International Journal Of Computer Science And Applications Vol. 2, No. 2, November / December 2009 ISSN: 0974-1003

Intelligent Multipath Routing Protocol For Mobile AdHoc Network

Rajiv V. Dharaskar
G. H. Raisoni College of Engineering
Hingna Road, Nagpur
+91-7104-236383
rvdharaskar@yahoo.com

M.M.Goswami
PG Dept. of Computer Sc. & Engg.
G.H.Raisoni College of Engg.
Nagpur,India
mm_gos@yahoo.com

ABSTRACT

Conventional routing algorithm for mobile adHoc network hoc networks such as AODV or DSR consider only one metric, for example, hop count to select best path from source to destination. However due to special characteristics of MANET such as nodal mobility, unstable links and limited resources, conventional routing algorithm found to be unsuitable for routing multimedia traffic or real time applications which require optimization of more than one metric. The paths chosen by conventional routing algorithm deviate far from optimal paths. In the proposed algorithm called Fuzzy Stochastic Multipath Routing (FSMR) multiple metrics such as hop count, battery power, signal strength are considered using fuzzy logic to give multiple optimal paths. Nodes then forward data stochastically on these multiple paths resulting into automatic load balancing and fault tolerance. Simulation results show the great improvements over the conventional routing algorithm (for example AOMDV) in terms of various parameters like packet delivery ratio, no of route discoveries, delay, etc

General Terms

Algorithms, Measurement, Performance, Design, Reliability, Experimentation, Verification.

Keywords

Mobile Adhoc Networks,Multipath routing, Ant Colony optimization,Fuzzy logic.

1 INTRODUCTION

Mobile ad hoc network consists of a collection of wireless mobile nodes, which dynamically exchange data among themselves without the reliance on a fixed base station or carried backbone network [1]. Each mobile node acts as a terminal or router and the control of the network activity is distributed to these nodes. This kind of network is very flexible and suitable for applications such as temporary information sharing in conferences, military actions and disaster rescues. However mobile nodes have lower battery power and lower computation ability. Also, the network topology is generally dynamic because the connectivity among the nodes may change with time due to nodal mobility, the effect of radio communication, and power limitations. These features of MANET have posed a lot of challenges in designing an effective, reliable and scalable routing protocol [2].

Swarm intelligence technique based on biological swarm cooperation has found to be catering to the certain characteristics of MANET. For example, ant colony optimization [3, 4] is a novel evolutionary algorithm, which has the characteristics such as positive feedback, distributed computing and the use of a constructive heuristics etc. They can work in a fully distributed way, are highly adaptive to network and traffic changes, use mobile agents for active path sampling, are robust to agent failures, provide multipath routing, and automatically take care of data load spreading. Recently, swarm intelligence based multipath routing has received a lot of attention, both in order to improve reliability (fault tolerance) and end-to-end delay. Some ant-based multipath routing algorithms for the characteristics of MANET have been proposed. However in these algorithms route is decided by choosing one or two selection parameters without considering the interplays of different selection parameters. As mentioned above the topology of MANET is determined by many factors such as battery capacity, traffic pattern, link stability and nodal mobility. All of these factors are correlated. Consideration of only one or two factors is not sufficient for choosing an optimal path. For example if the shortest path is decided by the number of intermediate hops and the algorithm is not power aware or mobility aware then the algorithm may select unstable routes or lead to shortening the lifetime of a node which can result in route failures in between active communication sessions due to expiration of batteries of intermediate nodes.

2 LITERATURE SURVEY

In recent years a large number of MANET routing algorithms have been proposed (see [6] for an overview). These algorithms all deal with the dynamic aspects of MANETs in their own way, using reactive or proactive behavior, or a combination of both. *Reactive behavior* means that an algorithm only gathers routing information in response to an event, usually an event which triggers the need for new paths, such as the start of a data session or the failure of an existing paths. *Proactive behavior* means that the algorithm also gathers routing information at other times, so that it is readily available when needed. In the MANET literature, the classical distinction is between purely proactive, purely reactive, and hybrid algorithms. In *purely proactive* algorithms (e.g., DSDV [7]) nodes try to maintain paths to all other nodes at all times. This means that they need to keep track of all topology changes, which can become difficult if there are a lot of nodes or if they are very mobile. In *purely reactive* algorithms (e.g., AODV [8] and DSR [9]), nodes only gather routing information on demand: when a data session to a new destination starts, or when a path which is in use fails. Reactive algorithms are in general more scalable [10] since they greatly reduce the routing overhead, but they can suffer from oscillations in performance because they are never prepared for disruptive events. In practice, many algorithms are *hybrid algorithms* (e.g. ZRP [11]), using both proactive and reactive components in order to try to combine the best of both worlds.

2.1 ACO routing algorithms.

The basic idea behind ACO algorithms for routing [12, 4] is the acquisition of routing information through the sampling of paths using small control packets, which are called *ants*. The ants are generated concurrently and independently at the nodes, with the task to test a path from a source node *s* to an assigned destination node *d*. The ant collects information about the quality of its path (e.g. end-to-end delay, number of hops, etc.), and uses this on its way back from *d* to *s* to update the routing information at the intermediate nodes and at *s*. Ants always sample complete paths, so that routing information can be updated in a pure *Monte Carlo* way, without relying on bootstrapping information from one node to the next [13].The routing tables contain for each destination a vector of real-valued entries, one for each known neighbor node. These entries are a measure of the goodness of going over that neighbor on the way to the destination. They are termed *pheromone* variables, and are continually updated according to path quality values calculated by the ants. The repeated and concurrent generation of path-sampling ants results in the availability at each node of a bundle of paths, each with an estimated measure of quality. In turn, the ants use the routing tables to determine which path to their destination they sample: at each node they stochastically choose a next hop, giving higher probability to links with higher pheromone values. In the following we call routing tables also *pheromone tables*. This process is quite similar to the pheromone laying and following behavior of real ant colonies. Like their natural counterparts, the artificial ants are in practice autonomous agents, and through the updating and stochastic following of pheromone tables they participate in a stigmergic communication process. The result is a *collective learning behavior*, in which individual ants have low complexity and little importance, while the whole swarm together can collect and maintain up-to-date routing information. The pheromone information is used for routing data packets, more or less in the same way as for routing ants: packets are routed *stochastically*, giving higher probability to links with higher pheromone values. Like this, data for a same destination are spread over *multiple paths* (but with more packets going over the best paths), resulting in *load balancing*. For data packets, mechanisms are usually adopted to avoid low quality paths, while ants are more explorative, so that also less good paths are occasionally sampled and maintained. This way *path exploration* is kept separate from the use of paths by data. If enough ants are sent to the different destinations, nodes have up-to-date information about the best paths and automatically adapt their data load spreading.

2.2 ACO routing in MANETs.

The above description highlights a number of key ingredients of ACO routing: routing tables are adapted and maintained via repeated and concurrent Monte Carlo path sampling, data are stochastically spread over multiple paths, leading to automatic load balancing, routing and control decisions are taken locally, and the system is robust to agent failures. Some attempts have been made to incorporate these features into a MANET routing algorithm. Challenges hereby are the high change rate and in particular the limited bandwidth which conflicts with the continuous generation of ant packets. *Accelerated Ants Routing* [14] uses ant-like agents which go through the network randomly, without a specific destination, updating pheromone entries pointing to their source. In [15] the authors describe a location-based algorithm which makes use of ant agents to disseminate routing information; here the ants serve as an efficient form of flooding. *Ant-AODV* [16] is a hybrid algorithm combining ants with the basic AODV behavior: a fixed number of ants keep going around the network in a more or less random manner, proactively updating the AODV routing tables in the nodes they visit whenever possible. *Ant-Colony-Based Routing Algorithm (ARA)* [13] works in an on-demand way, with ants setting up multiple paths between source and destination at the start of a data session. During the data session, data packets reinforce the paths they follow. Also *Probabilistic Emergent Routing Algorithm (PERA)* [14] works in an on-demand way, with ants being broadcast towards the destination (they do not follow pheromone) at the start of a data session. Multiple paths are set up, but only the one with the highest pheromone value is used by data (the other paths are available for backup). Also other ACO routing algorithms [17, 18] have been proposed for MANETs. In general, however, most of all these algorithms move quite far away from the original ACO routing ideas trying to obtain the efficiency needed in MANETs, and many of them are not very different from single-path on-demand algorithms.2.4 Elements of ACO routing in other MANET routing algorithms Some of the ingredients of ACO routing appear separately in other MANET routing algorithms. Especially the idea of *multipath routing* has received a lot of attention recently, both in order to improve reliability and end-to-end delay (see [19] for an overview). The algorithms differ in the way multiple paths are set up, maintained and used. At path setup time, a number of paths are selected. Some algorithms allow braided multiple paths [20], whereas others look for link [21] or node [22] disjoint paths, or even paths which are outside each other's interference range [22]. Once the paths are set up, they need to be maintained. Most algorithms manage the paths in a reactive way: they remove paths when a link break occurs, and only take action when no valid path to the destination is left. The idea of *proactively probing paths* to obtain up-to-date information about them and to detect failures can be found in few algorithms [29, 24]. *Proactively improving existing paths* is quite rare in MANET routing algorithms, although one possible approach is presented in [25] (in the context of single-path routing). The use of the multiple paths differs strongly among algorithms. In many of them, only one of the paths is used for data transport, while the others are only used in case of a failure in the primary path [26, 27].Some algorithms spread data over the multiple paths in a simple, even way [28], and in a few cases *adaptive data load spreading* depending on the estimated quality of paths, similar to the ACO ideas, is explored [20, 24]. The quality of paths is usually assessed in terms of hop count or round trip time; *combining different metrics* is less common but can be important [29]. *Stochastic data spreading* is according to our knowledge unexplored 6 outside the area of ACO routing algorithms (although stochastic elements have been used otherwise in MANET algorithms, e.g. to improve flooding [30]).

2.3 Fuzzy Logic Based Routing

Evolutionary ad-hoc on-demand fuzzy routing (EAOFR) proposed in [31] find the more preferred routes by evaluating the alternative against the multiple objectives and selecting the route which best achieves the various objectives. The different routing metrics are combined together using a fuzzy logic system to produce a combined fuzzy cost metrc that efficiently captures the interplay of the various metrics. Route selection is then performed with the minimum fuzzy cost. E-AOFR models the uncertainty in MANET by fuzzy set theory. It incorporates a fuzzy logic function into every mobile node, which measures three parameters at a node (remaining battery capacity, buffer length, link stability), taking these three parameters as input and producing a single cost metric. E-AOFR is a single-path source routing protocol without redundant paths for routing.

Fuzzy logic wireless load aware multi-path routing protocol is described in [32]. FLWLAMR uses a similar method as SMR does for route discovery. FLWLAMR also chooses the route with the least delay as the primary route for delivering packets between the source node and the destination node, the second route is the path which is the maximally disjointed path with the primary one and has the shortest distance. However, in FLWLAMR the source node uses a fuzzy control system, of which the inputs are network status and the priority of data packets, and outputs are the number of paths used for routing specific data packets. Thus, the source node can differentiate resource allocation by considering traffic importance and network status. Traffic data is routed over zero or more maximally disjointed paths to the destination: important packets may be forwarded redundantly over multiple disjointed paths for guaranteed reliability, while the least important packets may be delayed at the source. The fuzzy control system of FLWLAMR is used to distinguish the wireless resource allocation, not to select an "optimal" set of multiple paths. For multi-path selection, it is almost the same as SMR which uses a crisp, simple selection parameter.

Adaptive genetic fuzzy multipath routing protocol is proposed in [33]. GFMRP consists of a route discovery, a route reply, and a route maintenance phase. Every node in MANET acts as both a terminal and a router. Each node can become a destination for data traffic; thus, FLS is embedded in every mobile node. Such FLS in a given destination node produces the crisp output rank values to indicate the fitness of all possible routing paths between the source node requiring route discovery and the destination node. According to the rank values, the destination node can make a decision for selecting an optimal reliable set of multiple paths as the candidates for delivering data traffic. To determine the accurate FLS, membership functions are constrained to a shape of trapezoids and then each membership function is parameterized by a small number of variables. The membership optimization problem is now reduced to a parameter optimization problem. Genetic algorithm is used to solve the optimization problem. The values of parameters are initially set through the expert knowledge, and then tuned by GA. Drawback is that offline training is used to tune the parameters of FLS in GFMRP that cannot reflect the real time conditions of MANETs

2.4 Multiple Selection Parameters

To the best of our knowledge, current multi-path protocols choose a set of multiple redundant paths via one or two route selection parameters without considering the correlations of the different selection parameters. However, there are lots of uncertain and varying conditions in MANET, and the topology of MANET is affected by many correlated parameters. Thus, consideration of only one or two parameters is not reasonable for determining an optimal set of multiple paths. We will investigate several parameters used to describe the network status and the mobile nodes. capacities in this section, and incorporate these route selection parameters in order to achieve the multi-path routing goal. The four routing parameters used are: (1) energy consumption rate at a node, (2) buffer occupancy rate at a node, (3) link stability between the neighboring nodes, and (4) the number of intermediate hops in a route. As we know, mobile nodes in MANET have limited battery capacity. So the saving of battery power is a vital issue when determining the network route. Most energy aware routing protocols often base themselves only on the parameters related to the remaining battery capacity, which alone cannot help to establish the best route between the source and the destination nodes. Even if a node currently has enough remaining battery capacity, and it accepts all route requests, more traffic load will be injected through that node, and the battery will be consumed very quickly. The result is that the battery of the node is depleted too soon. To mitigate this problem, other parameters, based on the traffic load characteristics, could be employed as represented in [48]. FSMR uses the energy consumption rate as the parameter to describe the battery power condition of every node *Ni.* We denote the battery power consumption rate as *BPC i*. The value of *BPC i* is evaluated in a very simple method, but has a similar principle used in [48]. Since the battery power consumption of a node is caused by

the transmission, reception, and overhearing of packets activities, *BPCi* is closely related to the amount of transmitted packets, received packets and overhead packets at a node and the power used for per packet transmission, reception or overhearing. So we define *BPC i* as a linear function shown below:

$$BPC_i = \frac{(W_r \times M_r + W_s \times M_s + W_O \times M_O)}{T}$$

where the *Wr*, *Ws*, and *Wo* are the battery power consumed by the network interface when a node sends, receives, or overhears a packet; *Mr*, *Ms*, and *Mo* are the amount of three types of packets respectively. Therefore, *BPC i* is obtained by averaging the total amount of the power consumed for every *T* seconds sampling intervals. Then the energy consumption rate at a node, *Ni*, is calculated in the following formula:

$$R_i = \frac{RBP_i}{BPC_i}$$

Because the maximum lifetime of a given path, *Lp*, is determined by the minimum value of *Ri* over the path, where we denote the set of all available paths as *P*, that is:

$$L_p = \min_{\forall n_i \in P} R_i$$

The congestion status of MANET is also imperative for selecting a reliable routing path. FSMR takes the buffer occupancy rate at a node as a parameter for selecting routes that are not congested. The congestion status of the network is measured as the work load at each node's interface, i.e., the number of the packets buffered at the interface. The ratio of qi/bi denotes the buffer occupancy rate at a node, where *qi* is the most recent packet queue length at a node, *Ni*, and *bi* is the buffer capacity at that node. The destination node estimates the congestion status of a specific routing path using the formula below:

$$congestion = 1 - \frac{\sum q_i}{\sum b_i}$$

Link stability parameter helps to select the routes, which are comparatively more stable and long-lived, in order to ensure lower packet loss rate, fewer route failures and less frequent route discovery. Link stability can be measured using the signal strength. The signal strength has a relationship with the receiver's antenna gain, and is inversely squared proportional to the square of the distance *d*. As *d* increases, the degree of signal strength becomes weak. FSMR adopts these selection parameters (battery capacity, congestion, signal strength and the number of intermediate hopes) in its fuzzy inference system as input values in order to choose the most optimal and reliable set of the multiple routing paths.

3 DESIGN OF FUZZY INFERENCE SYSTEM

We know that fuzzy set theory models the interpretation of imprecise and incomplete sensory information as perceived by human brain. Thus, it represents and numerically manipulates such linguistic information in a natural way via membership functions and fuzzy rules. For proper decision making by controller, heuristics or theory need to be incorporated into it. However the success of right decision making by controller depends upon the valid and accurate model. However in MANET, because of uncertainty due to nodal mobility, unstable links, and limited resources, a precise model is not available. Therefore, fuzzy set theory has been applied in a control decision system either to improve the performance or to handle the problem that conventional theory cannot approach successfully because latter relies on a valid and accurate model, which does not always exist. Fuzzy representations of control algorithms, as linguistic rules per se, offer a number of advantages over the conventional approach to the specification of control algorithms as algebraic formulas, particularly in ill-structured situations. The key concept is that linguistic rules describe the operation of the process of interest from the standpoint of some (human) operator of the process and capture the empirical knowledge of operation of that process that has been acquired through direct experience with the actual operation of the process. Clearly, this knowledge can be reflected in the rule set only to the extent that the operator can articulate the control action in linguistic form. It is this empirical knowledge, nonetheless, that a fuzzy controller effectively embodies, and which enables it to control the process as if it were the human operator. The inputs to the fuzzy controller to be designed for routing are: (i) buffer occupancy,(ii) remaining battery power and (iii) signal stability. These three selection parameters make the pheromone to reflect the network status and the node's ability to reliably deliver network packets. The steps involved in calculation of fuzzy cost are elaborated as follows:

3.1 STEP I. Fuzzification of inputs and outputs

The three input variables to be fuzzified are the energy consumption rate (B), the packet buffer occupancy rate (Q) and the signal strength (SS). On the basis of existing knowledge of MANET, the terms "Low","Medium" and "High" are used to describe the energy consumption rate and "Empty", "Medium" and "Full" to describe packet buffer occupancy rate. "Strong","Medium" and "Weak" are terms for representing the signal strength. Even though the choice and specification of the membership functions are widely subjective, there are several principles for membership function selection that can produce good adequate results. The triangular functions are chosen as the membership function since they have been extensively used in real-time applications due to their simple formulas and computational efficiency. Mathematically, triangular membership is given below:

$$\text{tri}(x; a, m, b) = \begin{cases} 0, x \le a & \\ \dfrac{x-a}{m-a}, x \in (a, m] & a \ne m \\ 0, a = m & \\ \dfrac{b-x}{b-m}, x \in [m, b) & b \ne m \\ 0, b = m & \\ 0, x \ge b & \end{cases}$$

We show these membership functions in Fig. 1,2,3,4. We normalize the linguistic values of inputs and outputs in the range from 0 to 1. The output of FIS is a fuzzy cost, which represents cost of node participating in the route. The fuzzy cost from lowest to highest are defined as LL(very low),LM,LH,ML,MM(Medium),MH,HL,HM, and HH(very high).

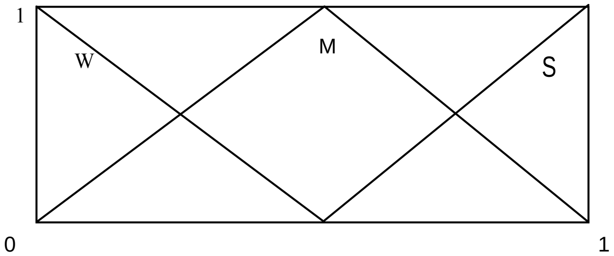


Figure 1. Fuzzy Membership function for signal strength

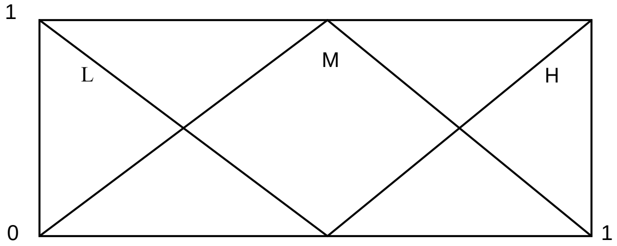
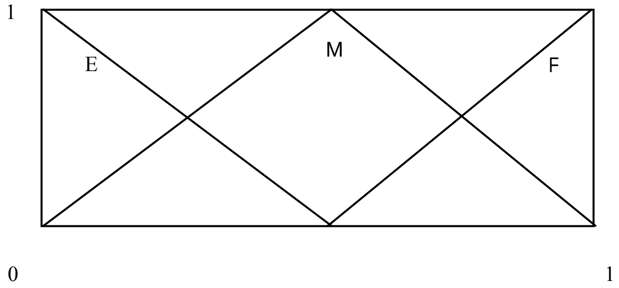


Figure 2. **Fuzzy Membership function for battery capacity**



Fuzzy Membership function for buffer occupancy

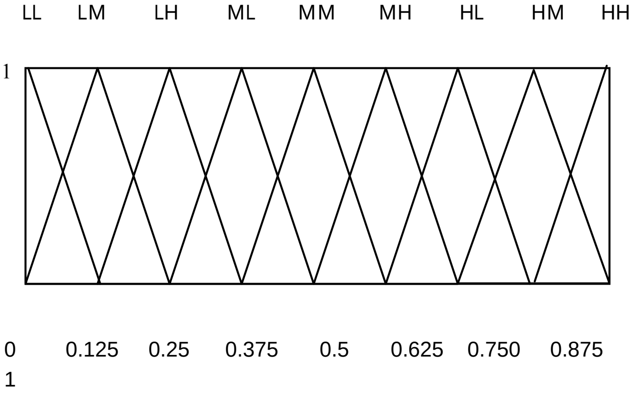


Figure 3. **Fuzzy Membership function for fuzzy_cost**

3.2 STEP 2. Inference engine and knowledge base

The knowledge base is a set of rules developed using expert knowledge. We design the knowledge based rules connecting the inputs and the output based on a thorough understanding of the system. The parameters and rules of our FLS are initially set, induced from many analytical results of MANET routing. The fuzzy rules have IF-THEN structure. The inputs are then combined using the AND operator. The following is an example of rule, which describes the input output mapping.

TABLE I. **FUZZY RULES TABLE FOR WEAK SS**

B / Q	**L**	**M**	**H**
E	MH	MM	ML
M	HM	MH	MM
F	HH	HM	MH

if battery power is medium (Bi) and buffer occupancy is empty(Dj) and signal strength is weak(Ck) then the fuzzy_cost is medium (Fl).

where Bi, Ck, Dj and Fl are fuzzy sets defined in the corresponding input spaces and output spaces respectively. Table 1 shows the fuzzy rules for the weak signal strength in fuzzy logic system. The fuzzy set parameters and rules of FSMR are set by expert knowledge and heuristics, for example, we have set higher cost for extreme values of signal strength. The interpretation is that as the received signal strength decreases, link stability worsens. On the other hand, when the signal strength is too high, it would mean that the nodes (transmitter and receiver) are too close to each other. This would lead to a higher number of intermediate hops thus resulting in a higher end-to-end delay. Similarly, fuzzy rule tables for medium and strong signal strength are formulated.

3.3 STEP3. Defuzzification

Defuzzification refers to the way a crisp value is extracted from a fuzzy set as a representation value. There are many kinds of defuzzifiers. Here we take the centroid of area strategy for defuzzification.

$$FC = \frac{\sum_{AllRules} x_i . \mu(x_i)}{\sum_{AllRules} \mu(x_i)}$$

where FC is the fuzzy cost, x_i is the element and $\mu(x_i)$ is its membership function. This is the most widely adopted defuzzification strategy, which is reminiscent of the calculation of the expected value of probability distributions.

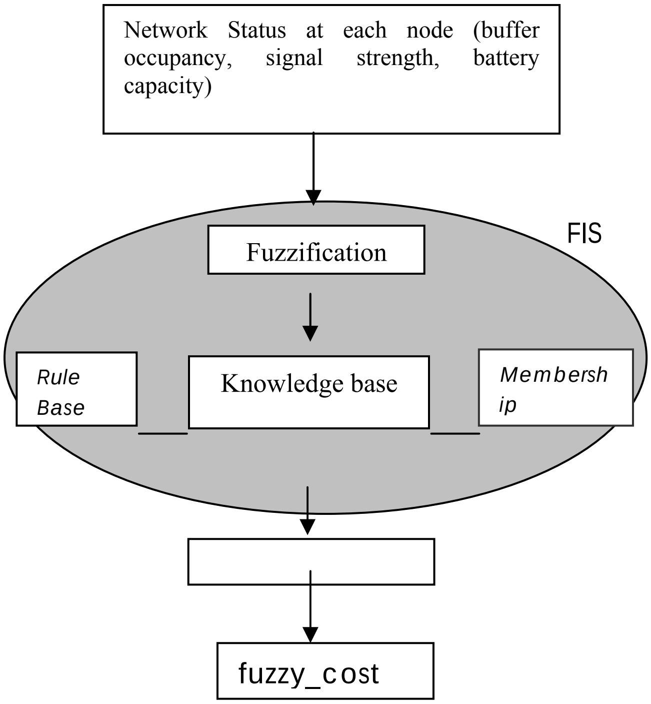


Figure 4. **Computation of fuzzy cost when forward ant visits the node**

4 DESCRIPTION OF PROPOSED PROTOCOL

In this section we describe our novel algorithm called FSMR in detail. FSMR is constructed with the communication model observed in ant colonies and fuzzy logic technique. In section III the Fuzzy Inference System is described and in this section the proposed method is explained. The sequence of FSMR algorithm is outlined as follows:

4.1 Route Discovery Phase

1. When a node wants to maintain a path to a destination, it generates forward ants. A forward ant creates a stack for holding fuzzy cost computed at each intermediate node and other information such as source address, the destination address, the intermediate node's ids.

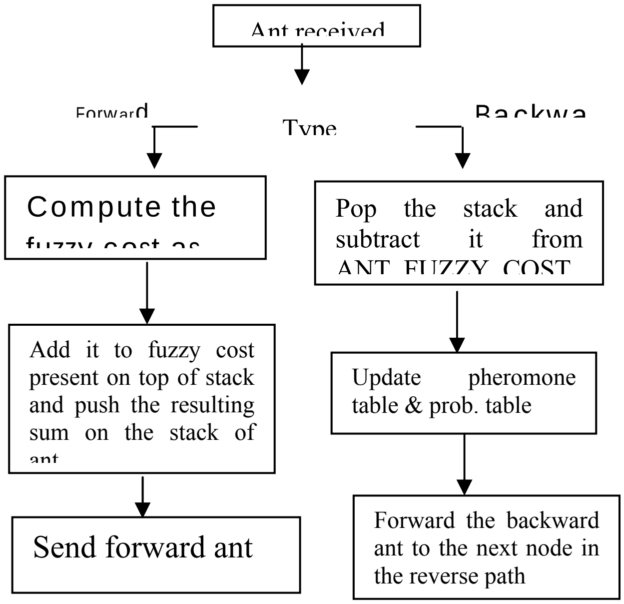


Figure 6. Response/Action of intermediate node when ant (forward/backward) is received

2. When intermediate node receives forward ant, it calculates its fuzzy cost of participating in the route and adds it to the fuzzy cost present on the top of stack of received ant. The resulting sum is then pushed on the stack and ant is forwarded to a neighbor node. The intermediate nodes as shown in fig. 5 make use of fuzzy logic to calculate the cost, which is dependent on multiple metrics mentioned earlier. Thus when ant is forwarded to its neighbor, the top of stack represents the sum of fuzzy costs for the individual links along the path from source node to intermediate node. The selection of neighbor node is done randomly using the probability routing table. The values of the probability routing table are calculated using the pheromone tables. One node of the neighbor nodes will be selected and the ant will be forwarded to it. The selection of the next node in the ants path is done as following:

At node i,

For Destination d,

The probability of selecting a neighbor j is:

$$P^{i}_{j,d} = \frac{\Phi^{i}_{j,d}(t)}{\sum_{l} \Phi^{i}_{j,d}(t)} \qquad (1)$$

Where l ∈ neighbor (i).

3. At the destination, a backward ant will be generated and it inherits the stack of forward ant. Also the total fuzzy cost for whole path, ANT_FUZZY_COST, is calculated as shown in fig. 7, which is carried along with the stack of backward ant. Backward ant follows the reverse path of its corresponding forward ant and updates the pheromone values on the path's links using fuzzy cost it carries.

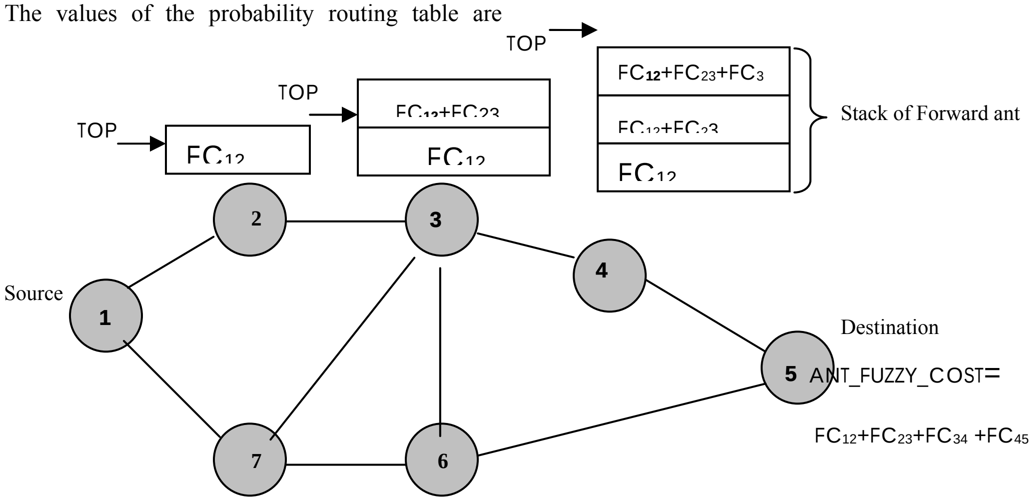


Figure 7: Stack contents of an forward ant is updated when it visits the node

4. When backward ant is received at intermediate node, it pops the stack entry and subtracts the fuzzy cost from the ANT_FUZZY_COST and follows the path in reverse. The result

is route_cost of a path from intermediate node at which backward ant is received to destination given by following Eq.(2)

$$Route\_\cos t^{i}_{j,d} = \sum_{l=1}^{t} FC_{l}^{l+1} \tag{2}$$

where t is the number of traversed routes(or links) in the path starting with current node i (*l*=1) and finished with node d (*l*=*t*) via neighbor node j. FC_{l}^{l+1} is the fuzzy cost between adjacent nodes l and l+1.

The pheromone is the inverse of (2) i.e.

$$\Phi^{i}_{j,d} = \frac{1}{Route\_\cos t^{i}_{j,d}} \tag{3}$$

The interpretation is that if route_cost is more then the concentration of pheromone is low on that path and vice versa.

5. Pheromone table corresponding to the forward ant's destination is then updated as follows:

$$\Phi^{i}_{j,d}(t) = (1-\rho)\Phi^{i}_{j,d}(t-1) + \rho\Phi^{i}_{j,d} \tag{4}$$

where ρ is learning rate and set to 0.7 and the probability table is updated by using (1) .

6. When backward ant reaches the forward ant's source node, it will be killed after updating the pheromone and probability table of the source node.

7. The source node uses the algorithm discussed in [14] to establish disjoint paths and select the routes according to concrete demands, such as bottleneck bandwidth, delay, transition probability, etc.

4.2 Route Maintenance

The congestion in network will worsen the capacity of the network; even invalidate the part of the network. Since FSMR can balance the traffic by multiple node-disjoint paths, probability of congestion happening will bound to be lowered. When the congestion happens in the node *i* of a certain route, node *i* will retrace the path of forward ant to inform the source S to change route. S reduces the pheromone value of the route and updates the relevant probability table to increase the probability of other usable routes being selected.

Also, this phase is concerned with the routing failures, which are caused especially through node mobility and thus very common in mobile ad-hoc networks. FSMR recognizes a route failure through a missing acknowledgement. If a node gets a ROUTE_ERROR message for a certain link, it first deactivates this link by setting the pheromone value to 0. Then the node searches for an alternative link in its routing table. If there exists a second link it sends the packet via this path. Otherwise the node informs its neighbors, hoping that they can relay the packet. Either the packet can be transported to the destination node or the backtracking continues to the source node. If the packet does not reach the destination, the source has to initiate a new route discovery phase.

5 EXAMPLE

Consider the intermediate node 3 shown in fig7. Suppose backward ant is received at the node. As a result, the fuzzy cost stored on top of stack in node 3 will be subtracted from ANT_FUZZY_COST i.e.

$FC_{12}+FC_{23}+FC_{34}+FC_{45} - FC_{12}+FC_{23} = FC_{34}+FC_{45}$

So, the routing cost from node 3 to destination will be equal to sum of FC_{34} and FC_{45}. Assuming that FC_{34}= 0.3 and FC_{45} =0.5.According to Eq.(2)

$$Route\_\cos t^{3}_{4,5} = \sum_{l=1}^{t} FC^{3}_{1} = 0.8$$

The pheromone is then given by

$$\Phi^{3}_{4,5} = \frac{1}{Route\_\cos t^{3}_{4,5}} = 1.2$$

Assuming $\Phi^{3}_{4,5}(t-1) = 0$,we get

$$\Phi^{3}_{4,5}(t) = 1.2$$

Probability of selecting the route though neighbor node 4 is then given by:-

$$P^{i}_{j,d} = \frac{\Phi^{i}_{j,d}(t)}{\sum_{l} \Phi^{i}_{j,d}(t)}$$

$$= \frac{\Phi^{3}_{4,5}(t)}{\Phi^{3}_{4,5}(t) + \Phi^{3}_{6,5}(t) + \Phi^{3}_{7,5}(t)}$$

$$= \frac{1.2}{1.2 + 0.5 + 0.3} = 0.67$$

6 PERFORMANCE ANALYSIS

Usually the performance of routing protocol is reflected by validity, capability and practicability. So, FSMR will be analyzed from such three aspects.

A. Validity

Property 1: let G=(V,E), source node s Є V, destination node d Є V, d ≠s, and if there exists a path then algorithm returns a at least one path from source s to destination d satisfying the constraints.

Proof: we will use proof by contradiction. Assume that algorithm failed to return a path even if there exists a path. This means that source which initiated route discovery doesn't receive backward ant indicating that either forward ant failed to reach the destination or otherwise backward generated by destination has lost while coming back to source. But if there is a path then this could never happen since it means that node is not broadcasting forward ant, a contradiction.

B. Capability:

Property 2: The FSMR algorithm's time complexity is O (k+|V|), where |V| represents the number of nodes in ad hoc network, k represents the maximal number of paths which satisfy the constraint.

Proof: In normal node, each decision node has to select the most qualified path from k paths, So, each decision node's time complexity is O(k). However, forward nodes need not compute and only forward the message. So, forward node's time complexity is O(1).In normal mode, if let L be the length of path selected ,only the source node need to make decision. So, the time complexity of the proposed algorithm is O(k+L-1).However, maximal length of any simple path is (|V|-1).Therefore, FSMR algorithm's time complexity is O(k+|V|) in the worst case in the normal mode.

C. Practicapability

Property 3: The FSMR has a message complexity is O($|V|^2$) in the worst case .

Proof: Since the algorithm is built on the top of DSR, the algorithm inherits the time complexity of DSR which is proved to be O ($|V|^2$).

7 IMPROVEMENTS PROPOSED BY FSMR

One possible problem with this FSMR algorithm is that the distribution of probabilities eventually "would freeze" with a probability value, near to one, while the other values remain insignificant. To avoid this problem we defined in our simulation system a noise factor of *γ*, *γ* Є (0,1), so that at every time slice an ant has the probability *γ* of choosing a purely random path, and probability 1−*γ* of choosing its path according to the pheromone tables on each node. In our experiments we set *γ* to be 0.05. Furthermore, for having a better initialization of the pheromone table for each node, a greater pheromone value is assigned to the neighbor node *j* when it becomes destination *d*. Then the pheromone values are initialized in the pheromone table by

$$\tau^{n}_{j,d} = \begin{cases} \dfrac{1}{L_n} + \dfrac{3(L_n - 1)}{4L_n^2}, & j = d, \\ \dfrac{1}{L_n} - \dfrac{3}{4L_n^2}, & j \neq d, \end{cases}$$

where *d* Є *Neighbor*(*n*) and $L_n$is the number of neighbors, n is the number of nodes in the underlying network.

If the destination *d* is not a neighboring node, then a uniform distribution is initially assumed as

$$\tau^{n}_{j,d} = 1/L_n, \; d \notin Neighbor(n).$$

8 SIMULATION AND RESULTS

We conducted experiments to evaluate and compare the performance of the following multipath routing protocols: FSMR, AODV, and AOMDV. In these experiments, we used the discrete time network simulator, OMNET++, which offers high fidelity in wireless ad hoc network simulation by including an accurate implementation of data link and physical layers. Fifty mobile nodes were moved according to the random waypoint mobility model within a 1500 m * 300 m area. Each node had a radio propagation range of 250m and channel capacity was 2Mb/s. All simulations were run for 600 seconds of simulated time. We did our experiments with movement patterns for 7 difference pause times: 0, 100, 200, 300, 400, 500 and 600 seconds. Thirty mobile nodes acted as traffic sources generating 4 packets/second each, and data traffic was generated using constant bit rate (CBR) UDP traffic sources. The medium access control protocol was the IEEE 802.11 DCF. The size of data packet was 512 bytes. The minimum and the maximum speeds were set constant to zero and 20m/s respectively.

Packet delivery ratio is important as it describes the loss rate that will be seen by the transport protocols, which in turn affects the maximum throughput that the network can support. Fig. 8 presents that packet delivery ratio is the

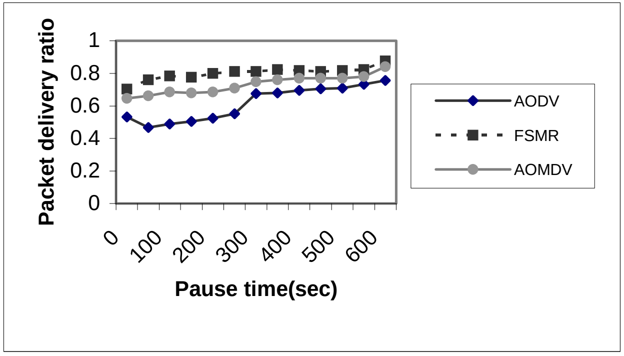


Figure 8. **Packet delivery ratio**

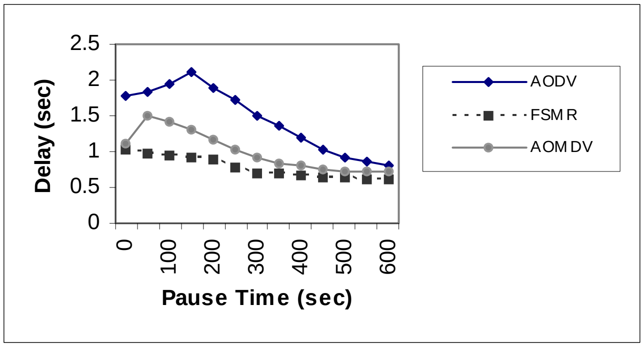


Figure 9. **End-to-end delay**

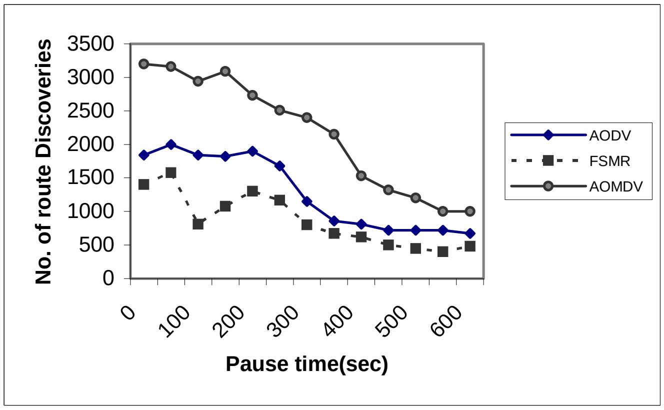


Figure 10. **No. of route discoveries**

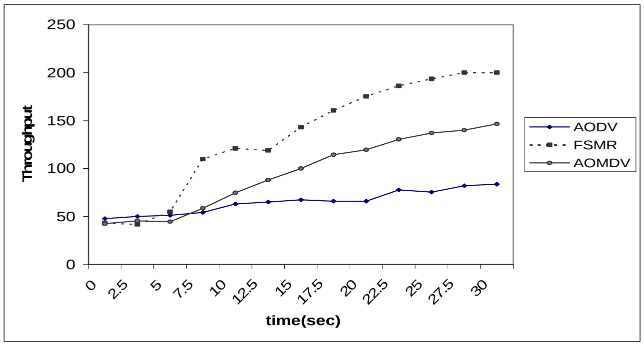


Figure 11. Throughput

Table 2. Simulation results

Routing Algo Metric	AODV	AOMDV	FSMR
End to End delay	16.10	9.64	6.80
Avg. Throughput	40.5	112.5	156.7
Packet Drop Ratio(%)	35	22	24
Overhead	3	3	3

highest for FSMR, which is due to its ability to select a set of stable and least congested routes thus having the amount of congestion loss and very few route failures.

The average end-to-end delay is the average elapsed time to deliver a packet from the source node to the destination node, and it includes all possible delays before data packets arrive at their destinations. The average end-to-end delay for FSMR is the lowest compared with AODV and AOMDV (Fig. 9). It is obvious that AODV and AOMDV have the higher delay because of high congestion. As the mobility decreases (increasing pause time) the delay also decreases due to less route failures at low mobility. Route failures have an impact on the delay, because route failures require re-rerouting and storing of packets in the send buffer.

Route rediscovery is needed to locate an alternate route for the given destination. It is an expensive task. So the less frequency of routing discovery process means the less route discovery latency and lower routing overhead. Fig. 10 shows that the frequency of route rediscovery of FSMR is the lowest among those of the compared routing protocols. Because FSMR deals with the uncertainty of MANET and considers the effects of different correlated parameters on network performance, FSMR decreases the route failures significantly.

Throughput is the fraction of packets sent by a source node that arrive at the destination node. Fig. 11 show the comparison of the delivery rate among three algorithms in above strategies. Upto time 7.5 sec., Throughput of AOMDV and FSMR is delivered at the same rate, but then as time increases, the FSMR outperforms AOMDV since no. of dropped packets will be less due to intelligently selected paths in comparison to other algorithms, thereby increasing throughput.

Dropped packets: The dropped packets are the data packets that are dropped during the routing process because the buffer of the node is full or the life time of a packet is expired.

Overhead is the number of packets (request or ant) that is used to maintain or control the network. Note that the number of control packets (ants) in FSMR are not more than

the conventional routing methods (i.e. OSPF) because updating the routing tables are done by ants in interval times and there is no necessity to have global updating mechanism such as flooding the routing tables among all nodes which is used in OSPF.

The experimental results in this simulation are gathered in table 2 which shows that the proposed method (FSMR) outperforms other routing algorithms in all evaluation metrics.

9 CONCLUSION AND FUTURE WORK

In this paper correlation of different route selection parameters that affect the network performance is captured by fuzzy ant technology. The results shown in the graphs and tables indicate that the FSMR algorithm does a better job at dispersing traffic in a more uniform manner throughout the network. It also handles an increased traffic load as well as decreased transmission delay by utilizing network resources more efficiently. The advantages of such an intelligent algorithm include increased flexibility in the constraints that can be considered together in making the routing decision efficiently and likewise the simplicity in taking into account multiple constraints. In the near future the next generation networks will have capabilities including soft-switches and grid networks, which allow such an intelligent agent-based routing algorithm to update the routing tables autonomously, and then they can be substituted with the conventional routing algorithms such as OSPF. The result of this research motivates use of fuzzy logic in swarm intelligence based multipath routing protocol to explore also other areas of routing in MANET, for example, position of node based routing.

10 REFERENCES

[1] Macker, J.P., Scott Corson, M. Mobile ad-hoc networking and the IETF in Mob. Comput. Commun. Rev. vol.2. ACM Press, New York, NY (1998) 9-15.

[2] M. Abolhasan, et al. A review of routing protocols for mobile ad hoc networks. Ad Hoc Networks 2 (2004) 1–22.

[3] M. Dorigo and G. D. Caro, “The ant colony optimization metaheuristic,”in New Ideas in Optimization, D. Corne, M. Dorigo, and F. Glover,Eds. New York: McGraw-Hill, 1999.

[4] V. Maniezzo and A. Cabonaro, “Ant colony optimization :An overview,”in metaheuristic Int. Conf., Angra dos Reis, Brazil.

[5] Mirabedini S.J., Teshnehlab, M. Rahmani, A.M.,“FLAR:An Adaptive Fuzzy Routing Algorithm for Communications Networks Using Mobile Ants,”International Conference On Convergence Information technology,2007.pp. 1308-1315.

[6] M. Abolhasan, T. Wysocki, and E. Dutkiewicz. A review of routing protocols for mobile ad hoc networks. Ad Hoc Networks, 2:1{22, 2004.

[7] C. Perkins and P. Bhagwat. Routing over multihop wireless network of mobile computers. ACMSIGCOMM'94: Computer Communications Review, 24(4).

[8] C.E. Perkins and E.M. Royer. Ad-hoc on-demand distance vector routing. In Proceedings of theSecond IEEE Workshop on Mobile Computing Systems and Applications, 1999.

[9] D.B. Johnson and D.A. Maltz. Mobile Computing, chapter Dynamic Source Routing in Ad Hoc Wireless Networks, pages 153{181. Kluwer, 1996.

[10] J. Broch, D.A. Maltz, D.B. Johnson, Y.-C. Hu, and J. Jetcheva. A performance comparison of multi-hop wireless ad hoc network routing protocols. In Proceedings of the 4th Annual ACM/IEEE International Conference on Mobile Computing and Networking (MobiCom98), 1998.

[11] Z.J. Haas. A new routing protocol for the reconfigurable wireless networks. In Proceedings of the IEEE International Conference on Universal Personal Communications, 1997.

[12] G. Di Caro. Ant Colony Optimization and its application to adaptive routing in telecommunication networks. PhD thesis, Universit¶e Libre de Bruxelles, Brussels, Belgium, 2004.

[13] R.S. Sutton and A.G. Barto. Reinforcement Learning: An Introduction. MIT Press, 1998.

[14] K. Fujita, A. Saito, T. Matsui, and H. Matsuo. An adaptive ant-based routing algorithm used routing history in dynamic networks. In Proceedings of the 4th Asia-Pacific Conference on Simulated Evolution and Learning, 2002.

[15] D. C^amara and A.A.F. Loureiro. GPS/ant-like routing in ad hoc networks. Telecommunication Systems, 18(1{3):85{100, 2001.

[16] S. Marwaha, C.K. Tham, and D. Srinivasan. Mobile agents based routing protocol for mobile ad hoc networks. In Proceedings of the IEEE Global Communications Conference (GlobeCom), 2002.

[17] M. Roth and S. Wicker. Termite: Emergent ad-hoc networking. In Proceedings of the Second Mediterranean Workshop on Ad-Hoc Networks, 2003.

[18] C.-C. Shen, C. Jaikaeo, C. Srisathapornphat, Z. Huang, and S. Rajagopalan. Ad hoc networking with swarm intelligence. In Ants Algorithms - Proceedings of ANTS 2004, Fourth International

[19] Workshop on Ant Algorithms, volume 3172 of LNCS. Springer-Verlag, 2004.

[20] S. Mueller, R. Tsang, and D. Ghosal. Multipath routing in mobile ad hoc networks: Issues and challenges. In Performance Tools and Applications to Networked Systems, volume 2965 of LNCS.Springer-Verlag, 2004.

[21] D. Ganesan, R. Govindan, S. Shenker, and D. Estrin. Highly-resilient, energy-efficient multipath routing in wireless sensor networks. Mobile Computing and Communications Review, 1(2), 2002.

[22] M. Marina and S. Das. On-demand multipath distance vector routing in ad hoc networks. In Proceedings of IEEE International Conference on Network Protocols (ICNP), pages 14{23, 2001.

[23] Z. Ye, S.V. Krishnamurthy, and S.K. Tripathi. A framework for reliable routing in mobile ad hoc networks. In Proceedings of IEEE INFOCOM, 2003.

[24] K. Wu and J. Harms. On-demand multipath routing for mobile ad hoc networks. In Proceedings of the European Personal and Mobile Communications Conference (EPMCC), 2001.

[25] L. Wang, Y.T. Shu, O.W.W. Yang, M. Dong, and L.F. Zhang. Adaptive multipath source routing in wireless ad hoc networks. In Proc. of the IEEE Int. Conf. on Communications (ICC), 2001.

[26] C. Gui and P. Mohapatra. SHORT: Self-healing and optimizing routing techniques for mobile adhoc networks. In Proc. of the Int. Sym. on Mobile Ad Hoc Networking and Computing (MobiHoc), 2003.

[27] S.-J. Lee and M. Gerla. AODV-BR: Backup routing in ad hoc networks. In Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC), 2000.

[28] A. Nasipuri, R. Castaneda, and S.R. Das. Performance of multipath routing for on-demand protocols

[29] in mobile ad hoc networks. Mobile Networks and Applications (MONET), 6(4), 2001.

[30] S.-J. Lee and M. Gerla. Split multipath routing with maximally disjoint paths in ad hoc networks.

[31] In Proceedings of the IEEE International Conference on Communications (ICC), 2001.

[32] D.S.J. De Couto, D. Aguayo, B.A. Chambers, and R. Morris. Performance of multihop wireless networks: Shortest path is not enough. In Proceedings of the First Workshop on Hot Topics in

[33] Networks (HotNets-I). ACM SIGCOMM, 2002.

[34] Y. Sasson, D. Cavin, and A. Schiper. Probabilistic broadcast for flooding in wireless mobile ad hoc networks. In Proc. of IEEE Wireless Communications and Networking Conference (WCNC), 2003.

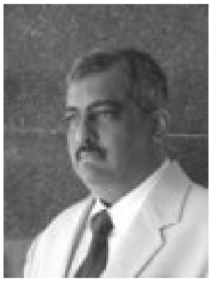
[35] Marwaha, S., Srinivasan, D., Chen Khong Tham and Vasilakos A., “Evolutionary fuzzy multi-objective routing

for wireless mobile ad hoc networks," Congress on Evolutionary Computation, 2004, Volume: 2, 19-23 June 2004, Pages:1964 – 1971

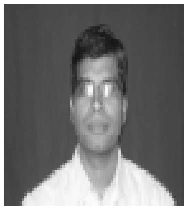
[36] Alandjani, G.and Johnson, E.E, "Fuzzy routing in ad hoc networks," Proceedings of the 2003 IEEE International Performance, Computing, and Communications Conference,2003. 9-11 April 2003, Pages:525 – 530

[37] Hui Liu; Jie Li; Yan-Qing Zhang; Yi Pan, "An adaptive genetic fuzzy multi-path routing protocol for wireless ad-hoc networks," First ACIS on Self-Assembling Wireless Networks.SNPD/SAWN Volume , Issue , 23-25 May 2005 Page(s): 468 - 475

Author's biography



Dr.Rajiv Dharaskar: He has obtained Ph.D degree in Computer Science and Engineering from Amravati University. His research interest includes Web Technologies, Multimedia programming, Expert Systems, Virus Programming, E-learning Softwares, System Utilities etc. He has total 23 years of teaching experience. He has published 08 research papers in reputed journals



Manish M. Goswami received the B.E. degree in computer science and engineering from Nagpur University,India, and the M.Tech. in computer science and engineering also from Nagpur University, India in 2009. He is currently an assistant professor with St. Pallotti College of Engineering. His research interests include soft computing, computer networking and compilers.