Energy-efficient Heuristics for Multihop Routing in User-centric Environments

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Abstract. This paper proposes and validates routing metrics focused on improving energy-efficiency of multihop approaches in heterogeneous wireless environments. The validation is carried out through discrete event simulations and for the specific case of AODV.

Keywords: Multihop routing; energy-efficiency; user-centric networks.

1 Introduction

The most recent advances in wireless technologies and enabled devices is leading to an expansion of wireless architectures where nodes are often carried or owned by regular Internet users. These environments, user-centric in nature, are often coined with the term *user-centric networks* [1]. Examples of such environments can be a network formed on-the-fly after a disaster of some nature or even a municipality network where some nodes are based on end-user devices (through Internet access sharing).

In user-centric environments, there is a behavior that we can root on social network theory, and where spontaneity is a main characteristic, due to the fact that individuals (humans) are not only carriers but also the decision makers for the operation of nodes that form the topology. Adding to the variability e.g. due to node movement, for instance, another key aspect is that some devices are multimedia capable with strong limitations in terms of energy capabilities.

Albeit being often spontaneously deployed, user-centric wireless 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 user-centric environments. On the other hand, there is considerable related work in the fields of energy-efficiency and energy-awareness for sensor networks, where nodes are normally considered to be *homogeneous* in terms of energy capability.

In contrast, in user-centric networks, nodes are expected to be *heterogeneous* in terms of energy.

In previous work [2, 3] we have discussed the potential of current energy-aware routing approaches for wireless networks, and whether or not they may make sense when applied to routing in user-centric environments. We have also proposed a few initial concepts that could assist in making multihop routing more efficient in terms of energy-awareness, without necessarily having to change operational aspects of the underlying algorithms, or protocols.

Following such line of thought, this paper proposes and validates two routing metrics to improve network lifetime based on current multihop approaches. The main goal of this work is focused on making current multihop routing approaches, i.e., *shortest-path* routing approaches for wireless networks, more adequate to be applicable in user-centric environments. We evaluate the proposed heuristics through discrete event simulations having as particular case the *Ad-Hoc On-demand Distance Vector protocol (AODV)* [4] and as performance goal improving the overall network lifetime.

The rest of this paper is organized as follows. Section 2 describes related work focused on multihop energy-efficiency. Section 3 goes over notions concerning energy-awareness in multihop routing. Section 4 describes our proposed energy-awareness heuristics. Then, in section 5, we present the performance evaluation based on simulations with statistically rigorous results. Conclusions and future work are presented in section 6.

2 Related Work

A few approaches [5, 6] have surveyed multihop proposals focused on energy-efficiency, considering both the energy spent when nodes are engaged in active communication or passive communication (e.g., in idle mode). Such work has as underlying scenarios homogeneous environments, and several proposals combine different energy-aware metrics to maximize the network lifetime.

Attempting to make multihop routing adaptive, some proposals [7–9] 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 [10] of different routing properties to consider in multihop routing. 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 and also the maximization of the lifetime of all nodes in the network.

The cost function of the *Maximum Residual Packet Capacity* (MRPC) protocol [11] comprises a node perspective parameter (battery of the node) and a link perspective 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 is more adequate to scenarios where the link transmission cost depends on the physical distance between nodes and on the link error rates. Hence, the approach does not consider energy-awareness as a primary resource of the network.

A recent work [12] proposes a multi-objective prediction approach to optimize three main aspects of network operation: minimize average end-to-end delay, maximize network energy lifetime, and maximize packet delivery ratio. The authors have as main purpose to make multihop routing more flexible in terms of the three mentioned parameters. In terms of energy they consider a composite energy cost based upon transmission power and residual energy. The energy cost is then computed based on a time series prediction model and the authors show that proactive routing (based on the *Optimized Link State Routing (OLSR)* protocol) benefits from their proposal. In contrast to their work, our heuristics are not based on prediction and instead on a more realistic assessment of the energy consumption and thus our approach is expected to incur on a lower operational cost, as less changes to the protocols are expected.

Finally, we highlight that The Internet Engineering Task Force (IETF) Working Group *Routing Over Low Power and Lossy Networks* (ROLL) is currently discussing multihop metrics tailored to energy-efficiency [13].

3 Energy awareness in Multihop Routing

This section provides a few notions concerning energy awareness in multihop routing. A *node* i represents a wireless heterogeneous device with a single or with multiple network interfaces. An edge interconnecting two nodes i and j is represented as *link* (i, j) with a cost $e_{(i,j)}$ which is a measure of energy expenditure. Such cost e can be obtained from a single node perspective (source or destination); from the link perspective; from a global network utilization perspective. From a single node perspective, there are three main modes of energy expenditure which depend on the node status. A node is in *Transmission 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 of information. Particularly for the case of 802.11, there are two additional states a node may be at. When the node is still passively listening to the shared medium (*overhearing*), is said to be in *Idle mode* which consumes energy. A fourth mode can be considered, *Sleep mode*. In this mode, the networking capabilities are shut down but the node still consumes little power.

Another relevant parameter to consider from an energy-awareness perspective is a node's degree, N_i as the surrounding nodes impact heavily not only the transmission channel, but also the rate of energy consumption. We use the node degree definition where N_i corresponds to the number of neighbors that a node i has at an instant in time. From an energy-awareness perspective, more relevant than the number of neighbors, is the history of variation of N_i through time as it can assist us in estimating potential fluctuations of energy levels - a faster or slower potential for energy consumption.

The most relevant energy-aware routing metrics for user-centric environments are the residual energy and drain rate of a node. The *Residual Energy (RE)* of a node i, $RE(i)$ [14] 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, $DR(i)$ [15] 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 a node i at an instant in time. Garcia-Lunes et. al. have considered the ratio between RE and DR, $C(i)$, as the estimated lifetime for node i, having in mind scenarios where nodes are homogeneous in terms of energy capability. Our heuristics proposed in the section 4 are based on the notion of $C(i)$.

A *node's lifetime* corresponds to the period of time since a node becomes active until the node is said to be dead, i.e., from a network perspective, the node ceases to exist.

Network lifetime is often associated in related literature to the time period that elapses since a topology becomes active, until a first node dies. In contrast, in our work we follow the definition where *network lifetime* *is associated to the time period since a topology becomes active, until the topology becomes disconnected, from a destination reachability perspective.* In other words, we consider that the energy lifetime covers the time a topology is stable enough to reach at least one of the destinations present at some instant in time.

4 Proposed Heuristics

This section is an overview on our metrics. Our belief is that they can assist multihop routing in becoming more energy-efficient without increasing a significant cost in terms of protocol implementation and operation.

4.1 Heuristic 1: Energy-awareness Ranking of a Node Based on Idle Time Periods

Based on the notion that a node still spends energy per bit when in idle mode, this first proposal explores the fact that nodes may be in idle mode for a long time. Nodes that have been in idle mode for a long period of time in the past and that still have a reasonable large estimated lifetime are, in our opinion, better candidates to be elements in a shortest-path.

Hence 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 of its lifetime has node i been in idle mode, to then provide an estimate towards the node's future energy expenditure, as this will for sure impact the node's lifetime. Such periods are the ones that are the most expensive to i in terms of energy. So we consider the total period in idle time, t_{idle} over the full lifetime expected for a specific node, which is given by the sum of the elapsed time period T with the estimated lifetime of the node, as provided in equation 1.

$$E_1(i) = \frac{T - t_{idle}}{T \times C(i)} \tag{1}$$

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 network lifetime. Hence, the smaller $E_1(i)$ *is,* the more likelihood a node has to be part of a path.

4.2 Heuristic 2: Energy-awareness Ranking of Node Based on Idle Time Periods and Node Degree History

Based on the previous line of thought, we consider a new parameter in terms of impact of energy expenditure of a node, namely, the node degree.

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.

$$E_2(i) = \frac{(T - t_{idle}) \times N_i}{T \times C(i)} \tag{2}$$

For instance, let us assume that node i has, at a specific instant in time, a lifetime that is rather large. If the node has an history of having a low number of neighbors around 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; shorter lifetimes), there is some variability associated which impacts the node lifetime, and the network energy lifetime.

The node degree history, N_i, is provided by an *Exponential Moving Average (EMA)* as provided in equation 3.

$$N_i = \alpha \times N_{i_{t-1}} + (1 - \alpha) \times N'_{i_t} \tag{3}$$

4.3 Brief Analysis of the Impact of the Different Parameters

To better explain how the different parameters may impact E_1 and E_2, Table 1 depicts the described parameters and the respective results in terms of E_1 and E_2. For each parameter we consider two extreme values, "low" and "high". The outcome in terms of E_1 and E_2 is ranked as a potential candidate, low potential for being a candidate to the path, and avoiding if possible (*avoid*).

For instance, in line 1 we consider a potential case where a node has been most of its lifetime in idle mode and yet it has a large estimated lifetime. This is likely to occur if the node is in fact isolated or if its energy is being regularly increased (e.g. large battery capacity or AC power on). If the node has been most of its lifetime in idle mode than the E_1 value is strongly dependent on the value of $C(i)$. Therefore, a node that has a large $C(i)$ is expected to be chosen when compared with a node with a small $C(i)$. The situation where a node has been most of its time in idle mode but has a small estimated lifetime is considered in line 2. The result is that E_1 tends to 1 and therefore the node has low potential to be part of a path, when compared to nodes that have smaller E_1 values.

Table 1: Ranking the node cost

t_{idle}	$C(i)$	E_1	N_i	E_2
high	high	candidate	high	low potential
			low	candidate
high	low	low potential	high	low potential
			low	good potential
low	high	good potential	high	good potential
			low	candidate
low	low	avoid	high	avoid
			low	low avoid

The impact of t_{idle} in E_1 becomes less significant for the cases where t_{idle} is small, assuming that the node has enough energy (large value for $C(i)$ cf. line 3).

To analyze E_2 following this line of thought, Table 1 considers also N_i, i.e., situations where a node has a few or some relevant number of neighbors in range. A large number of neighbors through time implies that the node may not be an adequate candidate as loaded networks may exhaust nodes faster. The node degree seems only to become less prominent for situations where the estimated node lifetime is large enough.

5 Performance Evaluation

This section provides a performance evaluation for E_1 and E_2 based on NS-2 (version 2.34) simulations. Scenarios have been modeled as close as possible to reality. We have considered the NS-2 default physical layer, two-ray ground propagation model and DCF (Distributed Coordination Function) for MAC layer with 802.11g parameters. In terms of topology we considered 25 nodes distributed across a square with an area of 1400m x 1400m, 5 nodes per row and per column. Hence, node degree varies as 2, 3, 4 according to the position of each node in the square. We then considered a simple model for *Voice over IP (VoIP)*, where calls follow a Poisson model, and where each flow is based on *Constant Bit Rate (CBR)*, average packet size of 40 bytes, inter-packet times of 0.02 seconds. Sources and destinations are randomly selected from the available nodes. Then, we consider 5, 10, and 15 flows as a way to represent three different load levels. The simulation time has been set to 100 seconds.

In these first set of experiments, all of the nodes are static, as what is relevant to us is to understand how the network behaves in terms of energy consumption. Hence, each node has been modeled to have different levels of energy parameters in order to represent heterogeneous devices.

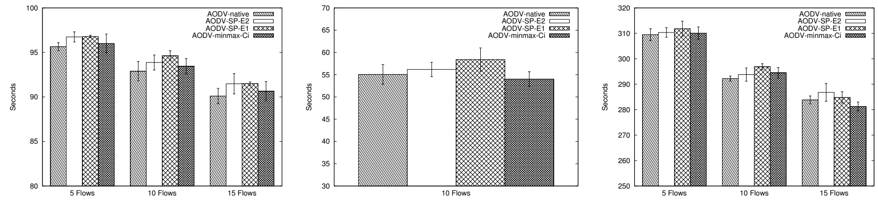
Albeit applicable to any shortest-path approach, in this paper the evaluation of the heuristics is performed based on AODV, being the reason simply the fact that this is still a first step towards a thorough evaluation of the heuristics in terms of its global applicability. For AODV we considered the native NS-2 module, here referenced as *AODV-native*. The *AODV-native* considers hop count as the metric to compute a shortest-path. Moreover, the original $C(i)$ has been developed to be applied to Dynamic Source Routing (DSR) protocol. The original specification of $C(i)$ 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 adapted the protocol to select the path in a min-max way as the original specification of the $C(i)$. We refer to this implementation as *AODV-minmax-Ci*. Moreover, *AODV-SP-E1* and *AODV-SP-E2* represent AODV running our two heuristics E_1 and E_2, respectively.

The results extracted intend to analyze benefits in terms of *network lifetime* as defined in section 3. Even though we analyze benefits in terms of network lifetime, we also want to understand the impact of the metrics in the overall network performance. For that, we consider three additional aspects: i) *average estimated node lifetime*, i.e., the estimated node lifetime, $C(i)$, across all nodes in the network; ii) *average end-to-end delay*, the time a packet takes between source and destination computed per destination and then averaged across all destinations; (iii) *throughput*, the average number of bytes reaching destination nodes, computed first per destination and then averaged across all destinations measured in Kbps.

To generate statistical sound results we relied on Akaroa2 [16] tool. All results have been computed within a 95% confidence interval.

5.1 Network Lifetime

In a first setting, based on the parameters described, all of the 25 nodes of the topology have been set with initial energy levels picked up randomly between 30 Joules and 180 Joules. Figure 1a shows the average network lifetime for the different approaches. The X-axis represents the number of flows, while the Y-axis provides the network lifetime in seconds.



(a) Network Lifetime (b) Network Lifetime, ten nodes without power after 40 sec. of simulation time. (c) Node Lifetime Impact

Fig. 1: Node and Network Lifetime Analysis

Even though the topology is simple in the sense that the nodes are equally placed, traffic is CBR based, and the network never becomes truly congested, from Figure 1a it can be observed that the behavior of *AODV-native* is constant, resulting in the lowest network lifetime.

AODV-SP-E1 and *AODV-SP-E2* do improve network lifetime, outperforming AODV. However, as the time-scale reflects seconds, it is not possible to state, based on this simple case, that the proposed heuristics provide an advantageous benefit when compared to the native behavior. For this concrete simulation scenario, Table 2 (col. 2, 3 and 4) shows that heuristics E_1 and E_2, when applied to AODV, seem to improve the overall network lifetime circa 1.5%. Moreover, it is also not possible to understand if an heuristic is truly better than the other.

Table 2: Network Lifetime Improvement.

Approach	5 flows	10 flows	15 flows	exhausted network - 10 flows
AODV-SP-E1	1.20%	1.87%	1.55%	6.06%
AODV-SP-E2	1.15%	1.05%	1.53%	2.02%
AODV-minmax-Ci	0.38%	0.59%	0.61%	-1.87%

To better analyze if our heuristics behave coherently across different scenarios, we run a simulation with ten flows (average network load) configured as before, but where now 10 nodes have an energy level which has been randomly picked to be exhausted after 40 seconds of simulation time, being the results depicted in Figure 1b. The intention is to create a topology where there is more variability in terms of nodes (and path) availability. From Table 2 (col. 5) the first conclusion we can draw relates to the fact that again *AODV-SP-E1* and *AODV-SP-E2* provide the best results, being *AODV-SP-E1* increases the network lifetime the most.

The E_1 and E_2 differ only in the application of the node degree. In the scenarios simulated, there is not a relevant benefit in applying the node degree, but this relates to the fact that the chosen topology does not provide adequate variability in terms of node degree, to reflect an adequate difference. This is an aspect we intend to explore in future work.

5.2 Node Lifetime Impact

Our approach is meant to improve network lifetime but nonetheless it is relevant to understand and to ensure that new metrics do not negatively impact node lifetime and other network operation parameters, while improving network lifetime. Hence, for the initial setting of 25 nodes described in section 5.1, we have also analyzed how the metrics proposed affect node lifetime, and the results are illustrated in Figure 1c.

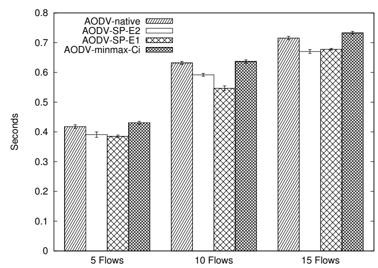
A first observation based on the results achieved is that the proposed heuristics do not impact negatively the node lifetime and in fact slightly improve the behavior when compared to *AODV-native*. For a low load, *AODV-SP-E1* outperforms all other approaches. When the number of flows increases, however, *AODV-SP-E2* is the heuristic that provides a better node lifetime at the expense of more variability. We believe this may be related to the node degree impact and the way we model such impact (product), which may be more severe than expected.

5.3 End-to-end Delay and Throughput

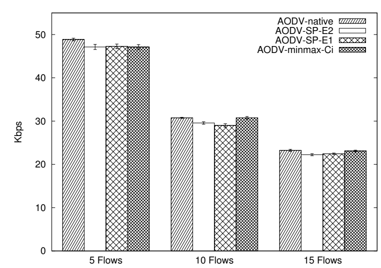
As our main goal is to extend network lifetime without penalizing the end-to-end delay and throughput. Figure 2a shows the average end-to-end delay of the E_1 and E_2 heuristics, *AODV-native* and *AODV-minmax-Ci*. It is represented by the average end-to-end delay in seconds and by number of flows according to the degree of load in the network.

According to the results, our E_1 and E_2 heuristics result, for AODV, in a lower end-to-end delay. There is a slight gain due to node ranking favoring more robust paths by selecting a good path regarding energy resources and also for delay constraints. The heuristics seem to provide AODV with lower end-to-end delays and across all scenarios *AODV-SP-E2* is more stable than *AODV-SP-E1* in terms of gain. The reason for E_2 to be more stable relates to the application of the node degree. Our simulated environment corresponds to a static topology where node degree does not vary. Over time, node degree smooths out variability in

E_2 and overall is the heuristic that seems to result in more stability. *AODV-minmax-Ci* is the approach that provides additional delay. This is not surprising, as $C(i)$ has been developed as a metric for source-based routing.



(a) Average End-to-End Delay.



(b) Average Throughput.

Fig. 2: Delay and Throughput Analysis.

We have then analyzed throughput impact and Figure 2b shows the average throughput represented in Kbps for different number of flows. There is a slight decrease of all of the approaches in comparison to *AODV-native* which we believe to be due to the fact that when in the presence of multiple shortest-paths computed at different instants in time between a source and a destination, AODV will select the first one available. While the three other approaches will always opt for a more robust path, independently of the previous selection of AODV. This is a hypothesis that we intend to further analyze by testing future, more variable scenarios.

6 Conclusions and Future Work

Out of the possible energy-efficiency aspects, choosing paths having in mind optimal network lifetime is an aspect that introduces more flexibility in multihop routing approaches and makes then better suited for user-centric environments. In this paper we address and propose energy-aware routing metrics that can provide a level of stability in terms of network lifetime to shortest-path based routing, without incurring strong penalties in terms of operational changes and maintenance.

We have evaluated both heuristics under realistic settings for a specific case of on-demand routing, AODV. Albeit this work provides initial validation results concerning the proposed heuristics, results obtained are promising in the sense that the heuristics seem to overall improve the network operation without making the network incur a heavy cost.

We are carrying on this work both by fine-tuning not only scenarios but also the proposed metrics and also by evaluating their potential contribution for other forms of multihop routing, e.g. OLSR.

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