Applied Soft Computing 11 (2011) 5684–5694

Contents lists available at ScienceDirect

Applied Soft Computing

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

Minimum energy broadcasting in wireless sensor networks: An ant colony optimization approach for a realistic antenna model☆

Hugo Hernández, Christian Blum*

ALBCOM Research Group, Universitat Politècnica de Catalunya, Barcelona, Spain

ARTICLE INFO

Article history:
Received 31 August 2010
Received in revised form 20 January 2011
Accepted 23 March 2011
Available online 8 April 2011

Keywords:
Minimum energy broadcasting
Wireless sensor networks
Realistic antenna model
Ant colony optimization

ABSTRACT

The classical minimum energy broadcast (MEB) problem in wireless adhoc networks, which is well-studied in the scientific literature, considers an antenna model that allows the adjustment of the transmission power to any desired real value from zero up to the maximum transmission power. However, when specifically considering sensor networks, a look at the currently available hardware shows that this antenna model is not very realistic. A first contribution of this work is therefore the re-formulation of the MEB problem for an antenna model that is realistic for sensor networks. In this antenna model transmission power levels are chosen from a finite set of possible ones. The second contribution concerns the adaptation of ant colony optimization, a current state-of-the-art algorithm for the classical MEB problem, to the more realistic problem version. The obtained results show that the advantage of ant colony optimization over classical heuristics even grows when the number of possible transmission power levels decreases.

1. Introduction

Sensor networks are wireless adhoc networks that are being used in practical scenarios such as the monitoring of certain events [1]. Sensor nodes are generally equipped with omni-directional antennas for sending and receiving information. They have a packet-forwarding capability in order to communicate via shared and limited radio channels. In order to transmit information, a sender node must adjust its transmission power in order to reach the desired receiver node. As network lifetime is limited by batteries, energy saving is critical. A fundamental problem in sensor networks arises when one node is required to transmit data to all other nodes of the network. This scenario is known as *broadcasting*. Obviously, for broadcasting to be energy-efficient, the transmission powers of the sensor nodes should be adjusted such that the sum of the energy spent by all nodes is minimized. This problem is know as the *minimum energy broadcast* (MEB) problem in the literature [2]. To our knowledge, all existing works from the literature use an antenna model which allows the adjustment of the transmission powers to any real value between zero and the maximum transmission power. However, available hardware such as SunSPOTs (see http://www.sunspotworld.com/) or iSense sensor nodes (see http://www.coalesenses.com/) are equipped with antennas that offer a limited set of different transmission power levels; 201 in the case of SunSPOTs and seven in the case of the iSense hardware. Note that SunSPOTs are among the most widely used sensor hardware, while iSense nodes are used by two of the currently largest European projects on sensor networks, FRONTS and WISEBED.[1]

1.1. Related work

The classical *minimum energy broadcast* (MEB) problem, assuming omni-directional antennas whose transmission power can be adjusted to any desired real value between zero and the maximum transmission power, has mainly been tackled with centralized heuristics. Only very few distributed approaches can be found in the literature (see [3,4]). Due to the fact that the ACO approach proposed in this paper is centralized, we focus in the following on other centralized proposals.

Centralized heuristics include the ones presented in [2,5,6]. The most popular constructive technique is the broadcast incremen-

---

☆ This work was supported by grant TIN2007-66523 (FORMALISM) of the Spanish government, and by the EU project FRONTS (FP7-ICT-2007-1). In addition, C. Blum acknowledges support from the *Ramón y Cajal* program of the Spanish Government, and H. Hernández acknowledges support from the *Comissionat per a Universitats i Recerca del Departament d'Innovació, Universitats i Empresa de la Generalitat de Catalunya* and from the *European Social Fund*.

* Corresponding author.
E-mail addresses: hhernandez@lsi.upc.edu (H. Hernández), cblum@lsi.upc.edu (C. Blum).

[1] Concerning FRONTS, see http://fronts.cti.gr; concerning WISEBED, see http://www.wisebed.eu.

1568-4946/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.asoc.2011.03.023

tal power (BIP) algorithm proposed in [2]. Moreover, local search methods including tree-based methods such as [7,8] and power-based methods such as [9] have been developed. More recently the MEB problem was also tackled by metaheuristics [10–13]. The latest approaches are an ant colony optimization (ACO) approach proposed in [14] and the hybrid genetic algorithm presented in [15]. Even though no direct comparison is available between ACO and the hybrid genetic algorithm, a rough comparison can be made based on the results obtained by the two algorithms for a commonly used set of benchmark instances from the literature. In particular, for benchmark instances with 50 nodes, ACO finds on average for each instance an optimal solution in 29.7 out of 30 trials. On the contrary, the hybrid genetic algorithm on average only finds in 22.9 trials an optimal solution for the same problem instances. Moreover, the results of ACO are achieved in less computational time. Therefore, the ACO algorithm from [14] can currently be regarded as a state-of-the-art approach among the centralized techniques.

A comprehensive survey of existing work for the MEB problem and other related problems can be found in [16].

1.2. Our contribution

This work offers two contributions. The first one concerns a re-formulation of the classical MEB problem for an antenna model that is frequently encountered, for example, in antennas of sensor nodes such as SunSPOTs and iSense nodes. While the classical MEB problem is formulated for antennas where the transmission power can be adjusted to any desired real-value between 0 and the maximum transmission power, our re-formulation considers an antenna model where transmission powers must be chosen from a finite set of discrete values, as it is the case for the antennas found in SunSPOTs and iSense sensor nodes.

The second contribution of this article concerns the adaptation of the current state-of-the-art algorithm for the classical MEB problem to the re-formulated problem. The obtained results show that the advantage of this algorithm over classical heuristics even grows when the number of possible transmission power levels decreases.

1.3. Organization of the paper

Section 2 is devoted to the description of the minimum energy broadcast problem with realistic antennas. Then, in Sections 3 and 4 are described the adapted BIP algorithm, respectively the adapted ant colony optimization algorithm. Finally, in Section 5 we provide an experimental evaluation of the presented algorithms, whereas Section 6 will offer conclusions and an outlook to future work.

2. Minimum energy broadcasting with realistic antennas

Given a set of sensor nodes V, we assume that each node $i \in V$ can choose a transmission power level p_i such that $p_i \in P = \{tp_1, \ldots, tp_m\}$, where P is a finite set of m different transmission powers such that $tp_1 = 0$ and $tp_l < tp_{l+1}$ for all $l = 1, \ldots, m-1$. Moreover, we assume that signal power diminishes at a rate proportional to $r^{-\alpha}$, where r is the distance to the signal source, and α is a parameter that, depending on the environment, takes typically values between 2 and 4. In our work we choose $\alpha = 2$, as in most other works (see, for example, [2]). A sender node i is able to successfully transmit a signal to a receiver node j if $p_i \geq k \cdot d(i, j)^\alpha$, where $d(i, j)$ is the Euclidean distance between i and j, and k is the receiving node's power threshold for signal detection which is usually normalized to 1.

The minimum energy broadcast problem with realistic antennas (MEBRA), as introduced in the following, is *NP*-hard. This easily follows from being a generalization of the standard MEB problem as defined in the literature [17]. It can be stated as follows. Given is a set V of nodes with fixed positions in a 2-dimensional area. Introducing a directed link (i, j) between all (ordered) pairs $i \neq j$ of nodes such that $d(i, j)^\alpha \leq tp_m$, where $d(i, j)$ is the Euclidean distance between i and j, induces a directed network $G = (V, E)$. Given a source node $s \in V$, one must find transmission powers for all nodes such that a broadcast from s to all other nodes is possible, and such that the sum of all transmission powers is minimal. This corresponds to finding a directed spanning tree $T = (V, E_T)$ with root node s in G such that function $f()$, whose definition is given in the following, is minimized:

$$f(T) := \sum_{i \in V} \max_{(i,j) \in E_T} p_{ij} \tag{1}$$

where p_{ij} is the minimum transmission power level with which node j can receive the signal sent by node i. Technically, p_{ij} can be defined as follows:

$$p_{ij} := \min \left\{ tp_l \in P | l \in \{2, \ldots, m\},\, tp_l \geq d(i,j)^\alpha,\, tp_{l-1} < d(i,j)^\alpha \right\} \tag{2}$$

Note that a solution T is easily converted to a transmission power level p_i for each node $i \in V$ as follows. For all leaf nodes of T we choose $p_i = 0$, and for all other nodes $p_i := \max_{(i,j) \in E_T} p_{ij}$. An example of the MEBRA problem is given in Fig. 1.

3. BIP-algorithm for the MEBRA problem

As mentioned already in Section 1.1, the classical heuristic for the original MEB problem is the broadcast incremental power (BIP) algorithm proposed in [2]. In the following we outline the adaptation of this algorithm for the MEBRA problem, for two reasons. First, the way of constructing solutions that is employed by the BIP algorithm is also used by the ACO algorithm that will be outlined in Section 4. Second, the adapted BIP algorithm will be used as a benchmark method for comparison in Section 5.

The BIP algorithm starts off with a partial solution $T = (V_T, E_T)$, where $V_T := \{s\}$ and $E_T := \emptyset$. In other words, T only contains the source node s. Henceforth we denote by $\overline{V}_T$ the set of sensor nodes which are not included in the current partial solution, that is, $\overline{V}_T := V \setminus V_T$. At each construction step, an additional link is added to the current partial solution. The set $\mathcal{N}_T$ of potential links that can be added to T is defined as follows:

$$\mathcal{N}_T := \{(i, j) \in E | i \in V_T, j \in \overline{V}_T\}, \tag{3}$$

where E is the edge set of the directed network G as defined in Section 2. More specifically, $\mathcal{N}_T$ consists of those links whose source node is in T whereas the goal node is not in T. The choice of a link from $\mathcal{N}_T$ is done by means of a greedy function $\eta()$ that assigns a value to each $e \in \mathcal{N}_T$. The BIP algorithm uses the following greedy function:

$$\eta(e) := f(T') - f(T), \tag{4}$$

where T' is defined as T with link e already added.[2] In other words, the greedy function accounts for the increase of transmission power caused by adding a link e. At each step of the BIP algorithm, the link $e \in \mathcal{N}_T$ with minimal greedy value is chosen.

After choosing a link $e = (i, j)$ for the expansion of the current partial solution T, all the other links from $\mathcal{N}_T$ (if any) that can be added to T without any further increase of transmission powers are also added to T (in addition to e). This concerns all links $e' = (i, k) \in \mathcal{N}_T$ with $d(i, k) \leq p_{ij}$. Note that the solution construction stops when $\overline{V}_T = \emptyset$.

---

[2] Remember that $f(\cdot)$ denotes the objective function of the MEBRA problem as defined in Equation 1.