Using Gravitational Search Algorithm for Finding Near-optimal Base Station Location in Two-Tiered WSNs

Marjan Kuchaki Rafsanjani, and Mohammad Bagher Dowlatshahi

***Abstract*—In designing the Wireless Sensor Networks (WSNs), the main issue is limited resource for each sensor. Hence, offering ways to optimize energy consumption in WSNs which eventually increases the network lifetime is strongly felt. In this paper, a Gravitational Search Algorithm (GSA) is proposed for finding nearly optimal Base Station (BS) location in two-tiered heterogeneous WSNs, where Application Nodes (ANs) may own different data transmission rates, initial energies and parameter values. Experimental results and comparisons with Particle Swarm Optimization (PSO) and Exhaustive Grid Search show the appropriate performance of our proposed approach.**

***Index Terms*—Gravitational search algorithm, two-tiered wireless sensor networks, base station location, energy consumption, network lifetime.**

I. Introduction

Recent advances in wireless communication and embedded systems, has caused development of Wireless Sensor Networks (WSNs) by using wireless sensor in most electronic equipments. A WSN consists of many sensors that each sensor has a computational power. These networks are used in tasks such as: identifying and collecting information, controlling the situation and so on. Indeed, these networks with their applications in the fields of military, health, environment, industry, agriculture, entertainment and etc., has created a small revolution in the evolution of information and hence those are an attractive field for computer science researchers [1].

In designing WSNs, the main issue is limited energy source for each sensor. Moreover, due to the large number of sensors in the network or lack of access to them, battery replacement for sensors is not practical. Hence, offering ways to optimize energy consumption which eventually increases the network lifetime is strongly felt.

In this paper, we use Gravitational Search Algorithm (GSA) [2] for finding near-optimal Base Station location in two-tiered Wireless Sensor Networks, so that the Base Station location will be decreased power consumption and thereby will be increased network lifetime. A physical and logical view of two-tiered WSN shown in Fig. 1. Each two-tiered WSN consists of a number of SN/AN clusters and at least one BS. In each cluster, there are many SNs and at least one AN. SNs are responsible for all sensing-related activities. Once triggered by an internal timer or an external event, an SN starts to capture and encode live information sent directly to an AN in the same cluster. SNs are small, low cost, and disposable, and can be densely deployed within a cluster. SNs do not communicate with other SNs in the same or other clusters, and usually are independently operated. ANs, on the other hand, have much more responsibilities than SNs. First, an AN receives raw data from all active SNs in the same cluster. It may also instruct SNs to be in sleep, idle, or active state, if some SNs are found to always generate uninterested or duplicated data, thereby allowing these SNs to be reactivated later when some existing active SNs run out of energy. Second, the AN creates an application-specific local view for the whole cluster by exploring correlations among the data sent from SNs. Excessive redundancy in raw data can be alleviated, and the fidelity of captured information should be enhanced. Third, the AN forwards the composite bit-stream toward a BS that generates a comprehensive global-view for the entire WSN. Optionally, ANs can be involved in inter-AN relaying, if such activities are applicable and favorable [3].

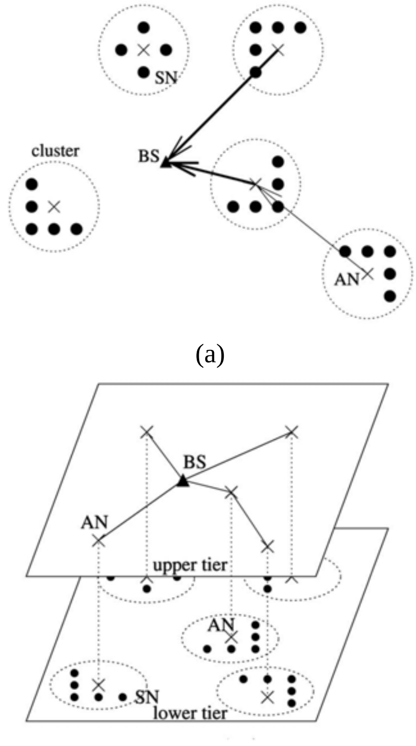

Fig 1. A two-tiered architecture of Wireless Sensor Networks; (a) physical view; (b) logical view [3].

The remaining parts of this paper are organized as follows: related works is reviewed in Section 2. The brief description

Manuscript received May 27, revised June 26, 2012.

Marjan Kuchaki Rafsanjani (Corresponding author) is with the Department of Computer Science, Shahid Bahonar University of Kerman. Kerman, Iran, Postal code: 76169-14111 (e-mail: kuchaki@uk.ac.ir).

Mohammad Bagher Dowlatshahi is with the Department of Computer Science, Shahid Bahonar University of Kerman. Kerman, Iran (e-mail: mb.dowlatshahi@yahoo.com).

of GSA is reviewed in Section 3. The proposed algorithm to find near-optimal location for BS in a two-tiered WSN is presented in Section 4. Experimental results and comparisons described in Section 5 and finally conclusions are stated in Section 6.

II. Related Work

In the past, many approaches were proposed to efficiently utilize energy in Wireless Sensor Networks. For example, good algorithms for allocation of BSs and SNs were proposed to reduce power consumption [4-8]. Also, Pan *et al.* [3] proposed an algorithm to find the optimal locations of BSs in two-tiered homogeneous Wireless Sensor Networks. Let d be the Euclidean distance from an AN to a BS, and r be the data transmission rate. Pan *et al.* proposed Eq. (1) to calculate the energy consumption per unit time.

$$p(r,d) = r(a_1 + a_2 d^b) \tag{1}$$

where a_1 is a distance-independent parameter (e.g., the power consumed in transmitter circuit) and a_2 is a distance-dependent parameter. Based on Eq. (1), the energy consumption related to Euclidean distances and data transmission rates. Pan *et al.* assumed each AN has the same a_1, a_2 and initial energy. Although, Pan *et al.* extended their approach to find the optimal BS location for ANs with different transmission rates, but if the ANs have different initial energies and parameter values, their approach also can't work [3].

Unfortunately, the ANs of a WSN may own different data transmission rates, initial energies and parameter values. Hence, Hong *et al.* [9] presented a PSO-based approach to find a near-optimal location for BS in two-tiered heterogeneous WSNs, where ANs may own different data transmission rates, initial energies and parameter values. Hong *et al.* also extended this PSO-based approach in [10].

In this paper, we proposed a GSA-based approach to find a near-optimal location for BS in two-tiered heterogeneous WSNs and compare our proposed method with PSO-based approach presented in [10].

III. Gravitational Search Algorithm

In physics, gravitation is the tendency of objects with mass to accelerate towards each other. In the Newton gravitational law, each mass (object) attracts every other mass with a force, which is the "gravitational force". For example, suppose an n-dimensional space which includes masses M_1, M_2, M_3 and M_4. As seen Fig. 2, n-dimensional vector F_{1j} ($j \in \{2, 3, 4\}$) is the force that acting on M_1 from M_j ($j \in \{2, 3, 4\}$), and n-dimensional vector F_1 is the overall force that acts on M_1 and generates the n-dimensional acceleration vector a_1.

Gravitational Search Algorithm (GSA) is one of the newest stochastic population-based meta-heuristics that has been inspired by Newtonian laws of gravity and motion. In the basic model of the GSA which originally has been designed to solve continuous optimization problem, a set of agents, called masses, are introduced in the n-dimensional search space of problem to find the optimum solution by simulation of Newtonian laws of gravity and motion. In GSA, the position of each mass demonstrates a candidate solution to the problem, and hence is represented by the vector Xi in the search space of the problem. Masses with a higher performance get a greater gravitational mass, because a heavy mass has a large effective attraction radius and hence a great intensity of attraction. In during the life time of GSA, each mass successively adjusts its position Xi toward the positions of K best masses of population using gravitational law and laws of motion. [2].

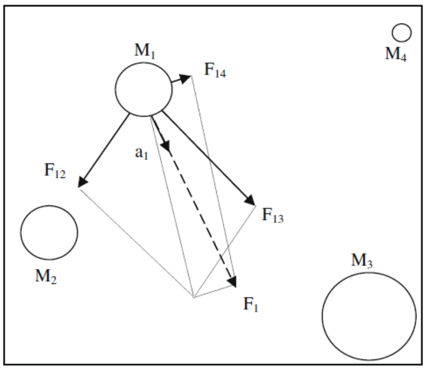

Fig. 2. Every mass accelerate toward the result force that act on it from the other mass [2].

To describe the GSA consider a system with s masses in which position of the i-th mass is defined as follows:

$$X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^n) \;\; ; \; i=1, 2, \ldots, s, \tag{2}$$

where x_i^d is position of the i-th mass in the d-th dimension and n is dimension of the search space. Based on [2], mass of each agent is calculated after computing current population's fitness as follows:

$$q_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}, \tag{3}$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^{s} q_j(t)}, \tag{4}$$

where $M_i(t)$ and $fit_i(t)$ represent the mass and the fitness value of the agent i at t, respectively, and $worst(t)$ and $best(t)$ are defined as follows (for a minimization problem):

$$best(t) = \underset{j \in \{1,\ldots,m\}}{Min} fit_j(t), \tag{5}$$

$$worst(t) = \underset{j \in \{1,\ldots,m\}}{Max} fit_j(t). \tag{6}$$

To compute acceleration of an agent, total forces from a set of heavier masses that apply on it should be considered based on the law of gravity (Eq. (7)), which is followed by calculation of agent acceleration using the law of motion (Eq. (8)). Afterwards, next velocity of an agent is calculated as a fraction of its current velocity added to its acceleration (Eq. (9)). Then, its next position can be calculated using Eq. (10):

$$F_i^d(t) = \sum_{j \in Kbest, j \neq i} rand_j \, G(t) \frac{M_j(t) M_i(t)}{R_{ij} + \varepsilon} (x_j^d(t) - x_i^d(t)), \tag{7}$$

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} = \sum_{j \in Kbest, j \neq i} rand_j \, G(t) \frac{M_j(t)}{R_{ij} + \varepsilon} (x_j^d(t) - x_i^d(t)), \tag{8}$$

$$V_i^d(t+1) = rand_i \times V_i^d(t) + a_i^d(t), \tag{9}$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1), \tag{10}$$

where:

- $rand_i$ and $rand_j$ are uniformly distributed random number in the interval [0,1],
- ε is a small value,
- $R_{ij}(t)$ is the Euclidean distance between two agents *i* and *j*, defined as $\|X_i(t), X_j(t)\|_2$,
- *Kbest* is the set of first *K* agents with the best fitness value and biggest mass, which *K* is a function of time, initialized to $K_{initial}$ value at the beginning and the its value is decreased with time, and
- $G(t)$ is *the* gravitational constant that will take an initial value, $G_{initial}$, and it will be reduced with time toward end value, G_{end}, by Eq. (11):

$$G(t) = G(G_{initial}, G_{end}, t). \tag{11}$$

In GSA, the K and G parameters are two main components to balance its intensification and diversification. It is obvious that each meta-heuristic in order to avoid trapping in a local optimum must use the diversification at beginning iterations. In GSA, this important is accomplished by assignment high values to K and G parameters at beginning, i.e. the value of Kinitial and Ginitial must be high. It is obvious that the high value for K parameter allows that a mass moves in the search space based on the position of more masses and consequently the diversification of algorithm is increased. Also, a high value for G parameter increases the mobility of each mass in the search space and hence the diversification of algorithm is increased. With high value for K and G parameters, we can hope that the good regions of solution space are recognized in premier iterations. Hence, by laps of iterations, the diversification of GSA must fade out and the intensification of it must fade in. This important is accomplished by reducing the value of K and G parameters by laps of iterations. It is obvious that the low value for K parameter causes that a mass moves in search space based on the position of few masses and consequently the intensification of algorithm is increased. Also, the low value for G parameter decreases the mobility of each mass in the search space and hence the intensification of the algorithm is increased. Therefore, we can hope that the good regions of search space are exploited in the ultimate iterations.

The pseudo code of the original GSA is shown in algorithm (1).

Algorithm 1: Template of original Gravitational Search Algorithm.

```
Generate initial population;
Evaluate the fitness for each agent;
While stopping criteria is not satisfied Do
    Update G, K, and Kbest;
    Calculate the acceleration of each agent by Eq. (7);
    Calculate the velocity of each agent by Eq. (9);
    Update the position of each agent by Eq. (10);
    Evaluate the fitness for each agent;
Endwhile
Output: Best solution found.
```

IV. The Proposed Algorithm: GSA to Find Near-Optimal Base Station Location

When different kinds of ANs exist in a two-tiered WSN, it is usually hard to find the optimal BS location. For this reason, a heuristic algorithm based on GSA to find near-optimal location for BS when different kinds of ANs exist is proposed. Let $e_j(0)$ be the initial energy, r_j be the data transmission rate, a_{j1} be the distance-independent parameter, and a_{j2} be the distance-dependent parameter of the *j*-th AN. The lifetime $l_{ij}(t)$ of an application node AN_j for the *i*-th mass is calculated by the following formula:

$$l_{ij}(t) = \frac{e_j(0)}{r_j(a_{j1} + a_{j2} d_{ij}^n)}, \tag{12}$$

where d_{ij}^n is the *n*-order Euclidian distance from the *j*-th AN to the *i*-th mass [3]. The fitness function used for evaluating each mass is shown below:

$$fit_i(t) = \underset{j \in \{1,\ldots,m\}}{Min} l_{ij}(t), \tag{13}$$

where *m* is number of ANs. In this algorithm, a larger fitness value denotes a longer lifetime of the whole system and therefore the corresponding BS location is better. The proposed algorithm for achieved near-optimal location is stated in algorithm (2).

Algorithm 2: Template of proposed algorithm.

```
Randomly generate a group of n masses, each representing a possible Base Station location;
Evaluate the fitness for each agent;
Randomly generate an initial velocity for each mass;
Set value of K with n (n is the number of population);
While stopping criteria is not satisfied Do
    Calculate the lifetime l_ij(t) of the j-th AN for the i-th mass in step t by Eq. (12);
    Calculate the lifetime of the whole sensor system for the i-th mass by Eq. (13);
    Calculate K and identification Kbest masses;
    Calculate G(t), best(t), worst(t), M_i(t), F_i(t), a_i(t) and V_i(t+1) by Eq. (3-9);
    Update the position of each mass, X_i(t+1), by Eq. (10);
Endwhile
Output: Best solution found.
```

V. Experimental Results

In this section, the performance of the proposed GSA approach on finding the near-optimal position of BS is investigated. For this purpose, experiments performed in C language on an Intel PC with a 2.0GHz processor and 1G main memory and running the Microsoft Window XP operating system. The simulation was done in a two-dimensional real-number space of 1000m*1000m.

The data transmission rate of each AN was limited within 1 to 10 and the range of initial energy was limited between 100000000 to 999999999. Also, the number of ANs is equal to 50. Some data of all ANs such as: its own location, data transmission rate and initial energy, were randomly generated based on mentioned assumptions. Also, for each AN the distance-independent parameter (aj1) was set at zero, and the distance-dependent parameter (aj2) was set at one.

For tuning the parameters of GSA, considered number of masses equal to 15 (i.e. n=15), number of generations equal to 50, and at the start of the algorithm, Kinitial is equal to n (i.e. number of masses) and Ginitial is equal to 200.

The lifetime comparison of proposed approach, PSO algorithm and the exhaustive search with different grid sizes [10] are shown in Table I.

TABLE I: THE LIFETIME COMPARISON OF THE PROPOSED ALGORITHM, PSO ALGORITHM [10], AND EXHAUSTIVE GRID SEARCH [10]

Method	Lifetime
The proposed GSA	72.0765
The PSO algorithm [10]	72.0763
The exhaustive grid search (grid size = 1) [10]	72.0048
The exhaustive grid search (grid size = 0.1) [10]	72.0666
The exhaustive grid search (grid size = 0.01) [10]	72.0752

As seen in Table I, the lifetime obtained by our proposed algorithm is nearly better than PSO algorithm and exhaustive grid search with grid size 1, 0.1 and 0.01.

VI. CONCLUSION

In designing Wireless Sensor Networks (WSNs), the main issue is limited energy source for each sensor. Hence, offering ways to optimize energy consumption in WSNs which eventually increases the network lifetime is strongly felt. In this paper, two-tiered heterogeneous WSNs where Application Nodes (ANs) may own different data transmission rates, initial energies and parameter values, has been considered and an algorithm based on Gravitational Search Algorithm (GSA) has been proposed for finding near-optimal Base Station (BS) location for it. To evaluate the performance of the proposed algorithm, experiments are performed and result of this experiment compared with a Particle Swarm Optimization-based (PSO-based) algorithm and an Exhaustive Grid Search with grid size 1, 0.1 and 0.01. Comparisons show the good performance of the proposed GSA.

REFERENCES

[1] D. Estrin et al., *Embedded, Everywhere: A Research Agenda for Networked Systems of Embedded Computers,* Nat'l Research Council Report 2001.

[2] E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, "GSA: A gravitational search algorithm," *Information Sciences*, vol. 179, pp. 2232–2248, 2009.

[3] J. Pan, L. Cai, Y.T. Hou, Y. Shi, and X. Shen, "Optimal base-station locations in two-tiered wireless sensor networks," *IEEE Trans. on Mobile Computing*, vol. 4, pp. 458-473, 2005.

[4] V. Rodoplu, and T.H. Meng, "Minimum energy mobile wireless networks," *IEEE J. on Selected Areas in Commun.* vol. 17, 1999.

[5] V. Kawadia, and P.R. Kumar, "Power control and clustering in ad hoc networks," in *Proc. 22nd IEEE Conf. on Computer Commun. (INFOCOM)* , 2003.

[6] N. Li, J.C. Hou, and L. Sha, "Design and analysis of an mst-based topology control algorithm," in *Proc. 22nd IEEE Conf. on Computer Commun. (INFOCOM)*, 2003.

[7] R. Ramanathan R and R. Hain, "Topology control of multihop wireless networks using transmit power adjustment," in *Proc. 19th IEEE Conf. on Computer Commun.s (INFOCOM),* 2000.

[8] J. Pan, Y. Hou, L. Cai, Y. Shi, and X. Shen, "Topology control for wireless sensor networks," in *Proc. 9th ACM Int. Conf. on Mobile Computing and Networking* , pp. 286-299, 2003.

[9] T. P. Hong, and G.N. Shiu, "A PSO-based heuristic algorithm for base-station locations," in *Proc. Int. Conf. on Soft Computing and Int. Symp. on advanced Intelligent Systems (SCIS&ISIS)*, 2006.

[10] A. Lazinica, *Particle Swarm Optimization*, In-Tech Education and Publishing, 2003, Ch. 16.

Marjan Kuchaki Rafsanjani received her Ph.D. in Computer Engineering, Iran in 2009. She is currently assistant professor at the Department of Computer Science in Shahid Bahonar University of Kerman, Iran. She published about 80 research papers in international journals and conference proceedings. Her main areas of interest are Computer Networks (Wireless Networks, Mobile Ad hoc Networks (MANETs), Wireless Sensor Networks (WSNs)), Electronic Commerce, Artificial Intelligence fields, Grid & Cloud Computing.

Mohammad Bagher Dowlatshahi was born in 1988 in Khoramabad, Iran. He received his M.Sc. degree in Computer Science from Shahid Bahonar University of Kerman, Iran, in 2012. His current interest is in Theory of Computation, Cognitive Science, Soft Computing, and Computer Networks.