

Improvement of Network Lifetime using Ant Colony Optimization in Wireless Sensor Network

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Abstract: Network lifetime is the essential parameter of efficient wireless sensor network. This can be achieved by using different localization and routing algorithms. In this paper, we propose the hybridization of Support Vector Machine (SVM) and Ant Colony Optimization (ACO). SVM is the supervised learning model, which is used to train the dataset points and classify them into two classes: dead nodes and alive nodes. Whereas ACO, selects the optimal or shortest path among all adjacent possible paths from source node to destination node for data transmission. The proposed technique improves the network lifetime as well as detects failure nodes in wireless sensor network. The proposed work is compared with Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) algorithms at different nodes.

Keywords: WSN, ACO, SVM, wireless sensor network

I. INTRODUCTION

Nowadays, advances in technology wireless sensor networks require failure node detection, low power, and low cost sensor nodes. The main purpose of wireless sensor networks is to sense the data process them and then transmit to the sink. However, the major constraint of wireless sensor networks is power consumption, battery harvesting and communication failure and connect with failure nodes [1][2]. Localization and routing are the supporting key techniques in WSN. Localization approaches collect the whole network information into one place and process it accordingly. In WSN, many techniques are available to detect failure nodes like MANNA, tree structure and using clustering heads etc. In these techniques, there are some disadvantages like high communication cost, accuracy, and high power consumption etc. These issues are solved by using support vector machines [3]. The support vector machine is a type of supervised learning algorithm, which is used for classification, outliers' detection, and regression problems. In SVM, we have given a set of training dataset points, where each dataset point is marked for belonging to either one or two categories. SVM has two main categories i.e. kernel function and set of support vectors. The data point located near to the separating hyperplane is called support vector. Based on the category SVM training algorithm prepares a new model, assigns new dataset in both categories, and makes a linear classifier [4].

SVM model plots each data as a point in feature space. SVM can be linear classifier and nonlinear classifier. In linear classifier, samples are mapped into space separated by hyperplane, whereas nonlinear classification is done by using different kernel tricks. The advantages of SVM are that it gives accurate localization of sensor nodes in rough and sparse environment [5].

The main constraint in WSN is limited battery power and memory of sensor nodes. When designing routing protocols two main challenging issues are generated that are network energy efficiency and maximum network lifetime. The maximum network lifetime can be achieved by minimizing the energy consumption of the nodes. The proposed technique increases the network lifetime and makes energy efficient.

ACO is based on the foraging behavior of ants that is used to discover the shortest path from source node to destination node. ACO is also used to improve network efficiency and reduce power consumption of sensor nodes [6].

In this paper, we propose hybridization of SVM and ACO, used to achieve maximum network lifetime. This can be done by SVM training the samples and classifying them between dead nodes and alive nodes. Whereas ACO, discovers the shortest path from source node to destination node among all possible paths.

This paper is organized as follows: Section I gives introduction about proposed technique and explains, section II gives a brief review on previous work done on support vector machine and ant colony optimization techniques used for maximizing network lifetime, section III explains the proposed algorithm and section IV provides simulation results and section V and VI give conclusion and future scope of the proposed work.

II. RELATED WORK

Many optimization techniques have been done in order to maximize network lifetime and detect failure nodes in wireless sensor networks.

Some of them are discussed here:

In [7] proposed they collect different types of fault feature and integrate them to identify the fault nodes, by rough set theory and support vector machine. The rough set theory is used to reduce impute of sampling data for taking the decision making attributes and make simple dataset. This new simple dataset trained by support vector machine. The failure nodes of WSN has classified through the trained SVM model.

In [8] proposed that the WSN monitored dynamic behaviour of environment that rapidly changes with time. This caused by external factors or by the system designer. To eliminate such unnecessary issues sensor network adopt machine-learning technique. The machine learning technique is inspired by many practical solutions that maximize network lifetime and resource utilization.

In [9] presented the WSN are mainly constrained by limited energy resources as well limited memory and functionality to support communications. Hence enhance the network lifetime and improve energy efficiency is the major challenging issue in designing of routing protocol for wireless sensor networks. Here they propose a wireless sensor network routing protocol based on ACO. The Ant Colony Optimization approach used to find the optimal shortest path between sensor nodes; it also counts the node energy, which effectively balances the sensor nodes power consumption and enhance the network lifetime as long as possible. The simulation result shows improvement in throughput against same energy consumption by named as throughput aware protocol TANARP.

In [10] presented WSN consist of many sensor nodes which has limited power. The sensor node has to receive useful information from the given field but the problem is limited power supply. In this paper, they used ACO based on Bio-Inspired mechanism for routing. Ant colony optimization is a reliable and dynamic protocol. They define implementation of wireless sensor network and comparison of its performance parameter.

III. PROPOSED ALGORITHM

The effective self-positioning of sensor nodes in estimated geographical area can determine by Support Vector Machine. SVM based on supervised learning algorithm in which first step to train the support vector machine and then use this trained machine to classify new data[11]. To train the support vector machine (or support vector network) we consider the matrix of data points (test set) in which each row corresponds to observation and each column corresponds to a variable. Apply this test set to the training sets (group of sensor nodes) of wireless sensor network. After that, the sets of support vector make a group of these new-trained data points and classify them into dead nodes and alive nodes. So using this procedure, we can identify the failure nodes in wireless sensor network [12].

Now ants have specific numbers of alive nodes through which the maximum possible path can be established. The Ant colony optimization technique is an inspired by the real ant behaviour. Ants randomly start to search and discover food from their nest. While returning towards its nest, it drop pheromones trail on the way [13]. An extensive pheromone trail indicates the food source. Other ants select the path according to the quantity of pheromones. However, the pheromone vanishes over a short period so pheromones accumulated in the shortest path between nests to food source. In this proposed algorithm after training of sensor node, we apply Ant Colony Optimization Technique, which discover the shortest path between source node to destination node [14][15].

In this approach ants tries to discover the minimum distance to cover from nest to food source in the network. Before path searching we have taken some initialization parameters as follows. The 'n' is the environmental phenomenon that shows the least amount of pheromones in the transmission path. The transition probability is use for an ant r to move from source node x to Destination node y, which represent the routing information. The probability decision rule

$$P_{xy}^r = \left[\frac{[\tau_{xy}]^\alpha [\eta_{xy}]^\beta}{\sum [\tau_{xy}]^\alpha [\eta_{xy}]^\beta} \quad \text{if } y \in L^r \right] \quad (1)$$

Where τ_{xy} the amount of pheromone and η_{xy} is the heuristic function. The α and β are the constant parameter use to control the influence of the τ_{xy} and η_{xy} . In ACO algorithm ants contain the memory L^r which has the information about nodes that already visited or not. The heuristic function (η_{xy}) is the reciprocal of Euclidean distance (d_{xy}) between x and y sensor node [16][17]. After completion of ant tours the amount of pheromones updated accordingly to the

$$\tau_{xy}(t + N) = (1 - \delta) \cdot \tau_{xy}(t) + \Delta\tau_{xy} \quad (2)$$

where δ is the local pheromone spoil parameter. Pheromone updates after completion of ants tour so above equation shows that pheromone updates at time of t+N, where t is the previous pheromone update time. $\Delta\tau_{xy}$ represent the additional pheromone quantity at the t + N point. This iteration process repeated until ants discover the best possible path from source node to destination node[18]. The lifetime of the sensor network, calculated by the energy consumption of the sensor node at optimal path and whole energy consumption of the ant r.

$$\text{Energy cost} = \frac{E_c^2}{\sum_{x=1}^n \sum_{y=1}^n e_{xy}^\alpha W_y^\beta P_{xy}^r} \quad (3)$$

Here n is the sum of the network node and e_{xy}^α is the energy consumption between source node to destination node. W_y^β is the available power destination node. If ant r

has travel edge (x,y) then the value of P_{xy}^r is one otherwise zero.

IV. SIMULATION RESULT

The simulation performed in MATLAB 2013b. The proposed algorithm is the hybridization of support vector machine (SVM) and ant colony optimization (ACO). In proposed algorithm, we take various number of sensor nodes and deploy them randomly. After that, these sensor nodes are trained by support vector machine at different data points, which classify them into dead nodes and alive nodes.

After that we apply ant colony optimization algorithm to these trained sensor nodes. In which ants discover the optimal path from source node to destination node. In proposed algorithm, we have taken 50 sensor nodes and placed randomly. We have taken the node 5 and 30 select as a source node and destination node. SVM algorithm trained all these sensor nodes and classified into dead node and alive nodes. Through alive nodes, ants discover the optimum path from source node to destination node as shown in figure 1.

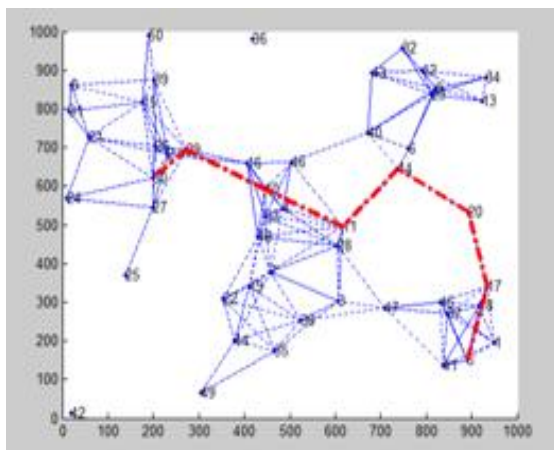


Figure.1. Shortest path from source node to destination node

Table.1 and figure.2 shows the network lifetime at different number of sensor nodes for proposed algorithm, ABC and PSO. It has been shows that the proposed algorithm having larger network lifetime comparison to existing algorithm.

Table. 1. Network Lifetime comparison of proposed algorithm with existing algorithms.

S.N.	No of Nodes	Network lifetime using ABC	Network lifetime using PSO	Network lifetime proposed algorithm
1	100	700	700	1000
2	150	1100	1100	1750
3	200	1400	1340	1800
4	250	1820	1700	1850

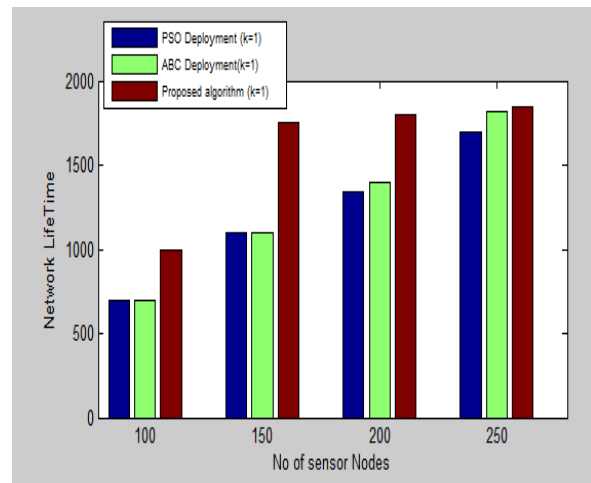


Figure.2. Network lifetime at various numbers of nodes for proposed algorithm, ABC and PSO algorithm

V. CONCLUSION

In this paper, we proposed a hybridization of SVM and ACO. The proposed routing algorithm is use to find the shortest path between nodes. This algorithm gives reliable communication between sources to destination node even when some nodes are dead. We get maximum network lifetime by proposed algorithm in comparison to existing optimization technique. The proposed optimization algorithm performs better than artificial bee colony and particle swarm optimization algorithm.

VI. FUTURE WORK

Network lifetime is the essential parameter in WSN. Therefore, this technique has proposed to detect dead nodes and discover the shortest path of source to destination node. Future work can be done to enhance network lifetime by using combine it with other effective routing algorithm to get maximum network lifetime.

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