Ant Colony Optimization for Energy-Efficient Broadcasting in Ad-Hoc Networks*

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Abstract. In wireless ad-hoc networks, nodes are generally equipped with batteries, making energy a scarce resource. Therefore, power consumption of network operations is critical and subject to optimization. One of the fundamental problems in ad-hoc networks is broadcasting. In this work we consider the so-called minimum energy broadcast (MEB) problem, which can be stated as a combinatorial optimization problem. We develop an ant colony optimization algorithm for two scenarios: networks in which nodes are equipped with omni-directional, respectively directional, antennas. The results show that our algorithm consistently outperforms other methods for this problem.

1 Introduction

Wireless networks such as ad-hoc and sensor networks are useful in many practical scenarios. While sensor networks find applications, for example, in healthcare and weather forecast, ad-hoc networks are often used, for example, to connect laptops or PDAs. The flexibility and low infrastructure cost they offer make them quite popular, and, as a consequence, they have received much attention from the research community in recent years. Nodes in ad-hoc networks, acting potentially both as routers and hosts, are generally equipped with either omni-directional or directional antennas for sending and receiving information. They have a packet-forwarding capability in order to communicate via shared and limited radio channels. Communication may be performed by one-to-one transmissions (single-hop) or using other nodes as relay stations (multi-hop). In both cases each sender node must adjust its emission power in order to reach the respective receiver node. In cases where energy is supplied by batteries, the network lifetime is limited by the batteries of the wireless devices. Therefore, energy saving is critical in all network operations.

A fundamental problem in ad-hoc networks arises when one node is required to transmit data to all other nodes of the network. This scenario is known as

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broadcasting. In this work we study this problem for two cases. In the first one, each network node is equipped with an omni-directional antenna. However, omni-directional antennas often waste energy, for example, when information must only be sent to one neighboring node. Therefore, we also study the case of directional antennas, which additionally provide the advantage of reducing the interference with other nodes due to the reduced submission area.

As most other works in this area we consider the following wireless communication model (see [1]). Given a set of network nodes V, each node $i \in V$ can choose an emission power p_i such that $0 \leq p_i \leq p_{\max}$, where $p_{\max}$ is the maximum emission power possible. By setting $p_{\max}$ to ∞ we ensure that broadcasting is always possible. 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 (as in most other works; [2]) $\alpha = 2$. 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 p_i is the emission power, $d(i,j)$ 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.

In the case of directional antennas we use an idealized model (as used, for example, in [2]) in which we assume that the transmitted energy is concentrated uniformly in a beam of width θ, that is, we neglect fading effects at the borders of the beam. We assume that the beam-width θ can be chosen for each antenna so that $\theta_{\min} \leq \theta \leq 360$. As in [2] we chose $\theta_{\min} = 30$. Furthermore, we assume that each antenna beam can be pointed in any desired direction in order to provide connectivity to a set of the nodes that are within communication range and within the sector covered by the beam. The energy spent by a node i transmitting to a node j at a beam-width of θ_i is:

$$p_{ij}^{\theta_i} := \frac{\max\{\theta_i, \theta_{\min}\}}{360} \cdot d(i,j)^\alpha \tag{1}$$

This shows that a node i equipped with a directional antenna only uses 1/12 of the energy used by an omni-directional antenna to transmit information to just one other node j.

1.1 Minimum Energy Broadcast (MEB)

The MEB problem is an NP-hard optimization problem [3] both in case of omni-directional and directional antennas. 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 $d(i,j)^\alpha \leq p_{\max}$, where $d(i,j)$ is the Euclidean distance between i and j, induces a directed network $G = (V, E)$. In the following we first deal with the case of omni-directional antennas. Given a source node $s \in V$, one must find emission powers for all nodes such that a broadcast from s to all other nodes is possible, and such that the sum of all emission powers is minimal. This corresponds to finding a directed spanning tree $T = (V, E_T)$ with root node s in G such that function $P_o()$ is minimized:

$$P_o(T) := \sum_{i \in V} \max_{(i,j) \in E_T} d(i,j)^\alpha \tag{2}$$

In the case of directional antennas, in addition to an emission power, a beam-width θ_i and a beam direction must be chosen for each node $i \in V$. Again, this corresponds to finding a directed spanning tree $T = (V, E_T)$ with root node s in G such that function $P_d()$ is minimized:

$$P_d(T) := \sum_{i \in V} \frac{\max\{\theta_i, \theta_{\min}\}}{360} \cdot \max_{(i,j) \in E_T} d(i,j)^\alpha \ , \tag{3}$$

where θ_i is set to the minimum beam-width possible such that all children of i in T are reached. The beam direction follows automatically from the known locations of all the children of i in T.

1.2 Existing Work

The MEB problem in case of omni-directional antennas has been tackled with centralized heuristics as, for example, [4,5,6]. The most popular constructive technique is the *broadcast incremental power* (BIP) algorithm by Wieselthier et al. [4]. 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 [10,11,12,13]. The case of directional antennas is less studied. Constructive algorithms include, for example, the version of BIP for directional antennas: DBIP [2]. Other approaches can be found, for example, in [14,15]. Finally, in [16] is proposed a mixed integer linear programming (MILP) formulation that solves the case of directional antennas, which also includes—in case $\theta_{\min} = 360$—the case of omni-directional antennas. A comprehensive survey on existing work is given in [17].

Our paper is organized as follows. First, a detailed description of our algorithm proposal will be given in Sec. 2. In Sec. 3 we present an experimental evaluation of our algorithm, comparing the results to recent techniques. Finally, in Sec. 4 we provide conclusions and an outlook to future work.

2 The Algorithm

In this work we propose an ant colony optimization (ACO) algorithm [18] for the MEB problem. In the following we give an algorithm description that covers both the case of omni-directional and the case of directional antennas. Differences between both cases will be pointed out when necessary.

Local Search: r-shrink. The local search procedure r-shrink was originally developed in [9] for the case of omni-directional antennas. Here we use an adaptation that can also be applied for directional antennas. Given a solution $T = (V, E_T)$ and a parameter $r \leq |V| - 1$ as input, our version of r-shrink works as follows. First, a permutation of all nodes is produced. Nodes with $k \geq r$ children

Algorithm 1. Variable neighborhood descent (VND)

1: INPUT: the network $G = (V, E)$, a source node $s \in V$, a spanning tree $T = (V, E_T)$ of G rooted in s, a parameter $r_{\max}$
2: $r := 1$
3: **while** $r \leq r_{\max}$ **do**
4: $T' := r$-shrink(T)
5: **if** $P(T') < P(T)$ **then** $T := T'$ and $r := 1$ **else** $r := r + 1$
6: **end while**
7: OUTPUT: a (possibly) improved tree T

are treated as explained in the following, in the order given by the permutation. When a node i is treated, first, the children of i are ordered in a decreasing manner concerning the emission power reduction achieved by disconnection. Note that an emission power reduction of i may result from a possible distance reduction and, in the case of directional antennas, also from a possible beam-width reduction. Then the first r children are disconnected from i, and the algorithm tries to reconnect them to any of their non-descendants in the best way possible, that is, in a way that is least energy consuming.

In [9] only the 1-shrink procedure was experimentally evaluated. In contrast, we decided to utilize the general r-shrink procedure within a variable neighborhood descent (VND) algorithm [19], which is outlined in Alg. 1. Note that $P()$ stands either for $P_o()$ (in the case of omni-directional antennas) or $P_d()$ (in the case of directional antennas). The VND algorithm requires an appropriate setting of the parameter $r_{\max}$ (see Sec. 3).

ACO for the MEB Problem. The specific ACO algorithm that we implemented for the MEB problem is a $\mathcal{MAX}$–$\mathcal{MIN}$ Ant System ($\mathcal{MM}$AS) in the Hyper-Cube Framework [20]. It works roughly as follows. At each iteration $n_a = 10$ artificial ants construct a tree rooted at the source node s. Local search is applied to each of these trees. The pheromone model $\mathcal{T}$ used by our ACO algorithm contains a pheromone value τ_e for each link $e \in E$. After the initialization of the variables T^{bs} (i.e., the best-so-far solution), T^{rb} (i.e., the restart-best solution), and cf (i.e., the convergence factor), all the pheromone values are set to 0.5. At each iteration, after the generation of solutions, some of them are used for updating the pheromone values. The details of the algorithmic framework shown in Alg. 2 are explained in the following.

$\mathsf{ConstructBroadcastTree}(G,s)$: A solution construction starts with the partial solution $S = (V_S, E_S)$ where $V_S := \{s\}$ and $E_S := \emptyset$. Remember that s is the source node of the directed spanning tree to be constructed. Henceforth we denote by $\overline{V_S}$ the set of nodes which are not included in the current partial solution, that is, $\overline{V_S} := V \setminus V_S$. At each construction step, one link (and one node) is added to the current partial solution. The set E_{add} of potential links that can be added to S is defined as follows: $E_{\text{add}} := \{(i, j) \in E | i \in V_S, j \in \overline{V_S}\}$. In words, E_{add}

Algorithm 2. ACO for the MEB problem

```
INPUT: the network G = (V, E) and a source node s ∈ V
T^bs := NULL, T^rb := NULL, cf := 0, bs_update := FALSE
forall e ∈ E do τ_e := 0.5 end forall
while termination conditions not satisfied do
  for j = 1 to n_a do
    T^j := ConstructBroadcastTree(G,s)
    T^j := LocalSearch(T^j)
  end for
  T^ib := argmin{f(T^1), ..., f(T^{n_a})}
  Update(T^ib,T^rb,T^bs)
  ApplyPheromoneValueUpdate(cf,bs_update,𝒯,T^ib,T^rb,T^bs)
  cf := ComputeConvergenceFactor(𝒯, T^rb, T^bs)
  if cf ≥ 0.99 then
    if bs_update = TRUE then
      forall e ∈ E do τ_e := 0.5 end forall
      T^rb := NULL, bs_update := FALSE
    else
      bs_update := TRUE
    end if
  end if
end while
OUTPUT: T^bs
```

consists of those links whose source node is in S and whose goal node is not in S. From these links, one link is chosen according to the following probabilities:

$$\mathbf{p}(e) := \frac{\tau_e \cdot \eta(e)}{\sum_{e' \in E_{\text{add}}} \tau_{e'} \cdot \eta(e')} \ , \tag{4}$$

where $\eta(e)$ is the heuristic information of a link $e = (i, j)$ which is computed as follows: $\eta(e) := (P_o(S') - P_o(S))^{-1}$ (respectively, $\eta(e) := (P_d(S') - P_d(S))^{-1}$ in the case of directional antennas), where $S' = (V_S \cup \{j\}, E_S \cup \{e\})$. In words, the heuristic information accounts for the increase of emission power spent by the partial solution when adding link e. After choosing a link $e = (i, j)$ for the expansion of the current partial solution S, all the other links of E_{add} (if any) that can be added to S without any further increase of emission powers are also added to S (in addition to e). For example, in the case of omni-directional antennas, this concerns all links $e' = (i, l) \in E_{\text{add}}$ with $d(i, l) \leq d(i, j)$. In the case of directional antennas, the node l is additionally required to be within the beam implicitly defined by all links $e(i, *)$ that are already in S (including $e = (i, j)$).

As E_{add} might contain quite a lot of bad-quality links (especially at the beginning of the construction process) we decided to study also ways of restricting E_{add}. In the following we refer to the use of the unrestricted set E_{add} as *mode 1*.

In contrast, *mode 2* works as follows. $\forall\, j \in \overline{V_S}$ let $E_{\mathrm{add},j} := \{(*, j) \in E_{\mathrm{add}}\}$, that is, $E_{\mathrm{add},j}$ contains all links of E_{add} with goal node j. Moreover, let $b(E_{\mathrm{add},j}) := \mathrm{argmax}_{e \in E_{\mathrm{add},j}}\{\eta(e)\}$, that is, $b(E_{\mathrm{add},j})$ is the link of $E_{\mathrm{add},j}$ with the best heuristic information value. Given these definitions, in *mode 2* set E_{add} is restricted as follows: $E^{\mathrm{m2}}_{\mathrm{add}} := \cup_{j \in \overline{V_S}}\{b(E_{\mathrm{add},j})\}$, that is, only the best link to each node in $\overline{V_S}$ is considered. In the following, let $l := \mathrm{argmax}_{j \in \overline{V_S}}\{\eta(b(E_{\mathrm{add},j}))\}$. Note that l can be regarded as the *best node* in $\overline{V_S}$. Then, the restriction of set E_{add} in *mode 3* is obtained as follows: $E^{\mathrm{m3}}_{\mathrm{add}} := \{(*, l) \in E_{\mathrm{add}}\}$, that is, $E^{\mathrm{m3}}_{\mathrm{add}}$ contains all the links of E_{add} that have l (the best node) as goal node. In addition to the 3 modes outlined above we tested a fourth mode that is obtained by assigning *mode 2* and *mode 3* each to half of the ants used by the algorithm.

$\mathsf{LocalSearch}(T^j)$: In the case of omni-directional antennas, solutions constructed by the ants may contain nodes whose emission powers can be reduced without destroying the broadcast property of the solution. Therefore, in case of omni-directional antennas, we first apply the so-called SWEEP procedure (see [4]) in order to detect and fix these cases. Then, the VND algorithm as outlined before is applied in both antenna cases.

$\mathsf{Update}(T^{ib}, T^{rb}, T^{bs})$: In this procedure T^{rb} and T^{bs} are set to T^{ib} (i.e., the iteration-best solution), if $P_o(T^{ib}) < P_o(T^{rb})$ and $P_o(T^{ib}) < P_o(T^{bs})$ (respectively, $P_d(T^{ib}) < P_d(T^{rb})$ and $P_d(T^{ib}) < P_d(T^{bs})$ in the case of directional antennas).

$\mathsf{ApplyPheromoneUpdate}(\mathit{cf}, \mathit{bs\_update}, \mathcal{T}, T^{ib}, T^{rb}, T^{bs})$: Our ACO algorithm may use three different solutions for updating the pheromone values: (i) the iteration-best solution T^{ib}, (ii) the restart-best solution T^{rb} and, (iii) the best-so-far solution T^{bs}. Their influence depends on the convergence factor cf, which provides an estimate about the state of convergence of the system. To perform the update, first an update value ξ_e for each link $e \in E$ is computed: $\xi_e := \kappa_{ib} \cdot \delta(T^{ib}, e) + \kappa_{rb} \cdot \delta(T^{rb}, e) + \kappa_{bs} \cdot \delta(T^{bs}, e)$, where κ_{ib} is the weight of T^{ib}, κ_{rb} the weight of T^{rb}, and κ_{bs} the weight of T^{bs} such that $\kappa_{ib} + \kappa_{rb} + \kappa_{bs} = 1.0$. The δ-function is the characteristic function of the set of links in a tree T, that is, $\delta(T, e) = 1$ if $e \in E(T)$, and $\delta(T, e) = 0$ otherwise. Then, the following update rule is applied to all pheromone values τ_e:

$$\tau_e := \min\{\max\{\tau_{\min}, \tau_e + \rho \cdot (\xi_e - \tau_e)\}, \tau_{\max}\} \quad ,$$

where $\rho \in (0, 1]$ is the learning rate, set to 0.1. The upper and lower bounds $\tau_{\max} = 0.99$ and $\tau_{\min} = 0.01$ keep the pheromone values always in the range $(\tau_{\min}, \tau_{\max})$, thus preventing the algorithm from converging to a solution. After tuning, the values for κ_{ib}, κ_{rb} and κ_{bs} are chosen as shown in Table 1.

$\mathsf{ComputeConvergenceFactor}(\mathcal{T}, T^{rb}, T^{bs})$: This function computes, at each iteration, the convergence factor as

$$\mathit{cf} := \frac{\sum_{e \in E(T^{rb})} \tau_e}{(|E(T^{rb})| - 1) \cdot \tau_{\max}} \text{ ,respectively } \mathit{cf} := \frac{\sum_{e \in E(T^{bs})} \tau_e}{(|E(T^{bs})| - 1) \cdot \tau_{\max}} \quad ,$$

Table 1. The schedule used for values κ_{ib}, κ_{rb} and κ_{bs} depending on cf (the convergence factor) and the Boolean control variable *bs_update*

	bs_update = FALSE			*bs_update* = TRUE
	$cf < 0.7$	$cf \in [0.7, 0.9)$	$cf \geq 0.9$	
κ_{ib}	2/3	1/3	0	0
κ_{rb}	1/3	2/3	1	0
κ_{bs}	0	0	0	1

if *bs_update* = FALSE, respectively if *bs_update* = TRUE. Here, $\tau_{\max}$ is the upper limit for the pheromone values. The convergence factor cf can therefore only assume values between 0 and 1. The closer cf is to 1, the higher is the probability to produce the solution T^{rb} (or T^{bs} analogously).

3 Experimental Evaluation

We implemented our algorithm in ANSI C++ using GCC 3.2.2 for compiling the software. Our experimental results were obtained on a PC with an AMD64X2 4400 processor and 4 GB of memory. We used the same set of benchmark instances as in [12,13]. This set consists of 30 problem instances with 20 nodes each, and further 30 problem instances with 50 nodes.

Results for Omni-Directional Antennas. First, we conducted tuning experiments concerning parameter $r_{\max}$ of the VND algorithm (see Alg. 1), the construction mode, and a so-called candidate list strategy, which is a mechanism that reduces the set of all possible choices (in a solution construction step) to the best k choices, where k is a parameter. We tested $k \in \{4, 8, \text{all}\}$, where "all" means that no candidate list strategy is used. The best results were achieved with $r_{\max} = |V| - 1$, construction *mode 2*, and a candidate list of size 8. See [21] for more details.

We applied our algorithm 30 times for 5 seconds to each of the 30 problem instances with 20 nodes and for 20 seconds to each of the 30 problem instances with 50 nodes. Concerning the problem instances with 20 nodes our algorithm produced an optimal solution for each instance in each run. On average our algorithm needed 0.001 seconds to find these solutions. The ELS algorithm published in [13] finds (on average) in 24 cases (out of 30) an optimal solution. Moreover, the average computation time needed by ELS is 0.43 seconds on a computer with a 2.8 GHz Pentium IV processor.

The results for the problem instances with 50 nodes are shown (in comparison to NP [12], ELS [13], ILS [11], and BIP + VND) in Table 2. For comparison reasons we decided to use the same way of presenting the results as in [13]. The first table column contains the instance names. The second table column provides the values of the best solutions known. In case values are not marked with a $\leq$-sign, they are known to be optimal. For algorithms NP, ELS, and ACO we provide three values: The column headed by **excess** gives the excess (in percent) of the average of the values of the best solutions found in 30 trials over the optimal (respectively, best known) value. The column with heading **found** provides the number of trials in which the optimal (respectively, best known) value was found. Finally, the column titled **time (s)** contains the average computation times (in seconds) over 30 runs. For ILS we were not able to provide the computation time as it was not given in [13]. For algorithm BIP + VND we only provide the excess over the optimal (respectively, best known) solutions. Finally, the last table row gives averages over all instances. The results show that, first, our algorithm outperforms all other algorithms in terms of solution quality. Only in 2 cases our algorithm is not able to find the optimal (respectively, best known) solution in all trials. On average it is found in 29.7 out of 30 trials. The second-best algorithm, ELS, only finds an optimal (respectively, best known) solution in 17.3 trials on average.

Results for Directional Antennas. We conducted the same tuning experiments as outlined in the case of omni-directional antennas also for the case of directional antennas. With respect to these experiments we chose $r_{\max} = |V| - 1$, *mode 1* for solution construction, and a candidate list of size 8.

The results for the instances with 20 nodes are shown in Table 3 and for the instances with 50 nodes in Table 4. The format of these tables is as follows. The first column provides the instance name, the second column the result of DBIP + VND, and the remaining columns give the results of the ACO algorithm. Concerning ACO we provide the following information. The column with heading **best** gives the value of the best solution found in 30 trials, whereas the column titled **deviation** provides the improvement over DBIP + VND (in percent). Furthermore, the column **saving** shows how much emission power (in percent) could be saved in comparison to the case of omni-directional antennas. The remaining columns provide the average of the best solutions found in 30 trials (+ standard deviation), and the average of the computation times over 30 trials (+ standard deviation). The last table row provides the average improvement (over 30 instances) over DBIP + VND, the average emission power saving, and the average computation time over 30 instances.

The results show that both for instances with 20 nodes and instances with 50 nodes the improvement of ACO over DBIP + VND is on average more than 12%. Moreover, the average computation times are very low (0.08 seconds for the small instances, and 4.42 seconds for the big instances). It is interesting to note that the computation times are higher than in the case of omni-directional antennas. This accounts for the fact that the computation of the heuristic information is more complicated for directional antennas. Finally, it is also worth mentioning that the saving of emission power is enormous: on average 85.70% in the case of 20 nodes, and 85.86% in the case of 50 nodes.

For showing the difference between solutions in the case of omni-directional antennas in comparison to solutions for the same instance in the case of directional antennas we graphically present the best solutions that we found in Fig. 1. For example, while node 47 has a very high emission power in the solution for omni-directional antennas, it only sends information to two neighboring nodes in the solution for directional antennas.

Table 2. Results for instances with 50 nodes (omni-directional antennas)

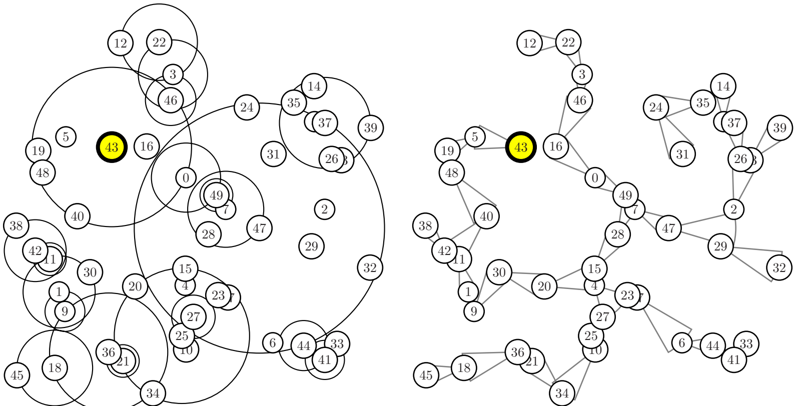
Instance	Best known	NP			ELS			ILS		BIP + VND	ACO		
		excess	found	time (s)	excess	found	time (s)	excess	found	excess	excess	found	time (s)
p50.00	399074.64	6.22%	0/30	11.4	0.41%	15/30	57.0	3.31%	0/30	9.89%	0.0%	30/30	0.52
p50.01	≤ 373565.15	3.68%	0/30	7.1	0.16%	5/30	47.0	3.30%	0/30	22.79%	0.0%	30/30	1.97
p50.02	393641.09	10.11%	0/30	10.3	0.28%	13/30	46.0	12.06%	0/30	17.39%	0.0%	30/30	2.84
p50.03	316801.09	6.43%	0/30	6.1	1.71%	11/30	57.0	6.48%	0/30	18.43%	0.0%	30/30	0.36
p50.04	≤ 325774.22	5.22%	0/30	7.5	0.30%	25/30	40.0	7.22%	0/30	17.04%	0.0%	30/30	1.89
p50.05	382235.90	3.28%	1/30	10.9	0.83%	16/30	31.0	2.57%	0/30	7.69%	0.0%	30/30	3.42
p50.06	≤ 384438.46	1.19%	5/30	10.2	0.0%	30/30	29.0	0.14%	18/30	13.50%	0.0%	30/30	3.54
p50.07	≤ 401836.85	6.70%	0/30	8.9	0.54%	24/30	64.0	7.80%	0/30	11.50%	0.0%	30/30	0.54
p50.08	334418.45	0.10%	27/30	4.6	0.0%	30/30	29.0	0.0%	30/30	11.43%	0.0%	30/30	0.73
p50.09	≤ 346732.05	9.20%	0/30	12.9	3.29%	0/30	102.0	11.42%	0/30	15.22%	0.0%	30/30	1.88
p50.10	416783.45	2.14%	0/30	8.9	1.16%	13/30	40.0	2.05%	0/30	12.80%	0.0%	30/30	0.85
p50.11	≤ 369869.41	4.34%	0/30	7.7	2.87%	1/30	28.0	4.62%	0/30	9.99%	0.0%	30/30	4.47
p50.12	≤ 392326.01	3.18%	0/30	13.5	0.57%	7/30	66.0	0.44%	0/30	6.82%	0.0%	30/30	0.42
p50.13	≤ 400563.83	6.63%	0/30	11.2	0.04%	29/30	74.0	1.20%	0/30	21.16%	0.0%	30/30	1.38
p50.14	388714.91	0.08%	22/30	6.6	0.34%	3/30	11.0	0.0%	30/30	34.93%	0.0%	29/30	2.26
p50.15	371694.65	0.40%	0/30	8.1	0.20%	5/30	35.0	1.40%	0/30	9.62%	0.0%	30/30	1.12
p50.16	≤ 414587.42	5.28%	0/30	15.1	0.30%	26/30	81.0	6.06%	1/30	5.51%	0.0%	30/30	0.48
p50.17	355937.07	2.17%	1/30	11.9	1.88%	17/30	33.0	4.94%	2/30	9.00%	0.0%	30/30	0.38
p50.18	376617.33	5.96%	0/30	11.3	0.24%	8/30	65.0	0.98%	12/30	7.28%	0.0%	30/30	0.55
p50.19	335059.72	2.27%	5/30	9.8	0.0%	30/30	28.0	10.49%	1/30	33.60%	0.0%	30/30	0.39
p50.20	414768.96	3.14%	0/30	10.4	0.15%	0/30	35.0	6.33%	0/30	9.54%	0.1%	21/30	5.85
p50.21	≤ 361354.27	2.93%	2/30	10.4	0.0%	30/30	41.0	0.0%	30/30	9.01%	0.0%	30/30	0.29
p50.22	329043.51	0.0%	30/30	7.2	0.0%	30/30	14.0	4.61%	0/30	25.49%	0.0%	30/30	0.74
p50.23	383321.04	6.39%	0/30	11.1	0.0%	30/30	109.0	2.47%	0/30	10.95%	0.0%	30/30	1.06
p50.24	404855.92	5.69%	0/30	10.0	0.07%	17/30	37.0	0.87%	3/30	10.42%	0.0%	30/30	0.53
p50.25	363200.32	0.0%	30/30	3.2	0.0%	30/30	7.0	0.0%	30/30	24.65%	0.0%	30/30	0.45
p50.26	406631.51	9.59%	0/30	11.5	2.17%	2/30	60.0	11.63%	0/30	12.67%	0.0%	30/30	2.16
p50.27	451059.62	4.18%	0/30	9.5	0.18%	22/30	40.0	3.35%	0/30	9.09%	0.0%	30/30	1.50
p50.28	≤ 415832.44	4.48%	0/30	11.6	0.47%	23/30	78.0	0.28%	0/30	8.63%	0.0%	30/30	0.38
p50.29	380492.77	0.0%	30/30	5.9	0.08%	27/30	18.0	0.60%	0/30	14.62%	0.0%	30/30	1.92
		4.03%	**5.1/30**	**9.5**	**0.61%**	**17.3/30**	**46.0**	**3.89%**	**5.23/30**	**14.37%**	**0.004%**	**29.7/30**	**1.49**

Table 3. Results for instances with 20 nodes (directional antennas)

Instance	DBIP + VND	ACO						
		best	deviation	saving	average	(std.)	time (s)	(std.)
p20.00	64822.56	63199.93	-2.51%	84.48%	63199.93	(0.00)	0.06	(0.05)
p20.01	76436.49	68398.52	-10.52%	84.70%	68398.52	(0.00)	0.02	(0.01)
p20.02	65690.63	47978.29	-26.97%	85.68%	47978.29	(0.00)	0.07	(0.07)
p20.03	68942.34	57398.42	-16.75%	88.25%	57398.42	(0.00)	0.04	(0.02)
p20.04	69845.03	66887.32	-4.24%	87.04%	66887.32	(0.00)	0.01	(0.01)
p20.05	51662.20	45238.84	-12.44%	84.96%	45238.84	(0.00)	0.04	(0.02)
p20.06	60070.64	51729.84	-13.89%	79.35%	51729.84	(0.00)	0.07	(0.06)
p20.07	55895.63	51571.88	-7.74%	85.16%	51571.88	(0.00)	0.03	(0.02)
p20.08	54367.14	49937.22	-8.15%	87.22%	49937.22	(0.00)	0.15	(0.21)
p20.09	65553.86	59488.68	-9.26%	86.71%	59488.68	(0.00)	0.07	(0.06)
p20.10	56304.30	48060.81	-14.65%	84.83%	48060.81	(0.00)	0.06	(0.06)
p20.11	61803.98	52576.87	-14.93%	81.82%	52576.87	(0.00)	0.06	(0.08)
p20.12	47662.65	46448.20	-2.55%	85.23%	46448.20	(0.00)	0.01	(0.01)
p20.13	73334.40	57650.44	-21.39%	83.35%	57650.44	(0.00)	0.03	(0.02)
p20.14	48983.67	39342.53	-19.69%	86.95%	39342.53	(0.00)	0.12	(0.12)
p20.15	63590.04	63346.56	-0.39%	86.15%	63346.56	(0.00)	0.01	(0.01)
p20.16	84518.63	70879.81	-16.14%	85.37%	70879.81	(0.00)	0.05	(0.03)
p20.17	95860.33	69089.46	-27.93%	81.83%	69089.46	(0.00)	0.06	(0.06)
p20.18	47485.69	46477.60	-2.13%	85.49%	46477.60	(0.00)	0.03	(0.02)
p20.19	72365.45	64180.43	-11.32%	86.09%	64180.43	(0.00)	0.07	(0.03)
p20.20	76200.32	66069.32	-13.30%	83.63%	66069.32	(0.00)	0.07	(0.08)
p20.21	45734.98	43714.14	-4.42%	83.93%	43714.14	(0.00)	0.02	(0.01)
p20.22	49408.07	47693.55	-3.48%	85.49%	47693.55	(0.00)	0.03	(0.02)
p20.23	53427.61	51555.92	-3.51%	84.22%	51555.92	(0.00)	0.02	(0.01)
p20.24	57184.69	49804.65	-12.91%	87.42%	49804.65	(0.00)	0.45	(0.45)
p20.25	97379.75	75132.03	-22.85%	83.43%	75132.03	(0.00)	0.46	(0.40)
p20.26	112701.77	83211.94	-26.17%	81.97%	83211.94	(0.00)	0.06	(0.04)
p20.27	66935.67	52136.30	-22.11%	86.60%	52136.30	(0.00)	0.01	(0.01)
p20.28	55028.32	52897.18	-3.88%	81.06%	52897.18	(0.00)	0.09	(0.05)
p20.29	57176.02	52294.99	-8.54%	82.54%	52294.99	(0.00)	0.06	(0.02)
			-12.16%	**84.70%**			**0.08**	

Table 4. Results for instances with 50 nodes (directional antennas)

Instance	DBIP + VND	ACO						
		best	deviation	saving	average	(std.)	time (s)	(std.)
p50.00	67637.45	57143.89	-15.52%	85.68%	57148.02	(2.97)	5.37	(5.12)
p50.01	60089.71	55020.28	-8.44%	85.27%	55022.15	(10.26)	4.33	(2.96)
p50.02	63117.46	55592.02	-11.93%	85.88%	55668.98	(77.17)	8.84	(5.25)
p50.03	49914.53	44151.86	-11.55%	86.06%	44151.86	(0.00)	1.29	(0.83)
p50.04	52739.20	49258.11	-6.61%	84.88%	49281.38	(27.07)	6.54	(5.36)
p50.05	62925.57	54624.04	-13.20%	85.71%	54628.36	(23.65)	3.36	(3.35)
p50.06	59134.80	51440.18	-13.02%	86.62%	51440.18	(0.00)	3.07	(2.17)
p50.07	60529.65	53677.16	-11.33%	86.64%	53677.16	(0.00)	0.84	(0.43)
p50.08	59745.12	53915.98	-9.76%	83.88%	53922.06	(33.31)	6.41	(4.58)
p50.09	55269.83	45721.73	-17.28%	86.81%	45721.73	(0.00)	2.26	(1.55)
p50.10	71832.64	60454.61	-15.84%	85.50%	60472.57	(79.99)	9.94	(5.68)
p50.11	58924.18	50641.36	-14.06%	86.31%	50641.36	(0.00)	1.41	(1.41)
p50.12	71670.15	52365.95	-26.94%	86.65%	52462.37	(150.22)	11.04	(4.95)
p50.13	56645.94	50693.12	-10.51%	87.34%	50693.12	(0.00)	3.32	(2.82)
p50.14	72412.21	58263.43	-19.54%	85.01%	58263.43	(0.00)	4.25	(2.34)
p50.15	55379.00	47647.14	-13.97%	87.18%	47647.14	(0.00)	1.77	(1.25)
p50.16	62602.95	53963.57	-13.81%	86.98%	53963.57	(0.00)	2.39	(1.58)
p50.17	62421.55	50597.19	-18.95%	85.78%	50597.24	(0.22)	4.66	(3.45)
p50.18	59991.97	53211.01	-11.31%	85.87%	53241.50	(56.21)	5.51	(5.21)
p50.19	57547.85	52356.87	-9.03%	84.37%	52387.81	(98.69)	7.37	(4.54)
p50.20	62215.55	55986.52	-10.02%	86.50%	55986.52	(0.00)	1.51	(0.94)
p50.21	57325.62	51102.38	-10.86%	85.86%	51136.06	(25.56)	9.07	(5.48)
p50.22	60044.05	52484.70	-12.59%	84.05%	52484.70	(0.00)	1.96	(1.40)
p50.23	58439.32	51386.64	-12.07%	86.59%	51386.64	(0.00)	5.59	(4.08)
p50.24	68262.05	57834.24	-15.28%	85.71%	57834.24	(0.00)	2.20	(1.52)
p50.25	70594.71	60369.77	-14.49%	83.38%	60406.47	(65.84)	9.93	(5.37)
p50.26	61786.70	56527.63	-8.52%	86.10%	56527.63	(0.00)	5.16	(3.21)
p50.27	66161.21	59330.71	-10.33%	86.85%	59330.71	(0.00)	1.29	(0.53)
p50.28	61571.83	55646.64	-9.63%	86.62%	55646.64	(0.00)	0.72	(0.26)
p50.29	61768.29	54511.41	-11.75%	85.67%	54511.41	(0.00)	1.21	(0.72)
			-12.94%	**85.86%**			**4.42**	



(a) Value: 316801.09 (b) Value: 44151.86

Fig. 1. Best solutions found for instance p50.03. (a) shows the solution in the case of omni-directional antennas, and (b) shows the solution for directional antennas.

4 Conclusions and Future Work

In this work we presented an ant colony optimization algorithm using a sophisticated local search procedure for the minimum energy broadcast problem in static wireless ad-hoc networks. In the case of omni-directional antennas our algorithm outperforms existing metaheuristics and heuristics in solution quality as well as in computation time. In the case of directional antennas we could show that our algorithm greatly improves over the results of a well-known heuristic enhanced by our VND algorithm. In the future we plan to adapt our algorithms to the case of multicasting. Moreover, we plan to develop distributed algorithms that are more practical in real applications.

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