

Optimal Cooperative Virtual Multi-input and Multi-output Network Communication by Double Improved Ant Colony System and Genetic Algorithm

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Abstract—This paper we research on the problem of cooperative virtual multi-input and multi-output (MIMO) network communication distance under the assumption of nodes placed along an appointed direction. The objective here is to choose the parameters value to solve this model based on the double improved ant colony system (DIACS) and genetic algorithm (GA) to optimize the set of relays to satisfy the outage probability constraint. We use experimental analyses to carry out the reasonable selection value of all the parameters in the algorithm. The simulation experiments compared during DIACS with Ant Colony System (ACS) and particle swarm optimization (PSO) algorithms, the simulation results proves DIACS is effective, and has an advantage of high accuracy and time saving especially when optimize the parameters' value, and the results are better than the other two algorithms.

Index Terms—Virtual Multi-input and Multi-output (MIMO) Network, Cooperative Communication, Double Improve Ant Colony System (DIACS), Genetic Algorithm (GA), Parameters' Value Optimization

I. INTRODUCTION

THE coverage problem of the wireless sensor networks (WSN) is always an important research hot pot as the development of WSN. And the range expansion is a promising feature offered by cooperative communication which is also called as distributed virtual multi-input and multi-output (MIMO) network. Cooperative communication is a physical layer communication scheme, in which spatially separated users to form a virtual antenna array. The purpose of this paper is range expansion along an appointed direction using number of WSN nodes relayed along a stripe, to cover the longest distance, with the network connectivity.

Range extension provides a new freedom to the network, which can be exploited to achieve faster broadcast, balanced energy consumption, and survivability against network partition. [1][2] proposed cooperative communication technology CCT by using single-antenna mobile terminals to build a

virtual MIMO strategy under the definition of the diversity gain and the application of CCT to expand the network, then the communication network would obtain diversity gain, improve the network performance and cover more area[3][4]. [5] deployed the wireless network nodes in a straight line without using CCT to expand the network. We would like to find how the network range expansion with cooperative communication technology compared with [5]. [6]-[8] proved that CCT can effectively resist multi-hop path fading and improve the spectrum utilization, also with the advantage of increasing the coverage area. In [9], authors researched on how to apply the CT to the linear network, but require the same number of nodes in every cluster. In this paper, we explore how to best deploy the mobile wireless sensor network nodes along a line, to cover the longest transmission distance by using CCT technology with quickly deployed movements.

In our prior work, the CCT model was built[10], which had no normal solution. So we would like to use an optimization algorithm to get the global optimal solution. As we all know, even we use the same algorithm, different parameters' value would influence the optimal result, different algorithms would influence the convergent rate, such as the neural network and genetic algorithms which have slow convergence speed and poor quality in obtaining the optimal solution[11]. In 1990s, Dorigo proposed ant colony system (ACS), and applied ACS to solve the Traveling Salesman Problem (TSP), the ACS is a probabilistic method for discrete optimization problems [12]. The main idea of ACS is imitating the behavior of real ants on their way to find the shortest path to arrive at the food sources. ACS has been successfully applied to various problems for its the advantage of parallelism, positive feedback and good robustness, etc [13]-[17].

There still some difficulties in the application of ACS to CT model, how to choose the optimal parameters' value such as α , β and ρ , we use experimental analyses to carry out the reasonable selection of all the parameters under the help of [18]-[19]. [20] and [21] do some research on the ant colony algorithm to optimize the exact problem like our research.

The contribution of this paper are summarized as follows:

(1) In order to get the optimal parameters' value of IACS to apply in the CT model. We improve the ACS to get the optimal deployment under the constraint of outage probability, update the pheromone. So in our paper, it is the double IACS, the first is to optimize the cooperative transmission model and the second is to optimize the parameters value of

Manuscript received March 27th, 2017; revised November 6th, 2017. This work was supported in part by the CERNET Innovation Project Grant No. NGII20160610, the Online Education Research Funds of Online Education Research Center of Ministry of Education (Quantong Education) under Grant No. 2016YB132, the Heilongjiang Postdoctoral Fund (Grant No. LBH-Z16081), and the Fundamental Research Funds for the Central Universities under Grant No. HIT NSRIF.20169.

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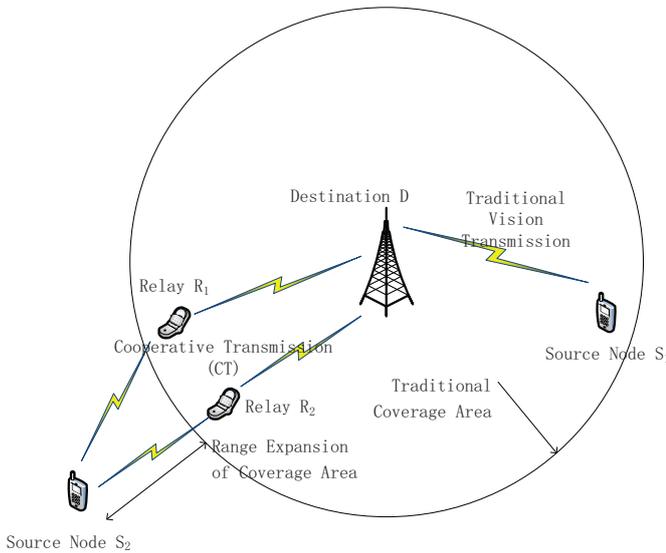


Fig. 1. Application of CT in wireless communications

IACS.

(2) We solve the transmission distance problem based on the IACS and cooperative transmission technology.

(3) The proposed framework performs joint optimization of relay selection for cooperative transmission.

The deployment is implemented and the simulation experiments compared IACS with ACS, which proves IACS is effective, and has an advantage of high accuracy and time saving especially when choosing the right parameters' value.

The rest of the paper is structured as follows. The problem formulation model and main objectives are expressed in Section II. The proposed optimization framework is detailed in Section III, along with the solution scheme and analysis. Comparative performance simulation results of the proposed strategies is presented in Section IV. Section V contains concluding remarks.

II. VIRTUAL MIMO NETWORK COMMUNICATION MODEL

We consider an N single-antenna virtual MIMO network (VMMN) which nodes are deployed along a straight strip. The source node is always isolated, while the other nodes can be in clusters and could move along the straight strip. In this way, we can say all the nodes could move along an appointed direction. We assume all transmitters emitting the same power P_t with only one antenna, and that the transmissions within a cluster are in orthogonal channels. The receiving node is assumed to be able to do maximal ratio combining (MRC) of the copies in each orthogonal channel. We assume model with the independent Rayleigh fading and the channels with path loss, which has a function of path loss exponent n . We assume that all the VMMN nodes in the same cluster are co-located. We assume block fading which is shown in Fig.1 by applying the cooperative communication technology.

An $N = 6$ 3-hop example which topology is 1-2-2-1, We also consider the case when the destination is part of a cluster. There are $2^{6-2} = 16$ different topologies for 6 nodes in the VMMN, and the number of possible topologies would increase as an exponential function with the number

of nodes in the VMMN increased. The bottleneck in this research is to get the optimal topology which could get the maximal communication distance. However we assume the nodes within a cluster are sufficiently separated to be able to assume uncorrelated fading of all the channels.

Our research is to get the maximum transmission distance D which is the distance from the source to the destination by cooperative communication under the constrain of outage probability, we define d_i denote the distance of hop i . we would have:

$$\text{Min}D = \sum_{i=1}^m d_i, \quad (1)$$

where m is the hops number of the network, and i is the hop number.

We consider the outage probability as the constraint, which is correlative with the SNR, for Rayleigh fading, the PDF of the SNR, γ , is given by

$$p(\gamma) = \begin{cases} \frac{\gamma}{\sigma^2} \exp(-\frac{\gamma^2}{2\sigma^2}) & (0 \leq \gamma \leq \infty) \\ 0 & (\gamma < 0), \end{cases} \quad (2)$$

We also know the freedom space model of Friis is that:

$$P_\gamma(d) = P_\gamma(d_0) \left(\frac{d_0}{d}\right)^n, \quad (3)$$

where $P_\gamma(d)$ is the received energy, $P_\gamma(d_0)$ is the received energy at position d_0 , n is the path loss exponent. While in order to get the optimal result,

Then the outage probability for every hop in any cluster is:

$$\begin{aligned} P_i(\gamma < \tau) &= 1 - \int_{\tau}^{+\infty} p(\gamma) d\gamma \\ &= 1 - \sum_{M=1}^{M_{max}} \frac{1}{(M-1)!} (\zeta\tau)^{M-1} e^{-\zeta\tau}, \end{aligned} \quad (4)$$

where M is the number of received signals at any node, M_{max} is the maximum number of received signals for any node could receive, and M_{max} should be no less than 1. L_i is the number of nodes in the i th hop, $\zeta = \gamma_0 \left(\frac{d_i}{d_0}\right)^n$, γ_0 and d_0 are known parameters and n is the path loss exponent.

We assume the message can be shared among the nodes in the same cluster; this means there would be at least one node in the same cluster that could decode the message from the previous hop. The message sharing assumption simplifies the analysis significantly [13]. Given that at least one node in a cluster decodes, we can assume all nodes in the cluster will retransmit the message. With message sharing, the probability of one receiver in the i th hop failing to achieve the SNR threshold, so we can get the probability that the message will be decoded by the last hop as

$$P(\text{success}) = 1 - P_{out} = 1 - \prod_{i=1}^m (1 - P_i(\gamma < \tau))^{L_i} \quad (5)$$

where α is the total hops in the network, and L_i is the number of nodes in the i th hop. , $P_i(\gamma < \tau)$ is the outage probability of the i th hop. And while there are more than one signals transmitted from the previous hop, every receive node in this cluster would combine all the received signals by Maximal

Ratio Combining (MRC) based on the CT technology to achieve the diversity gain.

We would like to get the maximum D_{SD} , but there is no solution for the Formula (1) through traditional method. we should use an optimal algorithm to get the closest result, we use the improved ant colony algorithm (IACS) to solve this problem, but how to choose is the best value of every parameter is the emphasis of this paper.

III. DOUBLE IMPROVED ANT COLONY ALGORITHM AND PROCEDURE ANALYSIS

Ant colony which is the generally social insect society, is distributed system in spite of the simplicity of the individuals, presents a highly structured social organization. The main idea of ACS consists of imitating the behavior of real ants on their way to find the shortest path to arrived at the food sources through the chemical which called pheromone on the ground to increase the probability that other ants will follow the same path. In recent years ACS has been widely used in various fields and achieved good results to get the solution of optimization and distributed control problems.

In order to suit ACS to our research, we would discrete the hop distance to ants number, it means if there are 10 ants in group, which is shown in Fig.2, there would be 10 different path (distance value) between any two neighbor hops, such as between two hops, 'S' and $R_{1,1}, R'_{1,2}$, there are ten different paths (different distance), every ant would choose a different path for the first hop, then choose the second hop path (which is also ten different distance paths between $R_{1,1}, R'_{1,2}$ and $R_{2,1}, R_{2,2}, R'_{2,3}$) randomly under the outage probability constraint, and so forth until the last hop, at last every ant would get a different path from the source to the destination.

The convergence rate is a little slow through the traditional ant colony algorithm, which gets the transition probability based on the old pheromone function. It is always easy to find the local optimal result instead of global optimal result, here we improved the function of ACA to get the shorter path by choosing prior knowledge or roulette wheel selection.

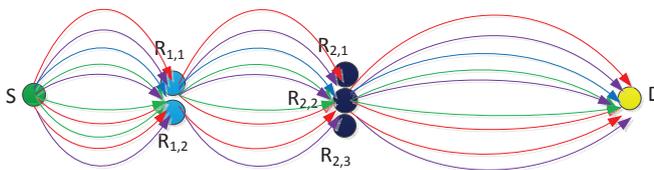


Fig. 2. 7 nodes wireless network model

In our previous work, we already solve the problem, but still have some doubts that how to choose the best parameters' value, in other literatures, they just get the value of different parameters based on selection by a lot of experiments, here, we would like to choose them by double improved ant colony system (DIACS), in this way, the optimize result would be better than only one round but cost more time.

A. Double Novel Heuristic Function

The traditional ant colony system get the transition probability based on the pheromone function, but the convergence

rate is a little slow. It is easy to get the local optimal result instead of global optimal result, so we improved the ant colony system to get a new shorter path through prior knowledge or roulette wheel selection. Here we propose a novel heuristic function which is more suitable to our research. So the novel heuristic function for the parameters is S :

$$p(\gamma) = \begin{cases} \arg \max_{S \in \text{allow}d_k} \{\tau_{i,j}^\alpha \eta_{i,j}^\beta\}, & \text{if } q \leq q_0 \\ \frac{\tau_{i,j}^\alpha \eta_{i,j}^\beta}{\sum_{S \in \text{allow}d_k} \tau_{i,s}^\alpha \eta_{i,s}^\beta}, & \text{if } q > q_0 \text{ and } j \in \text{allow } d_k \\ 0, & \text{others} \end{cases} \quad (6)$$

where i is the hop number, j is the path number in the i th hop, q_0 is the fixed value appointed by the problem, the value of q_0 is so important to determine the chosen of prior knowledge and roulette wheel selection, q is a random value between 0 and 1, $\eta_{i,j}$ is the heuristic function, $\tau_{i,j}$ is the density of the pheromone in this path, α and β are the weighted value of $\tau_{i,j}$ and $\eta_{i,j}$ in the transition probability, and apply the roulette wheel selection method to achieve the algorithm and finish the choice of the new path.

In ACS, the TSP problem get the shortest length path by choosing $\eta_{i,j} = \frac{1}{d_{i,j}}$ as the heuristic function, which is not available for our research that try to get the maximum range expansion by different topologies, the traditional one is too complex to calculate, cost more time, the rate of convergence is slow, the system would load more work, so we improve the heuristic function:

$$\eta_{i,j} = \frac{d_{i,j} - d_{j \min}}{d_{j \max} - d_{j \min}} * \kappa, \quad (7)$$

where $d_{i,j}$ is the distance of the i th path in the j th hop, $d_{j \min}$ and $d_{j \max}$ are the minimum and maximum value under the boundary condition of the i th hop. κ is the parameter determined by the outage probability.

B. Rule of Updating Pheromone

In traditional ACS, the rule of updating pheromone comes from the real ant world, the ants updating pheromone where they passed, but through this way, the rate of convergence is slow, it would cost more time to find the optimal path. In [8], the researcher improved the rule of updating pheromone based on the rule of wolf world, which is called law of the jungle (LJ), to increase convergence rate. The consist of the tabu list is different between our research and the traditional ACS, to avoid the local optimal solution and increase the rate of convergence, we combine the ant circle model and the LJ, update the pheromone based on the real rule plus the increased part which come from LJ after every cycle, the new rule of updating pheromone is:

$$\tau_{i,j} = (1 - \rho)\tau_{i,j} + \Delta\tau_{i,j}, \quad (8)$$

where Q is the constant value of pheromone, $\Delta\tau_{i,j}^k$ is the update of pheromone while ant k pass (i,j) in this circle, D_k is total path length of ant k in this circle.

C. Apply the Crossover and Mutation of Genetic Algorithm

In the model, in order to improve the convergence speed and avoid the local optimal result, we used the crossover and mutation of the genetic algorithm to solve this problem. In a genetic algorithm (GA), we started with a collection of solutions which we called the parents generation, and iteratively improve the generation by using reproduction, crossover, and mutation operators. The generation with which we start an iteration is called the parents generation, and the generation we called the children generation. At the end of the iteration, the parents generation is replaced by the children generation. Iterations continue until any stopping condition is reached. Stopping conditions are typically set based on the number of iterations performed, or the calculating time required by the GA and DIACS. After the iterations are over, the GA outputs the best solution it has encountered in all the generations it has processed as an approximation to an optimal solution.

We use some symbols to describe our crossover operator: p_a and p_b which means the parents generation, c_a and c_b means the children generation, $cp1$ and $cp2$ means the crossover points, a_p and b_p are the partial chromosomes between $cp1$ and $cp2$ in parents generation, respectively, a_c and b_c are the partial chromosomes between $cp1$ and $cp2$ in children generation, respectively.

The crossover operation selects genes from parents' chromosomes and creates the children chromosomes. The schedule of the crossover operation can be described as follows:

Step 1: p_a and p_b are selected as parents generation. Create c_a and c_b to host the children generation of the crossover operation.

Step 2: $cp1$ and $cp2$ which are the two crossover points are selected randomly .

Step 3: All the genes except a_p and b_p are moved to c_a and c_b .

Step 4: If the same gene exists the gene of a_p as compared with b_p , mutual position-information will be exchanged and it will move to a_c and b_c , respectively. Information is saved and the remaining genes are moved.

Mutation operation is described as below:

Step 1: Selected children are set to mutants B and P .

Step 2: Generate mutant C from mutant P using the mutation operation.

Step 3: If mutant C is better than mutant B , mutant C is set to mutant B .

Step 4: If the iteration number j is less than R_m which is set by the algorithm, go back to Step 2.

Step 5: If the best mutant is better than the worst individual in the population, it is selected as an offspring. Otherwise, make a set including all individuals in the population and the best of the overall individuals appeared at first. Then, the chromosome of the individual chosen from the set randomly is copied to an offspring.

Step 6: Replace all parents with all offspring.

D. The Nodes Deployment Principle and Complexity Analysis of the DIACS and GA

We use IACS to find the topology under the constraint of outage probability to achieve the maximum range expansion of fixed number of nodes along appointed direction by cooperative transmission where every discrete value is treated

as an individual path and deploy the nodes, if the chosen path can't satisfy the outage probability requirement, this path scheme would be sent into tabu list and choose the new scheme again. So the process to find the optimal scheme is shown in Fig. 3.

Based on the principle described above, we calculate the time complexity to analysis the algorithm, and we ignore influence of the space complexity as we would use the computer or other embedded device which would have enough space to support our algorithm.

Step 1: Initialize cooperative transmission model, the complexity is $O(1)$, and the boundary condition calculation is Newton's dichotomy which has the complexity $O(\log_2 n)$;

Step 2: Initialize every ant position in every hop of the search space base on the objective function and initialize the boundary condition value which has the complexity $O(1)$;

Step 3: The complexities of the probability of movement and the outage probability are both $O(m * k)$, where m is the glowworm's number and k is the dimension number in space.

Step 4: The equations calculation which have the complexity $O(1)$;

Step 5: DIACS calculation and update is $O(m^2)$.

Step 6: Nc times iteration for Step 3 to 5.

The total time complexity of DIACS algorithm is:

$$T = O(1) + O(\log_2 n) + O(Nc * m * k) + O(1) + O(Nc * m^2) = O(Nc * m^2), \quad (9)$$

Comparing the time complexity of DIACS which is $O(\nu * Nc * m^2 * k)$, where ν is a positive real number, and the time complexity of EAM is $O(n^k)$, so we can observe that $O(Nc * m * k) < O(\nu * Nc * m^2 * k) < O(n^k)$.

Because the computer is good enough to support the calculation and even though we use this algorithm in some embedded system, it is also enough to finish it, we don't analysis on the space complexity.

IV. ANALYSIS OF SIMULATION RESULTS

In order to test whether DIACS is correct or effective to deploy the wireless nodes by CT, the simulation hardware is CPU i3-2130, the RAM is 4GB, the system is windows 7 and the software is Matlab R2010a. First choose the topology 1-2-3-1 of the wireless nodes, where the path loss exponent n is 2, φ is 0.1, d_0 is 1, χ is 10^{-4} , $\tau = 10$ and the ants number in a colony is 10, 20 and 30 separately, the maximum iteration times is 50, 100, 200 and 500 separately, α is 1, β is 3, ρ is 0.4, and the length precision is 0.01 meters.

A. Convergence Analysis of DIACS

Fig. 4 shows the simulation results of the application by IACS to topology 1-3-2-1, where the ant number m is 10, and there would one time dispersion for every 100 iteration times to get the path more and more precise, in the Fig.2 there are 4 parts from No.1 to No.4 with total 400 iteration times, the IACS get the optimal longest range expansion result (The above curve in every part) and the average longest range expansion (the below curve in every part), we can observe that the optimal results are different during the first 100 iteration times because the independent calculation of our

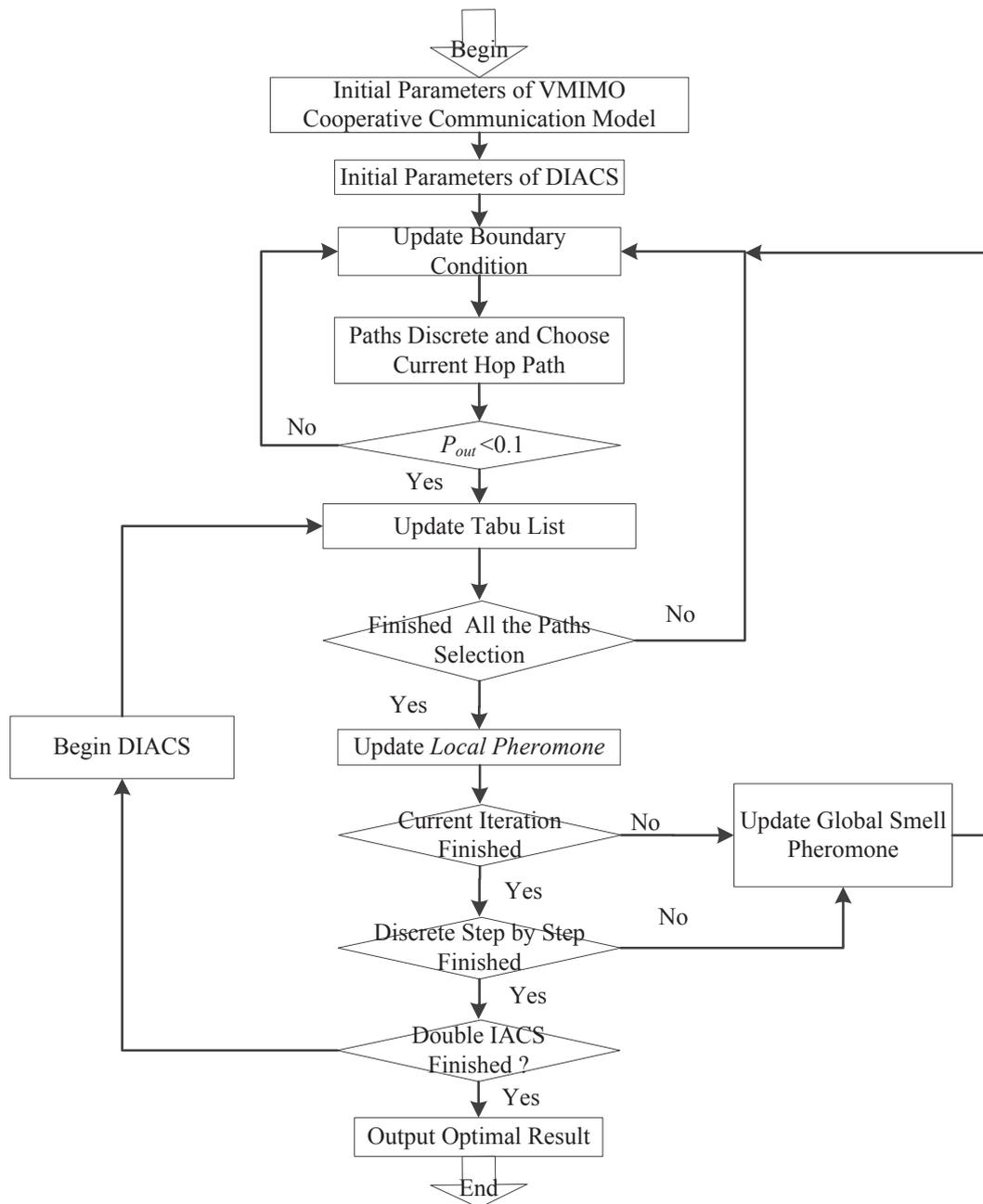


Fig. 3. The DIACS Algorithm Flow Chart to Optimize the Model and Parameters' Value

research, the convergence rate of IACS is higher for every 100 iteration times which is set by the algorithm (N_c). And the average result is also convergent as the iteration times higher. The simulation results conform to the ACS and the requirements of our research. We can observe that IACS is convergent.

B. Parameters Value Optimization by DIACS

There are several parameters which are so important to determine the precision and complexity of IACS, so we need to do some experiments analysis to find the optimal value of these parameters.

1) *The ant colony number m* : which is the total hops number in the WSN. In the ACS, the ant colony number m is a very important parameter which would influence the ability of the ACS, the number of m would influence the

global search ability and the convergence rate of ACS, even more about the stability. As the number of ants increases, the precision of the optimal solution would be higher, but the drawback is there maybe have more repeat solutions, and the initial pheromone of ACS is almost uniform in every path, so the convergence speed is very slow, it would be slower to get the optimal solution of the CT model, then there would cost more and more resource, which is a waste of resource and the time complexity would be bigger than before. In the opposite, if the number of ants is small, the solution would be convergent to the optimal one too quickly, we would just get the local optimal solution, not the global one, the precision would be low.

As usual, the simulation experiments would be repeated several times to determine the best value of ants number m .

2) *Pheromone trail decay coefficient ρ* : it would be initiated between 0 and 1, which will influence the search area

TABLE I
SIMULATION RESULTS OF PARAMETER ρ

ρ	0.2		0.4		0.6		0.8	
	D_{max}	Time (s)						
Experiment 1	75.13	0.38	75.14	0.41	75.14	0.39	75.14	0.38
Experiment 2	75.14	0.40	75.14	0.39	75.16	0.38	75.13	0.37
Experiment 3	75.11	0.38	75.15	0.40	75.14	0.38	75.14	0.38
Experiment 4	75.13	0.38	75.15	0.37	75.14	0.38	75.12	0.38
Experiment 5	75.13	0.38	75.15	0.38	75.08	0.38	75.13	0.38
Average	75.13	0.38	75.15	0.39	75.13	0.38	75.13	0.38

TABLE II
SIMULATION RESULTS OF PARAMETER α

α	0.5		1		3		5	
	D_{max}	Time (s)						
Experiment 1	75.14	0.40	75.12	0.37	75.14	0.39	75.14	0.40
Experiment 2	75.13	0.38	75.14	0.37	75.13	0.39	75.14	0.39
Experiment 3	75.16	0.39	75.14	0.39	75.13	0.38	75.12	0.46
Experiment 4	75.14	0.38	75.14	0.39	75.13	0.41	75.13	0.38
Experiment 5	75.12	0.37	75.14	0.37	75.14	0.39	75.14	0.42
Average	75.14	0.38	75.14	0.38	75.13	0.39	75.14	0.41

TABLE III
SIMULATION RESULTS OF PARAMETER β

β	1		3		5		7	
	D_{max}	Time (s)						
Experiment 1	75.14	0.52	75.14	0.44	75.14	0.44	75.13	0.40
Experiment 2	75.12	0.44	75.12	0.44	75.14	0.47	75.14	0.43
Experiment 3	75.14	0.44	75.15	0.43	75.14	0.42	75.14	0.40
Experiment 4	75.16	0.40	75.14	0.41	75.14	0.42	75.16	0.41
Experiment 5	75.11	0.43	75.14	0.41	75.13	0.45	75.14	0.42
Average	75.13	0.45	75.14	0.43	75.14	0.44	75.14	0.41

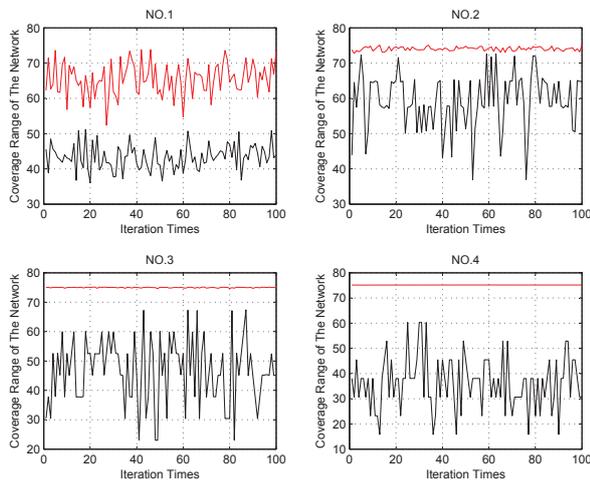


Fig. 4. The Application of DIACS to Topology 1-3-2-1

and convergence speed. While the ρ is too small, the decayed pheromone would be small, it would be more easier to get the original path as the current one, it would be difficult to find a new route, the convergence speed is slow, in the opposite, if the ρ is too big, the pheromone value would be determined by the new choose of next path, it would also have a slow convergence speed, so we should choose a

suitable pheromone trail decay coefficient value, through the simulation results from Table. I, we can observe that while ρ equal to 0.4, the average optimal result would have the best value, while it equal to 0.8, the cost time would be the shortest, by comparing the time cost and precision, we choose 0.4 as the ρ value.

3) *Relative weight of pheromone trail value α* : if the α is bigger, it will have a bigger probability to choose the old path, in the opposite, it will be easier to choose a new path. We can get the result from Table II, while α equal to 1, it will have the optimal result and save more time.

4) *Relative weight of pheromone heuristic value β* : if β is bigger, the convergence speed would be more quickly, but it will have a greater probability to get the local optimal result, not the global one. From Table. III, we can observe that β equal to 7 would have both optimal result and shortest time cost.

C. Multi-Nodes Placement Analysis Simulations

This research project is not an unalloyed ant colony problem, so we do the DIACS to satisfy the constraint of this research which has its specificity in order to make the result more precise and save more time, such as the number of ants in one colony would influence the result precision. Table I just shows the results of a 3 hops topology, and as the hops number increased, the advantage of IACS would

express more and more, such as calculate time would save more and avoid the local optimal result.

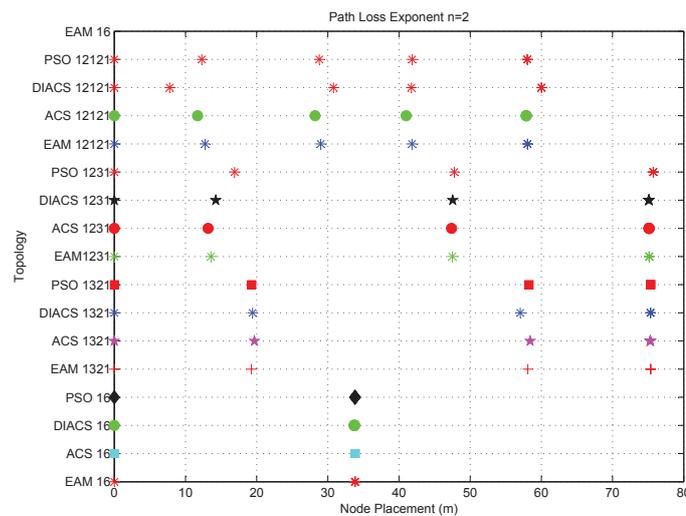


Fig. 5. Deployment Comparing and Application of 7 Nodes

The next analysis is the experiment about health monitoring of a bridge, 7 VMIMO network nodes are placed along a bridge to monitor the environment or the status of the bridge, including data collection, environment analysis and etc. after building the bridge. Nodes are placed with the maximum communication distance to coverage more area and distance to finish more work. Table IV shows the nodes deployment results of the DIACS, ACA and EAM algorithm applied to different topologies, every node placement in the Table IV express a cluster of nodes (based on the topology). We can observe that the calculating time of DIACS is bigger than ACA, but the error range is smaller, it means even DIACS has the double IACS, but the results is better. Except that, we can also observe that as the number of ants and iteration times increased, the error range can't reduce more as the limit of error range. So we don't have to choose much more ants in the algorithm and control the iteration times, as we use the DIACS, this problem could be solved by the optimization algorithm, but if we also optimize the ant number, maybe it would cost more time.

We can observe from the all the experiment that the DIACS have the advantage of high precision, quick calculate, save time and etc. in solving the wireless network nodes deployment based on cooperative transmission, DIACS is better than EAM and ACA method.

D. Topology 1-2-1-2-1-2-1-2-1 Analysis by EAM, D-EAM, DIACS, PSO and ACS

Table V shows the all the simulation results by EAM, D-EAM, DIACS, PSO and ACS in wireless network with topology 1-2-1-2-1-2-1-2-1, we can observe that when all these three swarm intelligent algorithms have the same parameters' value, PSO would have the shortest calculation time but worst precision, DIACS cost most time but highest precision, ACS is the middle one both in time cost and precision. This table can be part of proof that DIACS is useful to solve current problem in different topologies, and the precision is good enough to support our research.

TABLE V
RESULTS OF 1-2-1-2-1-2-1-2-1 BY FIVE ALGORITHMS

Algorithm	Calculation Time	Total Distance (m)
EAM	$\gg 200$ h	NA
D-EAM	20.7 h	96.5
DIACS $m=20, N_{cmax}=200$	5 s	90 – 105
ACS $m=20, N_{cmax}=200$	3 s	90 – 102
PSO $m=20, N_{cmax}=200$	0.7 s	91 – 115
DIACS $m=50, N_{cmax}=500$	35 s	95-100
ACS $m=50, N_{cmax}=500$	22 s	90-96
PSO $m=50, N_{cmax}=500$	5 s	105-110

V. CONCLUSION AND FUTURE WORK

Because the challenge of the VMIMO nodes placement that there is no solution of the cooperative communication model to get the communication distance expansion. In this paper, we proposed an double improved ant colony system method to get the optimal result of our proposed model.

The contribution of this paper is choose the best parameters value of IACS by DIACS, we observed that the DIACS is effective to solve our research problem to get the optimal parameters' value, then solve the model by high precision, but a little more time than IACA, which is only solve the model without the optimize the parameters' value.

The overall conclusion is that VMIMO network could be arranged accordingly for cooperative transmission to expand the communication range through DIACS, which is useful and effective.

In the next step, we would focus more on the energy efficient to organize the network.

ACKNOWLEDGMENT

The authors would like to thank Prof. Mary Ann Ingram for her help during the research period of Dr. W.B. Zheng as a visiting scholar at Gatech in the USA.

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TABLE IV
COMPARING RESULTS OF THREE ALGORITHMS WITH DIFFERENT PARAMETERS VALUE

Algorithm's Name	Ant's Number	Iteration Times	Time (s)	Average Communication Distance (D)	Error Range (%)
EAM	NA	NA	9427	75.15	0
D-EAM	NA	NA	0.49	75.15	0
DIACS	10	50	0.42	75.05	0.13
ACS	10	50	0.27	74.98	0.23
DIACS	10	100	0.55	75.10	0.07
ACS	10	100	0.43	75.04	0.15
DIACS	20	100	0.85	75.12	0.04
ACS	20	100	0.72	75.11	0.05
DIACS	20	200	1.29	75.16	0.01
ACS	20	200	0.85	75.16	0.01
DIACS	50	500	8.21	75.16	0.01
ACS	50	500	7.64	75.16	0.01

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