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An Ant-Colony Optimization Clustering Model for Cellular Automata Routing in Wireless Sensor Networks

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Abstract

Highly efficient routing is an important issue for the design of wireless sensor network (WSN) protocols to meet the severe hardware and resource constraints. This paper presents an inclusive evolutionary reinforcement method. The proposed approach is a combination of Cellular Automata (CA) and Ant Colony Optimization (ACO) techniques in order to create collision-free trajectories for every agent of a team while their formation is kept unchallengeable. The method reacts with problem distribution changes and therefore can be used in dynamical or unknown environments, without the need of a priori knowledge of the space. The swarm of agents are divided into subgroups and all the desired trails are created with the combined use of a CA path finder and an ACO algorithm. In case of lack of pheromones, paths are created using the CA path finder. Compared to other methods, the proposed method can create accurate clustered, collision-free and reliable paths in real time with low complexity while the implemented system is completely autonomous.

Keywords:
WSN, Cellular Automata, Ant-Colony Optimization, Clustering

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INTRODUCTION

Swarm intelligence has been successfully applied in various domains, e.g., path finding, resource allocation, network clustering and even data mining. One of the most challenging issues in network-based clustering is Wireless Sensor Network (WSN). A WSN is a collection of compact size low power computational nodes capable of detecting local environmental conditions, and forward such information to a central base station (sink) for appropriate processing. WSNs can be applied in several applications such as military, agriculture, nuclear systems, volcanic eruption, earthquake detection, healthcare monitoring, industrial and manufacturing automation, weather sensing, structural monitoring in buildings, tunnels, and bridges. Unlike the traditional wired systems, deployment cost in WSNs is set to minimum. In addition, a WSN has the ability to adapt dynamically with changing environment. The environment can be the physical world, a biological system, or an information technology framework. There are many soft computing and evolutionary methods in WSN Clustering problem such as ant colony optimization, particle swarm optimization, genetic algorithms and fuzzy logic have been applied to solve various types of WSN problems. When there are lots of uncertainties, fuzzy logic approach yields a better result, and hence, this approach is used in the proposed protocol. If CH selections are done by taking one parameter into consideration, then it may lead to an undesirable result. Hence, CH selection should be done very efficiently by considering all the parameters.

The rest of the paper is organized as follows: Section 2 concisely presents the concept of ACO algorithm, WSNs and their applications. Moreover, in this section the paper presented the concept of Cellular Automata (CA) and Vehicle Route Problem (VRP) as the case study of the paper. Section 3 briefly describes the proposed hybrid method and the novelty of the paper. The experimental results have been shown in Section 4 and the Section 5 concludes the paper and summarizes possible future research challenges.

RESEARCH BACKGROUND AND RELATED LITERATURES

This section introduces the main concepts from swarm intelligence, cellular learning, and evolutionary reinforcement learning. that this article is based on. Specifically, ACO and WSN clustering.

Some research's shows that first completely proposes a new algorithm – cellular ant algorithm– for function and discrete systems optimization based on Ant algorithm and cellular automata. The methods give convergence analysis for cellular ant algorithm and numerical simulation that show the algorithm is robust and efficient, and extends the application area to the multi-objective optimization. In their research provides a new kind algorithm for NP-hard problems and gives convergence proof of the algorithm. The proposed works solves the classical TSP by cellular ant algorithm through series of typical instances. The computational results show the effectiveness of the algorithm in numerical simulation. (Wang, 2010)

(Dorigo et al., 1991) and (Zhu, 2007) solved the PCB routing problem by using the idea of cellular ant colony optimization. Assisted route distributing and the rule of obstacle avoidance are used for via and route minimization. The algorithm is coded in Delphi. A real-world instance is solved and the results are within satisfaction compared with that of Protel. (Liu & ZHAO, 2008) applies cellular ant algorithm to the optimization controlling of Fuel Cell Engine in order to shorten the temperature rising time and advance the output power of Fuel Cell Engine. The algorithm raises its searching speed with evolving the living state of every node. Simulation in Fuel Cell (PEMFC) Engine cold start controlling shows that the result is better than ant algorithm. The methods of (He et al., 2013; Zhang & Ma, 2008; Dorigo, 1992) includes cellular ant algorithm in path planning of Unmanned Aerial Vehicle (UAV). A series of improvements were made in cellular ant algorithm on the basis of the basic ant colony algorithm. Then the improved ant colony algorithm was used together with evolutionary rule of cellular in cellular space. The simulation results showed that the cellular ant algorithm could help the solutions to escape from their local optimum and could find a better path at higher convergence speed and with a higher precision. Therefore, the cellular ant algorithm is an effective method for such kind of multi-objective optimization problems with multiple constraints as UAV path planning under complex environment.

(Huang et al., 2015) claimed that a point out through the evolutionary mechanism of cellular and the redistribution of pheromones, the searching of solution space is effectively improved and the case of getting into local optimization is avoided. A series of nonlinear-optimization problems are solved with satisfactory results. (Kacimi et al., 2013), propose that the path planning problem of the mobile robot based on discrete mathematics can be solved by combining CA and ACO. The tests show that both the state result and the numerical result were satisfied with the application requirement. Using the model of CA and ACO to solve the path planning problem is feasible. In a different approach, they design an improved cellular automata ant algorithm based on the discovery of the similar structure between the cellular automata and the search area of the rectilinear Steiner minimum tree. The computational results showed that this algorithm can improve the total length about 15than that of the minimum spanning tree, so the effectiveness of the algorithm has been validated. (Ye et al., 2011).

(Wang, 2010), implement a centralized energy-aware clustering PSO algorithm (PSO-C) for the cluster-head selection and data-routing problems. During the setup phase of PSO-C, each sensor notifies the sink of its position and residual energy level to compute the average residual energy among all sensors. Cluster-heads may only be selected from among sensors having above-average residual energy levels. To finish the setup phase, the PSO-C selects the k best sensors to serve as cluster-heads, based on a particle fitness function that rewards minimum intra-cluster distances and balanced energy consumption (Wang, 2009).

Wireless sensor network

A wireless sensor node consists of four major parts: sensor unit, processing unit, energy supply unit, and transceiver. The sensing circuitry transforms the sensed data into an electric signal. Each node sends the sensed data via radio transmitter to the sink, either directly or through the other intermediate nodes. A sensor node is basically constituted of four elements. The elements are sensing unit, a processing unit, a transceiver unit, and a power unit. The first element, the sensing unit, includes sensors and analog to digital converters. Sensor nodes need to work collaboratively to carry out the assigned sensing tasks.

Table 1: Summary of Literature review and related works

Method	Problem description	Method
cellular automata	Solve hexagon-based sensor density, provide a greedy protocol for routing	Grid-based sensor deployment and data-routing
PCB routing	Grid-based sensor deploymentand cluster-head selection	Near-minimum PCB-based algorithm for cluster-headselection
Cellular- UAV	Virtual backbone formation andscheduling	Near-minimum UAV-based algorithm for cluster-headselection
Non-linear evolutionary	Distributed virtual backboneformation	It used to determine a load-balanced backbone
Steiner minimum tree	Tree-based data fusion androuting	Minimum-cost perfect matching algorithm to construct fusion and routing tree
PSO-C	Virtual backbone formation andnon-backbone allocation	IP used to assign non-backbone sensors to backbone
NLP	Heuristic solution to NLP that distributes data among multiple low-energy paths	Grid-based data-routing

Sensor nodes are equipped with a battery, which is non rechargeable. Sensor nodes during the sensing of data, processing of data, and transmitting the collected data exhausted a lot of energy. Transmitting information consumes more energy when compared with sensing and computation. Because battery cannot be replenished, this energy consumption should be taken care of Energy conservation schemes of wireless sensor nodes are gaining much interest among researchers.

The base station (BS) collects data directly from each sensor nodes, but it may lead to higher network energy consumption. To reduce the energy consumption by the network, sensor networks are grouped together as per certain characteristics, to form a cluster. One leader, often called a cluster head (CH), is chosen among the clusters. Cluster members transmit their sensed data to the CH, which then aggregates the collected data and transmit to the BS. The role of CHs is to aggregate and transmit the data to the sink via single hop or multihop. The CH's responsibility is very high. Energy consumption can be reduced significantly by an efficient selection of CH. The hotspot problem is a common problem in WSNs. It is known as the nodes closer to the sink die quickly due to inter-cluster traffic relay. To reduce this problem, an approach called as unequal clustering has been widely adopted. In equal clustering, clusters of equal sizes are formed, while in unequal clustering, clusters of variable sizes are formed. The distance between the CHs and the sink will decide the inequality of cluster formation. With these, CHs near the sink form a small cluster while CHs far away from the sink handle large clusters.

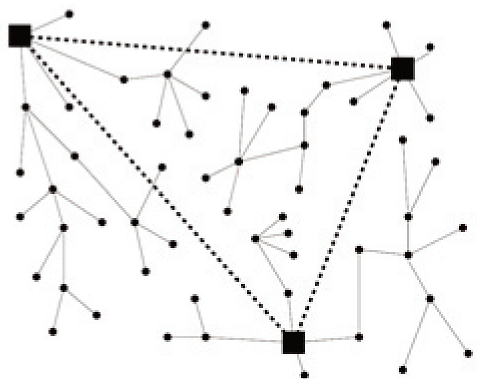

Fig.1. A representative sensor network architecture.

Vehicle route problem

Vehicle route problem (VRP) is designing delivery routes to meet some requirements and obtain minimal total cost synchronously. capacitated vehicle routing problem (CVRP) is an extension of VRP where vehicle capability is restrained. Researches on CVRP focus on two positions. On the one hand, average distance minimization is to diminish distribution cost. Large scale CVRP is deemed as a weighted incomplete undirected graph divided into subsystems by Tree Cut-Set (TCS).

Definition 1. In a tree, a tree-node i has and only has two different parents, has and only has one child node j, at the same time, node j has and only has two different children. Then, is called as a t-sepset couple nodes.

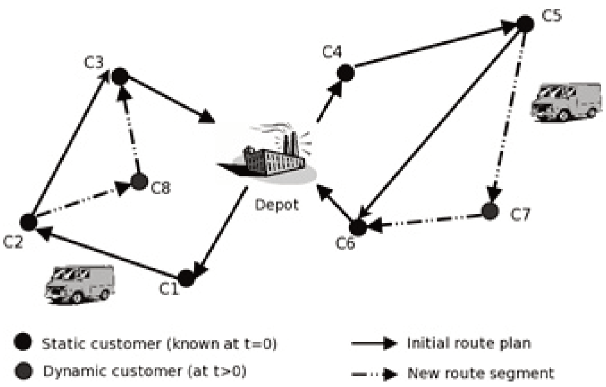

Fig.2. An Example of Vehicle Route Problem Structure

Ant colony optimization algorithm

The basic element of Ant Colony Optimization (ACO) algorithms is "ants" that is, agents with very simple capabilities which mimic the behavior of real insects, namely ants. Real ants are in some ways very unsophisticated insects. Their memory is very limited and they exhibit individual behavior that appears to have a large random component. However, acting as a collective, ants collaborate to achieve a variety of complicated tasks with great reliability and consistency, such as defining the shortest pathway, among a set of alternative paths, from their nests to a food source. This type of social behavior is based on a common feature with CA, called self-organization, a set of dynamical mechanisms ensuring that the global aim of the system could be achieved through low level interactions between its elements. The most vital feature of this interaction is that only local information is required.

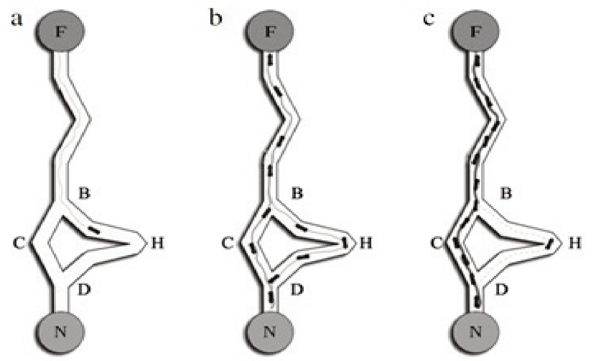

Fig.3. An example of a real ant colony: (a) An ant follows a BHD path by chance, (b) Both paths are followed with the same probability and (c) A larger number of ants follow the shorter path.

Ants could exchange information using two different ways: an indirect communication, called stigmergy and a direct communication. Stigmergy is biologically realized through pheromones, a special secretory chemical described by an evaporation ratio and deposited as a trail by individual ants when they move. More specifically, due to the fact that ants can detect pheromones, when choosing their way, they tend to choose paths marked by strong pheromone concentrations. In ACO algorithms, an ant will move from point i to point j with probability:

$$P_{ij}=\frac{(\tau_{ij}^{\alpha})(\tau_{ij}^{\beta})}{\sum(\tau_{ij}^{\alpha})(\tau_{ij}^{\beta})} \qquad (1)$$

where, and are the pheromone value and the heuristic value associated with an available solution route, respectively. Furthermore, and are positive real parameters whose values determine the relative importance of pheromone versus heuristic information.

Theory of cellular automata (CA)

CA can be considered as dynamical systems in which space and time are discrete and interactions are local. In general, a CA consists of a large number of identical entities with local connectivity arranged on a regular array. A finite Cellular Automaton could be defined by the quadruple:

$$\{d.q.N.f\} \qquad (2)$$

From Eq. 2 variable is a vector of two elements, m and n, denoting the vertical and horizontal CA dimensions, respectively. Both of these variables are expressed in number of cells. At each time step, every cell is labeled with a discrete value from the set called set of states. The neighborhood of each cell is defined by the variable . For a two-dimension CA, two neighborhoods are often considered, the Von Neumann and Moore neighborhoods. The Von Neumann neighborhood is a diamond shaped neighborhood and can be used to define a set of cells surrounding a given cell . Eq. 3 defines the Von Neumann neighborhood of range.

$$N^{v}_{(x0.y0)}=\{(x.y): |X-X0|+|y-y0|\leq r \qquad (3)$$

For a given cell and range r, the Moore neighborhood can be defined by the following equation:

$$N^{v}_{(x0.y0)}=\{(x.y): |X-X0|\leq r.|y-y0|\leq r \qquad (4)$$

PROPOSED METHOD

One of the main goals of the proposed method is to create collision free trajectories for every robot of a cooperative team. No a priori knowledge of the configuration area is required. Obstacle avoidance must be achieved in real time. Knowing their final position, that is the end of a straight-line path, robots can move randomly in the configuration area, according to the ACO algorithm. To prevent a scattered formation due to either an obstacle or a complete absence of pheromone, cooperation between the members of the team are applied so that their formation could be regained or retained immutable, respectively. According to the ACO algorithm, every single ant is governed by a set of simple behavior rules, leading to an uncomplicated approach of the path planning problem. Due to CAs, these behavior rules are applied simultaneously to all ants, in a discrete and iterative way. A concurrent evolution of the entire system ensures the rapid formation of all possible trajectories. Furthermore, the proposed method covers the need for self-organization, since the utilized artificial intelligence algorithms embody this particular attribute. In the following subsections, the proposed method is described in detail.

Algorithm 4.1: Pseudocode for Ant Colony System.

Input: ProblemSize,Populationsize,m,ρ,β,σ,q0

Output: Pbest

1. Pbest ← Create Heuristic Solution (ProblemSize);

2. Pbestcost ← Cost (Sh);

3. Pheromoneinit ← 1.0/(ProblemSize×Pbestcost)

4. Pheromone ← Initialize Pheromone (Pheromoneinit);

5. while Stop Criteria () do

6. for i = 1 to m do

7. Si ← Construct Solution (Pheromone, Problem Size, β, q0);

8. Sicost ← Cost (Si);

9. if Sicost ≤ Pbestcost then

10. Pbestcost ← Sicost;

11. Pbest ← Si;

12. end

13. Local Update And Decay Pheromone (Pheromone, Si, Sicost, σ);

14. end

15. Global Update And Decay Pheromone (Pheromone, Pbest, Pbestcost,ρ);

16. end

17. return Pbest;

- The local pheromone (history) coefficient (σ) controls the amount of contribution history plays in a components probability of selection and is commonly set to 0.1.
- The heuristic coefficient (β) controls the amount of contribution problem-specific heuristic information plays in a components probability of selection and is commonly between 2 and 5, such as 2.5.
- The decay factor (ρ) controls the rate at which historic information is lost and is commonly set to 0.1.
- The greediness factor (q0) is commonly set to 0.9.
- The total number of ants (m) is commonly set low, such as 10.

Cellular automata depict a discrete model with a finite number of states. Lattice cells work in communication, computation, construction, growth, reproduction and evolution. Simultaneously, CA masters at ordering, turbulence, chaos, symmetry-breaking and fractals in the dynamic system. Cell state at next time is dominated by current state and neighbors' current states. CAs structure consists of four parts: cellular-ant space, grid dynamics net, local principles and transition function. Cellular Space in subsystems has two-dimensional uncertainty states. Updated function with cellular ants' information at time t under extended Moore neighbor model is as:

$$f=S_{t+1}^{i}=f(S_t^{i}.S_t^{N}) \tag{5}$$

The key part of CAs is to establish corresponding neighbor's policies under extended Moore neighbor model where last-state performances are compared with neighbors. Thus, reward function of distributed multi-cellular-ant algorithm is written as:

$$f = f(S_t^i(a).\sum_{j=0}^{N} S_t^j(a)) \; and \; fv(s.a.s') = F(S_{t+1}^i):$$

$$R'(s.a.s') = R'^{(s.a.s')} + \sum_{r=0}^{2r} f(S_t^{i+r}(a).\sum_{j=0}^{N} f(S_t^j(a))$$

(6)

EXPERIMENTAL RESULTS

A simulation environment was created to test the effectiveness of the applied CA rules and ACO principles in order to create a robust and reliable cluster Table 2 shows a short comparison of network lifetime and stability region between TEEN, PCB, C-UAV, NLP, PSO-C, SMT and proposed method in terms of rounds. The ACO-Cellular Automata (ACO-CA) outperforms the other in terms of network lifetime and stability region.

Table 2: Comparison Table

Protocol	Average Stability	Average Lifetime	Environment	Delay-tolerant single mobile-sink models
TEEN	1207	1937	Homogeneous	Sink traversal on a uniformtwo-dimensional grid
PCB	1090	1967	Homogeneous	Sink traversal and routing varying delay restrictions
C-UAV	1179	1932	Homogeneous	Distributed sink traversal
NLP	1208	1910	Homogeneous	Partially-distributed sinktraversal and routing
PSO-C	1309	1978	Non- Homogeneous	Sink traversal
SMT	1189	1980	Non- Homogeneous	routing with non-negligible sink travel time
ACO-CA* (This work)	1318	1981	Homogeneous	Partially-distributed sinktraversal and routing

Statistical evaluation of analytic performance in general and specifically ROC curve analysis was conducted for calculating the performance of proposed model. The confusion matrix was calculated to define the performance of the suggested approaches. The confusion matrix describes all possible results of forecasting results in the table structure.

Specificity: The prospect of the test finding the correct class among all classes:

$$\frac{TN}{TN+FP} \tag{7}$$

Accuracy: The fraction of test results those are correct:

$$\frac{TP}{Total\ Negative} \quad for\ FP\ Rate \tag{8}$$

Precision: Precision or positive predictive value:

$$\frac{TP+TN}{TP+FN+TN+FP} \tag{9}$$

Sensitivity (Recall): Hit rate

$$\frac{TP}{TP+FP} \tag{10}$$

$$\frac{TP}{Total\ Positive} \quad for\ TP\ Rate \tag{11}$$

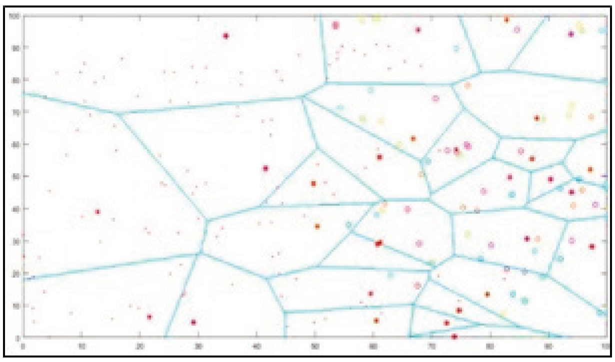

Fig. 4. First Level Clustering Without ACO Algorithm

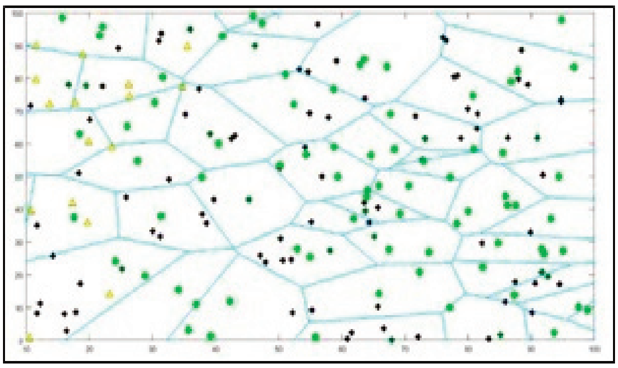

Fig.5. Second Level Clustering based on ACO Optimization along with CA

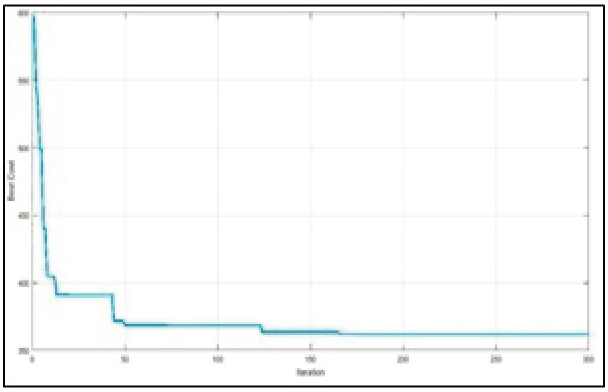

Fig.6. Algorithm convergence (cost reducing) in 300 iterations

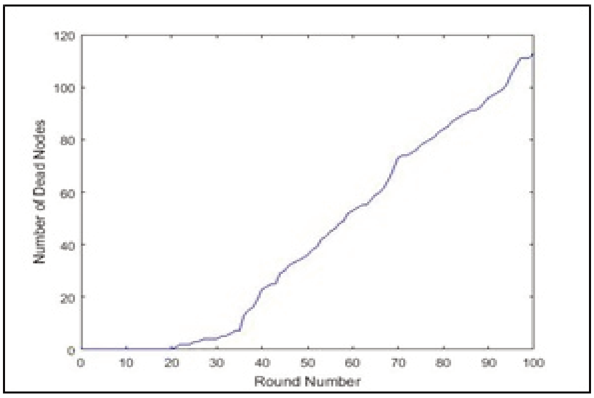

Fig.7. Number of Dead Nodes in 100 epochs

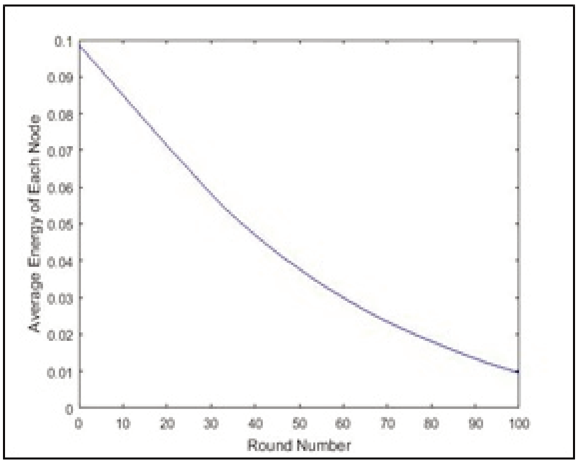

Fig.8. Average Energy of Each Node in 100 epochs

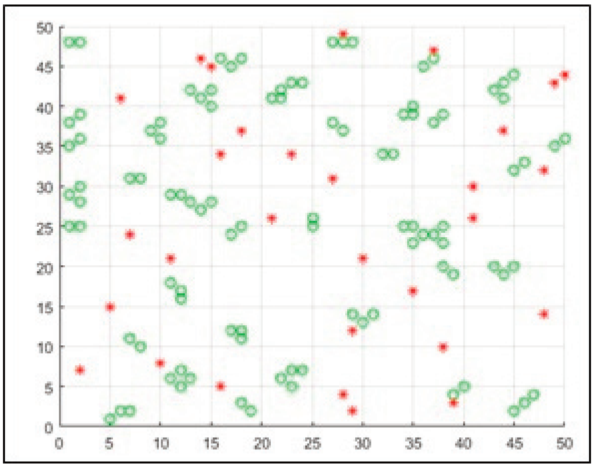

Fig.9. Nodes Distribution (Green are alive and Red are dead nodes)

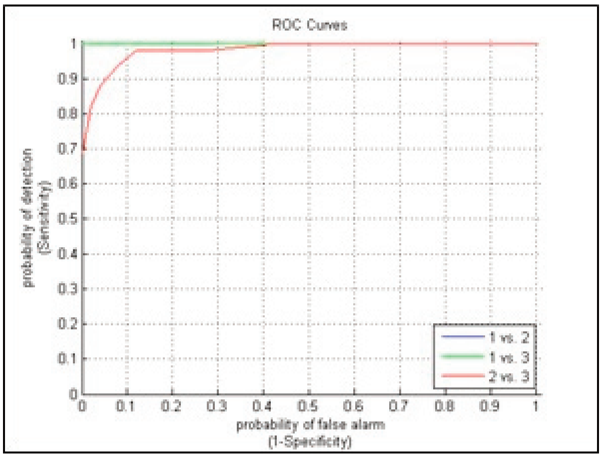

Fig.10. ROC Curve for proposed model in different setups

CONCLUSION

This paper has focused on the cellular ant algorithm for the WSN. The algorithm combines cellular automaton and ant colony optimization which cooperating together to optimize the capacitated vehicle routing problem. The above experiment shows that the cellular ant algorithm is feasible and effective for the VANET-WSN. The experimental results show that the proposed approach is significantly better than other clustering methods in terms of both speed and precision. It is adaptive, robust and efficient, achieving high autonomy, simplicity and efficiency.

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