# ANCOR: A NOVEL ANT COLONY ROUTING APPROACH FOR SENSOR NETWORKS

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**Abstract**

In this paper, we present a novel routing scheme for sensor networks. The essential idea behind the algorithm is imitating the real acts of ants for finding new food resources and bringing them to their nests or searching for a new or better place for their nests. In colonies of ants, there is a large number of individuals working together to achieve a single goal. Whatever the goal is, they work together in an organized manner, but in fact, there is no dedicated colony manager telling them what to do and how to act. Each ant follows some simple rules and is aware of the environment as well as being capable of communicating in a simple indirect method. However, in a broader perspective, they establish a complex living organism through the simple acts. We believe that such a behavior can be applied to the sensor networks as a self organizing and efficient routing algorithm. The overall approach of the novel algorithm, i.e. ANCOR, is explained in this paper. The features of ANCOR that could distinguish it from the others are discussed.

**Keywords**: Sensor networks, routing, ant colony optimization, swarm intelligence

## 1 Introduction

Ant colony optimization is a stochastic combinatorial optimization method, inspired by the natural behaviors of real ant colonies. Since there is no single authority in an ant colony, decisions are made collectively with local interactions and positive feedback. Ant colony optimization was founded on these properties [5] and had been a research area for the last two decades. Although various application areas such as feature selection [2], data mining [12] and various optimization problems [6, 7, 15] can be named as examples of the use ant colony optimization there are only a few studies applying the concept on routing over sensor networks [4, 14, 16].

## 1.1 The Nature of Large Ant Colony Life

Although there is a tendency to describe an ant colony life as a simple generic way of living there are essential differences between large and small ant colonies.

Large colonies communicate by emitting a chemical substance called pheromone that we consider as a broadcasting operation. However, pheromone is not available for the members of small societies. They make use of a supervised learning process named tandem-running [8, 13]. Emitting pheromone and tandem-running are the only existing methods to make a global decision in a distributed manner for large and small ant colonies respectively. Mallon et al. claim that a decrease in colony size increases the importance of individual decisions [10]. Since sensor networks with large number of nodes are taken as application area in this research and dramatic changes upon individual decisions have to be avoided, large ant colonies have been studied and the nature of small ant colonies is kept out of the scope of this research. Hereafter we use the term *ant colony* to indicate only *large ant colony* just for simplicity.

A large colony of ants can find new food resources and bring the food back to their nest in an optimal path, and can dynamically adapt to changing conditions. In realty, each ant is a simple agent following simple rules: follow the highest pheromone density, and emit pheromone on the road. Pheromone is an odorous chemical substance. In nature, a foraging ant follows the highest pheromone density to the food resource and back to the nest and refreshes the pheromone on the road for the followers. This autocatalytic [5] approach reinforces the road as the optimal path.

In order to provide a natural method for diversity, all of the ants do not follow the highest density of the pheromone. A few ants may search the space which enhances the possibility to find a better food resource or a shorter path than the existing one.

If a better resource is found, more and more ants will follow the new trail, reinforcing the pheromone density of the road. The pheromone on the old trail would evaporate in time, with the whole colony adapting to this new condition.

### 1.2 Sensor Networks

Sensor networks consist of a large number of nodes, capable of sensing events such as pressure, temperature, vibration.

A network of sensors differentiates from classical networks and ad-hoc networks. There are more nodes in sensor networks than ad-hoc networks, nodes can be densely placed, and topology may change rapidly. In a network of sensors, processing, memory and energy capacities are limited, and each node acts as a router [16]. Considering the energy constraints and the cost of broadcasting, sensors keep only local topological information. A sensor network must also be a fault tolerant and reliable system, in order to cope with node failures and malfunctioning. Furthermore, new sensors may also be deployed to the network through a redeployment strategy. The routing scheme must handle all these conditions while respecting low power consumption to enhance the overall working time [1, 3, 9]. We believe that this can be achieved with the use of ant colony optimization methods and underlying mechanism used by natural ant colonies can be adapted as a routing scheme for the sensor networks.

## 2 Ant Colony Routing

To the best of our knowledge, there are only a few articles in the literature on the use of ant colony optimization for sensor network routing. In [16] Zhang et al. claimed that, the existing ant colony based routing schemes, like *antnet* [9] by Dorigo et al. do not perform well on sensor networks. Zhang et al. argued that the existing methods spend a lot of time to find the destination on the network, and the asymmetric link feature of the sensor networks make the approach impractical.

Since there are few articles on the use of ant colony optimization on routing, we surveyed other application areas such as feature selection [2] and data mining [12] as well. In most of the existing ant colony routing algorithms for different applications, ants travel a route by carrying a list of the visited nodes and at the end of the travel they update the pheromone densities of the nodes composing the route.

The proposed novel ant colony routing approach for sensor networks (ANCOR) differentiate from the previous schemes because ants do not carry a visited node list. In the ANCOR at each step, ants only remember the previously visited node, and they update the pheromone density of the node being visited. The ANCOR provides a routing mechanism using a small data packet. The intention of using such a small data packet is to decrease broadcasting time of a sensor node. Hence reducing the power consumption and prolonging overall running time of the whole network. Each ant on the network knows only what it searches for, and the previous node. It follows pheromone densities previously left by predecessor ants.

## 2.1 The Mapping

In the previous subsection the ANCOR is explained briefly. However the resemblance between the ANCOR and natural ant colony systems has to be exploited more. In this subsection the mapping between the ANCOR and natural ant colony systems are given.

The list of concepts that we mapped are given in Table 1. In sensor networks using sink to target approach, a query is initiated at sink node disseminates over the network. Data acquired from the nodes are collected at the sink node. Therefore we can map the sink to the nest because ants bring their food back to their nest in nature. Food resources for ants resemble the sensor nodes with data i.e. targets.

**Table 1:** Mappings of natural concepts on sensor networks

| **Natural Concepts** | **Sensor Networks Concepts** |
|---|---|
| Ant | Data Packets |
| Nest | Sink |
| Food Resource | Target |
| Road | Path |

We consider each ant as either a query or a data packet traveling through the nodes within the network. Each sensor node can be considered as a mile stone on the road, so they must include pheromone information to form pheromone trails. A road for an ant colony is represented by a path on which some of the sensor nodes are located.

The natural pheromone concept constitutes the basis of the routing algorithm. Each node has a list of pheromones related to the neighboring nodes, so that an incoming ant can *"smell"* the odors and decide on the next node it will visit. The pheromone density is a tuning parameter which represents the selection probability of a neighboring node by an incoming ant. The basic properties of a real pheromone odor such as density and evaporation remain the same in the ANCOR.

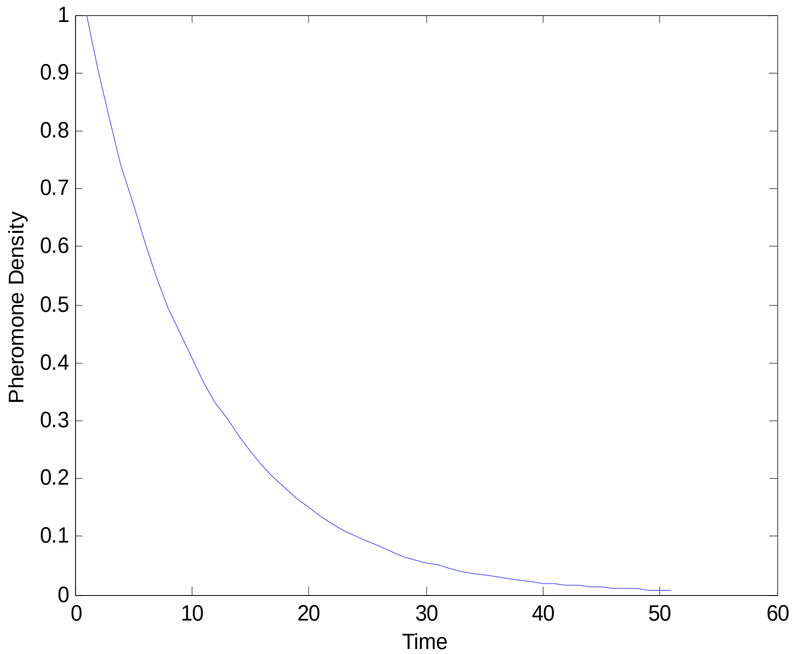


**Figure 1:** A Decay Model for Pheromone

As we can see in Figure 1, we assume that the density of a pheromone decreases by time just as in real world. This property causes a decrease of the selection probability of a neighboring node which is no longer as frequently used. The natural counterpart of this transition property is called *evaporation*.

A mathematical model for pheromone density vs. time is given as follows;

$$y = e^{-\left(\frac{x}{\partial}\right)} \tag{1}$$

where $\partial$ is an application specific tuning parameter. Note that $\partial$ is taken 20 in Fig. 1.

The same mathematical model proposed for pheromone density vs. distance phenomena, Eq. 1 with $\partial = 10$ is shown in Fig. 2.

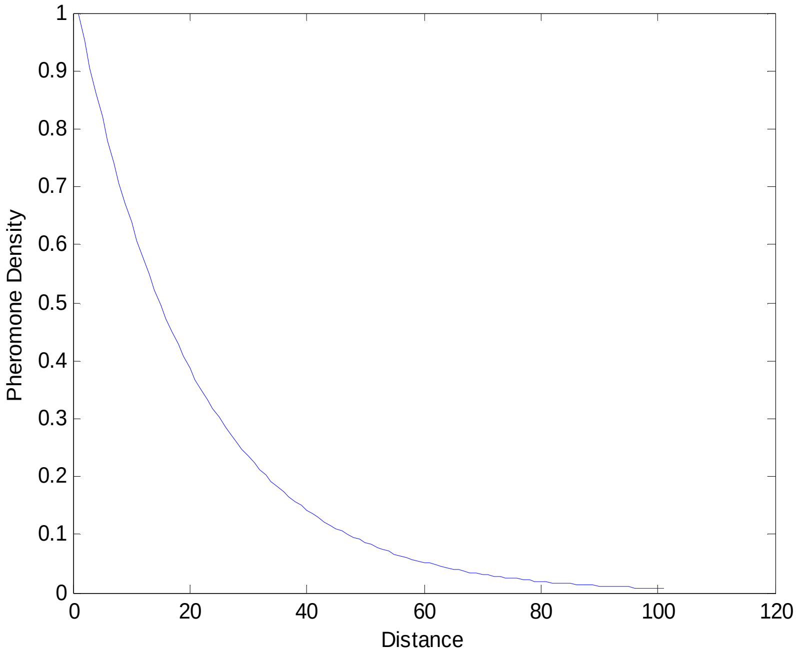


**Figure 2:** Distance vs. Pheromone Density

In figure 2, it can be seen that the effectiveness of the pheromone of a node decreases with the distance. This is how it occurs in real life as well.
The total amount of the pheromone from $node_j$ sensed at $node_i$ is given in Eq. 2;

$$ph_{ij} = e^{-\left(\frac{distance \times time}{density}\right)} \tag{2}$$

where

$ph_{ij}$ represents total amount of the pheromone odor from $node_j$ sensed at $node_i$;

*distance* represents the total distance between $node_j$ and $node_i$;

*time* refers to the evaporation mechanism representing the total amount of time from which the $node_j$ pheromone density has been updated recently;

*density* represents $node_j$'s total pheromone density value at $node_i$'s pheromone list.

## 3. The Proposed Algorithm: ANCOR

The ANCOR remains the basic components of an ant colony. Each node on the network has a pheromone table of the neighbor nodes, so an ant can decide its next move based on the pheromone density which it senses. When an ant arrives at a node and changes its pheromone density, the node broadcasts its new odor to let neighboring nodes to update their tables. Each node is responsible of the evaporation process over its own pheromone table, so each node does not have to broadcast his new evaporated pheromone density. Note that evaporation process is a preset function known to all nodes.

We can divide the whole routing process to three parts: initialization, reinforcement, and routing.

In the initialization phase, our foraging ants are spread around to search the area effectively. When an ant finds a new resource, in other words when an appropriate information is found on the sensor network, the reinforcement phase starts. The ant that finds the resource first; i.e. the *pioneer ant*, reinforces the path back to the nest (or the sink node) during reinforcement phase. After establishing a reinforced path, the routing process starts.

All the ants (packets) follow the most reinforced path based on the pheromone density, and a little percent of the ants runs out of the path to search for new resources i.e. to increase diversity. The ANCOR preserves the fundamental rules of a natural ant colony with some exceptions in the initialization and reinforcement phases.

In nature, the pheromone odor has an attractive effect which is also implemented in the ANCOR. However there are other control mechanisms in nature which lets ants to search the area for diversity. Ants are living organisms which have memory (although limited capacity), senses and some other mechanisms which are not completely known to biologist yet. In our work, in order to overcome such unknown features of ant colonies, we modified properties of the pheromone to maintain attractive and repulsive effect of the odor at the same time.

The *null pheromone*, which represents no pheromone, is represented with '1'. The nature like pheromone in our work, is represented by the pheromone values within an interval ]1..2]. An artificial repulsive odor, which does not exist in nature to the best of our knowledge, is represented in our work with values within an interval [0..1[, we call this special pheromone with repulsive effect *negative pheromone*. Although a similar approach was implemented by Montgomery et al. in [11], the pheromone approach explained in this paper differs from other approaches including that of Montgomery by combining attractive and repulsive effects of the pheromone, and the *null pheromone* in a single structure.

### 3.1 Initialization Phase

Initialization is the beginning of the algorithm. In this phase, ants gathered at the nest should spread to search the space effectively. Assuming that there is no ant previously traveled in the area, all of the nodes within the network must have an initial pheromone density of 1, i.e. *null pheromone*. That provides a fresh start.

An ant chooses its next hop randomly, if all the entries in the visiting node's phList have the same pheromone density (or there is more than one neighboring node which has maximum pheromone density). First ant on the sink node chose its next hop randomly, because each node on the sink's phList has the same pheromone density.

When an ant comes to a new node, it checks out whether the node is the target node. If not, ant updates node's pheromone density and chooses its next node to visit. The node with updated pheromone value, broadcasts his new odor, so neighboring nodes could update their list.

The pheromone updating process in the initialization phase is important, because the only way for spreading ants, is the pheromone odor of the nodes. So if an ant i visits a node k, the only way that the ant (i+1) does not visit the node k, is to make k. node's odor not attractive. To do this, $i^{th}$ ant diminish $k^{th}$ node's pheromone density by using negative pheromone in Eq. 2.
The initialization phrase continues until target node detection.

### 3.2 Reinforcement Phase

Initialization phase would be terminated when the target is discovered. Having the target discovered, a path to the sink must be established to enable data transfer.

In the reinforcement phase of the algorithm, the main objective is to establish an optimal path between sink and target nodes. In order to attract other ants to follow the same path, pheromone densities must be high. The new pheromone values of the nodes on the reinforced path would be expected to be greater than 1.

While the pioneer ant goes back to the sink, it would emit pheromone to its limits at every node to make sure that other ants would follow.

In order to establish such a path, the highest repulsive odor density has to be traced back to the sink. Note that finding path to the sink is the only use of repulsive *negative pheromone*.

Note that in Eq. 1, (*maxHopCount - hopCount*) is used as the denominator to insure that the early paths of the road back to the nest, does not affect from the vaporization phenomenon.

### 3.3 Routing Phase

Having attractive pheromone defined, routing (data packet transmission) algorithm can be given at three stages as follows;

1. At any node, check out pheromone densities of the neighboring nodes
2. Chose next node by following most pheromone density according formula
3. Update pheromone density of the node

Ants keep to this three stages algorithm in a forever loop in any phase except for the *pioneer ant* in the reinforcement phase. At each node, an ant chooses it's next node according to the next formula;

$$node_i\, prob = (\beta \times node_i\, phValue) + (1 - \beta) randomNumber \qquad (3)$$

where β is a trade-off parameter between random search and most frequently used path. Ant calculates the selection probability according to Eq. 3 for each neighboring node i, then chooses the node with the highest selection probability as the next hop to be visited. For $\beta > 0.5$, the algorithm will obviously follow the most frequently used path. For $\beta < 0.5$, algorithm converges to the random search.

The amount of increase in pheromone density at a node is given as follows;

$$phNew = \left[(maxHop - hop)ph\right]^{\alpha} phOld \qquad (4)$$

In Eq.4, *maxHop* is the maximum hop count that an ant can travels before it disperses. *hop* is the actual number of nodes traveled by the ant. *ph* represents the amount of pheromone emitted at the node by the ant. *phOld* is the previous value of the node's pheromone density, *phNew* is new pheromone density of the node. α controls the positive - negative pheromone concept as given in Eq. 5;

$$\alpha = \begin{Bmatrix} 1 & ph < 1 \\ -1 & ph \geq 1 \end{Bmatrix} \tag{5}$$

This routing phase is different from connection routing approach which adapts a policy to transmit data packet towards the sink. Similarly this routing phase is different from connectionless routing approaches since an adaptive mechanism as introduced through pheromone emission and evaporation.

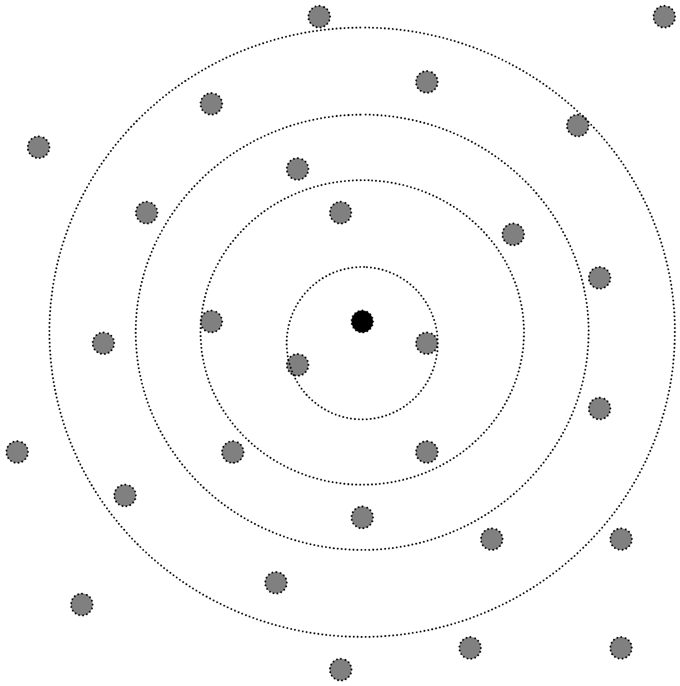

**Figure 3:** Sensor network representation (black node is sink node)

It was previously mentioned that the sensor network application is from sink to target is taken into consideration in this research. The user at the sink node makes a query, and nodes which meet the requirements (target nodes) are searched across the network. So when a new query at sink is generated, new ants would be created at the sink and spread across the network. Figure 3 shows that, there will always be a large amount of ants near the sink node (the black node), likewise the amount of pheromone will always be high near the sink node, because ants emit pheromone while trespassing over the nodes. In the initialization phase there will be a high density of negative pheromone, whereas in routing phase, negative pheromone replaces with normal pheromone.

Since ants are initially located at the sink, the nodes around the sink will be densely filled with pheromones. As ants traveled away from the sink, the density will decrease. If the density of the pheromone at the end of initialization phase is depicted, it seems like a chinese hat as shown in Fig. 3. Once the route is established the routing phase is started. At the routing phase an ant can find the target or the sink node by trespassing over these regions, since the internal regions possess denser pheromone.

In all phases, there is a trade-off between the most used path and a random selected path as given in Eq. 3. In reality this trade off is used to tune the ANCOR, and can be set as an application specific parameter. For the application including mobility such as tracking a moving vehicle, random search effect has to be increased to locate new coordinates of the target. In this application it is clear that our target nodes will change by time. In order to cope with such a case Eq. 3 can be modified in order to provide an adaptive increment on the random search effect as given in Eq. 6.

$$node_i\,prob = (\beta \times node_i\,phValue) + (1-\beta)\frac{randomNumber}{maxHop - hop} \qquad (6)$$

# 4 Simulation and Results

The size of the ant population and decision making over the next node to go are thought as two dominant issues that may have an impact on the performance of the ANCOR. The performance of the ANCOR depends on the initialization phase where the forward path establishment is done by the useful *negative pheromone* concept. Data for the back path finding process are produced at the same phase. Since decision making relies on the tradeoff between the degree of randomness and the pheromone density based pursuit. In order to find out the relation between the search area size and the ant population as well as the effect of β a number of tests are designed and performed.

In order to simulate a routing process of a sensor network using the ANCOR, a discrete time simulator called ANCORS (ANCOR Simulator), has been implemented in C++.

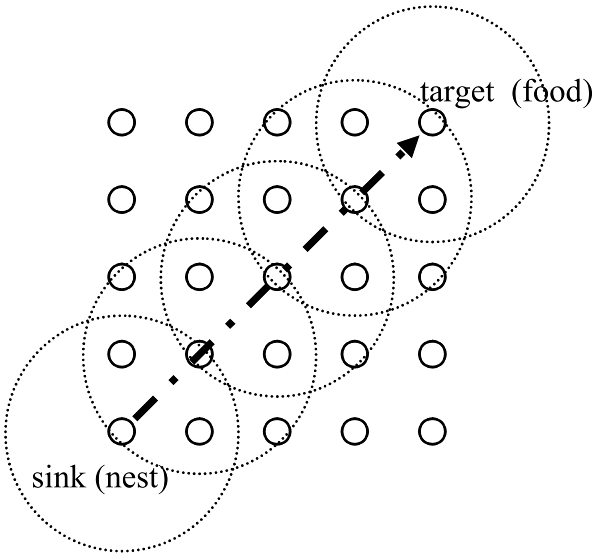


**Figure 4:** The optimal path in the experimental sensor network of size 5x5.

The nodes of the sensor network are assumed being distributed regularly in a square, with sink node at one corner and target node at the other as shown in Fig.4. It is assumed that there are 8 node within the neighborhood of a node except for the edge nodes. The next node in turn could be any of these eight nodes depending on the decision made according to Eq. 3 since the maximum transition range cover all of the eight neighbor nodes. Note that the most recently visited node is not considered as a candidate next node. Therefore the optimal path would be the diagonal of the square.

The experiments are performed on sensor networks of three different sizes that are 5x5, 10x10 and 25x25 node squares. Five different β values (0, 0.25, 0.5, 0.75, 1) for nine different ant populations (1, 5, 10, 15, 20, 25, 30, 35, 40) are applied on these networks.

It is already mentioned that the impact of β has to be observed in these experiments. According to Eq. 3, when β equals to zero a complete random search is performed with no pheromone effect, and when β equals to one a pheromone density based pursuit process with no randomness takes place. The randomness is provided by the native pseudo random number generator available in C++ library. Each experiment is run 10 times to ensure accuracy and average of the results are computed and plotted.

Fig.5, Fig.6 and Fig.7 shows that the performance of the search process in the initialization phase is significantly improved with increased number of ants as expected. However, Fig.8 indicates that increasing the population of ants does not have a consistent impact on the performance when β=0, i.e. a random search. The results of the experiments obtained with β=0 are not plotted along with the other β values as it represents a random search and considerably diminishes visibility of the graphs.

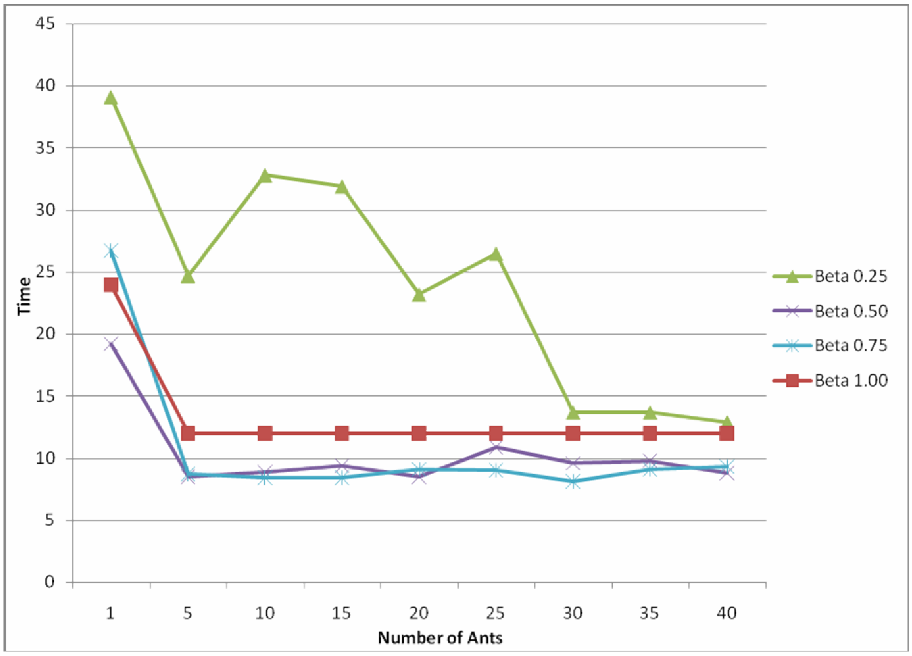


**Figure 5:** Search times at the initialization phase for 25 nodes

In Fig. 5, for a network with 25 nodes, β=0.75 and β=0.50 performs better than the other two. Since β=0.25 introduce 75% randomness the fluctuation is expected. The performance is worse for β=1.00 than for either β=0.75 or β=0.50 since pheromone density based pursuit process does not produce an efficient solution.

In Fig. 6 and Fig. 7, for a network with 100 and 650 nodes respectively, β=0.5 and β=0.75 values gives nearly the same results, especially for greater numbers of ants. Comparing Fig.6 and Fig.7 to Fig. 5, the fluctuation for β=0.25 gets smaller since randomness becomes effective with the increasing network size.

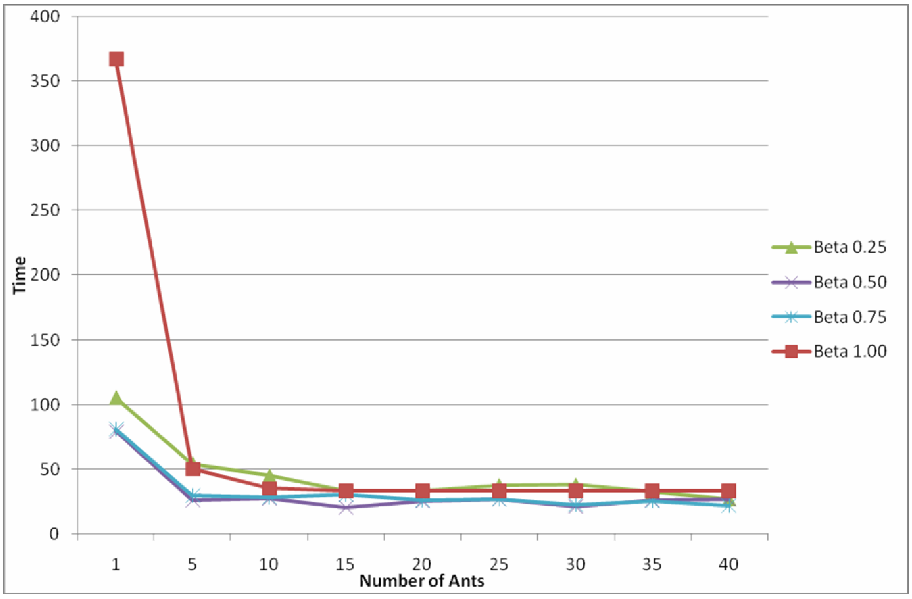


**Figure 6:** Search times at the initialization phase for 100 nodes

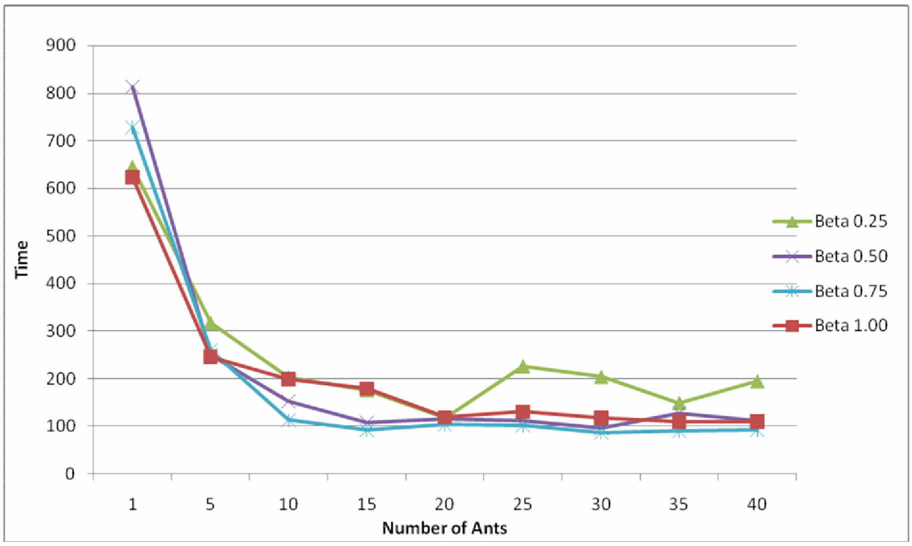


**Figure 7:** Search times at the initialization phase for 25 nodes

Another outcome that can be produced out of these figures is the greatest number of the minimum number of ants for a given network size. A close look to Fig.5, Fig.6, and Fig.7 for β=1 brings out the fact that the fluctuation is encapsulated in a reasonably smaller band. The number of ants where the band starts would be considered as the greatest number of the minimum number of ants. However, injecting randomness, i.e. β<1.00, would significantly improve performance. Thus the same or a better searching time may be obtained with smaller number of ants for smaller β values as can be seen in Fig.5, Fig.6 and Fig.7.

For any network size, a random search ( β=0 ) would not search the area efficiently and would consume more time than for any other β values. The result of such a random search for a network consisting of 625 nodes is depicted in Fig. 8. Compared with Fig. 7, the excessive consumption of time can be observed.

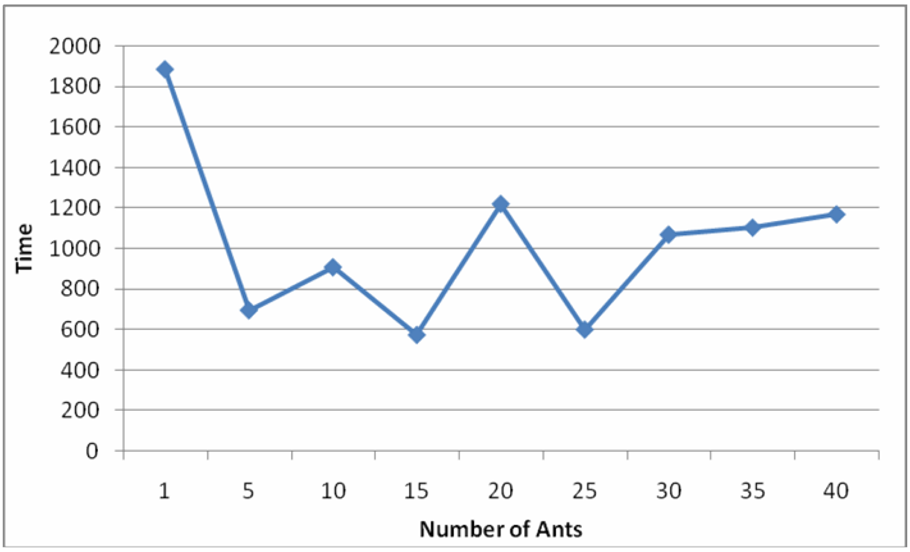


**Figure 8:** Search times at the initialization phase for 625 nodes with β=0

## 5 Conclusion and Further Studies

In this work, a novel routing algorithm for sensor networks is proposed and tested. It has been shown that mimicking nature would be an alternative way to design and develop routing algorithms. The ANCOR utilizes mostly the same mechanisms except the negative pheromone concept that an ant acts accordingly in nature. The effect of the β coefficient, which represents the choice of the ants between random search and most frequently used route, is examined. The relationship between the network size, the β coefficient and the optimal number of the ants to effectively search the area is found. It has been observed that β equals to 0.75 and 0.50 performed better than β equals to 0.25 and 1.00. Although such an observation indicated that the value of β would be greater than 0.25 and smaller than 1.00. The question of finding the optimal value of β has not been answered yet.

The optimal number of ants corresponding packets of a sensor node is a dominant parameter when low energy consumption is to be obtained. Therefore the observed optimal numbers for different network sizes would wield overall energy consumption figures for the respective networks

After a path is established between the source and the sink, the behavior and the success of the ANCOR relies on the β coefficient, the vaporization phenomena and the total amount of pheromone emitted by the ants.

The time requirements during the routing phase would be analyzed, and the effect of the total amount of pheromone emitted by ants as given in Eq. 4 and the effect of the vaporization phenomena as well as $\partial$ parameter as given in Eq. 1 would be further studied.

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