ENAMS: Energy Optimization Algorithm for Mobile Sensor Networks

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***Abstract*—This paper presents the design of an intelligent energy optimization algorithm which is based on Swarm Intelligence to increase the life time of swarmed wireless sensor networks. This algorithm represents a further autonomous stage to our previous work which was devoted to cluster Wireless Sensor Networks (WSNs) into independent clusters. Our Algorithm is mainly designed to keep the optimum distribution of clustered sensors while those mobile sensors are directed as a swarm to achieve a given goal. The algorithm presented in this research is suitable for large scale mobile sensor networks and provides a robust and energy- efficient communication mechanism. We are using the Particle Swarm Optimization (PSO) technique to decrease the energy consumption for the entire sensor network. One of the main strengths in the presented algorithm is that the number of clusters within the sensor network is not predefined, this gives more flexibility for the nodes' deployment in the sensor network. Another strength is that sensors' density is not necessary to be uniformly distributed among the clusters, since in some applications constraints, the sensor nodes need to be deployed in different densities depending on the nature of the application.**

Keywords*—*Energy Optimization, Particle Swarm Optimization, Swarm Intelligence, Wireless Sensor Networks

I. INTRODUCTION

Recent advances in micro-electro-mechanical systems, digital electronics, and wireless communications have led to the emergence of wireless sensor networks (WSNs), which consist of a large number of sensing devices each capable of detecting, processing and transmitting environmental information. A single sensor node may only be equipped with limited computation and communication capabilities; however, nodes in a WSN, when properly configured, can collaboratively perform signal processing tasks to obtain information pertaining to remote and potentially dangerous areas in an untended and robust way. Applications for wireless sensors networks include battlefield surveillance, environmental monitoring, biological detection, smart spaces, industrial diagnostics, etc. [1]. Any WSN is deeply involved in and related to the monitored environment, and any change occurring to the surroundings will significantly influence its performance; nevertheless, the network must be able to tolerate and 'survive'any change by implementing proper reactions and adaptation mechanisms sustaining communications for both sensed data and commands [2].

Energy efficiency has been deemed to be the main challenge for Wireless Sensor Networks. Generally, the power supply of a single sensor node relies on a battery with limited energy (e.g., an AAA battery). Changing or recharging a nodes' battery is very difficult, if not impossible, after sensor nodes have been deployed. Therefore; it is desirable to design energy efficient protocols to run on individual nodes, to ensure that the operation time of the deployed WSN is as long as possible. However, some classical information processing approaches do not consider the energy efficiency issue and require re-examination when applied in resource constrained WSNs. Geographically distributed nodes in a WSN may have different views of the physical phenomenon in the sensor field and thus their measurements may have some points of correlation. A well designed algorithm should also exploit this to accomplish the information processing task via collaboration between nodes. In this work we propose to design an algorithm for a large scale mobile sensors network. This algorithm should provide a robust and energy-efficient communication mechanism which enables the swarms of sensors to move while keeping optimum distances between the sensor nodes.

The rest of this paper will be structured into the follwing sections; Section 2 describes a background ideas and motivation for our work. In section 3, we are explaining the concepts of PSO technique to enable the clusters to move as Swarms while keeping the optimum distances. In section 4 the implementation of the proposed algorithm is explained by showing some snapshots of the simulation program. Section 5 shows the results discussion as well as comments for the output graphs are presented here including a critical review. Finally in section 6 we concluded our work and its objectives with possible future development and enhancments.

II. BACKGROUND AND MOTIVATION

As the Internet has revolutionized our life by the uncomplicated exchange of various forms of information among a large number of users, Wireless Sensor Networks (WSNs) may, in the near future, be equally significant in providing information regarding physical phenomena of interest; ultimately leading to detection and control, and where relevant enabling us to construct more accurate models of the physical world. WSNs have gained tremendous importance in recent years because of its potential use in a wide variety of applications. This, along with the unique characteristics of these networks, has spurred a significant amount of research for coming with network protocols specifically tailored for sensor networks [1]. Wireless sensor networks are developing quickly and have been widely used in both military and civilian applications such as target tracking, surveillance, and security management. Since a sensor is a small, lightweight, un-tethered, battery-powered device, it has limited energy [3]. Therefore, energy consumption is a critical issue in sensor networks. We are interested in sensor networks in which a large number of sensors are deployed to achieve a given goal. All data obtained by member sensors must be transmitted to a sink or data collector. The longer the communication distance, the more energy will be consumed during transmission [4]. Direct transmission networks are very straightforward to design but can be very power-consuming due to the long distances from sensors to the sink. Alternative designs that shorten or minimize the communication distances can extend network lifetimes. The use of clusters for transmitting data to a base station leverages the advantages of small transmit distances for most nodes, requiring only a few nodes to transmit far distances to the base station. Clustering means to partition the network into a number of independent clusters, each of which has a cluster-head that collects data from all nodes within its cluster [5], [6]. These cluster-heads then compress the data and send it directly to the sink point. Figure 1 shows an example of clustered sensor network.

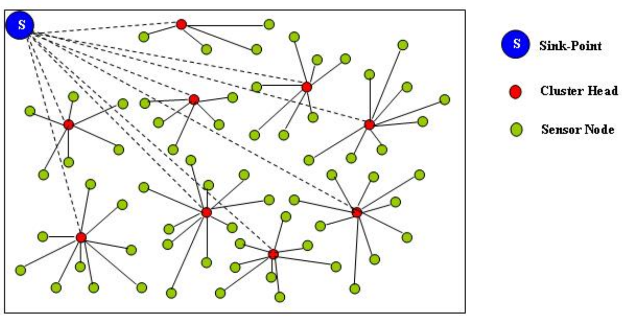

Fig. 1. Clustered Sensors Network

This research represents a further autonomous step to our previous work [7] which was based on Genetic Algorithms (GAs) to divide the WSN into independent clusters. The presented ENAMS algorithm enables clustered WSN to be self organized network while the sensors are moving on a swarm bases. Deployment of mobile swarms can enhance the sensor network in many ways. Firstly, the swarm nodes have much higher hardware capabilities than the sensor nodes. They can provide detailed information of the intended area (e.g. the hot spot). Secondly, the wireless radios of the swarm nodes usually have much longer range and higher channel bandwidth, which can support high quality and delay sensitive multimedia streams. Thirdly, the swarms are mobile [8]. They can be easily directed to the hot spots. A limited number of mobile swarms can easily cover a large scale sensor network. The sensor network can be deployed to cover a very large field due to the low cost of sensor nodes.

A. Energy-Aware Wireless Sensor Networks

Nodes in a WSN are usually highly energy-constrained and expected to operate for long periods from limited on-board energy reserves. To permit this, nodes and the embedded software that they execute must have energy-aware operation. Energy efficiency has been of significant importance since WSNs were first conceived but, as certain applications have emerged and evolved [9], a real need for ultra-miniaturized long-life devices has re-emerged as a dominant requirement. Because of this, continued developments in energy-efficient operation are paramount, requiring major advances to be made in energy hardware, power management circuitry and energy-aware algorithms and protocols.

The energy components of a typical wireless sensor node are shown in Figure 2. Energy is provided to the node from an energy source, whether this is a form of energy harvesting from sources such as solar, vibration or wind, or a resource such as the mains supply or the manual provision and replacement of primary batteries. Energy obtained from the energy source is buffered in an energy store; this is usually a battery or super capacitor. Finally, energy is used by the node's energy consumers; these are hardware components such as; the microcontroller, radio transceiver, sensors and peripherals.

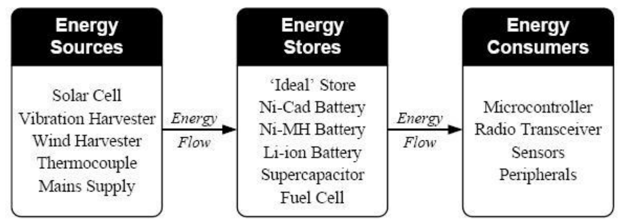

Fig. 2. Energy components of a typical sensor node

With the increased usage of energy sources in nodes [10], [11], the need for energy stores other than batteries (many of which suffer from only offering a limited number of charging cycles) is increased. This can be seen by the researchs that are now utilizing super capacitors (devices that are similar to standard electrolytic capacitors, but with capacities of many Farads) to store the node's energy [11], [12].

To be energy-aware, the embedded software executing on the node must be aware of the state of its energy components. This may be as advanced as monitoring the energy harvested from each source [13], inspecting the rate of consumption by different consumers [14], directing the flow of energy from and to different stores and managing the charging of rechargeable stores [12]. Alternatively, this may equate to simply being able to inspect the residual energy in a single store. Therefore, the embedded software must not only be capable of interfacing with energy hardware (this is generally a requirement of power management circuitry), but also interpreting the data that are obtained usually in the form of a sampled voltage into a remaining lifetime, power or energy. Based upon these values, the operation of the node is adjusted accordingly, usually to maximize the lifetime of the network.

B. Swarm Intelligence

Swarm Intelligence (SI) indicates a recent computational and behavioural metaphor for solving distributed problems that originally took its inspiration from the biological examples provided by social insects (ants, termites, bees, wasps) and by swarming, flocking, herding behaviours in vertebrates [15]. It is an attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insects and other animal societies. The common behaviours in all kinds of swarms are [15], [16], [17];

- Control is fully distributed among a number of individuals;
- Communications among the individuals happen in a localised way;

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TABLE I. THE PARAMETERS FOR PSO VELOCITY AND POSITION UPDATE

Parameter	Description
v_i^k	velocity of particle i at iteration k
w	inertia weight
v_i^{k+1}	velocity of particle i at iteration $k+1$
c_j	acceleration coefficients j=1,2
$rand_i$	random number between 0 and 1 i=1,2
s_i^k	current position of particle i at iteration k
$pbest_i$	$pbest$ of particle i
$gbest$	$gbest$ of the group
x_i^{k+1}	position of the particle i at iteration $k+1$

- System-level behaviours appear to transcend the behavioural repertoire of the single individual; and
- The overall response of the system is quite robust and adaptive with respect to changes in the environment.

Swarm intelligence as defined by Bonabeau, Dorigo and Theraulaz is "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies and other animal societies" [16]. The term "swarm" is used in a general sense to refer to any such loosely structured collection of interacting agents. The classic example of a swarm is a swarm of bees, but the metaphor of a swarm can be extended to other systems with a similar architecture. An ant colony can be thought of as a swarm whose individual agents are ants, a flock of birds is a swarm whose agents are birds, traffic is a swarm of cars, a crowd is a swarm of people, an immune system is a swarm of cells and molecules, and an economy is a swarm of economic agents. Although the notion of a swarm suggests an aspect of collective motion in space, as in the swarm of a flock of birds, all types of collective behaviour are considered here, not just spatial motion.

III. PSO BASED MOVABLE CLUSTERS

Our algorithm is designed to provide the distance management by using Particle Swarm Optimization (PSO) which makes the wireless sensor network self organised while the sensors are moving on a swarm bases. In PSO, the potential solutions are called particles, fly through the problem space by following the current optimum particles. The particles are initialised randomly [18]. Each particle will have a fitness value, which will be evaluated by the fitness function to be optimised in each generation. Each particle knows its best position $pbest$ and the best position so far among the entire group of particles $gbest$. The particle will have velocities, which direct the flying of the particle. In each generation the velocity and the position of the particle will be updated. The velocity and the position update equations are given below as (1) and (2) respectively.

$$v_i^{k+1} = wv_i^k + c_1 rand_1 * (pbest_i - s_i^k) + c_2 rand_2 * (gbest - s_i^k) \tag{1}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{2}$$

The parameters used in equations 1 and 2 are described in Table I.
The pseudo code for our proposed algorithm is shown in Algorithm (1).
In recent times, there has been a number of improvements to the original PSO [19]. In this paper we have explored two

PSO Initialization: Assume the initial population for PSO is the best solution generated by GAs from previous stage;
while *the stop condition is not satisfied* **do**
  Evaluate the fitness value for each particle's position in the swarm;
  if $fitness(p)$ *better than* $fitness(pbest)$ **then**
    $pbest = p$;
    Set best of $pbest$ as $gbest$;
  end
  Update the particles' velocity v_i^{k+1};
  Update the particles' position x_i^{k+1};
end

Algorithm 1: Pseudo code for PSO Algorithm

versions of PSO where the extension to the original algorithm is distinct from each other. These are discussed in the following sections.

A. PSO - Time Varying Inertia Weight (TVIW)

PSO-TVIW model is the same basic PSO algorithm with inertia weight parameter is varying with time from 0.9 to 0.4 and the acceleration coefficient is set to 2. This model is proposed by [20]. The time varying inertia weight is mathematically represented as follows:

$$w = (weight - 0.4) * \frac{(MAXITER - iter)}{MAXITER} + 0.4 \tag{3}$$

Where, MAXITER is the maximum iteration allowed, $iter$ is the current iteration number and $weight$ is a constant set to 0.9.

B. Particle Swarm Optimisation with Supervisor-Student Model (PSO-SSM)

In this method [21] proposed PSO-SSM to achieve low computational costs. The algorithm introduces a new parameter called momentum factor (mc) to update the positions of particles. In this algorithm, they also proposed a different velocity updation mechanism from the conventional PSO algorithms. Here velocity is updated only if each particle's fitness at the current iteration is not better than that of previous iteration. The velocity serves as a navigator (supervisor) by getting the right direction, while the position (student) gets a right step size along the direction. The velocity and the position are modified using the following equations:

$$v_i^{k+1} = v_i^k + c_1 rand_1 * (pbest_i - s_i^k) + c_2 rand_2 * (gbest - s_i^k) \tag{4}$$

$$x_i^{k+1} = (1 - mc) * x_i^k + mc * v_i^{k+1} \tag{5}$$

IV. IMPLEMENTATION AND EXPERIMENTATION

A. Energy Model for Optimisation

We are studying the impact of the transmission range of sensor nodes and positioning of the sink in minimising the communication energy in a sensor network. The important components of each sensor are the data and control processing unit and the radio for communication. The microprocessor used in the processing unit should be energy efficient with less energy consumption. The energy dissipation in the radio depends on the different characteristics of the radio. The energy model used in this work is adopted from [6], [22], [23] and summarised here. The energy dissipation for transmitting b bits to d distance is shown in Equation 6.

$$E_{tx}(b, d) = E_{elec} \times b + E_{amp} \times b \times d^2 \tag{6}$$

The energy dissipation in a node to receive b bits of data is shown in Equation 7.

$$E_{rx}(b) = E_{elec} \times b \tag{7}$$

Where E_{elec} is the radio energy dissipation and E_{amp} is the transmition amplifier energy energy disipation. Energy consumption of a wireless sensor node transmitting and receiving data from another node at a distance d can be divided into two main components: Energy used to transmit, receive and amplify data and energy used for processing the data, mainly by the microcontroller. Leakage current can be as large as a few mA for the microcontroller, and the effect of leakage current can be neglected for higher frequencies and lower supply voltage. Assuming the leakage current as negligible, the total energy loss for the sensor system due to the distance E_{dd} can be calculated according to Figure 3 using the following equation:

$$E_{dd} = \left(\sum_{j=1}^{k} \sum_{i=1}^{n_j} (d_{ij}^2 + \frac{D_j^2}{n_j}) \right) \tag{8}$$

For more details about the derivation and proof refer to [22].

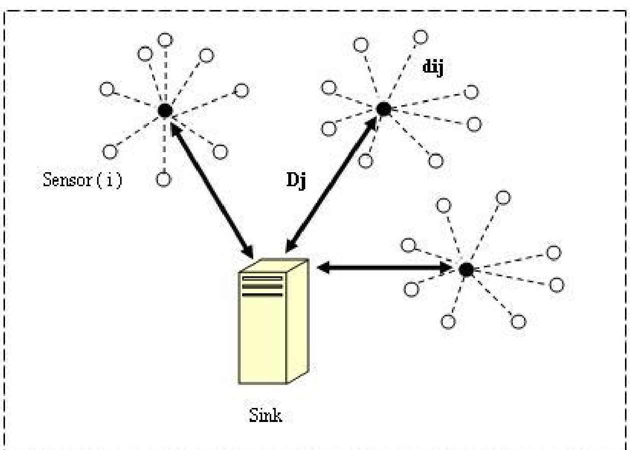

Fig. 3. Energy Model for distance based Sensor Network

B. Experiments and Simulation

In this section, we explore the use of PSO to solve the distance minimization problem for dynamic sensor networks. To implement our algorithm, we have used Java-Applet as a programming environment to simulate the experiments of our algorithm which enables the sensors to move as a swarm using PSO while keeping the optimum distances between the sensor-nodes and their related cluster-head, avoiding any unnecessary movements. Refering to Equation (8), we can conclude that by reducing the distance from a node to the cluster-head and the cluster-head to the sink we can minimise the energy dissipation in a sensor network. In our simulation, we cluster the nodes taking into consideration that each node can transmit or receive data from all the other nodes. Thus, nodes considered in this network do not have transmission range constraint. Sensors are clustered using entirely distance based Equation (8). The fitness function for this method is as follows [24]:

TABLE II. INITIALISATION AND PARAMETERS RANGE

Parameter	Range
Population size	100
$MAXITER$	1000
v_{max}	100
x_{max}	100
v range	0-100
x range	0-100

$$Fitness = min \left(\sum_{j=1}^{k} \sum_{i=1}^{n_j} (d_{ij}^2 + \frac{D_j^2}{n_j}) \right) \tag{9}$$

where,

$$\sum_{j=1}^{k} (n_j + k) = N.$$

N is the number of nodes in a network. For our simulations, we used 100-node networks that are uniformly distributed in a 2-Dimensional problem space [0:100,0:100]. We have studied the impact of sink location on the fitness value of the PSO algorithms. In one set of simulations we considered the sink-point to be located at the center of the network (50,50). In another set of simulations we considered the sink-point to be located remotely at (50,180). For both simulations we use the same set of nodes. The maximum number of generations we were running was 1000. The parameters used in the simulations are tabulated in Table II. Snapshots for the mobile swarmed sensor-nodes are shown in Figure 4. Figure 4-a shows the initial distribution for sensor-nodes which is produced by GAs from the previous phase of our algorithm. It can be observed from this distribution that the WSN is clustered into 4-clusters, each one represents a swarm to be directed and controlled by the PSO when it will start running in the second phase of the algorithm. During PSO phase, clusters will be self-organised while they are moving within the experimentation boundaries. This will avoid the mobile sensors to make any unnecessary movements to reserve energy and enlarge the lifetime for each sensor. It is clear from the screen shots shown in Figure 4 - b, c, d, e and f respectively, that the mobile sensors in each cluster keep adjusting their positions during the movements to keep the distances between the sensor-nodes as much as possible the same as it was in the initial distribution.

V. CRITICAL REVIEW AND RESULTS

In this work we observed the performance in terms of quality of the average optimum value for 10 trials to the **PSO-SSM** and **PSO-TVIW** models which are described earlier. We chose these two methods for the following reasones; the **PSO-SSM** model is the only model which has the ability to stop particles from moving beyond the boundary of the problem space, that is under the influence of mc parameter in it. The **PSO-TVIW** model is almost similar to the basic PSO algorithm with just the inertia weight varying with time

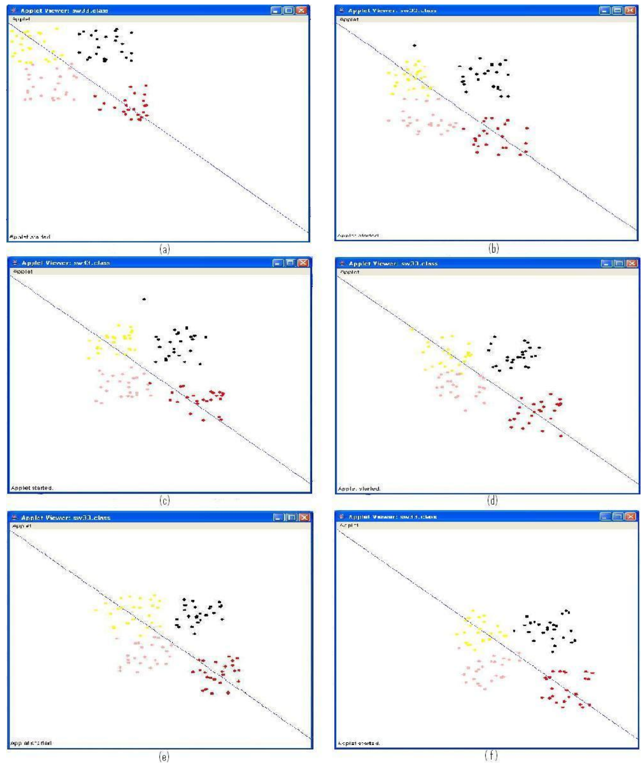

Fig. 4. Snapshots of swarmed WSN with 4 clusters crossing the problem space

from 0.9 to 0.4. From the graph shown in Figure 5 we can conclude that **PS-TVIW** convergence is slower as compared to the **PSO-SSM** algorithm. This was due to constant acceleration co-efficients used in this model which affects the rate of convergence.
Simulation results show that the proposed approach is an efficient and effective method for solving this problem with respect to distance minimization.

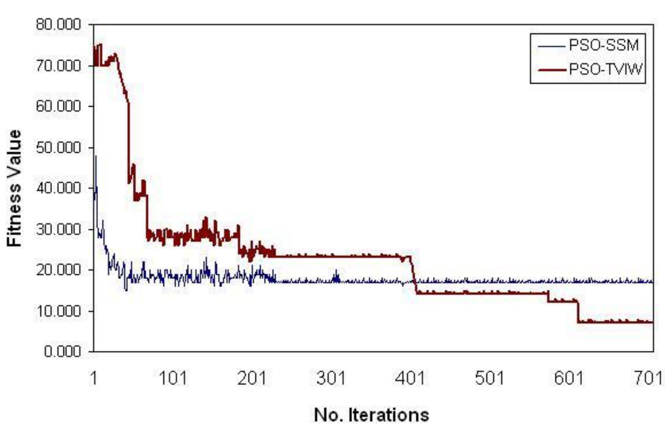

Fig. 5. Convergence for the PSO-SSM and PSO-TVIW Models

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we propose the use of PSO to make WSNs moves as a Swarm keeping the optimum distances between the sensors while they are directed to achieve a specific target. Our proposed approach starts by assuming the initial population for PSO to be the best solution generated by a previous stage of the algorithm which is achieved by using GAs. We also explored the results of the performance evaluation of four extensions to the standard Particle Swarm Optimization algorithm in order to reduce the energy consumption in Wireless Sensor Networks. Communication distance is an important factor to be reduced in sensor networks. We have simulated two models; the Supervisor-Student Model (PSO-SSM) and the time varying Inertia Weight (PSO-TVIW) model. In the (PSO-SSM) model the new parameter introduced called the momentum factor mc to update the position of particles. Also here the velocity is updated only if each particle's fitness at the current iteration is not better than that of previous iteration. Hence the computational costs for this algorithm will be decreased. An important modification proposed is to use boundary checking for re-initialization of particle which moves outside the set boundary. We can also conclude that (PSO-TVIW) convergence is slower as compared to other algorithm. As a future work, our program can be upgraded to cover the two other models described in this paper, then a comprehensive comparison could be done to analyze the behavior of the particles within each case.
We plan to extend the problem on hand by considering a hierarchical structure where a cluster-head can have a super cluster-head which sends data directly to the sink.

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