equiped with bluetooth capablitites. Eash device is capable of trasmitting packets at speed of 2Mbits/s upto 10m range. This simulation considers activities of nodes for one day. The length of the day is approximately 16 hours because after that a node assumes to be at home.Table I summarize the parameters used in this experiment.

TABEL I. PARAMETERS USED IN WDM SCENARIO

Parameters	**Value**
World's size for Movement Model	10000 X 8000m
Total simulation time	57000s
No. of Hosts [pedestrians, buses]	[150, 10]=160
Message TTL (time to live)	960 mins
Time to move nodes in the world before real simulation commence	7200s
Nodes speed [pedestrians, buses]	[0.5-1.5, 7-10]m/s
Nodes pause time [pedestrians, cars, trams]	[0-0, 10-30]s
Message sizes	500KB-1MB
Message creation interval	15-25s
Air data transmit speed	250kbps
Transmit range	10m
Working day length	28800s
Probability to go shopping after work	0.5
Own car probability	0.5
Range of message source/destination addresses	0-159 nodes
Queue sizes	0,20,40,60,80,100, 120,140,160,180 in MB
No. of each experiment runs	10

B. *Results*

Three algorithms BR, LI and ELI are evaluated by changing the queue size of the nodes and their results are compared. Overall performance of the network can greatly improve by increasing the size of queue. With large queue size a node can store more messages and chances of dropping packets due to queue over-flow lessen. Ten experiments are performed for each queue size using different seeds. Due to high computation requirement for ONE simulator, multiple high performance computers are used. Three metrics are compared to evaluate the performance of each algorithm: 1) Message delivery: number of packets reach at the intended destinations 2) Delays: time takes to reach at intended destinations 3) Forwarded messages: total number of messages exchanged (including duplicates) among nodes, defines the cost of the network, which ultimately effects the utilisation of system resources (bandwidth and energy). Each graph shown in this section contains three curves representing behaviour of BR, LI and ELI algorithms, respectively. X-axis represents varying queue sizes against which each graph is plotted.

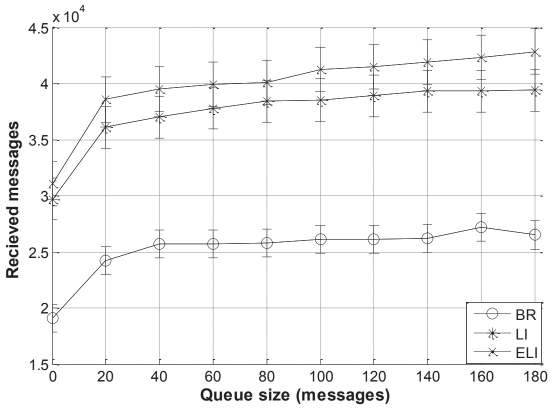

Figure 2. Average message delivery in WDM

Figure 2 shows the number of messages received at destination nodes in working day model scenario. The graph shows that ELI outperforms LI and BR in terms of message delivery. BR only uses popularity as a criterion for the selection of forwarding nodes, unless find more popular node, the current node keeps the messages. LI performs much better than BR, because LI exploits both popular nodes and un-popular with popular neighbours (high influential nodes). ELI is inherited from LI, so naturally it possesses all the characteristics of LI. In addition to these characteristics, ELI makes a node to keep the record of those destinations for which it acted as a final relay node. The graphs show that, this observation we made for ELI proves to be true; in WDM model same nodes have chances to meet each other in office, home or evening meeting points. Therefore, by allowing these nodes to keep the message until deliver directly to destination nodes, indeed improves the overall delivery rates.

Figure 3 shows the cost of the network communication i.e. number of messages forwarded during the experiment and plotted its average. LI proves to be more costly because selection of forwarding node is not only based on popularity but also on influential nodes; this naturally increases the communication cost compare to the BR which only uses popularity as forwarding criteria. ELI outperforms its predecessor LI, because ELI stop forwarding the messages, if it finds the message is intended for that destination for which it delivered before. This observation has significantly reduced the overall network communication cost. ELI even proves that it's cost is almost equal to the BR algorithm, as depicted in Figure 3.

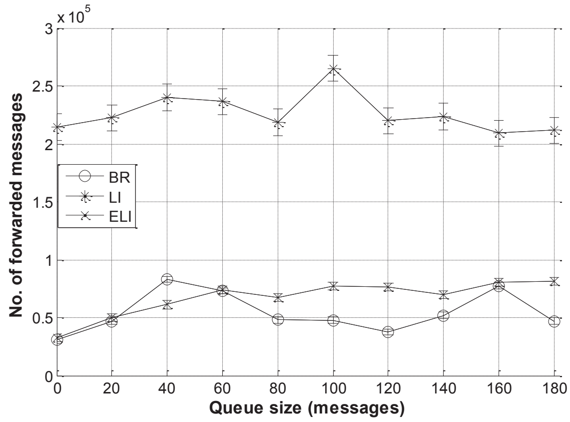

Figure 3. Average no. of forwarded messages in WDM

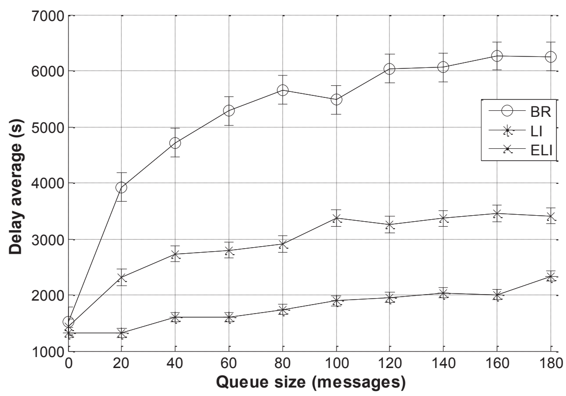

Figure 4. Average delay rates in WDM

Figure 4 shows the average time taken by the nodes to deliver messages, using different algorithms in WDM. BR has the highest delay, because in this algorithm nodes only forward messages to more popular nodes, otherwise discard the message when TTL expires. LI proves to be the fastest one because it keeps on forwarding messages by using popular nodes or un-popular nodes with popular neighbours. ELI proves to be faster than BR but slower than its predecessor LI. Two reasons causes delays in ELI 1) when searching for previous direct communication information in database 2) if found, the node keeps that message until deliver directly to the destination node. However, we are dealing in opportunistic network, where average delays shows by ELI are acceptable.

V. CONCLUSION & FUTURE WORK

Simulation results have confirmed that the observation based on which Enhance Lobby Influence is designed turns out to be accurate. Enhance Lobby Influence not only selects forwarding nodes as does by its predecessor Lobby Influence but also keeps the knowledge of previous direct encounters with intended recipients. This makes un-popular nodes with popular neighbours to share the burden of popular nodes but also stop forwarding the content unnecessarily to other nodes if destination is known during the previous course of communications. Algorithms we compared so far are designed for opportunistic networks, where delays are acceptable. ELI proves to be the better algorithm than LI and BR in terms of both message delivery and communication cost.

In real life application, ELI can be incorporated with Bluetooth enable mobile devices to communicate opportunistically for the applications such as emails or SMS. In case of disasters, where chances of traditional telecom network infrastructure could be damaged, this kind of opportunistic communication can be extremely helpful such as SOS messages. So far, we have implemented this work in synthetically developed working day movement model. There are many other synthetic models as well as real world mobility traces against which robustness of ELI can be further tested.

REFERENCES

[1] A. Vahdat and D. Becker, "Epidemic routing for partially connected ad hoc networks," Technical report, Duke University, 2000.

[2] P. Hui, J. Crowcroft and E. Yoneki, "Bubble rap: social-based forwarding in delay tolerant networks", Proc. ACM symp. Mobile ad hoc networking and computing (MobiHoc '08), 2008, pp. 241-250, doi: 10.1145/1374618.1374652

[3] S. K. A. Khan, R. J. Mondragon & L. N. Tokarchuk, "Lobby influence: opportunistic forwarding algorithm based on human social relationship patterns," International Workshop on the Impact of Human Mobility in Pervasive Systems and Applications (PerMoby 2012), in press.

[4] A. Bavelas, "A mathematical model for group structures," Human Organization, vol. 07, no. 03, 1948, pp. 16-30.

[5] S. P. Borgatti, "Network Analysis of 2-mode data," Social Networks, Vol. 19, 1997, pp. 243-269.

[6] G. Sabidussi, "The centrality index of a graph,"Psychomatrika, vol 31, 1966, pp. 581-603, doi: 10.1007/BF02289527

[7] A. Korn, A. Schubert and A. Telcs, "Lobby index in networks," Physica A: Statistical Mechanics and its Applications, vol. 388, issue 11, 2009, pp. 2221-2226, doi: 10.1016/j.physa.2009.02.013

[8] F. Ekman, A. Keranen, J. Karvo and J. Ott, "Working day movement model," Proc. ACM Conf. 1st ACM SIGMOBILE workshop on Mobility models (MobilityModels '08), 2008, doi: 10.1145/1374688.1374695

[9] P. Holme and G. Ghoshal, " The diplomat's dilemma: Maximal power for minimal effort in social networks," Adaptive networks: Theory, models and applications, 2009, pp. 269-288, doi: 10.1007/978-3-642-01284-6_13

[10] P. Hui and J. Crowcroft,"How small labels create big improvements," Proc IEEE conference. Pervasive Computing and Communications Workshops (PerCom Workshops '07), IEEE Press, March 2007, pp. 65-70, doi: 10.1109/PERCOMW.2007.55

[11] A. Keranen, J. Ott and T. Karkkainen, "The ONE simulator for DTN protocol evaluation ," Proc. ACM Symp. 2nd International Conference on Simulation Tools and Techniques (SIMUTools '09) , 2009, doi: 10.4108/ICST.SIMUTOOLS2009.5674