An Efficient Algorithm for Improving Qos in MANETs

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Abstract- A Mobile Adhoc Network is a collection of independent mobile nodes that can communicate to each other via radio waves. The mobile nodes that are in radio range of each other can directly communicate, whereas others needs the aid of intermediate nodes to route their packets. Each of the node has a wireless interface to communicate with each other.

These networks are fully distributed, and can work at any place without the help of any fixed infrastructure as access points or base stations, All networking functions such as routing and packet forwarding, are performed by nodes themselves in a self-organizing manner. For these reasons, securing a mobile ad -hoc network is very challenging.

We propose Ant Colony Optimization Technique along with Swarm Intelligence Mechanism to ensure the Quality of Service parameters and also to enhance the MANET security.

Index Terms- Ant colony optimization, AntQoS, QoS colony, self-organizing QoS framework, swarm intelligence.

I. Introduction

As the number of Internet users continues to grow, network performance requirements must increase right along with them. In addition, many of the latest online services require high amounts of bandwidth and network performance. Network performance is an element of concern both for the user and the service provider. Internet service providers need to apply techniques and technologies to provide the best service possible before their competitors beat them to it.

So we make use of QoS. Quality of service (QoS) refers to a network's ability to achieve maximum bandwidth and deal with other network performance elements like latency, error rate and uptime. Quality of service also involves controlling and managing network resources by setting priorities for specific types of data (video, audio, files) on the network. QoS is exclusively applied to network traffic generated for video on demand, IPTV, VoIP, streaming media, videoconferencing and online gaming.

The primary goal of quality of service is to provide priority to networks, including dedicated bandwidth, controlled jit supply the elemental building blocks that will be used for future business applications in campus, wide area networks and service provider networks.

There are three fundamental components for basic QoS implementation:

1. Identification and marking techniques for coordinating QoS from end to end between network elements
2. QoS within a single network element.
3. QoS policy, management, and accounting functions to control and administer end-to-end traffic across a network.

1.1 QoS parameters:

Different applications have different requirements regarding the handling of their traffic in the network. Applications generate traffic at varying rates and generally require that the network be able to carry traffic at the rate at which they generate it. In addition, applications are more or less tolerant of traffic delays in the network and of variation in traffic delay. Certain applications can tolerate some degree of traffic loss while others cannot. These requirements are expressed using the following QoS-related parameters:

- Bandwidth - the rate at which an application's traffic must be carried by the network
- Latency - the delay that an application can tolerate in delivering a packet of data.
- Jitter - the variation in latency
- Loss - the percentage of lost data

If infinite network resources were available, then all application traffic could be carried at the required bandwidth, with zero latency, zero jitter and zero loss. However, network resources are not infinite. As a result, there are parts of the network in which resources are unable to meet demand. QoS mechanisms work by controlling the allocation of network resources to application traffic in a manner that meets the application's service requirements.

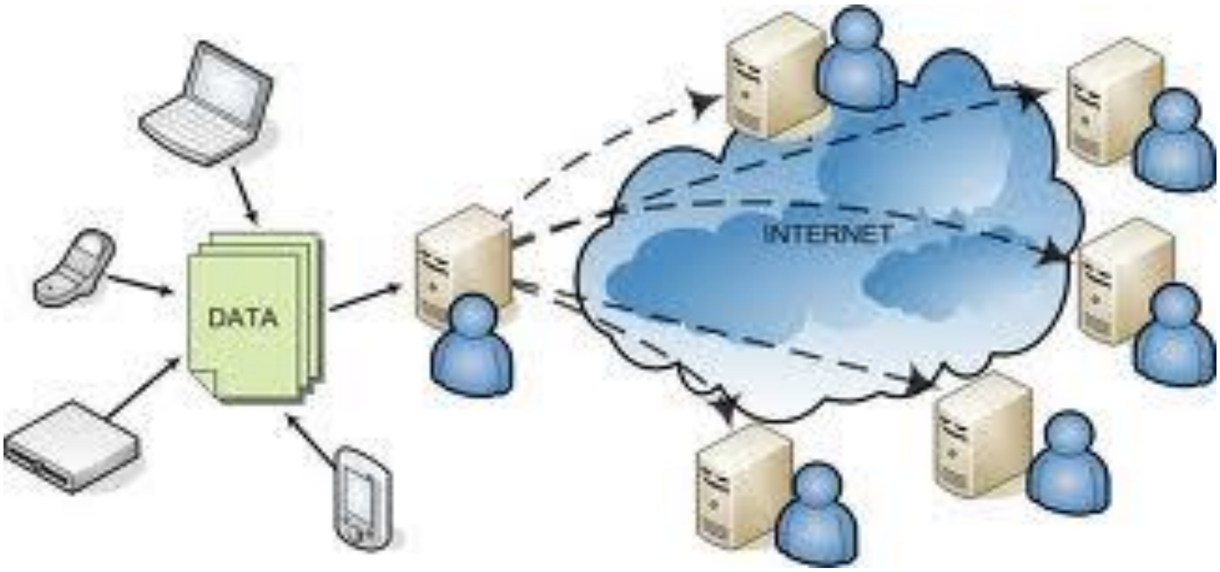

FIG: QUALITY OF SERVICE

II. LITERATURE SURVEY

In recent years, a large number of MANET routing algorithms have been proposed. These algorithms all deal with dynamic aspects of MANETs in their own way, using reactive or proactive behavior or a combination of both.

The proposed algorithm in this paper is hybrid one was said by Jianping Wang, Eseosa Osagie, Parimala Thulasiraman and Ruppa K.Thulasiram,"HOPNET "A hybrid ant colony optimization routing algorithm for mobile ad hoc network,"

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III. EXISTING FRAMEWORK

Unfortunately nodes in MANETs are limited in energy, bandwidth. These resources constraints pose a set of non trivial problems; in particular, routing and flow control**.**

The Internet Engineering Task Force (IETF) had standardized Integrated Services (IntServ) and Differentiated Services (DiffServ) for promising QoS-enabling frameworks.

IntServ provides end-to-end QoS guarantees to individual flows by performing per-flow resource reservation,but does not scale well for larger networks due to the perflow management.

DiffServ enhances the network scalability by aggregating individual flows into different traffic classes through the pre-defined QoS parameters per class, but does not perfectly guarantee.

The required QoS for individual flows.New attempts such as IntServ over DiffServ [1], DiffServ wit EAC [2], and DiffServ with MPLS-TE [3] had been made to combine the strengths of IntServ and DiffServ. Although these researches may accomplish their goals, class-based QoS mechanisms have some non-trivial engineering and technical issues:

1) how many classes should be provided,
2) how can QoS paramters be defined for each class,
3) what are best business models for each class, and
4) how can resource utilization be increased using the isolated resources per class.

And also the complexity increases due to various characteristics like dynamic topology, time varying QoS requirements, limited resources and energy etc. QoS routing plays an important role for providing QoS in wireless ad hoc networks. The biggest challenge in this kind of networks is to find a path between the communication end points satisfying user's QoS requirement.

An algorithm of ant colony optimization for mobile ad hoc networks has been described in [5]. But the QoS issues end-to-end delay, available bandwidth, cost, loss probability, and error rate is not considered in [5].

A hybrid QoS routing algorithm has been proposed in [6]. In [6], the authors used ant's pheromone update process approach for improving QoS.

But the authors described only bandwidth. Other QoS issues are not considered in [6]. Shahab Kamali. et.al [7] implemented a new ant colony based routing algorithm that uses the information about the location of nodes.

The problem of finding multiconstrained paths has high computational complexity,And thus there is a need to use algorithms that address this difficulty.

IV. PROPOSED FRAMEWORK

4.1 Ant Colony Optimization:

Ants have inspired a number of methods and techniques among which the most studied and the most successful is the general purpose optimization technique known as ant colony optimization.

Ant colony optimization (ACO) takes inspiration from the foraging behavior of some ant species. These ants deposit pheromone on the ground in order to mark some favourable path that should be followed by other members of the colony.
Ant colony optimization exploits a similar mechanism for solving optimization problems.

In ACO, a number of artificial ants build solutions to the considered optimization problem at hand and exchange information on the quality of these solutions via a communication scheme that is reminiscent of the one adopted by real ants.

Different ant colony optimization algorithms have been proposed. The original ant colony optimization algorithm is known as Ant System.

The main differences between the behavior of the real ants and the behavior of the artificial ants in our model are as follows:

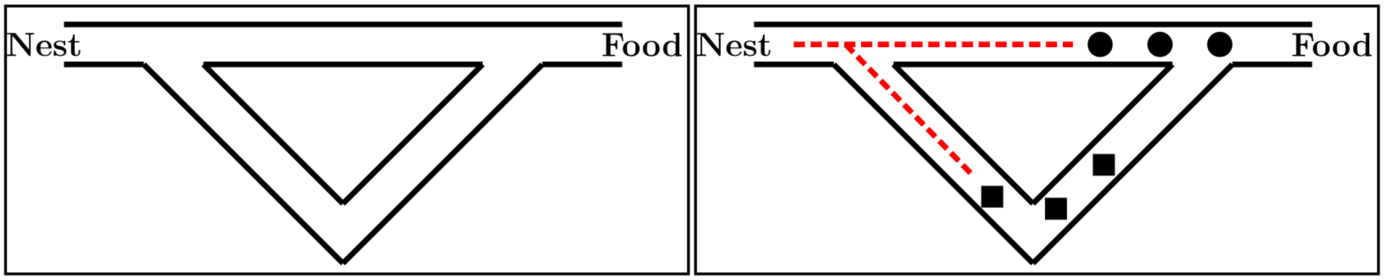
(1) While real ants move in their environment in an asynchronous way, the artificial ants are synchronized, i.e., at each iteration of the simulated system, each of the artificial ants moves from the nest to the food source and follows the same path back.

(2) While real ants leave pheromone on the ground whenever they move, artificial ants only deposit artificial pheromone on their way back to the nest.

(3) The foraging behavior of real ants is based on an implicit evaluation of a solution (i.e., a path from the nest to the food source).

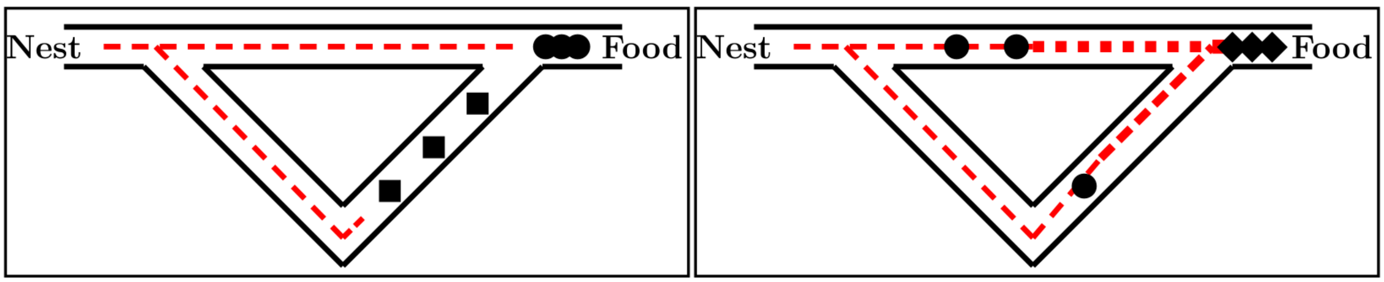
By implicit solution evaluation we mean the fact that shorter paths will be completed earlier than longer ones, and therefore they will receive pheromone reinforcement more quickly.

In contrast, the artificial ants evaluate a solution with respect to some quality measure which is used to determine the strength of the pheromone reinforcement that the ants perform during their return trip to the nest.



(a) All ants are in the nest. There is no pheromone in the environment.

(b) The foraging starts. In probability, 50% of the ants take the short path (symbolized by circles), and 50% take the long path to the food source (symbolized by rhombs).



(c) The ants that have taken the short path have arrived earlier at the food source. Therefore, when returning, the probability to take again the short path is higher.

(d) The pheromone trail on the short path receives, in probability, a stronger reinforcement, and the probability to take this path grows. Finally, due to the evaporation of the pheromone on the long path, the whole colony will, in probability, use the short path.

Fig. An experimental setting that demonstrates the shortest path finding capability of ant colonies. Between the ants' nest and the only food source exist two paths of different lengths. In the four graphics, the pheromone trails are shown as dashed lines whose thickness indicates the trails'strength

4.1.1 General Characteristics of ACO algorithms for routing:

The following set of core properties characterizes ACO instances for routing problems:

1) Providing traffic-adaptive and multipath routing.
2) Relying on both passive and active information monitoring and gathering.
3) Making use of stochastic components.
4) Not allowing local estimates to have global impact.
5) Setting up paths in a less selfish way than in pure shortest path schemes favoring load balancing.
6) Showing limited sensitivity to parameter settings.

Along with ACO,Swarm Intelligence Technique is used to improve the QoS Parameters.

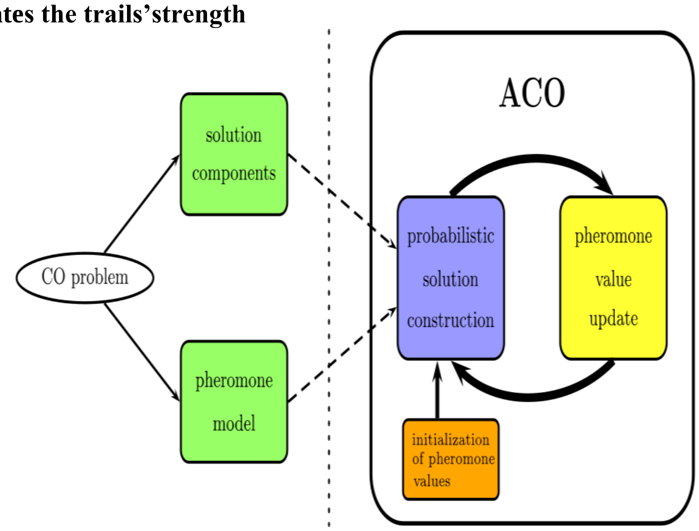


Fig:. The working of the ACO metaheuristic

Along with Ant Colony Optimization,Swarm Intelligent mechanism is used to enhance the QoS and provide the efficiency of network thoroughly.

4.2 Swarm Intelligence:

Swarm Intelligence (SI) is a growing new discipline that views intelligence as a function of social interactions between individuals. SI is based on the study of social insects like ants and bees, which as individuals are quite simple but have intelligent group behavior. Implementations are outperformed by evolutionary computation methods such as Particle Swarm Optimization (PSO).

4.2.1 Particle Swarm Intelligence:

A successful swarm intelligence model is Particle Swarm Optimization (PSO). PSO draws inspiration from the sociological behaviour associated with bird flocking. It is a natural observation that birds can fly in large groups with no collision for extended long distances, making use of their effort to maintain an optimum distance between themselves and their neighbours.

4.2.2 Particle Swarm Optimization Metaheuristic:

Particle Swarm Optimization (PSO) is a heuristic optimization technique. It is inspired by the intelligent, experience-sharing, social flocking behaviour of birds. PSO is a population-based search strategy that finds optimal solutions using a set of flying particles with velocities that are dynamically adjusted according to their historical performance, as well as their neighbours in the search space.While ACO solves problems whose search space can be represented as a weighted construction graph PSO solves problems whose solutions can be represented as a set of points in an n-dimensional solution space. The term particles refers to population members, which are fundamentally described as the swarm positions in the n-dimensional solution space. Each particle is set into motion through the solution space with a velocity vector representing the particle‘s speed in each dimension. Each particle has a memory to store its historically best solution (i.e., its best position ever attained in the search space so far, which is also called its experience).

The secret of the PSO success lies in the experience-sharing behaviour in which the experience of each particle is continuously communicated to part or the whole swarm, leading the overall swarm motion towards the most promising areas detected so far in the search space Therefore, the moving particles, at each iteration, evaluate their current position with respect to the problem‘s fitness function to be optimized, current fitness of themselves to their historically best positions, as well as to the other individuals of the swarm (either locally within their neighbourhood as in the local version of the PSO algorithm, or globally throughout the entire swarm as in the global version of the algorithm). Then, each particle updates its *experience* (if the current position is better than its historically best one), and adjusts its velocity to imitate the swarm‘s global best particle (or, its local superior neighbour, i.e., the one within its neighbourhood whose current position represents a better solution than the particle‘s current one) by moving closer towards it. Before the end of each iteration of PSO, the index of the swarm‘s global best particle (or, the local best particle in the neighbourhood) is updated if the most recent update of the position of any particle in the entire swarm (or, within a predetermined neighbourhood topology) happened to be better than the current position of the swarm‘s global best particle (or, the local best particle in the neighbourhood).

The original version of the PSO algorithm is essentially described by the following two simple ―*velocity*‖ and ―*position*‖ update equations, shown respectively.

- vid(t+1)= vid(t) + c1 **R**1(pid(t) **–** xid(t)) + c2 **R**2 (pgd(t) **–** xid(t))
- xid(t+1) = xid(t) + vid(t+1)

Where:

- *vid* represents the rate of the position change (velocity) of the *i*th particle in the *d*th dimension, and *t* denotes the iteration counter.
- *xid* represents the position of the *i*th particle in the *d*th dimension.
- It is worth noting here that **x***i* is referred to as the *i*th particle itself, or as a vector of its positions in all dimensions of the problem space.
- The n-dimensional problem space has a number of dimensions that equals to the numbers of variables of the desired fitness function to be optimized.
- *pid* represents the historically best position of the *i*th particle in the *d*th dimension (or, the position giving the best ever fitness value attained by **x***i*).

4.2.3 Basic flow of PSO :

1) Initialize the swarm by randomly assigning each particle to an arbitrarily initial velocity and a position in each dimension of the solution space.

2) Evaluate the desired fitness function to be optimized for each particle‘s position.

3) For each individual particle, update its historically best position so far, ***Pi,*** if its current position is better than its historically best one.

4) Identify/Update the swarm‘s globally best particle that has the swarm‘s best fitness value, and set/reset its index as ***g*** and its position at ***Pg***.

5) Update the velocities of all the particles using *equation* (1).

6) Move each particle to its new position using *equation* (2).

7) Repeat steps 2–6 until convergence or a stopping criterion is met (e.g., the maximum number of allowed iterations is reached; a sufficiently good fitness value is achieved; or the algorithm has not improved its performance for a number of consecutive iterations).

V. Performance Evaluation

By proposing Ant Colony Optimization and Swarm Intelligence Technique they can be successfully applied to the successfully applied to a wide-range of optimization problems. This ranges from fundamental combinatorial problems, such as sequential ordering problems, assignment problems, scheduling problems, the maximum clique problem, graph coloring, assembly line balancing and vehicle routing problems, to more recent continuous, multi-objective or dynamic problems in machine learning, data mining, telecommunication networks and bioinformatics.

VI. Advantages of Swarm Intelligence

Scalability: SI systems are highly scalable; their impressive abilities are generally maintained when using groups ranging from just sufficiently few individuals up to millions of individuals.

Adaptability**:** SI Systems respond well to rapidly changing environments, making use of their inherit auto-configuration and self-organization capabilities.

Collective Robustness**:** SI Systems are robust as they collectively work without central control, and there is no single individual crucial for the swarm to continue to function (due to the redundancy of their individuals).

Individual Simplicity**:** SI systems consist of a number of simple individuals with fairly limited capabilities on their own, yet the simple behavioural rules at the individual level are practically sufficient to cooperatively emerge a sophisticated group behaviour.

VII. Conclusion

The ACO and PSO can be analyzed for future enhancement such that new research could be focused to produce better solution by improving the effectiveness and reducing the limitations.

More possibilities for dynamically determining the best destination through ACO can be evolved and a plan to endow PSO with fitness sharing aiming to investigate whether this helps in improving performance. In future the velocity of each individual must be updated by taking the best element found in all iterations rather than that of the current iteration only.

In future, this work can be extended for multicasting by using swarm intelligence with other QoS objectives such as load balancing, energy conservation, etc.

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