An Energy-Flow Model for Self-Powered Routers and its Application for Energy-Aware Routing

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***Abstract*—Self-powered wireless mesh networks have gained popularity as a cheap alternative for providing Internet access in many rural areas of the developed and, especially, the developing world. The quality of service that these networks deliver is often bounded by such rudimentary issues as the unavailability of electrical energy. Dependence on renewable energy sources and variable power consumption make it difficult to predict the available energy and provide guarantees on the communication performance. We develop an energy flow model that accounts for communication and energy harvesting equipment hardware specifications; high resolution, time varying weather information; and the complex interaction among them. To show the model's practical benefits we introduce an energy-aware routing protocol, the Lifetime Pattern based Routing (LPR), specifically tailored for self-powered wireless networks. LPR's routing decisions are based on the energy level estimations provided by our energy flow model. The initial results are promising, and show our protocol outperform the existing work in rural-area wireless network routing.**

I. Introduction

Erratic and sporadic power supply is the most commonly reported problem observed in rural area networks [4]. One way of coping with the problem of unreliable renewable energy influx is to provide a greater safety margin by installing additional energy harvesting hardware. Unfortunately, this leads to unnecessary network over-engineering which, having in mind that the power supply related equipment already costs one order of magnitude more than the communication equipment relying on it [1], defies the purpose of using self-powered wireless routers - low cost. The other solution is to use the given energy budget more wisely. However, renewable energy sources and communication patterns express unstable behavior, making it difficult to estimate the amount of available energy. We develop a model that captures the impact of varying weather conditions on power generation. At the same time it takes into consideration the interaction between the system components, and accounts for possible losses and changing energy consumption. We use the model's ability to estimate energy availability to design a novel routing protocol that utilizes the estimations of future energy budget to select paths that offer a better user experience compared to the protocols that ignore such information.

In a typical rural area network such as AirJadi [4] in India or Tegola [1] in Scotland, a self-powered wireless network node consists of communication equipment (a routing board, wireless NICs, antennas) and energy harvesting equipment (solar panel and/or wind turbine, rechargeable battery, charging regulator). The former is the energy consumer while the latter is the only source of energy. Given that rural area networks are often subject to intermittent connectivity, they can be classified as delay tolerant networks (DTNs).

Although weather measurements and short term predictions can be derived from the data gathered at a local weather station, microclimate factors such as terrain ruggedness, equipment orientation and surrounding vegetation affect wind speed and solar irradiation sufficiently to render the information unusable. We propose the use of cheap on-site anemometer and solar sensors to gather data and use the history of readings for future wind speed and solar irradiation level prediction. The means of achieving accurate weather condition prediction is beyond the scope of this work.

II. Energy Model

Climate conditions are most often variable and unpredictable, such that any model that relies on annual (or any other long term average) values is inherently inaccurate. For example, the wind energy harvested is proportional to a cube of the wind speed. Therefore two sites that have the same average wind speed may have one order of magnitude different energy capacity - more variable wind speeds provide more power. Therefore, we aim to model the system's behavior on a time scale as small as is realistic. The main restriction is the granularity of the weather sensor data. Our approach closely follows the physical properties of the system - battery type, solar panel and wind turbine specification and available power consumption levels. We have identified the following as a good approximation of a lead-acid battery energy to voltage relationship:

(1) $V_{B,i} = V_{B,80} + \frac{V_{B,0} - V_{B,80}}{\log(E_{B,0} - E_{B,80} + 1)} * \log(E_{B,i} - E_{B,80} + 1)$

where $V_{B,i}$ is the current battery voltage, $V_{B,0}$ is the battery voltage when full, $V_{B,80}$ is the battery voltage when at 80% DoD (depth of discharge); while $E_{B,i}$ is the current battery energy, $E_{B,0}$ is the battery energy when full and $E_{B,80}$ is the battery energy when at 80% DoD. The charging/drainage process is determined with the equation:

(2) $E_{B,i+1} = E_{B,i} + k * REG_i * (E_{WG,i} + E_{PV,i}) - E_{C,i}$

where $E_{WG,i}$, $E_{PV,i}$ and $E_{C,i}$ are the energy generated by the wind turbine, generated by the solar panel and consumed by the communication equipment in the iteration time period, respectively. Regulation parameter REG_i dictates the amount of energy that is transferred to the battery. Its value depends on the current battery voltage level, while k represents the charging efficiency. In the above equations, i marks the iteration number. The logical step is to assume that all the variables keep their values between the two measurements, until the next iteration of the algorithm starts. The battery voltage/charge cannot change significantly in a small time period thus the assumption is reasonable. Given the current

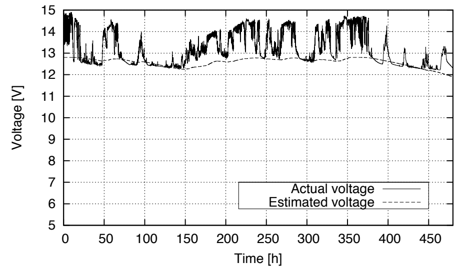

Fig. 1: Battery voltage under changing weather conditions.

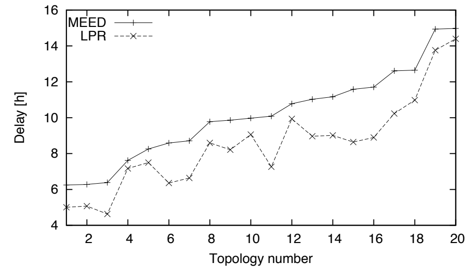

Fig. 2: Delay comparison of LPR and MEED: grid topologies.

solar sensor and anemometer readings and power consumption, the model calculates the battery voltage/charge in the next timestep; if the input is the expected sensor readings and power consumption, the model predicts the future energy supplies.

We evaluated the accuracy of the model by comparing the estimated battery voltage with the values recorded on-site at the Tegola network. Figure 1 depicts the model performance in a two week period. The spikes in the measured voltage occur when the battery is being connected to an active wind turbine/solar panel. We decided not to model them as they do not correspond the actual change in the battery charge.

III. Energy-aware Path Selection

Wireless routers and NICs, unless engaged in active transmissions, can employ a plethora of power saving techniques. In the ideal case these are low-power, sleep states resulting in an order of magnitude lower power consumption; even a simple switching of a wireless NIC mode from *send* to *idle* lowers the total energy consumption enough to result in considerable battery savings. In our solution, through routing decisions, we implicitly control energy consumption levels and improve the distribution of energy reserves amongst network nodes. The goal is to prolong or, if possible, avoid network partitioning and node battery death to lower packet delivery delay. LPR is constructed as a link-state routing protocol. There are multiple reasons why this type of a protocol is the most suitable for the target environment; a thorough discussion can be found in [2].

A. Link Cost Metric

Nodes use the energy model to estimate the remaining battery uptime. Each of the nodes propagates the information about the expected future up and down times to its neighboring nodes. At the end of the process every node has information on the expected failure patterns of its links (determined by the corresponding endpoints' up and down times). Link weights are assigned so that links expected to be down sooner have lower value. Additionally, if links are down, those that have sooner predicted uptime have larger weight. On each node there is enough information to run Dijkstra's algorithm and select a route for each destination that has the highest minimum link weight from the set of possible routes.

IV. Evaluation

We implement LPR in DTNSim2 - Java based simulator extended with an energy module we have developed. All nodes have identical hardware properties and infinite storage buffers. The node up and down time is dictated by the weather traces provided by actual sensor readings from the Tegola network [1]. LPR is compared to MEED [3], a metric used in DTLSR[2] and readily available in DTNSim2. We compare the protocols on a 5 by 5 node grid topology, through twenty different runs lasting four simulation days each; the nodes are randomly assigned different initial battery voltages in each run. To exclude the influence of network congestion, all the links have infinite bandwidth and zero propagation delay. We use the same traffic patterns as in [2]: every hour each of the nodes sends a single 64kB message to all other nodes in the grid.

In a DTN setting, end-to-end packet delay can be improved if the routing protocol correctly evaluates the links and sends packets over the paths that consist of the links that will be available the soonest. Hints from the energy flow model help LPR to accomplish that goal. Figure 2 shows the average packet delivery delay for MEED and LPR in 20 four day simulations.

V. Related Work

To the best of our knowledge, energy flow modeling for self-powered wireless networks has not been considered before. Intermittent connectivity has been observed in many real life situations and delay tolerant routing protocols have emerged in various flavors. Work that is most similar to ours is [2]. The authors specifically target rural-area networks, propose and justify a link-state protocol and select MEED as the most appropriate metric. Although targeting the deployments where the most probable cause of link-node failure is the lack of energy, the authors do not consider energy availability behavior.

VI. Discussion and Future Work

In this paper we develop an energy flow model for self-powered wireless network routers. The model serves as a basis for an energy-aware routing protocol targeting rural area wireless networks. Our routing protocol (LPR) strives to extend service and prevent node failure by avoiding the use of nodes that are likely to be left depleted if they serve as a communication bridge. We are currently investigating a variation of the protocol that minimizes the amount of traffic affected by failures as well as the impact of the failure on the traffic. The above goal is achieved if the nodes that are about to generate substantial traffic and are energy-critical are excluded from routing. In addition to the above, a precise energy flow model is applicable to a number of research challenges such as network planning and online energy consumption management to name a few.

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