Investigating Energy Consumption in Social Aware Opportunistic Networks with High Data Traffic

Diogo Soares (diogosoaresm@ufam.edu.br)
Federal University of Amazonas

Gilmara Santos
Federal University of Amazonas

Celso Carvalho
Federal University of Amazonas

Edjair Mota
Federal University of Amazonas

Research Article

Keywords: OppNets, Energy Consumption, Data Sharing in OppNets, Social Aware Routing

Posted Date: April 20th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1555584/v1

Investigating Energy Consumption in Social Aware Opportunistic Networks with High Data Traffic

Diogo Soares[1*], Gilmara Santos[1†], Celso Carvalho[1†] and Edjair Mota[1†]

[1*] Institute of Computing, Federal University of Amazonas, 6200, Av. Gen. Rodrigo Octavio - Coroado, Manaus, 69080-900, Amazonas, Brazil.

*Corresponding author(s). E-mail(s): diogosoaresm@ufam.edu.br; Contributing authors: gilmara@icomp.ufam.edu.br; ccarvalho_@ufam.edu.br; edjair@icomp.ufam.edu.br;
†These authors contributed equally to this work.

Abstract

In Opportunistic Networks (OppNets), mobility of and contact between nodes are explored to create communication opportunities, exchange messages, and information. In the era of data sharing, the data traffic from messages may be higher with nodes exchanging text messages, media or streaming. The use of social aspects to find better relay nodes has become popular in forwarding strategies to increase network performance. However, due to resource constraints such as energy level and buffer space, social aspects applied to forwarding strategies may lead to unexpected behaviors or even harvest more energy from the chosen relay nodes. This work designed a set of experiments to investigate the relationship between energy consumption and social aspects. It is evaluated three trace-based mobility models with increasing contact densities. In addition, it is implemented and collected some social aspects from the investigated scenarios: centrality, betweenness, and local clustering coefficient (LCC). The results presented that the mean contact time of node has more correlation to energy consumption than social aspects (Pearson correlation= 0.99792) for the mobility traces evaluated. Further, when the mean contact time is extensive, the energy consumption increases from 210% to the more sparse to

the denser scenario. We also verified that when the conditions for message exchanges are better, i.e., when contact time is enough to exchange all messages, the correlation between centrality and energy consumption is higher. Finally, with the extensive contact time, the energy of popular nodes was entirely harvested in our densest scenario.

Keywords: OppNets, Energy Consumption, Data Sharing in OppNets, Social Aware Routing

1 Introduction

The recent advances towards wireless networks are boosting promising paradigms such as data communication among people directly through their devices without using network infrastructure. In addition, the global Internet traffic has reached higher values year after year caused by: i) increasing number of personal devices such as smartphones or tablets and ii) the diffusion of content-oriented services such as chats, streaming and content shared among users. Meeting this steadily higher traffic has become a challenge for Internet providers. As a consequence, 5G is planning to have a higher capacity of data transmission, allowing a higher density of mobile broadband users, and supporting new paradigms of data transmission such as device-to-device communications [1].

To address these situations, some infrastructure-less paradigms of communications which allow the message exchanging to Wi-Fi devices, that use opportunistic connection, emerged, such as OppNets. OppNets are a particular case of Delay Tolerant Networks (DTN) and an evolution of Mobile Ad hoc Networks (MANETs), where messages exchange occurs during contact opportunities among mobile nodes that are in the same coverage area. Nodes carry copies of messages from other nodes to increase the delivery probability by replicating it through the network nodes, using the "store-forward" mechanism [2]. Thus, nodes can opportunistically communicate and share their resources using short-range and high-speed wireless interfaces, such as Wi-Fi and Bluetooth, which can significantly reduce the traffic of the cellular network [3]. In addition, these networks are an interesting alternative for data sharing among near nodes and it can be applied in various applications, such as notification of events in a campus environment, sales in a mall, chatting, file sharing [4] and communication in emergency situations [5].

Due to resource constraints and in order to increase network overall performance, many routing protocols exploit social and human aspects to design their strategies. Thus, some metrics such as popularity, friendship, and centrality are commonly used to choose which nodes are considered better nodes for forwarding messages beyond the network. These strategies have been presented to perform well in several OppNets environments [6–10].

In their method of experiments, most proposed routing protocols suppose nodes from the network are fully cooperative, and they are willing to share their resources for network communication. In real-world scenarios, however, nodes may interact with each other differently. As a result, they can expose unexpected behaviors such as not cooperating in communication or dropping forwarded messages, primarily due to resource constraints such as energy consumption, storage constraints, frequent disconnections, limited bandwidth, contact duration time, etc. However, they have advantages as this type of network can operate with the absence of network infrastructure. Further, in scenarios where there is the presence of social characteristics such as communication among people, the data traffic can overload some nodes because data traffic will pass more constantly through some nodes from the network, called preferable nodes [9]. In a specific case, energy may be an overloaded feature since high data traffic will pass through just some network nodes.

Although the impact of buffer space has been widely studied in the literature, to the best of our knowledge there is a lack of studies addressing the relation between energy consumption and social aspects in OppNets, especially the impact on nodes in case of high data traffic. Since energy may be a crucial resource to decide if a node will carry a message or not, we highlight that investigating its impact is important. Also, our main hypothesis is that social-based routing protocols may overload some nodes leading to energy consumption.

In the background, but not least, high data traffic scenarios were considered. We highlight that high data traffic scenarios are the same as creating a considerable amount of messages on network lifetime.

In this work, we present a study of energy consumption by using the social aware routing protocol Bubble Rap [6]. We carried out the simulation analysis by making use of trace-based mobility models, high data traffic, and we evaluated how social characteristics such as centrality and betweenness can bias the node energy consumption.

The main contributions of this paper are: *i*) to investigate how social aspects can correlate with energy spent on message exchanges and *ii*) to indicate possible research fields on message forwarding with the objective of build a fair energy consumption to nodes in OppNets.

Our results show that social aspects are difficult to correlate with energy consumption when data traffic is high. We show that the mean contact time of nodes have a strong correlation ($p = 0.99792$) with energy consumption when data traffic is higher. Since we are interested in energy consumption of message exchange in OppNets, this paper reports that in scenarios where there is high data traffic or traffic bursts among nodes, and also the mean contact time of nodes are high, the energy level is a feature that can be exposed to large consumption if nodes have so much messages to send during the contact. Thereby, we concluded that mean contact time should be a feature to pay attention in congestion control or routing algorithms.

The remainder of paper is organized as follows. First, we review a set of related works exploring resource usage in OppNets in Section 2, then in Section

3, we present our network architecture used in our experiments. We describe the methodology of experiments in Section 4, then we present the results of our experiments and discuss our findings in Section 5. Finally, our conclusions and future remarks are presented in Section 6.

2 Related Works

2.1 Energy Harvesting, Battery Model and Energy Impact on OppNets

OppNets are compounded by users carrying smartphones. Each user smartphone receives the required energy to work from its battery. Typically, a rechargeable battery is deployed to the device, and it is charged to store energy for smartphone usage. Due to continuous discharging, and the fact the battery life is limited, devices need to be recharged periodically, and even several times in a 24 hour period [11]. All operations related to OppNets harvest energy from these devices.

As summarized by Ahmad et al. [12], the signaling and network modules, both, consume more than 50% of energy level in a smartphone. Since OppNets are based on communication among devices using any network technology (Wi-Fi or Bluetooth), some considerations about how energy is harvested on those devices: power consumption on wakeup, power consumption for device discovery and for data communication. Furthermore, Wi-Fi technology is extremely energy-hungry due to energy spent in the discovery process (in the same order of magnitude of energy spent for transmit/receive) [13].

In the study by Dede et al. [14], authors describe in further detail how energy consumption works on OppNets devices. The authors highlight that to characterize and emphasize the different aspects of energy consumption battery models are classified: the battery model, the power generator model, and energy consumption. In the battery model, the idea is considering the battery as a finite value of capacity for usage. The power generator refers to the battery recharging mechanisms. Finally, energy consumption reflects the usage of the energy value through device utilization and network functionalities activity. Hence, the energy consumption is implemented according to the network operation state, such as idle, transmitting, receiving, or scanning for each network device (802.15.4, Bluetooth, etc.).

Despite the use of device resources through network communications, the power consumption also depends on the usage patterns and user activities [14]. For instance, consider two users: the first one has its wireless interface always on, and the second only switches when necessary. Consequently, the second user may face higher energy expenditures to turn on his wireless interface, especially if he requests the network many times. As we consider modeling device usage complex to model at this point, in this work, we highlight that we only consider energy harvested with network transactions for the sake of simplicity.

In order to assess the impact of the power level on OppNets, we applied an assessment in the form of a questionnaire with real users, considering the existence of an opportunistic network between their devices. We carried out a questionnaire to understand the user behavior in an OppNet when there is a specific amount of battery level. We conducted this experiment on the Federal University of Amazonas (UFAM) with 351 participants to answer the following questions:

1. What do you do if someone sends you a contact request on an opportunistic network while your battery level is critical? **Possible answers: (a) accept the request; (b) do not accept the request; (c) wait for the battery to recharge**
2. What battery level would make you leave an opportunistic communication? **Possible answers: (a) below 10% (b) between 10% and 20% $\cdots$ (j) between 91% and 100%**

The questionnaire results showed that more than 70% of the participants would not accept the request to participate or wait for their batteries to recharge and then rejoin OppNet. Further, we found that 68.10% of the users would no longer cooperate in communication if the battery was lower than 30% and only 19.65% of the users agreed to cooperate with the network operation if their energy level was above 50%.

This result corroborates with other papers that evaluated nodes cannot participate in OppNets based on energy levels or other resource levels [15–18]. Thus, the results highlight a significant energy consumption impact on OppNet performance evaluation and usage. However, since we consider this subject a necessary research field to analyze, we do not intend to evaluate the cooperation level in this paper.

The authors identified as main references for this work [7, 9, 15–19], applied an energy expenditure model in their experiments. In this model, the battery is modeled to reflect how battery level is harvested based on a chain of states: idle, transmitting, and receiving. In this case, the modeling depends on the granularity values, and device shutdown is required when the battery is depleted. This model is also referred as **Energy Expenditure** model by Dede et al. [14].

2.2 Social Awareness Routing

In the OppNets literature, there are a large amount of routing protocols proposals. In many of them, social aspects are used to build these protocols. Since OppNets are compounded by humans, it is reasonable to claim social networks models are a better alternative for building social routing protocols [20]. Also, we can find many routing protocols in the literature that emphasize the importance of social aspects in the design phase, such as tie strength, popularity, or centrality metrics [6–8].

Further, resource constraints are an important aspect to define the willingness to forward messages in OppNets. As resource constraints, we highlight

energy level and free buffer space, where free buffer space leading strategies were widely studied in the literature [10, 21, 22]. However, we found there is a lack of deep studies related to energy level or energy consumption and its impacts.

The present work emphasizes that the primary references used applied a mechanism based on a two-state finite machine with operating state and sleep (or power-off state).

For instance, in [23], the authors concluded that the use of social characteristic may be unfair and cause node overload. Their results showed that only 10% of nodes handle 63% of all data traffic. Further, Gupta et al. [19] presented that network performance degrades to about 62% when the proportion of nodes which do not cooperate to forward messages goes from 0% to 50%. That was an important contribution to present how OppNets algorithms should consider resource constraints in its design.

On the other hand, Junior and Campos [9] proposed a modified version of Bubble Rap [6] protocol which leads to the problem of overloaded nodes by social routing protocols. They randomly chose some nodes among the most central ones to reduce their load, reducing the overall node overload. Although the proposed protocol led to a decrease in node overload, the authors did not evaluate the effects of social aspects used by their protocol concerning energy consumption.

Similarly, in Souza et al. [7], authors handled the problem of unwillingness to cooperate based on energy and buffer levels by presenting a novel routing protocol which supports a reputation system to find out the nodes tending not to cooperate. Even under the assumption of unwillingness to cooperate, the authors did not advance into the research issue of energy level impact on their results or the correlation between energy consumption and social characteristics.

In the work of Socievole et al. [24], authors evaluated the residual energy analysis by using C-Window centrality algorithm and they realized that, in most situations, residual energy decreases when centrality takes higher. We highlight our paper and this work presented some similar aspects in research assumptions, however, while they used energy level to force the decreasing of centrality values to bypass social aspects used in social routing protocols, we aim to evaluate in deeper other social aspects in energy consumption and we are also interested only in energy consumption harvested in message exchanges. The authors considered scanning in their simulation, while we point is necessary to evaluate only energy harvested during message exchanges since our first simulations show energy harvested during scanning phase may act as an outlier.

Amah et al. [25] investigate and proposed a method to measure the burden and fairness in routing in pocket switched networks, a similar network to OppNets. They led experiments of buffer utilization and energy consumption using a human pattern mobility model and they found that it was very difficult to estimate the determinant factors for the burden on nodes due to the fact of

resources usage depending on various variables which may not correlate such as TTL, number of destinations that can be encountered, the queuing policy, routing protocol, etc.

Recently, Santos et al.[18] investigated the energy consumption of nodes during message forwarding in OppNets networks and applied machine learning techniques for learning about the energy consumption of nodes in order to forward messages to nodes that have a high residual energy history. The main objective was to mitigate resource usage of low battery nodes.

3 Network Model

In this section, we present how the network was modelled for our experiments in the context of the energy model used and the implemented social characteristics. We considered the network a set of N nodes and each opportunistic contact as a bidirectional edge e. Also, we considered an infinite buffer size in all nodes. Since the buffer is a more complex and more studied feature in OppNets, we choose not to use it in this work. Further, we chose not to use TTL (Time-to-live) in messages to avoid any bias caused by dropped messages due to TTL.

3.1 Social Characteristics

Social aspects have been widely used for modeling referral protocols in the literature. These characteristics can be used to quantify how important a node can be to the network. In this context, we apply some metrics to our network in order to quantify social characteristics.: betweenness, clustering coefficient and C-Window centrality.

3.1.1 Betweenness

Betweenness [26] is a measure of node centrality in a network and is based on possible shortest paths and it is represented by Eq. 1, where $sp_{j,k}$ represents the number of shortest paths and $sp_{j,k}(i)$ represents all possible most concise shortest paths between source j and target k that go through node i. Thus, betweenness measures which nodes have most part of the flow of forwarding messages, i.e., as a static predictor of congestion and load on networks [27].

$$B_i = \sum_{j=1}^{N} \sum_{k=1}^{j-1} \frac{sp_{j,k}(i)}{sp_{j,k}} \tag{1}$$

To summarize, in this setting the paths found can be considered as the optimal routes between nodes, and thus nodes with high betweenness centrality values should expect to be more active on network data traffic [27].

3.1.2 Local Clustering Coefficient

The local clustering coefficient (LCC) measures how close the neighbors of a node are to being a community, i.e., a complete graph. Intuitively, it is an

important feature to describe if a node community is stronger or if it represents a sparse community and it is represented by Eq. 2, where e_i represents the number of edges among the k_i neighbours of node i.

$$C_i = \frac{2e_i}{k_i(k_i - 1)} \tag{2}$$

The LCC values close to 1 imply an almost or entirely connected neighborhood, whereas a value close to 0 implies nodes in the neighborhood are almost or entirely disconnected. In other words, it can represent if part of the network is dense or sparse.

3.1.3 C-Window Centrality

Finally, it was also implemented the C-Window [6], which we called centrality. In C-Window, centrality is calculated by using the average of K last node degrees per unit-time slot (slot window). In this work, we considered a 6-hour time slot. In addition, this centrality is implemented in the algorithm Bubble Rap, applied in the experiments.

For instance, consider a node i and $K = 4$, with the following degree values for a 6-hour time slot. The values of degree and C-Window are presented in Table 1.

Table 1: C-Window centrality example for node i

Last time slots	Degree	C-Window
0	2	C-Window $= \frac{2+4+0+2}{4} = 2$
2	4	
3	0	
4	2	

3.2 Energy Model

- **Off** - network node interface is off, or node energy is over.
- **Inactive** - reduced energy consumption since network interface is idle.
- **Scan** - energy which a node consumes to detect nearby nodes.
- **Transmission/Reception** - energy which a node consumes to transmit or receive a message.

In our evaluations, we assumed all nodes are fully recharged at the start of the simulation. Also, the energy level of all nodes is measured in Joules, and its values are based on the research of Silva et al. [28] and Amah et al. [25]. The values are presented in Table 2.

Since we are interested is only on energy consumed due to message forwarding, we set energy harvested in scan and inactive state to 0 to avoid any bias.

Table 2: Energy settings

Initial energy	600 Joules
Transmit energy	0.08 mW/s
Receive energy	0.08 mW/s

4 Performance Evaluation

For performance evaluation, we simulate our scenarios using The ONE simulator [29]. The simulation parameters are presented in Table 3. To represent mobility, we used three mobility traces, Infocom5 [30], Rollernet [31] and Sassy [32]. The central hypothesis for choosing these traces was that they represent different density levels and decrease values to mean contact time, as can be observed in Figures 1 and 2. Each scenario was simulated ten times, and measured values for each node are the mean values of all simulation runnings.

Table 3: Simulation parameters

	Infocom5	**Rollernet**	**Sassy**
Number of nodes	41	62	25
Duration (days)	3	≈0.13	79
Contacts per minute	4.902	≈355	1.651
Mean contact time (s)	231.755	113.95	9.476
TTL	∞		
Buffer size	∞		
Message generation rate	one MSG each 5 seconds		
Message size	100-500k		
Routing	Bubble Rap		
Network interface	Bluetooth		

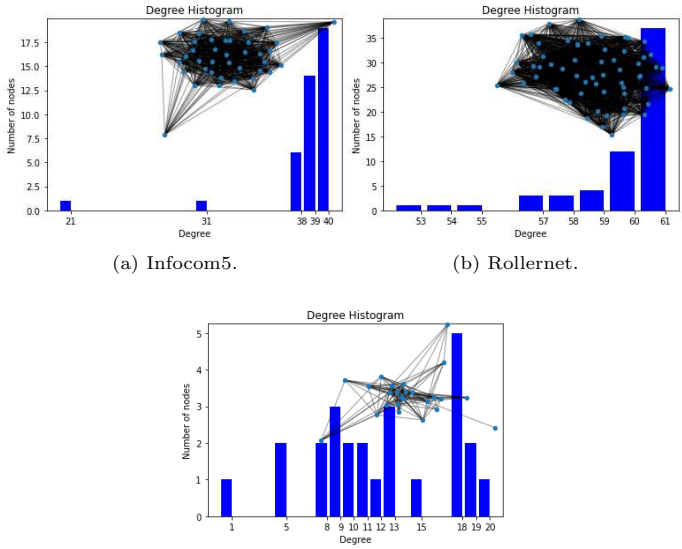
Our performance evaluation is defined as follows: in the first step, we simulated energy consumption on nodes, computed social characteristics from nodes as presented in Section 3.1, and computed the number of contacts and mean contact time of each node during simulation. In a second step, we analyzed the simulation results by using Pearson correlation, and we discussed the results in Section 5.

5 Results and Discussions

In this section we present our main results and the relevant discussions about key issues related to them.

5.1 Mean Contact Time and High Data Traffic

In the first simulations, we realized that energy consumption does not increase even when data traffic increases. Moreover, when we analyzed mean contact time, we realized that both energy consumption and mean contact time are not correlated.



(a) Infocom5. (b) Rollernet.

(c) Sassy.

Fig. 1: Mobility traces degree histograms.

Therefore, we analyzed only mean contact time for the three scenarios evaluated. The results presented in Figure 2 highlight that the denser a trace is, the mean contact time may be higher.

In a context of high data traffic, it can be decisive, due to the time of contact is too short to exchange all messages. Also, in your experiment, we used infinite TTL for messages and infinite size for nodes buffers. As we did not evaluate the energy harvesting in scanning states, we realized that, specially in Sassy, the energy consumption was very low.

The mean energy consumed for all scenarios are presented in Table 4. Our results demonstrated there is a close correlation among energy consumed and mean contact time in a context of high data traffic. We should remark that, in a context of not high data traffic, this correlation may be not exist, since it sounds sense that nodes will not need to use the entire contact time to exchange messages. Further, in dense scenarios with high data traffic, the energy consumed increased to about 210% for more sparse scenario compared to the denser scenario.

Table 4: Mean Energy Consumed

	Infocom5	**Rollernet**	**Sassy**
Mean energy consumed	64.80%	39.04%	20.85%

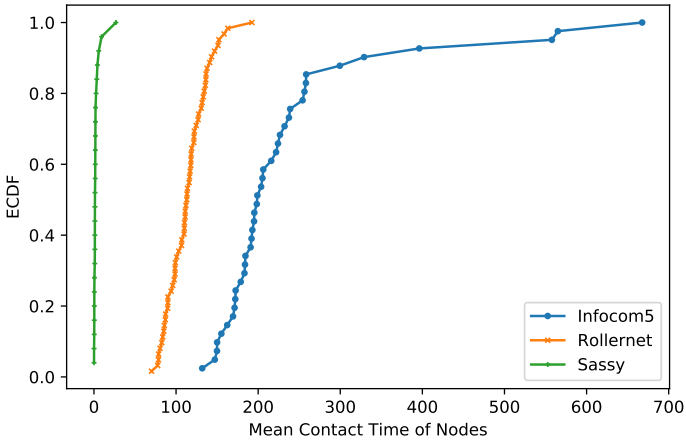


Fig. 2: ECDF for mean contact time in each scenario.

We concluded this section by remarking which contact time among nodes is decisive to allow nodes can exchange all messages in its buffer. Since data transfer harvests some energy from nodes it can be more resource consuming that in other data traffic ratios.

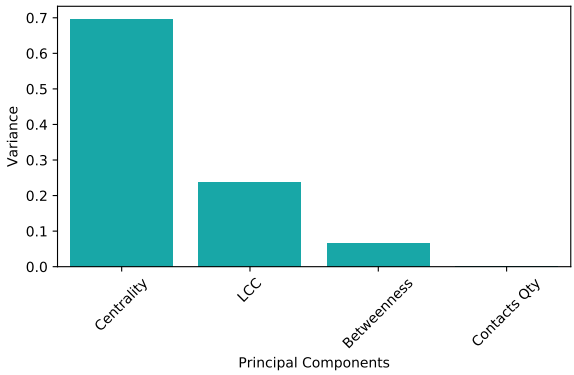
5.2 Social Aspects Matters?

To evaluate if social aspects can correlate with energy consumption, we executed our simulations and computed the social aspects mentioned at 3.1. After simulations, we computed centrality, betweenness, lcc and number of contacts (also referred here as the number of contacts) for each node. Also, we computed the mean of residual energy of each node at the end of the simulation.

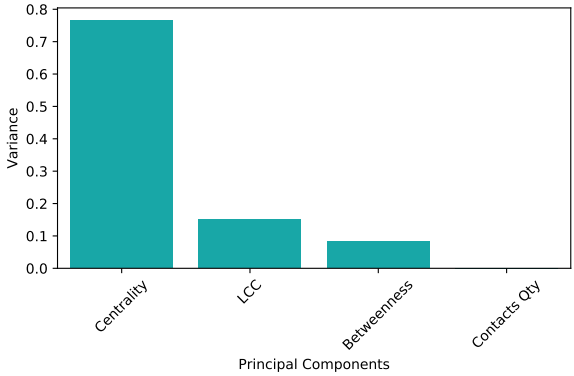
First of all, we evaluated the analysis of variance of all individual components and its relation to residual energy. Formally, the variance is a measure to define how much a variable can explain the total variance on data. The main reason for using this type of measure is to estimate what social aspect has more importance on energy consumption of network nodes.

The results for variance are presented in Figure 3. As we can obverse, in all scenarios, centrality fits better to energy consumption. Specially on denser scenarios, presented in Figure 3a and Figure 3b.

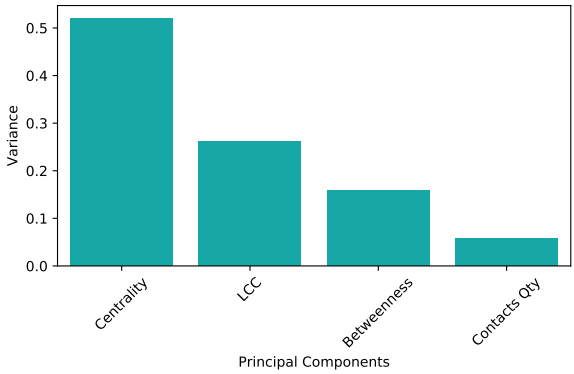
Further, we analyzed the relation among centrality and residual energy. The results for Infocom5 (denser scenario) are presented in Figure 4. As we can see, as higher node centrality, in general, residual energy is lower. For instance, we can realize that when centrality is greater than 10, the nodes with less than 100 J of residual energy is about three times higher than nodes with centrality lower. Also, we remarked that correlation between this two variables is not strong. One of our main hypothesis before the experiments was that we can correlate both variable, but that was not possible in any scenario. Nevertheless,



(a) Infocom5.



(b) Rollernet.



(c) Sassy.

Fig. 3: Social aspects versus PCA variance.

when we lead to denser scenarios, we can observe a slight trend line to claim centrality higher may imply in higher energy consumption.

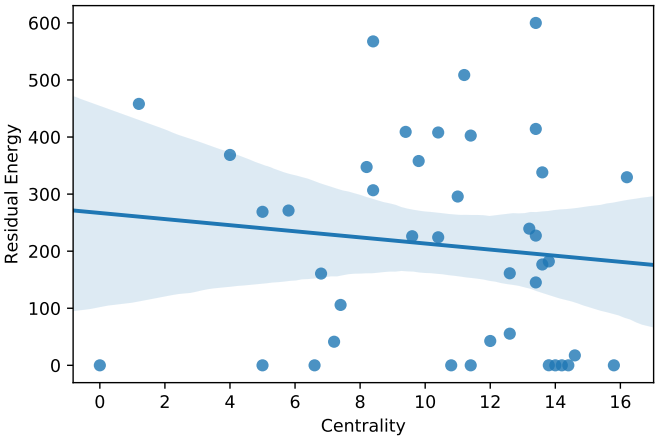


Fig. 4: Centrality versus Residual Energy remaining in each node at Infocom5 scenario.

The results for Rollernet are presented in Figure 5. We can observe that our trend line is in a reverse direction, even though, we have more nodes with less residual energy remaining when centrality is higher. Similarly, in Sassy scenario our results, presented in Figure 6, show that the trend line is slightly positive. Thus, we can conclude that centrality and residual energy are variables very difficult to correlate. The main reason for this behavior is mean contact time of nodes is even more significant than social aspects.

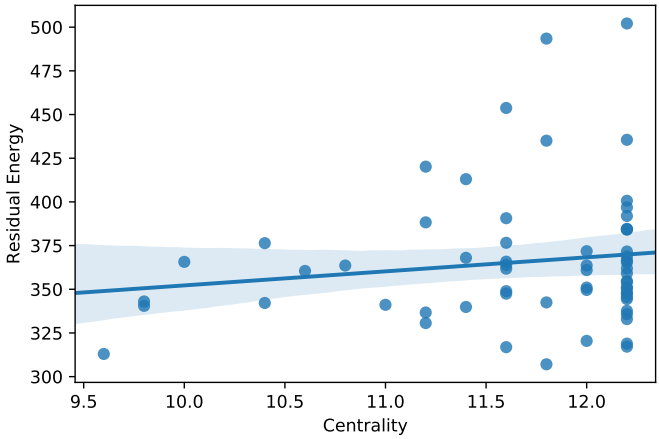


Fig. 5: Centrality versus Residual Energy remaining in each node at Rollernet scenario.

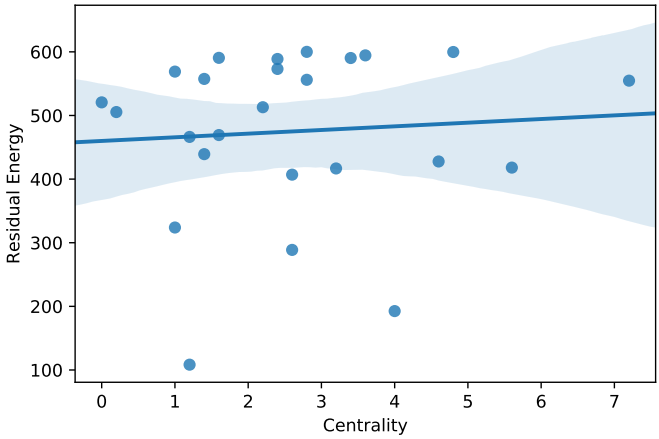
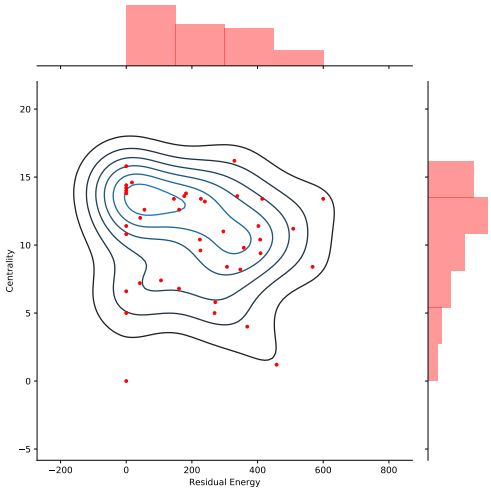


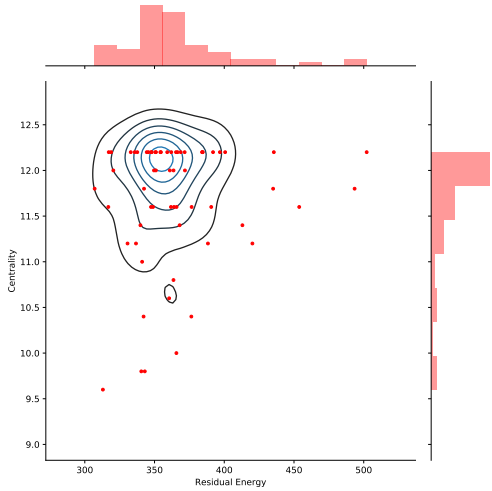
Fig. 6: Centrality versus Residual Energy remaining in each node at Sassy scenario.

However, we can also observe how much dense a network graph is, there is a trend on energy consumption to be higher when nodes with centrality values higher as shown in Figure 7.

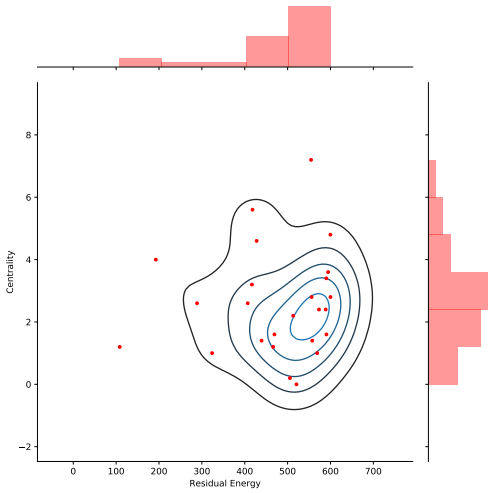
Thus, we found that centrality and energy consumption are very difficult to correlate due to a large amount of variables that can impact on the number



(a) Infocom5.



(b) Rollernet.



(c) Sassy.

Fig. 7: Kernel density estimation for centrality versus residual energy observations.

of messages to be forwarded such as TTL, buffer size or even willingness to cooperate. Further, in scenarios where nodes have so little time to exchange messages, we cannot infer the energy consumption in a fair manner. Considering OppNets, we can admit that nodes may have a sufficient time to forward a large amount of messages due to social patterns of humans. For instance, in

a building, a person working has low mobility that may increases the contact time, and therefore, increasing energy consumption.

6 Conclusions and Future Remarks

In OppNets, devices carried by humans such as smartphones or tablets can exchange messages such as data or media by storing messages from other nodes and carrying them to the destination through opportunistic contacts. However, nodes have resource constraints such as energy level or buffer space that can influence network performance and communications. While there are many workarounds for increasing buffer space, such as large SD cards, few devices have considerable battery lifetime options. Further, OppNets led to social behavior in real scenarios, so nodes called popular can be energy overloaded in message exchanges. It raises the following question: can we consider processing overhead for OppNets? Thus, what was the possible energy impact for the called popular nodes. We think that a deeper research can be applied in this research field.

In this work, we experimented on energy consumption in message exchange in OppNets, especially in cases of high data traffic. Our objective was to investigate the main feature that could impact energy consumption and the real relevance of social aspects in energy consumption. We performed simulated experiments using three real-world mobility scenarios to address it. Also, only energy consumed on message exchanges was considered to avoid bias due to network interfaces' scanning state.

Our results showed that the mean contact time strongly correlates ($p = 0.99792$) with energy consumption, where energy consumption increases 210% when the mean contact time increases in the Infocom5 scenario. Also, we found that social aspects have a low correlation with energy consumption, especially in sparse scenarios such as Sassy, in which the duration of contact and the amount of contact are smaller than the other two scenarios evaluated.

Future works include the implementation of learning mechanisms to build congestion control mechanisms. Since high data traffic requires more message exchanges on nodes, and, in denser scenarios, energy will be a very overloaded feature, we intend to decrease congestion control to decrease energy consumption in popular nodes.

Declarations

6.1 Funding

This research, according to Article 48 of Decree n 6.008/2006, was partially funded by Samsung Electronics of Amazonia Ltda, under the terms of Federal Law n 8.387/1991, through agreement n 003/2019, signed with ICOMP/UFAM.

6.2 Conflict of interest/Competing interests

The authors declare that they have no conflicts of interest.

6.3 Ethics approval

Not applicable.

6.4 Human and Animal Ethics

Not applicable.

6.5 Consent to participate

Not applicable.

6.6 Consent for publication

All authors of this research consent to publication if the article is accepted.

6.7 Availability of data and materials

All data used in this research and that were not generated in this research are publicly available and can be found through the citations mentioned in the text.

6.8 Code availability

All the codes used in our experiments were implemented in a open source simulator called The ONE. The other implemented codes can be made available by contacting the corresponding author.

6.9 Authors' contributions

D.S., G.S. conceived the idea; D.S., G.S. designed and implemented the protocol optimization; D.S., G.S. and E.M. performed the experiments; D.S., G.S., E.M., C.C analyzed the data. D.S., G.S., C.C. and E.M. wrote the paper. All authors have read and agreed to the published version of the manuscript.

6.10 Authors' information

Diogo Soares received his B.S and M.S from Federal University of Amazonas. He is currently a Ph. D. student at Federal University of Amazonas. His research interest includes opportunistic networks, delay tolerant networks, machine learning, and internet of things.

Gilmara Santos received her B.S from FUCAPI (Foundation of Analysis Research and Technological Innovation-Amazonas/Brazil), and her M.S from Federal University of Amazonas. She is currently a Ph. D. student at Federal University of Amazonas. Her research interest includes opportunistic networks,

delay tolerant networks, machine learning, and energy consumption on network devices.

Celso Carvalho received the B.S. degree in Electrical Engineering at Federal University of Amazonas (UFAM), and both the M.S. and the Ph.D degrees in Electrical Engineering at Federal University of Rio de Janeiro (COPPE/UFRJ), Brazil. He has more than 20 years of experience in engineering and education, integrated the Research and Development (RD) teams of FUCAPI (Foundation of Analysis Research and Technological Innovation-Amazonas/Brazil), Siemens Mobile (BenQ-Amazonas/Brazil) and CETELI (Center for Research in Electronics and Information-Amazonas/Brazil) where he worked as a RD Engineer and project manager.

Edjair Mota received his PhD in Computer Science from the Technical University of Berlin, Germany in 2002, on distributed stochastic simulation of wireless networks. His interests include wireless networks, delay tolerant networks, opportunistic networks, Internet of Things. He is currently a full professor in the Institute of Computing (IComp) at the Federal University of Amazonas, Brazil.

References

[1] Hernandez-Orallo, E., Murillo-Arcila, M., Cano, J.-C., Calafate, C.T., Conejero, J.A., Manzoni, P.: An analytical model based on population processes to characterize data dissemination in 5g opportunistic networks. IEEE Access **6**, 1603–1615 (2017)

[2] Fall, K.: A delay-tolerant network architecture for challenged internets. In: Proceedings of the 2003 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications, pp. 27–34 (2003)

[3] Jedari, B., Xia, F., Ning, Z.: A survey on human-centric communications in non-cooperative wireless relay networks. IEEE Communications Surveys Tutorials **20**(2), 914–944 (2018). https://doi.org/10.1109/COMST.2018.2791428

[4] Reis, D.M., Lins, T.S., Nogueira, J.M.S., Mota, V.F.: Sharefile: Sharing content through device-to-device communication. In: 2018 IEEE Symposium on Computers and Communications (ISCC), pp. 00736–00741 (2018). IEEE

[5] Wu, J., Chen, Z.: Data decision and transmission based on mobile data health records on sensor devices in wireless networks. Wireless personal communications **90**(4), 2073–2087 (2016)

[6] Hui, P., Crowcroft, J., Yoneki, E.: Bubble rap: Social-based forwarding in delay-tolerant networks. IEEE transactions on mobile computing **10**(11),

1576–1589 (2010)

[7] Souza, C., Mota, E., Galvao, L., Manzoni, P., Cano, J.C., Calafate, C.T.: Fsf: Friendship and selfishness forwarding for delay tolerant networks. In: 2016 IEEE Symposium on Computers and Communication (ISCC), pp. 1200–1207 (2016). IEEE

[8] Li, F., Jiang, H., Li, H., Cheng, Y., Wang, Y.: Sebar: Social-energy-based routing for mobile social delay-tolerant networks. IEEE Transactions on Vehicular Technology **66**(8), 7195–7206 (2017)

[9] Junior, N.M., Campos, C.A.V.: Socleer: A social-based energy-efficient forwarding protocol for opportunistic networks. In: 2015 International Wireless Communications and Mobile Computing Conference (IWCMC), pp. 757–762 (2015). https://doi.org/10.1109/IWCMC.2015.7289178. IEEE

[10] Souza, C., Mota, E., Manzoni, P., Cano, J.C., Calafate, C.T., Hernndez-Orallo, E., Tapia, J.H.: Friendly-drop: A social-based buffer management algorithm for opportunistic networks. In: 2018 Wireless Days (WD), pp. 172–177 (2018). https://doi.org/10.1109/WD.2018.8361714

[11] Pramanik, P.K.D., Sinhababu, N., Mukherjee, B., Padmanaban, S., Maity, A., Upadhyaya, B.K., Holm-Nielsen, J.B., Choudhury, P.: Power consumption analysis, measurement, management, and issues: A state-of-the-art review of smartphone battery and energy usage. IEEE Access **7**, 182113–182172 (2019)

[12] Ahmad, R.W., Gani, A., Hamid, S.H.A., Shojafar, M., Ahmed, A.I.A., Madani, S.A., Saleem, K., Rodrigues, J.J.: A survey on energy estimation and power modeling schemes for smartphone applications. International Journal of Communication Systems **30**(11), 3234 (2017)

[13] Trifunovic, S., Kouyoumdjieva, S.T., Distl, B., Pajevic, L., Karlsson, G., Plattner, B.: A decade of research in opportunistic networks: challenges, relevance, and future directions. IEEE Communications Magazine **55**(1), 168–173 (2017)

[14] Dede, J., Förster, A., Hernández-Orallo, E., Herrera-Tapia, J., Kuladinithi, K., Kuppusamy, V., Manzoni, P., bin Muslim, A., Udugama, A., Vatandas, Z.: Simulating opportunistic networks: Survey and future directions. IEEE Communications Surveys & Tutorials **20**(2), 1547–1573 (2017)

[15] Soares, D., Matthaus, B., Mota, E.S., Carvalho, C.B.: A feasibility study of watchdogs on opportunistic mobile networks. In: 2018 IEEE Symposium on Computers and Communications (ISCC), pp. 00123–00128

(2018). IEEE

[16] Shan, A., Fan, X., Wu, C., Zhang, X., Fan, S.: Quantitative study on the impact of energy consumption based dynamic selfishness in manets. Sensors **21**(3), 716 (2021)

[17] Akhbari, A., Ghaffari, A.: Selfish node detection based on fuzzy logic and harris hawks optimization algorithm in iot networks. Security and Communication Networks **2021** (2021)

[18] Santos, G., Soares, D., Carvalho, C., Mota, E.: An energy-saving forwarding mechanism based on clustering for opportunistic networks. Sensors **21**(22), 7427 (2021)

[19] Gupta, S., Nagpal, C., Singla, C.: Impact of selfish node concentration in manets. International Journal of Wireless & Mobile Networks (IJWMN) Vol **3**, 29–37 (2011)

[20] Zhu, Y., Xu, B., Shi, X., Wang, Y.: A survey of social-based routing in delay tolerant networks: Positive and negative social effects. IEEE Communications Surveys Tutorials **15**(1), 387–401 (2013). https://doi.org/10.1109/SURV.2012.032612.00004

[21] Silva, A.P., Burleigh, S., Hirata, C.M., Obraczka, K.: A survey on congestion control for delay and disruption tolerant networks. Ad Hoc Networks **25**, 480–494 (2015). https://doi.org/10.1016/j.adhoc.2014.07.032. New Research Challenges in Mobile, Opportunistic and Delay-Tolerant Networks Energy-Aware Data Centers: Architecture, Infrastructure, and Communication

[22] Liu, Y., Wang, K., Guo, H., Lu, Q., Sun, Y.: Social-aware computing based congestion control in delay tolerant networks. Mobile Networks and Applications **22**(2), 174–185 (2017)

[23] Xu, K., Li, V.O., Chung, J.: Exploring centrality for message forwarding in opportunistic networks. In: 2010 IEEE Wireless Communication and Networking Conference, pp. 1–6 (2010). IEEE

[24] Socievole, A., De Rango, F.: Energy-aware centrality for information forwarding in mobile social opportunistic networks. In: 2015 International Wireless Communications and Mobile Computing Conference (IWCMC), pp. 622–627 (2015). IEEE

[25] Amah, T., Kamat, M., Abu Bakar, K., Moreira, W., Oliveira-Jr, A., Batista, M.: Measuring burden and routing fairness in pocket switched networks. (2017)

[26] Freeman, L.C.: Centrality in social networks conceptual clarification. Social networks **1**(3), 215–239 (1978)

[27] Kirkley, A., Barbosa, H., Barthelemy, M., Ghoshal, G.: From the betweenness centrality in street networks to structural invariants in random planar graphs. Nature communications **9**(1), 1–12 (2018)

[28] Silva, D.R., Costa, A., Macedo, J.: Energy impact analysis on dtn routing protocols (2012)

[29] Keränen, A., Ott, J., Kärkkäinen, T.: The one simulator for dtn protocol evaluation. In: Proceedings of the 2nd International Conference on Simulation Tools and Techniques, p. 55 (2009). ICST (Institute for Computer Sciences, Social-Informatics and

[30] Scott, J., Gass, R., Crowcroft, J., Hui, P., Diot, C., Chaintreau, A.: CRAWDAD dataset cambridge/haggle (v. 2009-05-29). Downloaded from https://crawdad.org/cambridge/haggle/20090529 (2009). https://doi.org/10.15783/C70011

[31] Benbadis, F., Leguay, J.: CRAWDAD dataset upmc/rollernet (v. 2009-02-02). Downloaded from https://crawdad.org/upmc/rollernet/20090202/imote. traceset: imote (2009). https://doi.org/10.15783/C7ZK53

[32] Bigwood, G., Henderson, T., Rehunathan, D., Bateman, M., Bhatti, S.: CRAWDAD dataset st_andrews/sassy (v. 2011-06-03). Downloaded from https://crawdad.org/st_andrews/sassy/20110603 (2011). https://doi.org/10.15783/C7S59X