Energy-efficient Heuristics for Multi Hop Routing in People-centric Environments

Antonio Oliveira-Jr, Rosario Ribeiro, Tercio Filho, Dalton Matsuo, Marcos Batista, Claudio Souza
University Federal of Goias (UFG), Brazil
Email: {antoniojr, rosarioribeiro, tercioas, dalton_tavares, marcos.batista, clsouza}@ufg.br
José-Ricardo Ribeiro
Centro Universitário de Goiás - Uni-ANHANGUERA, Brazil
Email: jricardo@anhanguera.edu.br

Abstract—This paper explores different heuristics that may be applied to provide a node-based cost for energy-aware multihop routing for wireless environments which integrate heterogeneous devices that are carried or owned by Internet end-users. We analyzed based on simulations of the different heuristics when applied to distance-vector approach, namely the Ad Hoc On Demand Distance Vector (AODV) routing protocol.

Index Terms—Multihop routing; energy-efficiency; user-centric networks; AODV.

I. INTRODUCTION

People-centric wireless environments integrate a highly dynamic behavior of mobile nodes, in particular of nodes that are owned or carried by humans. Examples of such environments and dynamism are the need to autonomously start a network based on end-user devices after a disaster of some nature (e.g., disaster networks) or even the need to assist emerging markets in remote areas, sometimes highly populated. Such people-centric environments attain specific requirements, of which energy efficiency is one of them.

Albeit being spontaneously deployed, people-centric environments rely on traditional multihop routing approaches. Multihop routing has been extensively analyzed and optimized in terms of resource management, but in terms of energy efficiency there is a lack of a thorough analysis in particular in what concerns people-centric environments such as User-provided Networks (UPNs) or Mobile Ad-hoc Networks (MANETS). On the other hand, there is considerable related work in the fields of energy efficiency and energy awareness for sensor networks.

Even though it is relevant to consider the results achieved in such networks, there are specific requirements of people-centric environments which makes energy awareness and efficiency problems not trivial to be solved. Firstly, nodes in people-centric networks are expected to be heterogeneous in terms of resources such as battery capacity. Secondly, such nodes exhibit frequent movement and are also expected to frequently join and leave a network. We refer heterogeneous for the different nodes regarding mobile devices, such as the technology itself (e.g., laptop, smart phone), battery capacity, energy consumption, energy parameters and processing. Regarding movement, we consider a social mobility model which the parameters, such as frequency of movements, are characterized by the mobility pattern.

The main goal of this work is focused on making current multihop routing approaches, i.e., shortest-path based, adequate for people-centric environments. In such environments there are several requirements to be met in terms of energy awareness, by exploring new routing metrics that take into consideration the state of a node, i.e., node-based perspective, or not only the originating node’s perspective, but also the potential of successors, i.e., link-based perspective, in terms of energy awareness. Our expectations are to optimize network utilization by optimizing the energy-awareness of multi hop routing approaches.

In this paper we explore different energy-efficient heuristics as node-based cost to apply in multi hop routing with heterogeneous mobile devices. We evaluate based on simulations the heuristics in a multi hop distance vector approach, namely the AODV [1] routing protocol. We show the heuristics applied as a cost function improve the network lifetime without penalizing the end to end delay and throughput.

The rest of this paper is organized as follows. Section II describes selected related work focused on multihop energy efficiency. Section IV presents the notions, parameters and the current energy-aware routing metrics for multi hop routing. Section V is our proposed heuristics with discussions regarding network lifetime. Then, in section VI, we present the performance evaluation based on simulations with statistically rigorous results. Conclusions and future work are presented in section VII.

II. RELATED WORK

There are few approaches [2], [3], [4] that have surveyed multihop proposals focused on energy efficiency, considering both the energy spent when nodes are engaged in active communication or inactive communication (e.g., in idle mode). Such work has as underlying scenarios homogeneous environments, and many proposals combine a different energy-aware metrics to maximize the network lifetime.

Attempting to make multihop routing adaptive, some proposals [5], [6], [7] have explored new metrics having in mind different types of optimization, e.g., reduction of energy spent across a path or avoiding nodes with low residual energy, on the global network.
C. K. Toh provides a relevant overview [8] of different routing properties to consider in multihop routing that one of them is efficient utilization of battery capacity. In this work, the author also addresses the performance of power efficiency in ad-hoc mobile networks by analyzing four approaches which have as common goal to select an optimal path, being the optimum the minimization of the total power required on the network (across all nodes) and also the maximization of the lifetime of all nodes in the network.

The cost function of MRPC (Maximum Residual Packet Capacity) protocol [9] comprises a node-parameter (battery power of node) and a link-parameter (packet transmission energy in a link) across the link between nodes. MRPC identifies the capacity of a node not just by its residual battery energy, but also by the expected energy spent in reliably forwarding a packet over a specific link. However, such formulation better captures scenarios where link transmission costs depend on physical distances between nodes and the link error rates, which does not consider energy as a prime metric.

Considering power constraint as a metric, Senouci et. al. [10] propose three routing algorithms unless the shortest path routing. However, the routing algorithms was devised as three different routing protocols based on AODV modifying the routing process. Our work consider a node-based cost as a metric to use any distance vector or link state multihop routing protocols.

A recent work [11] proposed a multi-objective approach which consider three routing metrics (delay, energy and link lifetime) in a prediction way. The methods are predicting queuing delay and energy consumption, and predicting residual link lifetime using a heuristic of the distributions of the link lifetimes. However, the energy resource is combined with another metrics that is hard to find a trade off considering the energy-efficient routing.

The Working Group ROLL (Routing Over Low Power and Lossy Networks) of the IETF (Internet Engineering Task Force) have working on routing metrics to consider in this type of networks, which energy-aware is one of them [12]. A node energy object is used to provide information related to node energy and may be used as a metric or as constraint.

We emphasize that our proposed heuristics is to consider routing metrics that can be coupled to any multihop routing protocol, i.e., distance vector or link state approaches, to provide multihop routing with better energy-awareness.

We provide an example of a generic scenario, where groups of mobile nodes are depicted by a dotted line. Within each group, nodes may move in an independent way according to human movement behavior (social mobility). Furthermore, nodes may also move in groups, also mimicking human social behavior. Groups have a spatial-temporal correlation, e.g., a group at an instant in time may dissolve in a different instant in time and space. The illustrated nodes can be either static or mobile. In addition, nodes may behave as a regular node, or a micro-provider node. A micro-provider node is basically a node that provides Internet access to other nodes. It should be noticed that in contrast to the notion of gateway in MANETs, a micro-provider may simply relay Internet access from a gateway to a group of nodes. In addition, a micro-provider node may be completely mobile. Therefore, the topology shows a highly dynamic behavior, where not only links are bound to frequent changes, but also where the nodes that provide Internet access can also change on-the-fly, e.g., due to congestion of the micro-provider(s) in the group, due to better network conditions. Adapting to the variability due to node movement, for instance, another key aspect is that some devices are multimedia capable with strong limitations in terms of energy capabilities.

IV. Energy Awareness in Multi Hop Routing

A node \(i\) represents a wireless heterogeneous device with a single or multiple network interfaces. Edges interconnecting nodes are represented as links \((i, j)\) with a cost which is a measure of energy expenditure. Such energy expenditure can be obtained from a single node, a link, or network utilization perspective. From a single node perspective, there are three main modes of operation which depend on the node status. A node is in Transmit mode when transmitting information. Hence, Transmit Power (Tx Power) for a node corresponds to the amount of energy (in Joules) spent when the node transmits a unit (bit) of information. A node is in Receive mode if it is receiving data. Hence, Reception Power (Rx Power) for a node corresponds to the amount of energy (in Joules) spent when the node receives a unit (bit) of information. Particularly for the case of 802.11, there are two additional states a node may be at. When not receiving or transmitting, the node is still listening the shared medium (overhearing) and is said to be in Idle mode. When the node is not overhearing, then it is said to be in Sleep mode. In this mode, no communication is possible but there is still a low-power consumption.

Another relevant parameter to consider from an energy-awareness perspective is a node’s degree, \(N_i\), as the surrounding nodes impact the transmission channel heavily, as well as on energy consumption. We use the node degree definition where \(N_i\) corresponds to the amount of neighbors that a node \(i\) has at an instant in time. More relevant than the number of neighbors, is the history of variation of \(N_i\) through time.

The main energy-aware metrics for people-centric environments are the residual energy and drain rate. The Residual Energy (RE) of a node \(i\), \(RE_i\) [13] is defined as the amount of energy units that the battery of node \(i\) has at an instant in time. The Drain Rate (DR) of a node \(i\), \(DR_i\) [14] is...
defined as the amount of energy being spent by node $i$ through time, due to the activities the node is performing. $DR(i)$, can be computed by applying an Exponential Weighted Moving Average (EWMA). The DR alone simply provides a way to measure energy being spent by nodes.

For heterogeneous environments, a combination of the DR with the RE of a node is significant to capture both the expenditure and the resources still available. Such combination can be provided in several ways. Kim et. al. consider also the ratio between RE and DR as $C_i$ defined as the node lifetime. However, all of these metrics still is not sufficient to people-centric environment which there are mobile devices in different capacities and states affecting path robustness.

V. PROPOSED HEURISTICS

This section provides an overview on the heuristics that we are currently testing, to provide multihop routing with better energy-awareness. As mentioned our proposal is to consider routing metrics that can be coupled to any multihop routing protocol. In other words, the proposed heuristics are not expected to be tied to a specific protocol.

A. Heuristic 1: Energy-awareness Ranking of Node Based on Idle Times

In this first heuristic we take into consideration the periods over time where $i$ is in idle mode. In other words, over time we estimate how much time of its lifetime has node $i$ been in idle mode, to then provide an estimate on a potential behavior in the future, as this will for sure impact the node’s lifetime. Such periods are the ones the most expensive to $i$ in terms of energy, and in those periods, the node degree becomes highly relevant as the more nodes surround node $i$, the worst the energy expenditure of $i$. So we consider the total period in idle time, $t_{idle}$ over the past period together with the estimated lifetime of the node, as provided in equation 1.

$$E_1 = \frac{t_{idle}}{T + C_i}, \ E_1 \in [0, 1] \quad (1)$$

$E_1$ is therefore a node weight which provides a ranking in terms of the node robustness, from an energy perspective, and having as goal to optimize the lifetime.

B. Heuristic 2: Energy-awareness Ranking of Node Based on Idle Times and Node Degree History

This second heuristic considers also the potential impact that the node degree may have in the energy expenditure of a node. Surrounding nodes impact the conditions of the wireless media and as such, the node degree history, in particular the variability of the node degree is one additional aspect that may impact node lifetime. Hence, still following a simplistic approach, we consider ways to combine the history of the node degree with $E_1$, having derived as a first approach $E_2$, provided in equation 2.

$$E_2 = \frac{t_{idle}}{T + C_i} \ast N'_i, \quad (2)$$

For instance, let us assume that node $i$ has, at a specific instant in time, a lifetime that seems to be long. If the node has an history of a low number of neighbors as happens in the case of less dense networks, then in contrast to a node that has the same lifetime but a larger number of nodes around, we can decide on which node to opt. Deciding for a node that has a higher node degree implies having more alternate paths being the flip-side to this the possibility of seeing an abrupt change in the time left until the node exhausts energy. Opting for a node with a lower node degree may provide more robustness at the cost of having less alternate paths. Depending on the situation of the nodes around (e.g. movement; short lifetimes), there is a variability associated.

The node degree history, $N'_i$, is provided by an Exponential Moving Average (EMA) as provided in equation 3.

$$N'_i = \alpha \ast N'_{i-1} + (1 - \alpha) \ast N'_i \quad (3)$$

C. Discussion

The ranking of a node considering the different heuristics can be seen from an energy-wise point of view on the global network and the impact of the heuristic considering the slope variations of the cost functions as shown in Table I.

A ranking of the node is based on the values of $t_{idle}$ and $C_i$ for the heuristic E1. In case of high idle time and high lifetime is a good candidate to opt the nodes on the path. On the other hand, nodes with low idle time and low lifetime is a node that can be avoided to select on the path. Then, we want to favor the inactive nodes with long lifetime since they are spend energy but not too much like an active node.

<table>
<thead>
<tr>
<th>$t_{idle}$</th>
<th>$C_i$</th>
<th>Ranking $E_{1i}$</th>
<th>$N'_i$</th>
<th>Ranking $E_{2i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>high</td>
<td>high</td>
<td>candidate</td>
<td>high</td>
<td>low potential</td>
</tr>
<tr>
<td>high</td>
<td>low</td>
<td>low potential</td>
<td>high</td>
<td>low potential</td>
</tr>
<tr>
<td>low</td>
<td>high</td>
<td>good potential</td>
<td>high</td>
<td>good potential</td>
</tr>
<tr>
<td>low</td>
<td>low</td>
<td>avoid</td>
<td>high</td>
<td>avoid</td>
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<tr>
<td>low</td>
<td>low</td>
<td>avoid</td>
<td>low</td>
<td>low avoid</td>
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</tbody>
</table>

For the case of heuristic E2, which we consider the node degree history, the ranking of a node is based on both the values of E1 and $N'_i$. In this case, a node with high idle time, high lifetime and low node degree history is the best candidate to opt on the path. Depending of the lifetime of node, a node with low idle time and low node degree is also a good candidate, while a node with low lifetime, low idle time and high node degree is a node ranking that be avoided to be selected. We want to favor nodes with low node degree, but finding a balance having less alternate paths.

Next sections presents the performance evaluation of the proposed heuristics applying as cost function energy-aware metrics based on simulations with different energy metrics when applied to distance vector approach.
VI. PERFORMANCE EVALUATION

This section covers the tools and scenarios to evaluate the proposed heuristics. The simulator considered is the NS-2 simulator (version 2.34) \cite{15}, a discrete event networking simulator. We have used a realistic physical layer including a radio propagation model, radio network interfaces and the IEEE 802.11 MAC protocol using the Distributed Coordination Function (DCF). To simulate adequately the MAC layer we have considered the 802.11g parameters, namely, a data rate of 54 Mbps and a radio range of 250 meters.

We simulate a static network with 25 nodes distributed in a flat grid topology. For the traffic models, we use CBR sources as VoIP standard with the source-destination pairs randomly chosen over the scenario. There are 5, 10 and 15 connections pairs to represent different degrees of traffic load in different sets of simulations.

The nodes are static and have been simulated to hold different energy characteristics, in order to represent heterogeneous portable devices, e.g. laptop, PDA, a device with continuous power.

A. Routing Mechanism: AODV

Our heuristics are being developed to be applicable to any shortest-path based protocol. In this work we evaluate the heuristics with AODV protocol as distance vector approach. In this section we explain how we have implemented the routing protocol, what has been changed to accommodate our heuristics.

We have considered the native AODV, in NS-2 simulator referenced in this work as AODV-native. Native AODV considers hop count as the metric to compute a shortest-path. Moreover, the original 1 has been developed to be applied to DSR \cite{16}. The original specification of 1 therefore selects a best path based on a min-max approach, where the best path is the one that has the lowest bottleneck in terms of energy. So, we adapt the protocol to select the path in a min-max way as the original specification of the 1. The modifications is only regarding using the energy metric instead of hop count by change the control messages of the AODV. We refer as AODV-minmax-Ci for this implementation.

To be as realistic as possible, we consider the native AODV with our proposed heuristic which we call AODV-SP-E1 and AODV-SP-E2 to represent a shortest path (SP) node cost applying our heuristics as a metric.

B. Simulation Results

The heuristics are being analyzed from a perspective where the purpose is to increase network lifetime. As such, the results that are being extracted, are: (i) Average end-to-end (e2e) delay, (ii) Average throughput and (iii) Average aggregate node lifetime.

To generate statistical sound results to attend the credibility aspects on simulations analysis, we are currently using the Akaroa2 \cite{17} tool which can be integrated to NS-2 to provide credible and efficient simulations. Akaroa2 can assist us in adequately devising results to extract statistically independent results, which it provides heuristics to detect the beginning of the steady-state and eliminates the correlation by means of the spectral analysis method. The simulations were carried out with infinite time horizon, where for each run, there are about 2500 to 30000 samples and a confidence interval of 95%.

Figure VI-B show the average aggregate node lifetime, i.e. average network lifetime, of the E1 and E2 heuristics, native AODV and AODV in a min-max way with Ci cost function. The average lifetime is represented in seconds in X axis while in Y axis we represent the number of connections according to the degree of load in the network.

We can see the heuristic E1 and E2 outperforms the native AODV and AODV in a min-max way with Ci cost function. This results show that a node ranking considering the idle time and node degree history can select a more robust path in terms of energy prolonging the network lifetime. The higher traffic load favor the heuristics since more robust paths are selected. The worst performance of the native AODV is expected since it uses the shortest path hop count as metric, which does not consider the energy resources of the nodes. The more traffic load is the worst performance of the native AODV. The AODV-minmax-Ci is expected to have a better performance than native since this mechanism consider the best path is the one that has the lowest bottleneck in terms of energy. However, nodes with low energy ranking is still selected on the path.

Figure 2 show the average end-to-end delay of the E1 and E2 heuristics, native AODV and AODV in a min-max way with Ci cost function. The X axis represents the average end-to-end delay in seconds, and the Y axis represents the number of connections. The bars represent the average delay for different number of flows.
delay in seconds while in Y axis we represent the number of connections according to the degree of load in the network.

According to the results, our E1 and E2 heuristics are not penalized regarding the average end-to-end delay, unless the higher traffic load the gain is more since the node ranking is favor to more robust paths. The AODV native and AODV in a min-max way with Ci cost function have around the same delay values. It is surprise since we expect the min-max way should have higher delay than others because the mechanism selects path with excessive hop count depending the scenario and node energy costs.

![Figure 3. Average throughput](image)

Figure VI-B show the average throughput of the E1 and E2 heuristics, native AODV and AODV in a min-max way with Ci cost function. The X axis represents the average throughput in Kbps while in Y axis we represent the number of connections according to the degree of load in the network.

The results show our E1 and E2 heuristics are not penalized regarding the average throughput for all traffic load. It is expected due to robust paths selected according to the node ranking. The heuristics, AODV native and AODV in a min-max way with Ci cost function have around the same throughput values. It is important to emphasize since the our goal is optimize the network lifetime without penalize the other network performance metrics.

VII. CONCLUSIONS AND FUTURE WORK

Energy efficiency is a key aspect to consider in people-centric routing environments. We proposed a energy-awareness ranking of node based on idle times, which a node provides a ranking in terms of the node robustness to optimize the node lifetime as well as the global network lifetime. Then we consider the impact of node degree history for ranking the node to extend the lifetime.

We evaluated both heuristics in a distance vector multihop routing protocol, namely AODV, showing that a more robust in terms of energy is selected allowing to preserve the energy resources and selecting a path robust too.

As a future work, we are working on providing an analysis based on simulations of the different metrics and heuristics for link-based cost when applied to distance vector approach. For the link state approach, i.e., OLSR [18] routing protocol, we will provide analysis of the heuristics for node-based cost and link-based cost. We also are providing analysis with different networks scenarios with different load traffic and also with a social mobility pattern regarding mobility.

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