Ad Hoc Networks 67 (2017) 11–23

Contents lists available at ScienceDirect

Ad Hoc Networks

journal homepage: www.elsevier.com/locate/adhoc

A distributed routing scheme for energy management in solar powered sensor networks

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ARTICLE INFO

Article history:
Received 24 February 2017
Revised 1 October 2017
Accepted 2 October 2017
Available online 5 October 2017

Keywords:
Distributed routing
Energy management
Sensor networks
Solar powered WSN

ABSTRACT

Energy management is critical for solar-powered sensor networks. In this article, we consider data routing policies to optimize the energy in solar powered networks. Motivated by multipurpose sensor networks, the objective is to find the best network policy that maximizes the minimal energy among nodes in a sensor network, over a finite time horizon, given uncertain energy input forecasts. First, we derive the optimal policy in certain special cases using forward dynamic programming. We then introduce a greedy policy that is distributed and exhibits significantly lower complexity. When computationally feasible, we compare the performance of the optimal policy with the greedy policy. We also demonstrate the performance and computational complexity of the greedy policy over randomly simulated networks, and show that it yields results that are almost identical to the optimal policy, for greatly reduced worst-case computational costs and memory requirements. Finally, we demonstrate the implementation of the greedy policy on an experimental sensor network.

1. Introduction

Floods are one of the most common natural disasters, and causing more than 120,000 fatalities in the world between 1991 and 2005 [1]. They constitute a major problem in many areas in the world, and are expected to become worse due to ongoing global warming. In 2010, floods were not only responsible for more than 4000 deaths worldwide but also caused considerable economic loss. While these natural disasters are unavoidable, the intensity of the loss in urban regions can be minimized by a proper warning system displaying real-time flood propagation and forecast data, which could also give emergency responders real time data to organize their rescue operations.

Though rain monitoring systems have been used for flood prediction and estimation before [27], flood caused by extreme rains cannot be accurately predicted with these systems, as flood propagation models require many parameters which are difficult to estimate beforehand.

One of the most straightforward ways to monitor floods is to directly monitor water levels and precipitation rates in a variety of locations, for instance using a *wireless sensor network* (WSN). WSNs have the potential to address a number of operational issues in future cities (so called *smart cities*) as they are relatively inexpensive to deploy and do not require a specific wired infrastructure. Such issues include pollution monitoring [26,34], emergency response during catastrophic events [10], environmental monitoring [8], or traffic monitoring [7].

Using WSN for flood monitoring has previously been proposed as a system from the conceptual stage [13,14,25]. A recent effort to directly measure water levels in a river was investigated in [9,10], but the technology chosen for this study only applies to rivers. Pressure sensors are unfortunately unusable to monitor flooding in urban areas for multiple reasons related to aging and accuracy.

In this article, we investigate the energy management problem in a custom designed dual flood and traffic urban wireless sensor network [33]. The primary application of the system is to monitor traffic: indeed, floods are very rare events, and the installation of a dedicated sensor network which monitor floods only would not make economic sense. Indeed, the time interval between catastrophic flooding events (decades) far exceeds the practical lifetime of a sensor network (years). The sensor network is solar powered for cost reasons (connecting a node to the grid is usually very ex-

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https://doi.org/10.1016/j.adhoc.2017.10.002
1570-8705/

pensive). Since the urban flood sensing application is of high priority (*i.e.*, the sensor network has to be completely operational whenever a flood is likely to occur), the energy of the network has to be maximized at the likely onset of a flood event.

Using weather forecasts, high rain events can usually be detected a few hours in advance. However, since high rains are very common in numerous regions (for example 150 days per year in average in most eastern US locations), shutting down the traffic wireless sensing component to charge batteries or conserve power whenever a flood is likely to occur would severely affect the availability of the traffic sensing component of the system.

Our objective is to optimize the remaining energy (at a specified terminal time) in a solar powered wireless sensor network, taking into account the expected power input of the solar panel as well as the power usage for traffic sensing, computing and communications. We first show in Section 3 that such a problem can be cast both as mixed integer programming and dynamic programming. Both approaches are limited in their applicability because of excessive worst-case computational demands. In Section 4.1, we introduce a greedy policy that can be implemented in a distributed manner with a considerably lower computational cost, and low memory requirements. We compare the performance of both the greedy and optimal policies when computationally feasible, and show that the greedy policy yields very good results in practice, for a fraction of the computational cost of the optimal policy. The resulting numerical scheme can be implemented in typical motes, as its memory and computational power requirements are much lower than a centralized scheme. An implementation of this energy management framework in a wireless sensor network is discussed in Section 5.

2. Related work

Energy management in wireless sensor networks has been extensively studied in the literature [3,20,23,37,38]. In fact, most routing protocols used in wireless sensor networks are designed with energy management in mind, since WSNs are usually battery powered or harvest their energy from an unreliable source. Various strategies can be used to optimize the energy [5] in battery or solar powered wireless sensor networks. Most approaches use some feedback mechanism to increase the routing load on high energy nodes as described for instance in [4,15,31]. Other approaches based on game theory have been developed to enhance the performance of WSNs. For instance in [39], the authors proposed an acceptance algorithm analyzing selfishness in forwarding packets where nodes cooperate without incentives under certain conditions. Another study [35] deals with solar powered networks, and introduces an optimal energy management policy for a two state system (sleep and wake up) for energy conservation. The optimization problem is formulated as a bargaining game in which the Nash equilibrium is used as the solution.

A number of max-min optimization problems have been proposed in the field of WSN. For example in [29], the max-min energy efficient power allocation problem was solved based on a generalized fractional programing and sequential convex programing. Also, in [22], a max-min of the user energy efficiency in multicell multiuser joint beamforming system was solved by transforming the problem into a parametrized polynomial subtractive form using fractional programing. Then, an iterative algorithm was introduced to solve this max-min problem. A different study [40] briefly proposed a conditional max-min battery capacity routing scheme where the route with the minimum total transmission power is selected. Another work [24], proposed a game theoretical model for inter-cluster routing. This work considers the effect of path length and path energy simultaneously, to maximize the minimum length energy constrained in a bounded path length.

In this study, unlike previous work [11,12,16,24,40], the aim is not only to prolong the network lifetime or optimize the energy in a predefined constraints environment, but rather to ensure that the minimal (overall nodes) energy in the network at the final time horizon is maximized. Also, a different study [28] proposes an approximation algorithm called *max-min* $zP_{\min}$. However, this algorithm is centralized, and requires the node computing the solution to have a high computational performance, and a complete knowledge of the network structure. Such is also the case for the study in [30]. This feature makes it infeasible to perform computations for large networks thus, the network must be divided into different zones finding the solution for each alone. A recent study [21], aims at optimizing the network rate control, routing and energy by decoupling the original problem equivalently into separable subproblems that was locally solved. Also, a different work [43], designed a distributed sensing rate and routing control (DSR2C) algorithm by employing dual decomposition method and sub-gradient method. Additionally, the work proposed an improved algorithm to manage the energy allocation to reduce the computational complexity.

Another work [42] proposed an energy management approach to maximize the minimum energy reserve for a single node in a network utilizing both energy saving techniques, i.e., dynamic voltage scaling and dynamic modulation scaling. In their approach, instead of solving the problem directly, the solution was done backward by enumerating the list of possible resulting energy levels and check if there exists a feasible solution that yields max-min energy available in the list. They also proposed a decentralized version (DHASS) which is heuristic based. However, still a single node is needed to calculate the end to end latency and then disseminate to all the nodes.

In the proposed approach, our objective is to maximize the lowest energy in the wireless sensor network at a time horizon, under the sensing, communication and power constraints. We consider a fixed wireless sensor network in which solar power input is uncertain. We also model the physical effects of limited storage capabilities of batteries, which implies that during periods of high charge and high solar power input, some solar energy is lost. We presented the solution for this max-min problem using both a Mixed Integer Linear Programming formulation (MILP) and forward dynamic programing approach (FDP). Both methods give the optimal solution (if any exist). However, due to the nature of these methods (being centralized and demanding enormous data transmission) both cannot be implemented easily for large WSN on existing hardware platforms. Thus, we proposed a distributed greedy algorithm to solve this max-min problem where it can easily be implemented on existing hardware. We have tested this distributed greedy algorithm experimentally on WSN nodes and we compared the results with the optimal solutions obtained from both MILP and FDP.

3. Energy maximization at a finite time horizon

3.1. Assumption and notation

Let us consider a wireless sensor network, which can be described as a directed graph containing n nodes (vertices) labeled v_k, $k \in \{1, 2, \ldots, n\}$. We assume that the nodes transmit data to a single sink for simplicity, though multiple sinks could also be integrated in this framework.

For a node v_k, let us denote by $L(v_k)$ the minimal number of hops required to reach the sink from v_k, and $\mathcal{N}(k)$ the set of neighbors of v_k, that is, the set of nodes directly connected to v_k. Let us also define the set of children of a node k by $\mathcal{C}(k) = \{v_j \in \mathcal{N}(k) | L(v_j) = L(v_k) - 1\}$, and similarly the set of parents of a node k by $\mathcal{P}(k) = \{v_j \in \mathcal{N}(k) | L(v_j) = L(v_k) + 1\}$. For simplicity of the routing (to avoid loops), we assume that each node can only