This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE CCNC 2006 proceedings.

Data Dissemination Based on Ant Swarms for Wireless Sensor Networks

S. Selvakennedy
School of IT
Madsen Bldg F09
University of Sydney,
NSW 2006, Australia.
skennedy@it.usyd.edu.au

S. Sinnappan
Graduate School of Business &
Professional Development,
University of Wollongong, NSW
2522 Australia
suku@uow.edu.au

Yi Shang
Dept. of Computer Science,
University of Missouri-Columbia,
Columbia,
MO 65211, USA.
shangy@missouri.edu

Abstract— **There are many difficult challenges ahead in the design of an energy-efficient communication stack for wireless sensor networks. Due to the severe nodes' constraints, protocols have to be simple yet scalable. To this end, collective social insects behavior could be adopted to guide the design of these protocols. We exploit the simple behaviors of ant swarms in foraging and brood sorting to design a hierarchical and scalable data dissemination strategy. In order to allow a realistic evaluation, a comprehensive simulator involving critical components of the communication stack is incorporated. The proposed scheme promotes a uniform distribution of clusterheads, which subsequently enables substantial energy savings over other clustering algorithms.**

Keywords-clustering; data dissemination; energy efficient; swarm intelligence.

I. INTRODUCTION

Wireless sensor technology is garnering a lot of interests due to its promises, enabling it to evolve rather rapidly. For instance, in terms of the sensor node hardware, the Mica2 mote has roughly eight times the memory and communication bandwidth as its predecessor, the Rene mote, developed in 1999 for the same power budget [1]. These sensor nodes have found use in many applications such as earthquake monitoring, target tracking and surveillance, and structural monitoring. The nodes are typically less mobile due to their unique application needs, substantially more resource constrained and more densely deployed than mobile ad hoc networks (MANETs). Even though, there have been significant advances in recent years, more energy-efficient solutions are required within the communication stack for the conservation of the battery power. An approach that is likely to succeed is the use of a hierarchical structure [2], which also promotes scalability of wireless sensor networks (WSNs).

Clustering with data aggregation is an important technique in this direction, and it makes the tradeoff between energy efficiency and data resolution. Most clustering algorithms aim at generating the minimum number of clusters and transmission distance. These algorithms also distinguish themselves by how the clusterheads (CHs) are elected. The LEACH algorithm [3] and its related extension [4] use probabilistic self-election, where each sensor node has a probability *p* of becoming a CH in each round. In [4], the authors proposed the time-controlled clustering algorithm (TCCA) that allows the formation of multihop clusters dynamically. By considering both intra- and inter-cluster traffic, it was demonstrated that for TCCA's optimal operation, small multihop clusters of two or three hops seem to be the most appropriate size.

Another crucial design issue to consider is the network reliability. To this end, social insect swarm behavior may provide an ideal model for the design of such less controllable systems. To our knowledge, very few researchers have considered or adopted such nature-inspired approaches for WSN design. However, a number of recent works has been based on different swarm behaviors in the design of routing protocols for MANETs. As there are many important similarities between these two ad hoc technologies, we believe building on these knowledge may be useful for WSNs.

Most of these swarm-based routing algorithms are simple yet robust as well as adaptive to topological changes. However, such algorithms cannot establish the *best* paths before sufficient number of agents is flooded [5]. This implies that as the number of nodes in the network increases, the number of agents required to establish the routing infrastructure may explode. A way to overcome the overhead explosion and attain scalability is by using hierarchical routing approach. In a pioneering work [6], the authors had used swarm intelligence to implement a distributed network of mobile sensors and controlled the nodes physical movements. It was demonstrated that the swarm behavior could be used to ensure *safe separation* between the agents to ensure *coverage efficiency* while enforcing a level of *cohesion* that maintains a level of connectivity between the mobile agents.

In this paper, we propose a new clustered data dissemination strategy based on the ant swarm behavior. This scheme is realized based on our initial clustering algorithm proposal, TCCA [4]. Unlike TCCA, an ant swarm dynamically controls the CH election process instead. This new algorithm incorporating the **T**CCA clustering with this **ANT** election scheme is termed as the T-ANT algorithm. T-ANT achieves better performance than that of a flat dissemination strategy, LEACH and plain TCCA. The algorithm achieves the objectives by exploiting two swarm behaviors, namely foraging and brood sorting.

II. RELATED WORK

The approach that is likely to succeed to provide a scalable and energy-efficient solution is of a hierarchical structure. Initially, the clustering algorithms focused on the connectivity problem [7] but later energy-efficiency was more of interest [3, 4, 8]. However, almost all focuses on reducing the number of clusters formed, which may not necessarily entail minimum energy dissipation. Generally, clustering algorithms segment a network into non-overlapping clusters comprising a CH each. Non-CHs transmit sensed data to CHs, where the sensed data could be aggregated and transmitted to the sink.

LEACH [3] requires position knowledge to perform a precise transceiver power control, and self-elects CHs using a nominated probability p. The algorithm ensures that every node will be nominated as a CH only once in $1/p$ rounds for a certain fixed duration. However, it assumes that all nodes are in each other's radio range. In [9], a fixed clustering algorithm that performs energy-balancing to improve network lifetime was proposed. It also takes into consideration the interaction between clustering and routing.

Another crucial design aspect of WSNs to consider is the network reliability and fault-tolerance. It has been demonstrated in different context that the collective behavior of social insects has many attractive features, not the least robustness and reliability. However, only very limited WSN proposals have been inspired by nature or biologically.

In social insects, sophisticated community behavior emerges from the interaction of individuals where each insect carries out simple tasks. Some known collective behaviors are foraging, nest construction, thermoregulation, brood sorting and cemetery formation [10]. When ants die, they are removed from the nest by workers and deposited in piles outside the nest. The cause to this action appears to be an attraction between dead bodies, but remains to be confirmed. These collective behaviors of social insects have inspired computer scientists to replicate them as they exhibits many attractive features, such as robustness and reliability through redundancy [5, 10].

The first MANET routing algorithm based on ant colony principles is ARA [11]. It exploited the ant *pheromone* laying behavior. Pheromone is a quality metric indicating the goodness of a path. Although pheromone evaporates over time, subsequent ants leave additional pheromone and thus reinforce the path. Ants gradually establish the shortest path between food and their nest in a fully distributed and autonomous manner. The fact of the gradual decay of pheromone introduces a form of a negative feedback to prevent old routes from remaining in the forwarding tables when routes fall out of favor with ants. Routing schemes based on such colony behavior is both robust and adaptable. When the shortest route is lost due to some event, the longer routes provide alternative options.

There are three basic controlling behaviors that govern movements of agents within the swarm. Kadrovach and Lamont [6] have summarized these behaviors as shown:

- Separation: Avoid collisions with *nearby* agents.
- Alignment: Attempt to match velocity with *nearby* agents.
- Cohesion: Attempt to stay close to *nearby* agents.

Swarm behavior is solely based on locally observable phenomena, and is reflected above by the adjective *nearby*. The integration of these behaviors results in a stable swarm formation, where every agent is at least some minimum distance from others. We capitalize on the first two behaviors through pheromone control to achieve a near uniform distribution of the CHs nodes. Moreover, the algorithm converges faster to an optimal or near optimal solution when pheromone is also reduced drastically from those elements that make up the worst solution in each iteration. Thus, subsequent generations of ants are discouraged from returning to poorer solutions seen in the past. This constitutes the simplest way to implement *anti-pheromone* where the removal of pheromone is simulated by a reduction in existing pheromone levels.

III. THE T-ANT CLUSTERING ALGORITHM

T-ANT adopts two-phase clustering process involving the cluster setup and steady state phases. To guide the CH election, we chose to use a swarm of ants. Through the use of a swarm of ants, we would guarantee that the network always maintains an optimal number of clusters.

During the node initialization, the sink releases a number of ants (i.e. control messages). Ramos and Merelo [12] suggest that the ratio of the number of ants to the number of objects (i.e. sensor nodes) should equal 0.1. When the sink releases an ant, it chooses one of its neighbors at random. The ant could travel into the network as deep as restricted by its time-to-live (TTL) field. When an ant arrives at a node, the next node is randomly chosen (excluding the sender) for its subsequent stop if TTL has not expired. If TTL expires, the ant remains at this node. However, if the final ant location overlaps with another ant, the former ant must find another location.

The cluster setup (CS) phase is controlled through a CS timer. When this timer expires, a node checks to see whether it possesses an ant. If the node has an ant, it becomes a CH. When a node becomes a CH, it advertises to its neighbors by broadcasting an ADV message with its node id and a TTL field to constrain the ADV propagation. Upon receiving an ADV message, a regular node records the CH id, the sender's id as its parent, the hop distance to this CH, the number of ADV messages received so far and total hop distance to all *seen* CHs, and then rebroadcasts it if TTL permits. A node decides to join a cluster when its join-timer expires. It then computes its *pheromone* level based on its total hop distance (h) to CHs, the number of CHs (n) in its neighborhood, and its normalized residual energy. The pheromone expression is based on the forwarding probability formula used in the ant routing algorithm [5], but expanded as:

$$p = \frac{p + \Delta p}{1 + \Delta p} \tag{1}$$

where Δp is given by:

$$\Delta p = \frac{k}{h_*^2} \times \frac{E_{resi}}{E_{max}} \times \frac{\sum_{i=1}^{n} h_i}{n} \quad (2)$$

h_* is the node's hop distance to the selected CH, E_{resi} is the residual energy, E_{max} is the reference maximum battery energy and k is the learning rate of the algorithm (= 0.1). This expression ensures that Δp is higher when the node is only reachable by fewer CH nodes (smaller n), far from CHs ($\sum h_i$), has higher residual energy (E_{resi}) or is nearer to its selected CH (h_*). A regular node chooses the best cluster to join based on its hop distance to the CH, which would ensure minimal energy dissipation during the data dissemination rounds. The node joins a cluster by sending a JOIN message with its id, the selected CH id and its pheromone level. If the CH is in range, the message is transmitted directly; otherwise forwarded through its parent to the CH. When a CH receives JOIN messages, it finds the member with the highest pheromone level to attract its ant for the next round.

Before the next CS timer expires, the ants wander to the nodes with the highest pheromone level among their neighbors, and these nodes will be the future CH. Before an ant leaves its current node, an amount of anti-pheromone is laid to mimic a rapid decay of pheromone level. The pheromone removal is computed with the anti-pheromone rate (β).

The given pheromone expression guides the evolution of the swarm to achieve the *separation* behavior between ants in the swarm as discussed earlier. It is found empirically that separation is attained rather quickly within 3-5 rounds as an optimal swarm size is used. Another useful swarm behavior is *alignment*. In our context, the *area* served by each ant represents the alignment behavior. It is reflected by the number of members in a cluster. When the swarm evolves to achieve separation, alignment is also achieved as a side-benefit. The phenomena due to both behaviors are captured by the following fitness functions, respectively. The CH election fitness function S to capture the separation behavior is:

$$S = \sum_{i=1}^{n_c} \frac{n_i}{\sum_{j=1}^{n_i} h_{ij}} \quad (3)$$

where n_c is the number of CH nodes, n_i is the number of ADVs seen by CH i and h_{ij} is CH i's hop distance to CH j. The clustering fitness function A to represent the alignment behavior is as follows:

$$A = \sum_{i=1}^{n_r} h_i \quad (4)$$

where n_r is the number of regular nodes and h_i is node i's hop distance to its CH.

In the steady state phase, each regular node sends or forwards its sensory data to its CH. It is possible that the foraging ants may die due to the environmental uncertainty or node failure. To avoid a reducing number of ants in the network over time, ants have a finite lifetime. When ants die, the sink re-releases the same optimal number of ants to restart the process.

IV. RESULTS AND DISCUSSIONS

We investigate T-ANT performance against LEACH, plain TCCA and a flat strategy. Since LEACH can't be applied directly to a multihop network, we modified this algorithm to use a routing protocol to forward messages whenever the destination is not within the radio range. We termed this modified algorithm as multihop-LEACH (or m-LEACH).

For these simulation experiments, we assumed that there are 100 sensor nodes distributed randomly in a square $M \times M$ region with $M = 500$ m. The transceiver energy parameters are set as: $E_{elec} = 50$ nJ/bit and $\varepsilon_{fs} = 10$ pJ/bit/m^2. The energy for data aggregation is set to $E_{DA} = 5$ nJ/bit per signal [3]. The control and data message sizes are fixed at 30 bytes, and sensory data is generated at 2-second interval. Each CH node retains its CH status for 20 seconds. The number of ants is fixed at 10 and the anti-pheromone rate is 0.1.

The performance metrics being investigated are: *Clustering fitness*: It represents the goodness of the cluster formation involving all regular nodes; *CH election fitness*: It represents the goodness of all the elected CH nodes; *Average energy per round*: It represents the average energy usage by the nodes per round; and *Network lifetime*: It represents the period from the instant the network is deployed to the moment when the first sensor node runs out of energy.

Figure 1 depicts the clustering fitness value at different simulation time. For T-ANT, the initial value is high indicating that the swarm has not yet achieved the alignment behavior as the ants are randomly released into the network. However, as pheromone is laid and anti-pheromone takes effect during CS phases, the swarm alignment improves. Within the third evolution, the swarm is able to align. As for the other schemes, the fitness value varies rather wildly. Unlike T-ANT, TCCA mostly operates in sub-optimal fashion. Also for m-LEACH, the fitness value is always smaller than the other schemes due to the ADV messages being limited to first-hop nodes. Any u*ncovered* nodes would have to resort to *direct* transmission to the sink. Since m-LEACH and TCCA have probabilistic CH election, it is possible that the CHs may even be clumped. When the CHs are clumped, the disparity among clusters is large in terms of their number of members, as each CH contends for the same regular nodes pool.

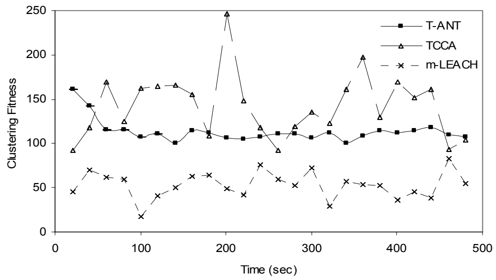


Figure 1. Clustering fitness at different simulation time for T-ANT, m-LEACH and TCCA.

In Fig. 2, the CH election fitness is depicted for the same three algorithms. Again, consistent behavior as above is obtained. For T-ANT, it has a higher function value initially, but it quickly converged somewhat. The ants move to a better node based on the calculated pheromone level, and within five rounds, the swarm is able to achieve the separation behavior. This behavior ensures the elected CHs are distributed as uniformly as possible. Even after the uniformity is achieved, the ants keep moving at each round to ensure that the CH role is shared among nodes, and energy-load balancing is attained. As for the other schemes, the topology barely settles and mostly has a lower value than T-ANT. A lower value indicates that the CHs in these schemes are mostly too close to each other. In m-LEACH, the fitness function quite often assumes a zero value compared to TCCA. This is mainly due to its restricted ADV propagation, where a CH is unable to recognize another CH located only two hops away.

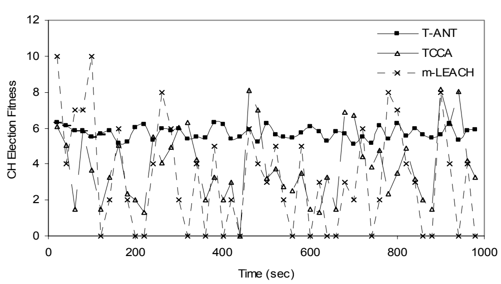
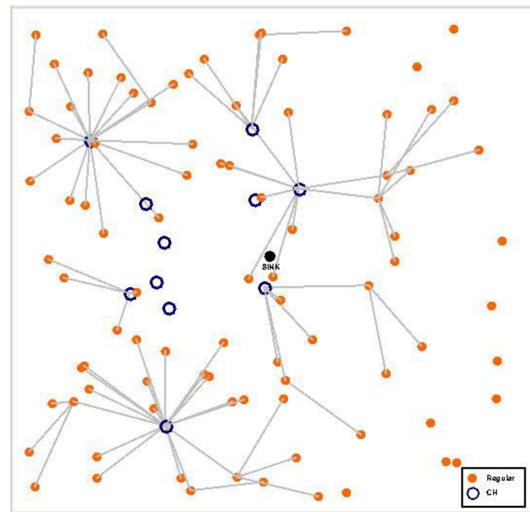
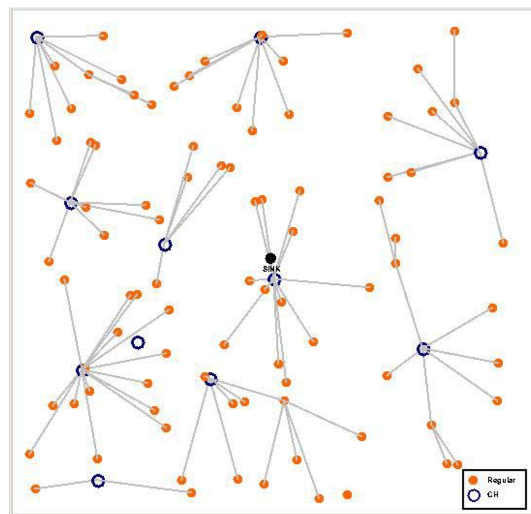


Figure 2. CH election fitness at different simulation time for T-ANT, m-LEACH and TCCA.

The following results demonstrates how T-ANT promotes uniform CH distribution in the network compared to TCCA (or m-LEACH). Fig. 3 depicts the clustered topology formation at different CH rounds for cluster size of two. We chose to use 11 ants. In the following figures, unfilled circles represent CHs, filled circles represent regular nodes, and the line segments link members to their CH or through their parent to CH. Unlinked regular nodes have to perform *direct* transmission to the sink. It is visually evident that when the sink randomly releases the ants, they could still be forced to neighboring nodes, which results in some regular nodes being *uncovered*, as shown in Fig. 3(a). However, as the swarm evolves, by round three the ants are able to achieve separation. At later evolutions, the ants are more uniformly distributed resulting in similar number members in each cluster. After reaching good separation, it is still possible for ants to be closer again at later rounds in order to promote load balancing.



(a)



(b)

Figure 3. Logical topology of T-ANT at round number: (a) 1 and (b) 3.

Since cluster size was shown to have a significant impact on clustering algorithms [4], we varied ADV's TTL value and compared T-ANT and TCCA. In Fig. 4, both algorithms exhibit the presence of an optimal cluster size, and this optimal size (i.e. two) is the same for both. However, T-ANT achieves significantly more energy savings than TCCA for cluster sizes up to four. When cluster size is two, T-ANT dissipates 27% lesser energy compared to TCCA. This observation is consistent with fitness values reported for both approaches in Figs. 1 and 2. Since TCCA mainly operates with sub-optimally formed topology, its energy dissipation is worse off. However, at larger cluster sizes, both schemes exhibit similar energy usage. This is mainly caused by the energy expended during the cluster setup phase that is significantly larger as ADV messages are flooded further, and the JOIN messages have to be forwarded many hops before reaching their CHs. Similarly, during the steady state phase, significant intra-traffic is generated. Note that the performance of m-LEACH is the same as TCCA with cluster size one, and has significantly higher energy dissipation experience.

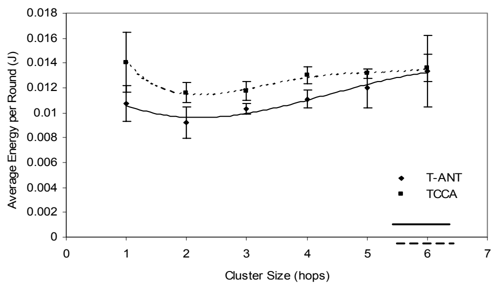


Figure 4. Average energy usage per round against the cluster size of T-ANT and TCCA (and m-LEACH).

In Fig. 5, the improvement gained through T-ANT is further exemplified by the network lifetime graph. For this investigation, we have fixed E_{max} at 0.1J as a reference level. It is evident that T-ANT exhibits the longest lifetime with all nodes remaining fully functional. It is found that T-ANT achieves almost 3.5 times the lifetime of m-LEACH and almost 5 times of the flat approach. It also supports 50% longer lifetime than TCCA.

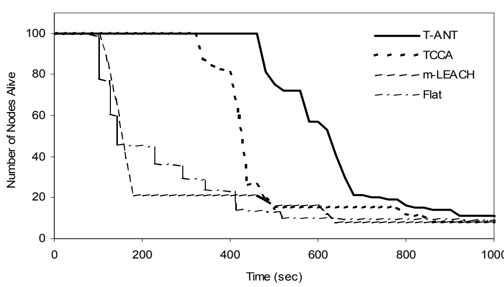


Figure 5. Network lifetime against simulation time of T-ANT, TCCA, m-LEACH and the flat strategy.

V. CONCLUSIONS

To our knowledge, the T-ANT clustering algorithm is the first nature-inspired approach for data dissemination in a quasi-stationary wireless sensor network. The algorithm uses a swarm of ants to control the clusterhead election in a totally distributed manner. It is evident that T-ANT is able to achieve two desirable swarm behaviors, namely separation and alignment. Due to these, a uniform distribution of clusterhead is almost guaranteed enabling the network to operate in an optimal manner throughout its lifetime. Even though it could also be achieved in a centralized approach as in LEACH-C [3], our algorithm is distributed, robust, does not require position knowledge and promises scalability. T-ANT also stores less than 10% of state overhead in memory compared to LEACH or TCCA.

ACKNOWLEDGMENT

This work was supported by USyd grant L2844 U3230.

REFERENCES

[1] J. Hill, M. Horton, R. Kling, and L. Krishnamurthy, "The platforms enabling wireless sensor networks," *Comms. of the ACM*, vol. 47, pp. 41 - 46, Jun 2004.

[2] K. Akkaya and M. Younis, "A Survey on Routing Protocols for Wireless Sensor Networks," *Elsevier Ad Hoc Networks*, vol. 3, pp. 325-349, May 2005.

[3] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Transactions on Wireless Communications*, vol. 1, pp. 660 - 670, Oct 2002.

[4] S. Selvakennedy and S. Sinnappan, "A Configurable Time-Controlled Clustering Algorithm for Wireless Sensor Networks," Proc. of 11th Int. Conf. On Parallel and Dist. Sys., Fukuoka, Japan, Jul 2005, pp. 368-372.

[5] Y. Ohtaki, N. Wakamiya, M. Murata, and M. Imase, "Scalable ANT-based Routing Algorithm for Ad-Hoc Networks," Proc. of 3rd IASTED Int. Conf. on Comms., Internet, and Information Technology, St. Thomas, US Virgin Islands, Nov 2004.

[6] B. A. Kadrovach and G. B. Lamont, "A particle swarm model for swarm-based networked sensor systems," Proc. of ACM symposium on Applied computing, Madrid, Spain, Mar 2002, pp. 918-924.

[7] D. Baker and A. Ephremides, "The Architectural Organization of a Mobile Radio Network via a Distributed Algorithm," *IEEE Trans. on Communications*, vol. 29, pp. 1694-1701, Nov 1981.

[8] C.-F. Chiasserini, I. Chlamtac, P. Monti, and A. Nucci, "An energy-efficient method for nodes assignment in cluster-based ad hoc networks," *Wireless Networks*, vol. 10, pp. 223-231, May 2004.

[9] T. Shu, M. Krunz, and S. Vrudhula, "Power balanced coverage-time optimization for clustered wireless sensor networks," Proc. of 6th ACM international symposium on Mobile ad hoc networking and computing, Urbana-Champaign, IL, USA, May 2005, pp. 111-120.

[10] V. Hartmann, "Evolving agent swarms for clustering and sorting," Proc. of conference on Genetic and evolutionary computation, conference on Genetic and evolutionary computation, Jun 2005, pp. 217-224.

[11] M. Genes, U. Sorges, and I. Bouazizi, "ARA - the ant-colony based routing algorithm for manets," Proc. of ICPP Workshop on Ad Hoc Networks, Vancouver, BC, Canada, Aug 2002, pp. 79 - 85.

[12] V. Ramos and J. J. Merelo, "Self-organized stigmergic document maps: Environment as mechanism for context learning.," Proc. of Spanish Conference on Evolutionary and BioInspired Algorithms, 2002, pp. 284–293.