Optimized Routing in Cognitive Networks using Ant Colony Algorithm

Nadia Tabassum
Virtual University, Lahore, Pakistan.
Nadiatabassum@vu.edu.pk

Tahir Alyas
Tahir Alyas is currently PhD Scholar in Computer Science in NCBA&E, Lahore, Pakistan and lecturer in Lahore Garrison University, Lahore, Pakistan
* E-mail of the corresponding author: tahiralyas@gmail.com

Abstract
Tactical communication through network faces various operational scenarios having complexity, heterogeneity, and reliability requirements for network optimization. Learning from the heterogeneous network environment, in order to adjust the network settings, is an essential requirement for providing efficient communication services in such complex and dynamic environments. Routing algorithms with learning capability for routing choice quality could determine wireless network efficiency and is a hot research area now a days.Cognitive networks are capable of reasoning and learning. They can energetically adapt to varying network conditions in order to optimize end-to-end performance and utilize best routing to overcome the network loads. In this paper, we are focusing on the feasibility and effectiveness of the ant colony algorithm in wireless routing. The Ant colony algorithm is applied to wireless cognitive network, to obtain the performance effect of wireless sensor network routing protocol under the different network nodes.
Keywords: Cognitive Network, Wireless Network, Routing Protocol

1. Introduction

Ant colony algorithm is a kind of evolutionary intelligent algorithm that inspired by the activities of real ant in nature. Ant colony algorithm has characteristic of probability seeking and adopts the catalytic mechanism of parallelism and positive feedback. Ant colony algorithm has strong robustness and excellent distributed computing mechanism and is easy to combine with artificial neural network, genetic algorithm, artificial immune algorithm and particle swarm optimization algorithm (Zhao & Zhong, 2011).

It was first proposed by M.Dorigo (Zhao & Zhong, 2011), an Italian researcher, who makes full use of the similarity between the paths of ant colony searching for food and the famous travelling salesman problem, to solve by artificially replicated the process of ant searching for food, namely finding the shortest path from ant-colony to food reserves through exchange of information and mutual cooperation.

Cognitive networking is a promising paradigm that deals with how heterogeneous systems learn relationships among network parameters, network events, and observed network performance, plan and make decisions in order to achieve local, end-to-end, and network-wide performance as well as resource management goals. Cognitive wireless networks are capable of reconfiguring their infrastructure, based upon experience, in order to adapt to continuously changing network environments. Cognitive networks are seen as a main facilitator of future heterogeneous internetworking and management, capable of continuously adapting to fluid network characteristics.

The term “cognitive network” has different interpretations with different emphasizes on the node behavior, operational objective, or the scope of the target problem.

Cognitive Radio (CR), with the ability to observe the surrounding network environment and reconfigure to adapt to network changes, is one of the most promising solutions. The core of cognitive radio as described by Mitola is the cognitive cycle, which consists of six processes observe, orient, plan, decide, act, and learn (Gao & Wu, 2011).

1.1 The Ant Colony Optimization Algorithm

For solving the problem with ACO algorithm, in most cases, the problem must be defined and represented with a graph. After that the ants start production of solutions in the graph and they are guided by pheromone trails and heuristic information. (Keivan & Behnam, 2010)

The ants release pheromone in their way. When the ant forwards along the path, it can feel this powerful hormone. The role of Pheromones in ants have attracted role. Therefore, higher ants incline to follow the path of pheromone strength. This causes the catalytic reactions, or their self-reinforcing positive feedback effect. The collective behavior composed of ants will show a kind of information positive feedback phenomenon. Through this kind of behavior, ant colony can find the best and optimized route to the destination.

2. Cognitive Network Route Protocol

Network Communication routing protocol is a mechanism of transmitting data from the source node to destination node. The main objectives are to meet the requirement while minimizing the network cost, to obtain the overall effectiveness of the use of resources, to expand the network throughput. The requirement generally refers to delay, delay jitter, packet loss rate and other factors like congestion and network overload (Gao & Wu, 2011).

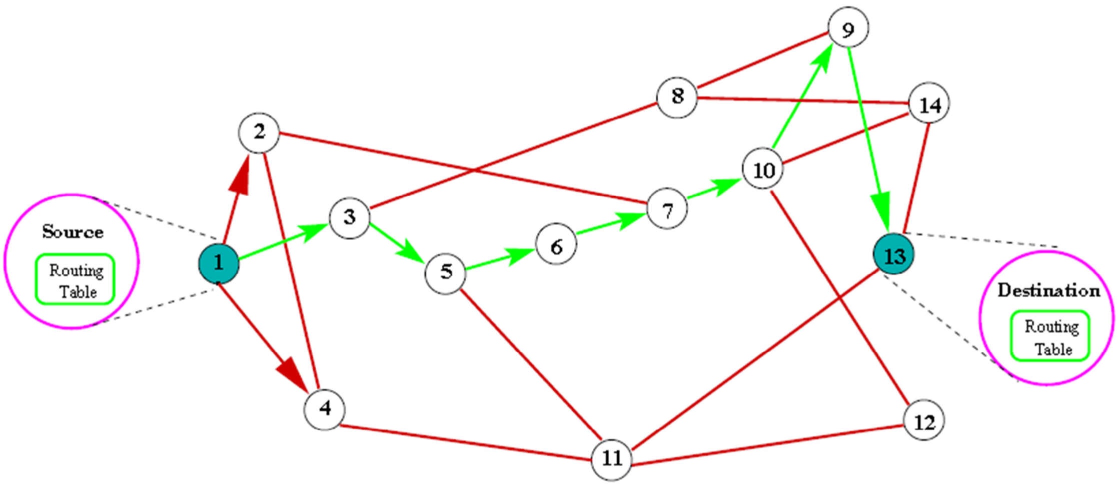

Figure. 1 Routing from Source to designation

Network routing protocol is the most significant and the core of the problem for network communication. The cognitive network routing protocol includes the routing path generation, path routing selection and maintenance of the routing path. The routing path is generated according to network status information and shortest path is selected as shown in fig.1. The routing selection is based on network status information and Operational status to select the most appropriate path (Caro, 2004).

3. Ant Colony Functions

After that the ants start production of solutions in the graph and they are guided by pheromone trails and heuristic information. The heuristic information is the measure of preference to move from state Si to Sj (in graph, from node i to node j) and the pheromone trails are the amount of pheromone deposited with ants in previous steps that shows the learning desirability of moving from state Si to Sj. Considering the solution that they have found, in every step ants update the amount of pheromone trails. In the next steps, the nodes with more amounts of pheromone trails are more likely to be selected by the artificial ants.
The suggested ant colony algorithm is composed of some main functions such as,

3.1 Pheromone matrix: For solving the problem with ACO algorithm, in most cases, the problem must be defined and represented with a graph and store in Pheromone matrix. At the end of any iteration, the pheromone matrices will be updated separately considering the solutions that have been generated up to the current iteration (Keivan & Behnam, 2010).

3.2 Searching parameter: Searching parameter for objective k for moving from node i to node j is equal to:

Eq:1 (Keivan & Behnam, 2010)

$$\eta_{ij}^{1k} = \min\left(1, \frac{C_{\max}^{k} - C_{ij}^{k}}{C_{\max}^{k} - C_{\min}^{k}} + \varepsilon\right)$$

where Ck max and Ck min correspond respectively to the arcs with maximum and minimum cost values for objective k in the entire of the network, ε is a nonzero small value added to prevent the parameter to be zero and Min function prevents the parameter to be more than 1. This parameter is defined between 0 and 1 to help the artificial ants to choose the arc with less cost among feasible arcs.

3.3 Transition rule: During the construction of a new solution/path the state transition rule is the phase where each ant decides which is the next state to move to. Transition rule provides a direct way to balance between exploration of new states and exploitation of a priori and accumulated knowledge. The following probability distribution shows how an ant moves from node i to its subsequent node.

- If $q \leq q_0$:

$$p_{ij} = \begin{cases} 1, & \text{if } j = arg \max_{u \in \omega(i)} \{ (\tau_{iu}^{1^{\alpha}} \cdot \eta_{iu}^{11^{\beta}})^{\lambda} \cdot (\tau_{iu}^{2^{\alpha}} \cdot \eta_{iu}^{12^{\beta}})^{1-\lambda} \cdot \eta_{u}^{2^{\delta}} \}, \\ 0. & \text{otherwise,} \end{cases}$$

- else

$$p_{ij} = \begin{cases} \dfrac{ (\tau_{ij}^{1^{\alpha}} \cdot \eta_{ij}^{11^{\beta}})^{\lambda} \cdot (\tau_{ij}^{2^{\alpha}} \cdot \eta_{ij}^{12^{\beta}})^{(1-\lambda)} \cdot \eta_{j}^{2^{\delta}} }{ \sum_{u \in \omega(i)} (\tau_{iu}^{1^{\alpha}} \cdot \eta_{iu}^{11^{\beta}})^{\lambda} \cdot (\tau_{iu}^{2^{\alpha}} \cdot \eta_{iu}^{12^{\beta}})^{(1-\lambda)} \cdot \eta_{u}^{2^{\delta}} } & \text{if } j \in \omega(i) \\ 0, & \text{otherwise} \end{cases}$$

Eq:2 (Keivan & Behnam, 2010)

3.4 Local update: When an ant moves from node i to node j, the pheromone trail on arc (i, j) will be multiplied by the local update evaporation rate, as follows:

$$\tau_{ij}^{1} = \tau_{ij}^{1} \cdot \varphi$$
$$\tau_{ij}^{2} = \tau_{ij}^{2} \cdot \varphi$$

Eq:3 (Keivan & Behnam, 2010)

3.5 Global update: At the end of each of the iterations, the pheromone trails of arcs belong to those non-dominated paths generated by ants at the current iteration, are globally updated as follows:

$$\tau_{ij}^{1} = \tau_{ij}^{1} \cdot \rho$$
$$\tau_{ij}^{2} = \tau_{ij}^{2} \cdot \rho$$
$$\tau_{ij}^{1} = \min \left\{ 1, \tau_{ij}^{1} + \frac{\Delta}{C_{ij}^{1}} \right\}$$
$$\tau_{ij}^{2} = \min \left\{ 1, \tau_{ij}^{2} + \frac{\Delta}{C_{ij}^{2}} \right\}$$

Eq:4 (Keivan & Behnam, 2010)

4. Propose Network Model

Step1: Suppose that a network with N nodes exists. The nodes are labeled from 1 to N and the objective is to find the optimized routing from node 1 to node N. In addition, suppose that the network is complete and all the nodes are connected to each other. Therefore, the network contains N(N−1)/2 arcs.

In any routing algorithm, the final quality of the routing policy critically depends on the characteristics of the information maintained at the network nodes. Initially all the routing tables are initialized with zero.

Step 2: The remarkable ability of ant colonies in selecting the shortest among the available paths can be precisely understood generating population (colony) of foraging ants, keeping the track of forward-backward path discovery using transition function. They update routing table locally and make local policy.

Step 3: Each ant can be considered as autonomous, and the overall control is completely distributed in this environment. In this perspective, the colony realizes a form of concurrent autonomic computation. Multiple paths are repeatedly tried out back and some information related to each followed path is released on the environment, which acts as a shared distributed memory preset in the pheromone trails and helping in to update local table. In turn, the local content of this memory affects the stochastic decisions of the ants, such that, when there is a significant difference in the lengths of the possible paths, implicit path evaluation gets the collective path optimization mechanism.

Step 4: Shortest path routing is the routing model most in use in real networks. In shortest path routing the optimizing strategy for path flows consists in using the minimum cost paths connecting all the node pairs in the network, where the paths are calculated independently for each pair. When we are talking about optimal routing, that is the other main reference paradigm has a network-wide perspective, since the path flows are calculated considering all the incoming traffic sessions throughout the network. Clearly, in order to adopt such a global strategy, optimal routing requires the prior knowledge of the statistical characteristics of all the incoming flows, a requirement which is usually quite hard to satisfy. Heterogeneous network environment often varies, the knowledge of network environment is key factor for optimizing factors.

Step 5: According to an optimization perspective, a major distinction can be also made between minimal and non-minimal routing algorithms. Minimal routers allow packets to choose only paths which are minimal with respect to some cost criterion, while in non-minimal algorithms packets can be forwarded along any of the available paths according to some heuristic decision strategy. Both optimal and pure shortest path routing implement minimal routers. Data traffic toward the same destination can be forwarded along always the same link or it can be spread along multiple paths. Actually, when all colonies are reached at final destination then they committed on one solution that is shortest path selection.

Step 6: The next stage of sensing the network environment by using different techniques like packet retransmission rate. We can use the different levels to express the network parameters. For example, delay can be defined by three levels {Small, Medium, Large}, the different levels indicate the different delay intervals, the small means the network delay is very small and the network performance is good. If Network Level is Large on that route, then the route will be reconsidered and alternate route which is not shortest path is decided.

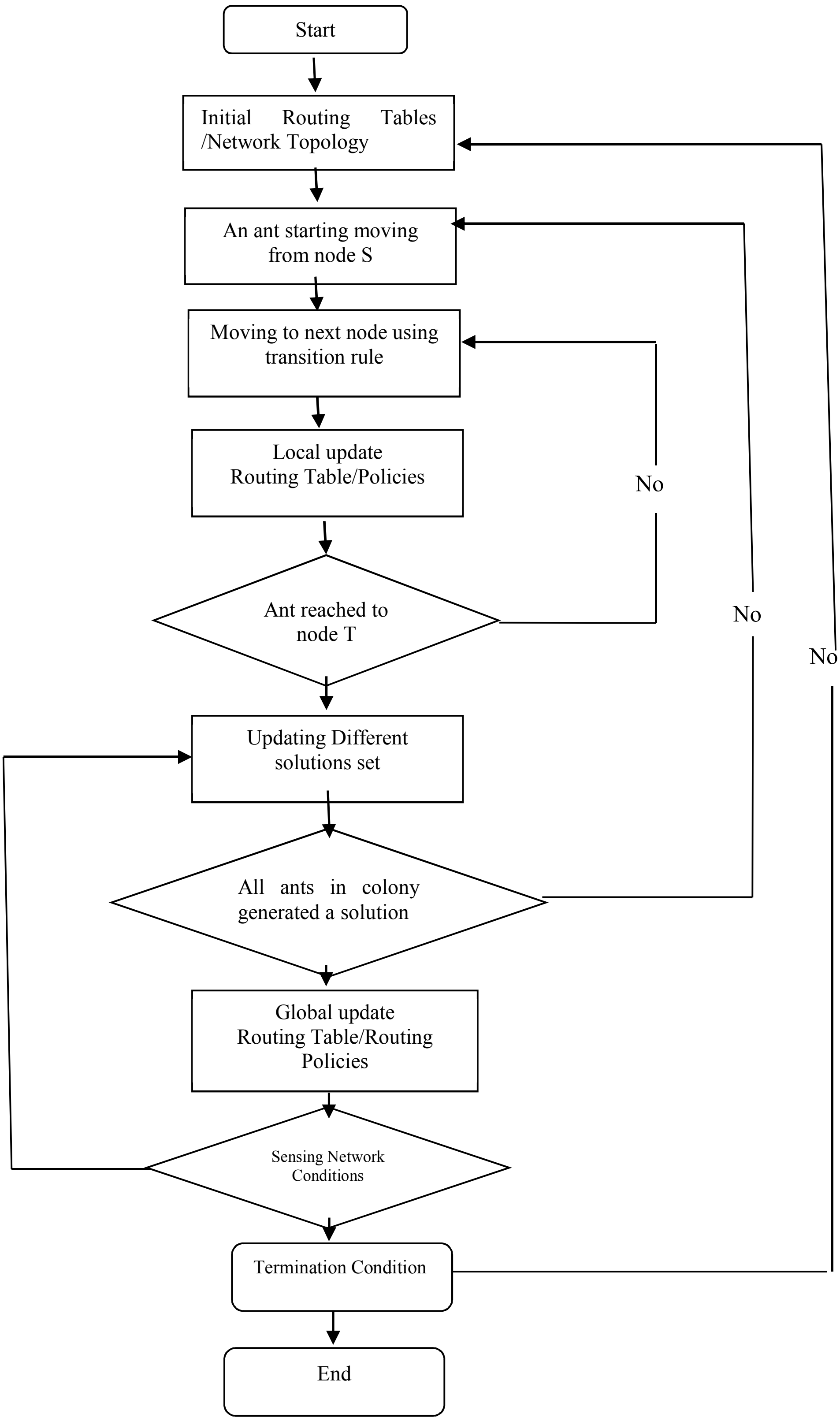

Fig. 2 Flow Chart of Algorithm

5. Conclusion

In this paper, routing algorithm based on Ant colony algorithm including the design characteristics in cognitive radio networks are purposed for optimized routing. Using ant colony algorithm optimize routing in cognitive network by sensing the heterogeneous environment and can perform better routing and can increase network efficiency.

References

Ahmed, T. H. (2005). Simulation of Mobility and Routing in Ad Hoc Networks using Ant Colony Algorithms. International Conference on Information Technology: Coding and Computing , 6.

Caro, G. D. (2004). Ant Colony Optimization and its Application to Adaptive Routing in Telecommunication Networks. Bruxelles: Institutions of the European Community.

Gai-ping, & Hai-wen, G. (2010). A Dynamic Ant Colony Optimization Algorithm for the Ad Hoc Network. International Conference on Genetic and Evolutionary Computing , 4.

Gao, R., & Wu, J. (2011). An Improved Ant Colony Optimization for Routing in Cognitive Radio. International Journal of Advancements in Computing Technology , 9.

Keivan, G., & Behnam, N. (2010). An ant colony optimization algorithm for the bi-objective shortest path problem. Elsevier Ltd , 10.

Zhao, Y., & Zhong, B. (2011). Ant Colony Algorithm's Shortest Path Principle and Its Convergence Performance. Elsevier Ltd , 9.