Routing Protocol for Wireless sensor networks Using Swarm intelligence-ACO with ECPSOA

Jeevan Kumar
Department of CSE,
Indian Institute of Technology
(Indian School of Mines) Dhanbad, India,
Jeevan_csc01@rediffmail.com

Sachin Tripathi
Department of CSE,
Indian Institute of Technology
(Indian School of Mines) Dhanbad, India,
tripathi.s.cse@ismdhanbad.ac.in

Rajesh Kumar Tiwari
Department of CSE,
R.V.S College of Engineering & Technology,
Jamshedpur, India,
rajeshkrtiwari@yahoo.com

Abstract--- In the wireless sensor networks(WSNs) with static and dynamic nodes, the movement of nodes or failure of sensor nodes may lead to the breakage of the existing routes. End-to-end delay, power consumption, and communication cost are some of the most important metrics in a wireless sensor networks when routing from a source to a destination. Recent approaches using the swarm intelligence (SI) technique proved that the local interaction of several simple agents to meet a global goal has a significant impact on WSNs routing. In this paper, a proposed routing algorithm that has an ant colony optimisation (ACO) algorithm with an endocrine cooperative particle swarm optimisation algorithm (ECPSOA) is used to improve the various metrics in WSNs routing. The ACO algorithm uses mobile agents as ants to identify the most feasible and best path in a network. Additionally, the ACO algorithm helps to locate paths between two nodes in a network. In the ECPSOA, finds the best solution for a particle's position and velocity, which can enhance the capacity of global search and improve the speed of convergence and accuracy of the algorithm. This routing algorithm has an improved performance when compared with the simple ACO algorithm in terms of delay, power consumption, and communication cost. Simulate with the help of network simulator OMNNET++, and analysis the result.

Keywords - *Wireless sensor networks, Routing, Endocrine, ACO, PSOA, ECPSOA*

1. Introduction

A WSN usually consists of many sensor nodes that communicate through wireless medium for information sharing and cooperative processing [1]. Generally, the nodes are statically deployed over vast areas. However, they can also be mobile and capable of interacting with the environment. Sensor nodes also can sense the environment, communicate with neighboring nodes, and in different scenario perform basic computations on the data being collected [2, 3]. Application of WSNs have different area are environmental monitoring, natural disaster rescue, military surveillance, nuclear-threat detection systems, weapon sensors for ships, structural faults in ships, volcanic eruption, earthquake detection, aircraft, biomedical applications, habitat sensing, and seismic monitoring. Most recently, WSNs have been employed in more advanced applications, such as, building automatic, industrial process automation, traffic control, medical interventions, networked biological, chemical sensors for national security applications, physical security, air traffic control, traffic surveillance, video surveillance, industrial and manufacturing automation, process control, inventory management, distributed robotics, weather sensing, Environment monitoring. WSNs also have the ability to adapt dynamically to changing environments. These can respond to changes in network topologies.

Swarm intelligence (SI) is a relatively novel field that was originally defined as ''Any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insects and other animal societies" [4, 5, 6]. However, now a day, SI refers more generally to the study of the collective behavior of multi-component systems that coordinate using decentralized controls and self-organization. From an engineering point of view, SI emphasizes the bottom-up design of autonomous distributed systems that can show adaptive, robust, and scalable behaviors. The SI has two popular frameworks such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) [7].

Author's Contributions can be summarized as follows:

- Proposed new routing algorithm model ACO with ECPSOA.
- Design flow chart diagram of ACO with ECPSOA.
- Simulation of the proposed routing protocol to demonstrate its performance against some of the existing protocol in static and dynamic WSNs scenario.

2. ANT colony optimisation

The first routing algorithms based on SI concepts came in second half of the '90s and were designed for wired networks. It is known as ant-based control (ABC). AntNet is another algorithm which is design for internet protocol networks. Both these algorithms were developed according to the principles of ACO, which is widely used in network routing. ACO derives from the reverse-engineering and the adaptation of the shortest path behaviour observed in foraging ant colonies. An ACO is a combinatorial search technique based on the collective behaviour of ants with features like foraging, division of work labour, cemetery construction, nest construction and ant brooding. Various types of ants are head ant, monitor ant, soldier ant, worker ant and child ant. Ants interact directly or indirectly and deposit a chemical substance known as

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pheromone, which gets evaporated over a period of time during the path traversal. Pheromone indicates indirect communication between ants. If many ants follow the same path, density of pheromone layer is increased and this indicates an optimal path followed by ant colony.

An ACO is a famous swarm intelligence approach that has received inspiration from the social behaviour of real world ants. In this algorithm, the best path for routing is identified by the pheromone deposited by ants. Upon finding the food, the ants return back to their nests and simultaneously deposit the pheromone along the paths. Therefore, the ants are likely to move through these paths and update the existing pheromone. Over time, the pheromone starts to evaporate, and its strength is reduced. At regular intervals, several ants are launched toward the destination node to discover the feasible, low cost path from the source node to the destination node. Each ant in an ACO considers two parameters to select its next hop. The first parameter is the amount of pheromone deposited on the path to the next node, and the second parameter is the queue length associated with the link. The flow chart for the ACO model formulation scheme is shown in Fig. 1.

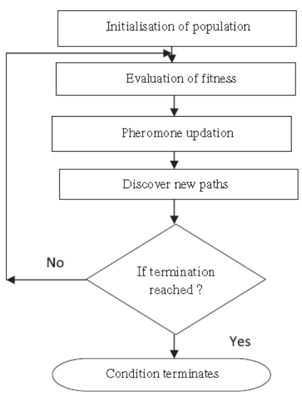

Fig 1: Flow chart representation for ACO.

3. Introduction of ECPSOA

As we known, particle swarm optimization algorithm (PSOA) searches for an optimum through each particle flying in the search space and adjusting its flying trajectory has become a widely adopted optimization technique [8, 9]. In the traditional PSOA, each particle is a potential solution to the problem. Assume N particles fly in the D-dimensional search space, the position of the i-th particle is $x_i^t = (x_{i1}^t, x_{i2}^t, \ldots, x_{iD}^t)^T$, and, its velocity is $v_i^t = (v_{i1}^t, v_{i2}^t, \ldots, v_{iD}^t)^T$. $p_i = (p_{i1}^t, p_{i2}^t, \ldots, p_{iD}^t)$ is the best previous position of the particle, and p_g is the best global position of the whole particle swarm. Therefore in each time step t, the velocity V and the position X of each particle is updated with following equations:

$$v_{id}^{t+1} = wv_{id}^t + c_1 rand_1\left(p_{id}^t - x_{id}^t\right) + c_2 rand_2\left(p_{gd}^t - x_{id}^t\right) \quad \ldots\ldots\ldots(1)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad \ldots\ldots\ldots\ldots\ldots(2)$$

Where, c_1, c_2 are learning factors, we select $c_1 = c_2 = 2$. $Rand_1$ and $Rand_2$ are random numbers uniformly distributed in (0, 1). In order to improve the performance of the PSOA, introduced the accelerating factor to modify the parameters c_1 and c_2 [10]. The static non-linear method of modifying the inertia weight was introduced in [11] to improve the performance of the PSOAs. Lin and Chen proposed a cooperative PSOA (CPSOA) [12], which used the cooperative behavior of multiple swarms to improve the PSOAs by jumping out local minimum. It can compensate the limitation of an individual by a number of individuals from other symbiotic groups in the interaction, thus avoid mistake of judgment caused by single exchange of information. The trajectory of each particle is unable to yield high diversity of particles to enlarge search space, so it may get a suboptimal solution. Therefore, we apply the adjustment mechanism of the endocrine system [13] i.e. the ECPSOA. We consider the best position of a particle and the global best position of a swarm in current generation. Then, we combine the supervision and controlling principle between stimulation hormones (SH) and releasing hormones (RH) of the endocrine system, and use the individual of the current solution set to control the nearest class of swarm. The particles are grouped by the SH, and the best positions of classes are proposed to update the positions of particles, so the convergence and distribution performance of the ECPSOA can be improved. The global optimization position of the class can reflect the influence of the nearest optimal particle to other particles, so that the ECPSOA can jump out of local optimization, improve the searching capability, and maintain the diversity of solution set.

The ECPOSA is used to address the problem of data transmission from the source nodes to the mobile sink. It can provide a fast recovery mechanism from path failure due to the sinks movement or physical damage and energy depletion of sensor node problem. The flowchart of the ECPSOA is shown in Fig. 2, and the detailed procedures are described as follows.

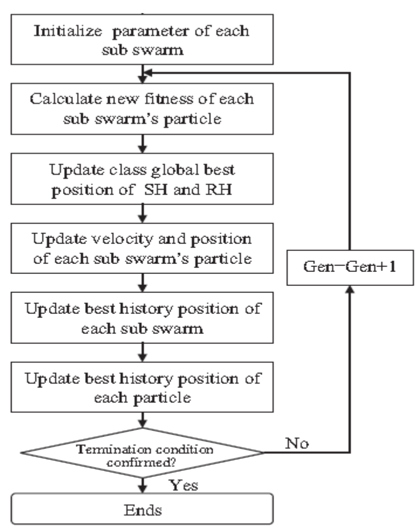

Fig 2: The flowchart of the ECPSOA.

3.1. Working process

Firstly, to initialize the ECPSOA, the population size of particle is n, the division factor is k, so each particle swarm includes n=k particles. Then the D-dimensional vector i.e. particle's position and velocity is divided into k swarms. The position and velocity of the i-th particle in t-th time is respectively, $x_i^t = (x_{i1}^t, x_{i2}^t, \ldots, x_{iD}^t)^T$ and $v_i^t = (v_{i1}^t, v_{i2}^t, \ldots, v_{iD}^t)^T$. As the path should have n points, the number of which is the same as the number of particles, so the initial particle swarm can be represented as a matrix by [D × 3n]. The first n columns of the matrix are the positions of particle, the middle n columns are the velocities of particle, and the last n columns are the amount of hormone (one column represents a particle). The optimal position vector of the whole sub-swarms is presented by a vector function b (.):

$$b(L, i) \quad (p_g S_1, \ldots, p_g S_{i-1}, L, p_g S_{i+1}, \ldots, p_g S_k)$$

Where, $x_m S_i$ represents the position vector of the m-th particle in the i-th swarm, $p_m S_i$ is the optimal history position vector of the m-th particle in the i-th swarm, and $p_g Si$ represents the optimal experience position vector of the i-th swarm.

In this process, according to the endocrine principle, we initialize two swarms for each sub-swarm: stimulation hormone (SH) S_t and releasing hormone (RH) R_t, which both have the same structure and size [14]. Firstly, we combine the swarm S_t and R_t, and generate the new swarm U_t (U_t - $S_t \cup R_t$). The optimal solution of U_t is selected as the candidate swarm CS_t of SH. Then all the solution crowding distances of CS_t are sorted in descending order according to the crowding distance algorithm.

4. Proposed routing algorithm model: ACO with ECPSOA

Several traditional algorithms were used to find a solution to the routing problem in the WSNs, including Genetic Algorithm and PSO algorithms. The ACO technique is independent of these routing problems, and the outcomes obtained using the ACO technique can be improved with ECPSOA. Thus, a novel routing model that combines the ACO and ECPSOA techniques can be suggested for the optimisation technique. The flow chart for the proposed novel routing algorithm model is shown in Fig 3. The steps involved in the proposed novel routing model are as follows:

Step 1: Initialise the number of particles and generate its value randomly.
Step 2: Initialise ACO parameters.
Step 3: Generate solutions from each ant's random walk.
Step 4: Update the pheromone intensities using Equation (3),

$$T_{xy} \leftarrow (1 - \rho)T_{xy} + \Sigma_K \nabla^K_{T_{xy}} \quad \ldots\ldots\ldots\ldots(3)$$

Where, $\rho \rightarrow$ Pheromone evaporation coefficient,
$\nabla^K_{T_{xy}} \longrightarrow$ Amount of pheromone deposited.
$K \rightarrow$ Ant that deposits the pheromone,
x is the index for the subsystem, and
y refers to the components in a subsystem.

Step 5: If the solution is not the best, initialize the swarm with random positions and velocities. Then calculate new fitness function.
Step 6: Select each particle's individual best value for each generation. Then update global best position with the help of HS and RH.
Step 7: Select the particle's global best value, i.e., the particle nearest the target is obtained by comparing all of the individual best values.
Step 8: Select the particle's individual worst value, i.e., the particle farthest away from the target.
Step 9: Update the velocity and position of the particle per Eqs. (1) and (2)
Step 10: Terminate the process if the maximum number of iterations is reached or if an optimal value is obtained. Otherwise, proceed to Step 3.

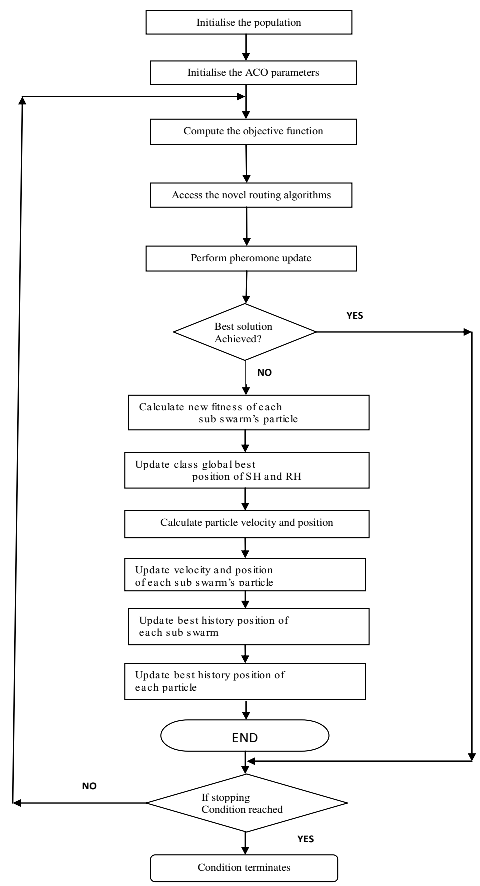

Fig 3: Flow chart representation of ACO with ECPSOA.

5. Results and discussion

In this section, discusses the performance evaluation and comparison of the ACO algorithm and the proposed algorithm (ACO with ECPSOA) in the network simulation tool. In the case of static scenario the performance of the proposed protocol is similar to the existing ACO protocol, and this is outperforms in the case of dynamic scenario. The ACO protocol is not find location of nodes in dynamic environment, but this problem is sort out with proposed protocol (ACO with ECPSOA), because with time nodes are change its location. The proposed routing algorithm was evaluated using a network of 100 nodes spread over a 1000m - 1000m region. Every node has a maximum transmit range of 250m. The routing parameters, such as distance, delay, capacity, power consumption, are used for the fitness evaluation using algorithms. The performance of the proposed ACO with ECPSOA is compared with the ACO algorithm using the routing parameters in dynamic scenario. The evaluation method for the parameters is given in Equations (4) – (7).

$$\text{Distance between two nodes}(AB) = [(A_2 - A_1)^2 + (B_2 - B_1)^2]^{1/2} \quad \ldots\ldots(4)$$

A_2 and A_1 are the latitudes, and B_2 and B_1 are the longitudes in real-time measurements. Delay can be determined using the formula in Equation (5).

$$Delay = \frac{\sum(\text{packet arrival time} - \text{packet forwarded time})}{\sum \text{number of nodes connection}} \quad \ldots\ldots..(5)$$

Capacity can be expressed as the sum of the capacity of the individual nodes, where as power consumption is assumed to be a random value for the nodes. Communication cost is the cost or money spent for the usage time as given in Equation (6).

$$t_{comm} = t_s + t_n + t_w \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

t_s→ (Start-up time) Time exhausted for sending and receiving nodes

t_n→ (Per-hop time) this time is a function of the number of hops

t_w→ (Per-word transfer time) this time includes all of the overheads determined by the length of the message.

The cost formula in Equation (6) is based on time. If the process is performed in a minimum amount of time, the cost is minimal. The communication cost increases as time increases. The power consumption is calculated using Equation (7).

$$\text{Power consumption} = |\text{Receiving power} - \text{Transmitting power}|. \quad \ldots\ldots(7)$$

The path delay is measured based on the number of iterations for the individual ACO and ACO with ECPSOA as shown in Fig. 4. ACO with ECPSOA is less delay as compared to ACO.

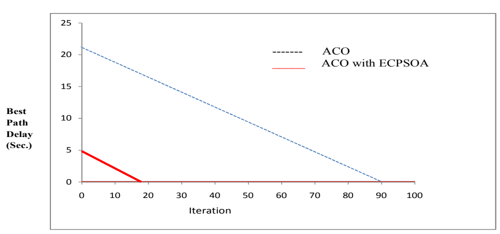

Fig 4: Path delay comparisons of ACO and ACO with ECPSOA for a number of iterations (100 nodes).

The power consumption between the ACO and ACO with ECPSOA is shown in Fig. 5 for 100 nodes. The proposed protocol has less power consumption from ACO.

The path cost parameter versus the number of iterations is shown in Fig. 6, for the ACO and the proposed protocol.

In Fig. 7, distance is used as a parameter to find the shortest distance between the nodes. The ACO with ECPSOA distance is less than the ACO distance. The shortest distance is referred to as distance. The shortest distance between the source and destination is shown in Fig. 7.

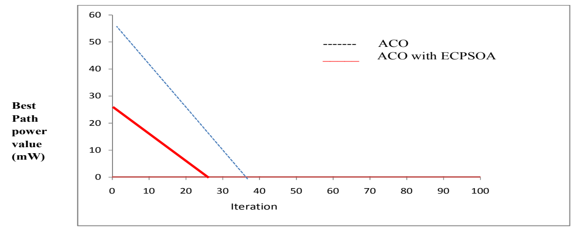

Fig 5: Power consumption (mW) of ACO and ACO with ECPSOA for a number of iterations (100 nodes)

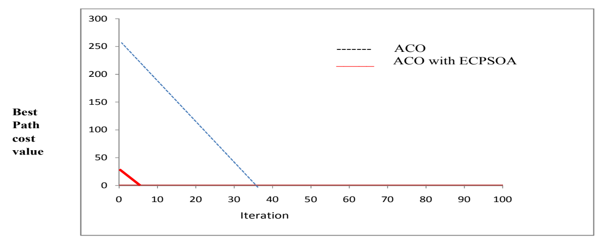

Fig 6: Communication cost using ACO and ACO with ECPSOA for a number of iterations (100 nodes)

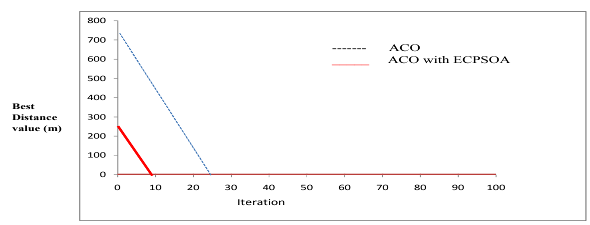

Fig 7: Distance comparisons of ACO and ACO with ECPSOA for a number of iterations (100 nodes).

Conclusion

The proposed novel routing protocol (ACO with ECPSOA) that combines the properties of both ECPSOA and ACO approaches for the WSNs. From the simulation point of view, we conclude that the path outcome using the novel routing intelligent algorithm has the shortest distance, a minimum delay, low power consumption, and low cost when compared with the individual performance of the ACO. The proposed protocol outperforms with ACO protocol in the dynamic scenario. For the future work, we will focus on improving the convergence performance, reducing the computational complexity, and validating the proposed protocol on different scenarios.

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