Intelligent Agent Based Delay Aware QoS Unicast Routing in Mobile Ad hoc Networks

V. R. Budyal[1] and S. S. Manvi[2]

[1]*Department of Electronics and Communication Engineering*
Basaveshwar Engineering College, Bagalkot, India
[2]*Department of Electronics and Communication Engineering*
Reva Institute of Technology and Management, Bangalore, India
vrbudyal@yahoo.co.in, sunil.manvi@revainstitution.org

Abstract

Quality of Service (QoS) support in Mobile Ad hoc NETworks (MANETs) is a challenging task due to bandwidth and delay constraints, varying channel conditions, power limitations, node mobility and dynamic topology. This paper proposes an intelligent agent based on-demand (source initiated) delay aware QoS routing scheme in MANETs by using software agents that employ neuro-fuzzy logic supported by Q-learning. The proposed scheme operates in following steps. (1) Source node uses an agent that uses Dynamic Source Routing (DSR) to find various paths, their bandwidth and packet loss rate to reach a destination. (2) Parallely, a static neuro-fuzzy agent at the source node is used to optimize membership functions of fuzzy parameters according to user delay requirement of the fuzzy inference system (FIS); also, a fuzzy Q-learning static agent at the source node is employed to optimize the consequent part of if-then rules of FIS. (3) Fuzzy static agent at the source node decides whether node on a path satisfies delay requirement for an application according to the user by considering fuzzy parameters, bandwidth, packet loss rate and delay. (4) A path with QoS satisfied nodes will be selected by fuzzy QoS static agent and (5) mobile agents are used to maintain and repair the path. The scheme has been simulated in various network scenarios to test operation effectiveness and observed that proposed scheme performs better than the existing fuzzy based DSR routing methods.

Keywords: *MANET, Routing, Neuro-Fuzzy, Fuzzy Q-learning, Software agents*

1. Introduction

Mobile ad hoc network (MANET) is a decentralized, self-organizing wireless network without any fixed infrastructure. Each node in a MANET behaves not only as a host, but also as a router [1]. Mobile multimedia ad hoc networks have created great demand in the services for the mobile users that require stringent Quality of Service (QoS). However, there are several problems and issues which have to considered for QoS support in MANETs including signaling, medium access control, security, reservation, and routing. Routing is considered as one of the most important aspect of MANET due to the dynamic topology. Even-though wireless ad hoc networking researchers have addressed (as given in Section 1.1) the routing problem since a decade; they have still not yet come up with a robust and efficient routing scheme. Thus, we have scope to develop efficient routing protocols for multimedia applications to decrease routing related overheads and find QoS routes with better packet delivery ratio, higher throughput and lower delays.

Examples of MANET applications include video telephony, business associates sharing information during meetings or conferences, soldiers relaying information on a battlefield, etc.

These applications are based on multimedia services and depend on QoS constraints for better communication. Unicast and multicast are the routing mechanisms used in MANETs. Unicast routing deals with one-to-one communication whereas multicast routing is used for group communication. The scope of this paper is limited to unicast routing.

MANET routing protocols may be generally categorized into two types: table-driven and source-initiated. Table-driven routing protocols maintain one or more tables at each node to store routing information. Source-initiated routing protocols establish a route only when a source node requests for a route [2]. Dynamic Source Routing (DSR) is one of the source initiated protocols that considers lowest number of hops for transmitting data from the source to the destination. A single route discovery yields multi-paths to the destination.

The state information in MANETs suffers from all kinds of uncertainty like randomness and fuzziness. The routing information gathered during route discovery may become invalid. In order to obtain accurate nature of the routing information, a fuzzy logic aided technique may be incorporated into the routing algorithm for diminishing the influence of imprecise and uncertain routing information. The disadvantage with fuzzy inference system (FIS) is that it requires expert knowledge to set up the fuzzy rules and membership function parameters. However, neuro-fuzzy based systems have the ability to optimize and handle the nonlinear and complex systems and tune FIS.

In this paper, we propose an agent based delay aware on-demand (source initiated) unicast routing scheme based on neuro-fuzzy logic in MANET that decides the delay satisfied paths from a source to the destination. We use an extension of DSR protocol to find all the multi-paths and their state (bandwidth and packet loss rate) from source to destination. The source selects a delay satisfied QoS path. With intermediate node's state information available at source node; the scheme uses FIS to decide whether nodes on the path satisfy required delay. As decision is made by FIS and is dependent on the fuzzy membership functions and if-then rules; membership functions and if-then rules are optimized based on neuro-fuzzy and fuzzy-Q learning technique, respectively. The scheme consists of a set of static and mobile agents that co-ordinate through knowledge base to discover and maintain the QoS satisfied path. Its effectiveness is verified by comparing with fuzzy logic QoS based DSR schemes [3, 4].

1.1. Related Works

The QoS satisfaction and routing problem in wireless ad hoc network has been studied by many researchers. Some of the related works on unicast routing protocols for MANETs based on fuzzy logic and other intelligent techniques are presented as follows. In [3], authors employ fuzzy logic technique (Fuzzy perfect DSR) to find the maximum route stability with route life time by using number of hops as inputs to the fuzzy system. Link life time is predicted from speed of nodes, travelling direction and position. Also, route cache expiration time is adjusted adaptively based on route life time.

The work given in [4] describes QoS routing algorithm based on DSR (FLQDSR) by adopting fuzzy logic to select appropriate QoS route among multiple paths. The work given in [5] presents a technique for optimizing the efficiency of route discovery by using a fuzzy logic system. The work given in [6] presents an optimized technique that assures that, data are always transmitted through the route with the lowest delay. The work given in [7] employs genetic algorithm to select the most optimum protocol based on network context.

In our previous work presented in [8] as a position paper; a unicast routing scheme is discussed which establishes a path between a pair of hosts on demand. The work is not supported with validation of the scheme and performance analysis, and also lacked proper formulation of components of the scheme. This paper provides an extension to the work by providing detailed functioning of the scheme and simulation based performance analysis. The work given in [9] explains intelligent cross-layer QoS support for wireless mobile ad hoc networks by using fuzzy QoS, which exploits fuzzy logic for improving traffic regulation and the control of congestion.

The work given in [10] provides QoS with service differentiation based on neural networks. Authors in [11] present a game theory approach to extract a core in MANET. The QoS aware routing protocol selects a path through the extracted core. The work given in [12] presents ant-based multi-QoS routing metric which builds a hierarchical network before choosing suitable paths to meet various QoS requirements from different kinds of traffic.

From the above literature, we find that there is still enough scope to improve the performance of unicast routing schemes to support better packet delivery ratio, improved throughput, low latency, reduced overheads and fault tolerance. FIS with a combination of neural networks, fuzzy logic, software agents and Q-learning may provide better intelligent solution for routing in MANETs. Thus, we have used this combination to offer intelligent delay aware unicast routing in MANETs.

1.2. Our Contributions

The proposed routing scheme for MANETs is motivated by observing inherent drawbacks of existing fuzzy based on-demand and other unicast routing schemes mentioned in related works (section 1.1). They are as follows: (1) fuzzy logic aided routing solution by considering fixed membership functions, (2) conclusion part of fuzzy if-then rules are not optimized, (3) lack of well established route management procedures, (4) less robust to mobility, and (5) low user request acceptance for route establishment. The decision of FIS can be drastically affected by the choice of membership functions and fuzzy if- then rules. Thus, methods for fine tuning of FIS are essential. This paper considers a problem of optimizing FIS to meet the delay aware QoS requirement of user by employing computational software with set of software agents as well as attempts to establish robust route discovery and maintenance procedures.

Our contributions compared to existing works are as follows. (1) Employs agent to optimize membership functions of FIS by using neuro-fuzzy technique. (2) Usage of agent to optimize if-then rules of FIS by using fuzzy Q-learning. (3) Engage agents to discover multiple paths from source to destination by extending DSR. Select delay constrained QoS path by using optimized FIS from multiple paths. (4) Robust path maintenance mechanism under link failure, node failure and mobility conditions by using mobile agents, and (5) comparing the results with existing fuzzy based schemes. We showed that our scheme works better in terms of packet delivery ratio, latency, acceptance ratio and overheads.

The remainder of this paper is organized as follows. Section 2 explains the proposed work. Simulation model is presented in Section 3. Section 4 discusses about results. Finally, conclusions are given in Section 5.

2. Proposed Work

The proposed scheme operates at the source node in the following steps by using a set of static and mobile agents [13-15]. (1) Employed DSR protocol to find all multi-paths from a given source to destination, and also collected QoS state information (bandwidth, packet loss rate) of intermediate nodes of each path. (2) In fuzzification process of Fuzzy Inference System (FIS), neuro-fuzzy technique is adopted to optimize selected membership function for fuzzy parameters (bandwidth, packet loss rate and delay) as per the requirements of a source; fuzzy-Q learning is adopted to optimize if-then rule's consequent part. The steps 1 and 2 operate in parallel. (3) Considers multi-paths one by one to verify whether each node of a path satisfies QoS by applying tuned FIS; if a path with QoS satisfied nodes are found, FIS stops. FIS operates in the following sequence for all nodes on a path until and unless a node violates QoS satisfaction. (3a) Fuzzification: finds degree of membership for the QoS parameters of intermediate node on a path. (3b) Decision making: rules are applied for aggregating (3c) Defuzzification: the crisp value obtained by defuzzification decides whether node on the path satisfies QoS. (4) Uses the QoS satisfied path for data transfer, and (5) maintains the path by either using local patch up or source to destination path reconstruction whenever either a node moves out of range or node fails or link fails.

This section describes the network environment, extension to DSR for state information gathering, computational models of FIS and routing agency for the proposed work.

2.1 Network Environment

MANET comprises of several number of mobile nodes which are distributed within a given area as shown in Figure 1. Each mobile node moves with a different speed in different direction within the given area. Each mobile node has a finite transmission range. The residual bandwidth and packet loss rate at each node is different at different times. The proposed agency is situated at every node. An agent platform is located in the nodes comprising of static and mobile agents. The scheme assumes availability of an agent platform at all the mobile nodes.

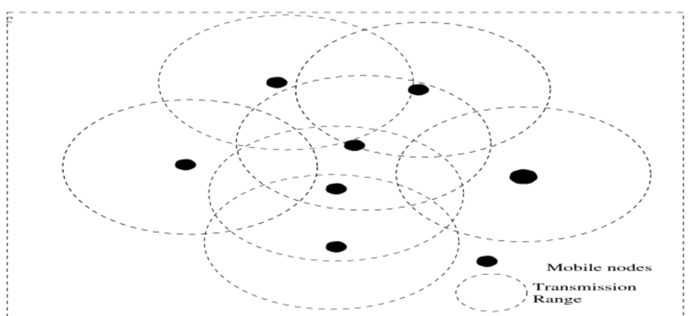

Figure 1. Network Environment

2.2 Extension to DSR

In DSR, a source node floods route request packet (RREQ) containing sender address, destination address, route record addresses [1… n], unique request ID determined by source, and hop limit. Whenever RREQ packet arrives at a node, appends its own address to the route record in the RREQ. Upon receiving a RREQ, the node checks for the destination. If node is not the destination, it further floods RREQ until it reaches destination. When the RREQ packet arrives at the destination, it copies the accumulated route record in route reply packet (RREP) along with other fields, but sender and destination address are reversed. RREP packet traverses the same path as that of RREQ. Upon receiving RREP packet, source caches the route in its route cache for subsequent routing. Source node waits until it collects all the multi-paths from source to destination (waits for all RREPs to arrive) and caches all multi-paths in its route cache. We have extended the RREQ packet by appending state information (including bandwidth and packet loss rate at visited nodes) along with route record. Similarly, RREP is also appended with state information. The state information will assist the source node to verify QoS satisfaction of the intermediate nodes on the path. In our scheme, mobile agents perform the functions of RREQ and RREP packets.

2.3. Computational Models

This section describes computational models for optimizing FIS, neuro-fuzzy optimizer and fuzzy Q-learning for the proposed agent based QoS routing.

2.3.1. Neuro-fuzzy based Membership Function Optimization: We optimize selected membership function for fuzzy parameters bandwidth, packet loss rate and delay using neuro-fuzzy technique as per the requirement of source [16]. The fuzzy membership functions can be any suitable parametrized functions such as triangular, trapezoidal or sigmoidal. The sigmoidal function is chosen in our scheme because of its continuous and differential property which is very suitable to apply back propagation learning algorithm in parameter optimizing phase.

The input fuzzy parameter considered are bandwidth (bw) and packet loss rate (pktls). The output fuzzy parameter considered is delay. Fuzzy linguistic terms described for bandwidth are '*Low*', '*Medium*' and '*High*'; for packet loss rate, the terms are *'Less', 'Moderate' and 'More';* and for delay, the terms are *'Small' and 'Large'*. The sigmoidal membership functions for the bandwidth, packet loss rate and delay are shown in Figure 2 along with optimization. It generates training data set from the selected sigmoidal functions as [x_1 , $x_2 ... x_n$, $O(x)_{required}$]. Where, x_n is given by membership functions for fuzzy parameters, i.e., [μ^n (bw_{Low}), μ^n (bw_{Medium}), μ^n (bw_{High}), μ^n ($pktls_{Less}$), μ^n ($pktls_{Moderate}$), μ^n($pktls_{More}$), $O(x)_{required}$]. For example, μ^n (bw_{Low}) is degree of membership value of bandwidth on a linguistic term '*Low'* and $O(x)_{required}$ is delay required by the source.

Neuro-fuzzy network employed for membership function optimization consists of five layers as shown in Figure 3. First layer consists of input fuzzy variables bandwidth and packet loss rate; different linguistic terms of input variables form second layer; if-then fuzzy rules form third layer; fourth layer has fuzzy output linguistic terms and fifth layer is defuzzified output. Layers 2, 3 and 4 form hidden layers. The first layer has as many nodes (neuron) as the number of the independent fuzzy input variables. The second layer has one node for every fuzzy linguistic term of each of the input variables and those nodes are connected to the corresponding input node only. The third layer is to be used for learning significant AND combinations between the fuzzy labels from the second layer forming the fuzzy if-then rules. The number of nodes is the number of rules formed. The fourth layer consists of as many nodes as the number of the output fuzzy linguistic values. The fifth layer consists of as many nodes as the output fuzzy variable.

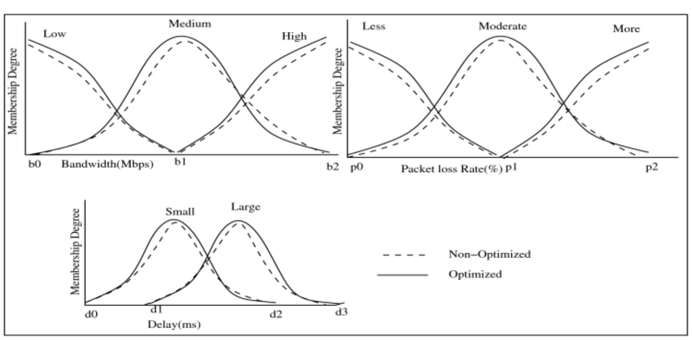

Figure 2. Membership Functions for Fuzzy Parameters

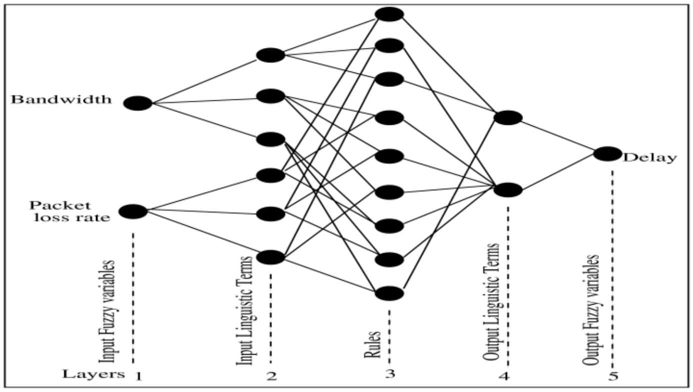

Figure 3. Neuro-Fuzzy Network for Optimization of Membership Functions

Neuro-fuzzy optimizes membership functions with two phases: (1) feed forward and (2) backpropagation. These phases are repeated until optimized membership functions are obtained for the input and output fuzzy variables for the given requirement.

Feed forward phase: During this phase, weights between two nodes of the neuro-fuzzy network are fixed and are assumed initially. The input is propagated layer by layer by computing the output at each node and every layer by using the equation (1).

$$O(x)_{\text{output}} = O^{i}_{j} = \frac{1}{1 + e^{(-\sum x_i w_i - t)}} \qquad (1)$$

Where, i= 1, 2....*n*. and *n* is the number of layers, w_i is the weight attached between two nodes, x_i is the actual bandwidth and packet loss rate value. Threshold '*t*' for each node is selected as zero. O^{i}_{j} indicates output for the j^{th} node in the i^{th} layer and acts as input to the $(i+1)^{th}$ layer node to which it is connected. $O(x)_{\text{Output}}$ is computed at each layer until the last layer. Output of last layer is compared with the required delay $O(x)_{\text{required}}$ which gives the error value. Error (δ) is computed by taking the difference of required delay and output obtained by last layer and is given by equation 2. The forward phase ends with the computation of an error signal. Error is distributed in the hidden layers by back propagation (BP) technique if error is more than acceptable error. Otherwise it stops learning.

$$\delta = \mathrm{O(x)}_{\text{required}} - \mathrm{O(x)}_{\text{output}} \qquad (2)$$

Back propagation phase: Compute E_j^i (error associated with j^{th} node of i^{th} layer) at each layer by using equation (3) until it reaches first layer.

$$E^{i}_{j} = O^{i}_{j}(1 - O^{i}_{j}) \sum w^{i}_{nj} E_j^{i+1} \qquad (3)$$

Where O^i_j is output of j^{th} node of i^{th} layer, E_j^{i+1} is an error associated with j^{th} node of $(i+1)^{th}$ layer, w^i_{nj} is a weight associated between n^{th} node of i^{th} layer to j^{th} node of $(i+1)^{th}$ layer. In this mode of BP learning, adjustments are made to the weights of the network. Training is done on an epoch by- epoch basis, where each epoch consists of the entire set of training data set. Weights are updated by using equation 4 between the nodes.

$$w^{i}_{nj}\,(new) = w^{i}_{nj}\,(old) + \beta E_j^{i+1}\, x_{nj} \qquad (4)$$

Where, w_{nj}^{i} is weight associated with the path connecting the n^{th} node of the i^{th} layer to the j^{th} node of the $(i+1)^{th}$ layer, β is learning constant, E_j^{i+1} is error associated with the j^{th} node of the $(i+1)^{th}$ layer, x_{nj} is input from the n^{th} element of the i^{th} layer to the j^{th} element of the $(i+1)^{th}$ layer. The final updated weights are the optimized membership functions for the input and output fuzzy variables for the $O(x)_{required}$.

2.3.2. Fuzzy Q-Learning to Optimize rules: The fuzzy if then rules are listed in Table 1, which are given by using intuition method at the beginning. Later, rules are optimized. Bandwidth denotes available bandwidth at an intermediate node and packet loss rate indicates packet loss at an intermediate node. We propose to optimize consequent part of fuzzy if then rules by adopting fuzzy-Q learning technique [17].

Table 1. Fuzzy if – then Rules

Rule No	Available Bandwidth	Packet Loss Rate	Delay
1	*Low*	*Less*	*Large*
2	*Low*	*Moderate*	*Small*
3	*Low*	*More*	*Large*
4	*Medium*	*Less*	*Small*
5	*Medium*	*Moderate*	*Small*
6	*Medium*	*More*	*Large*
7	*High*	*Less*	*Small*
8	*High*	*Moderate*	*Small*
9	*High*	*More*	*Small*

Several competing conclusions are associated with each rule. We need to find a best conclusion for each rule. The fuzzy 'rule i' is of the form:

If available bandwidth is *High* and packet loss rate is *Less* **then** delay is *small* with Q^i (s, *small*)

or delay is large with Q^i (s, *large*)

Where '*small'* and '*large*' are elements of set 'a[*small, large*]' which represent output linguistic terms of fuzzy output variables considered as '*small'* and '*large*'. Q^i (s, *small*) is a *Q* value of delay for rule '*i'*.

Fuzzy-Q learning consists of five layers similar to one used for membership function optimization (figure 3). Layers 1 to 3 achieve fuzzification in fuzzy Q-learning. Layers 4 and 5 generate continuous action by fuzzy inference and also generate associated Q vector. First layer receives the fuzzy input variable bandwidth and packet loss rate and transmits to the next layer. Each node in this layer corresponds to one input. Second layer consists of several linguistic terms for each input variable with sigmoidal functions to obtain optimized degree of membership function. The output value from layer 2 indicates a membership degree. One link from a node in layer 1 to the node in layer 3 corresponds to one antecedent part of FIS. That is, it represents the 'if ' part of each rule. The value of each node in layer 3 simply represents that how much current state 's' belongs to the 'rule i', and is obtained by fuzzy equivalence Tnorm operator. B and P represents membership functions B= μ(bw) and P = μ(pktls) of input variable of antecedent part of the rule. The truth value of rule i for state 's' is given by equation (5).

$$\mu_i(x) = 1 - |B - P| \quad (5)$$

Layer 4 corresponds to the 'then' part of each fuzzy rule where the Fuzzy-Q learning starts. There are nine states/rules in the system as shown in Figure 4 derived from Table 1. Consider state S_7 as a optimal goal state for multimedia application with certain delay requirement. Find an optimal policy for taking the best action at each state to reach the goal. Action taken on the state, reaches the another state and reinforcement reward is assigned for each action. In each state, two actions are possible. A fuzzy constraint on each state-action pair takes reward value 'r' as 0, 50 or 100 as given by equation (6). Lower the reward value, the harder is to take the action to reach the goal.

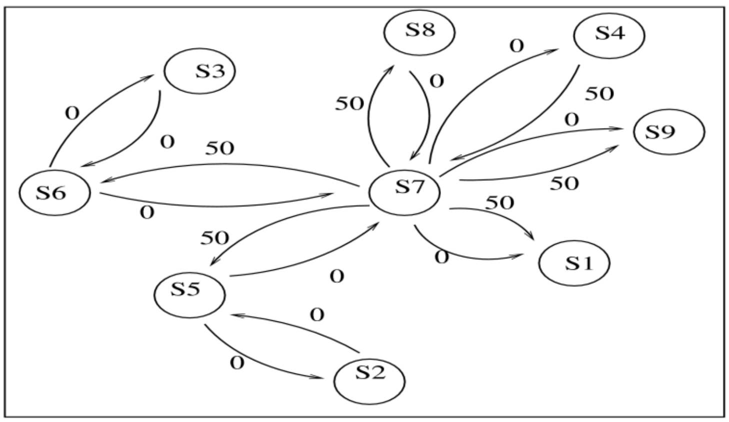

Figure 4. State Action Representation

$$r = \begin{cases} 0; & \text{if failure zone(punishment)} \\ 50; & \text{if approaching goal with 50\%} \\ 100; & \text{if it is a goal (reward)} \end{cases} \quad (6)$$

Based on Q values and state-action policy, one action from discrete action set is selected as a rule action. A Q-value is assigned to each action of the rule as given in equation (7).

$$Q^i{}_{st+1}(s, a) = \frac{\sum_{i=1}^{N} \mu_i(x_t)\, q[i, a]}{\sum_{i=1}^{N} \mu_i(x_t)} \quad (7)$$

The Q-value for each fuzzy rule can be represented in a vector form *q[i, a]* computed by equation (8) where *'i'* is the rule index and 'a[*small*, *more*]' is the linguistic term chosen from a set of output linguistic terms.

$$q[i, a] = q[i, a] + \frac{\alpha \mu_i(x_t)}{\sum_{i=1}^{N} \mu_i(x_t)} \left(r + \gamma q_{\max}[s_{t+1}, a'] - Q^i[s_t, a] \right) \quad (8)$$

Where $\mu_i(x)$ is truth value of rule i, N is the number of rules, r is reward given for state for performing an action, γ is discount rate (0-1), α is learning rate (0-1), $q_{max}[s_{t+1},a']$ is maximum *q*-value among all actions performed by next state. Optimal policy is obtained by argmax policy in this work where it selects an action with Q having maximum value. Layer 5 performs operation of defuzzification accepting the consequences learnt by fuzzy-Q learning.

2.4. Fuzzy Inference System (FIS)

Fuzzy Inference system is used for minimizing uncertainty present in the network due to mobility of the hosts or constrained network resources. This section describes Fuzzy inference system as shown in Figure 5 to decide satisfaction of QoS by a node on the path. FIS consists of fuzzification, decision making, defuzzification, neuro-fuzzy based membership function optimizer and fuzzy-Q learning based if then rule optimizer.

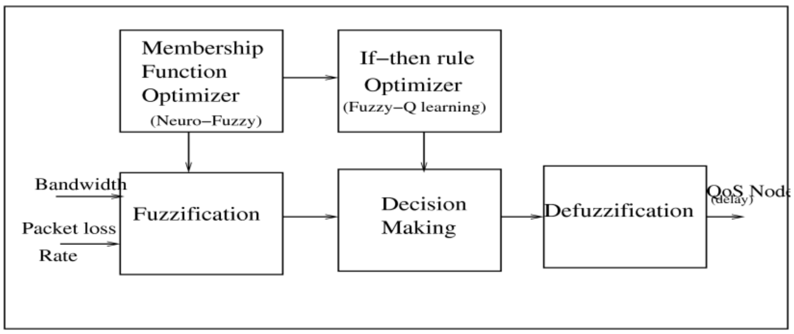

Figure 5. FIS at Each Node

Fuzzification: The proposed scheme employs bandwidth available, packet loss rate at node and delay required by source as fuzzy parameters. They have been represented by membership functions as shown in Figure 2. The membership functions assigned are the optimized membership values obtained by neuro-fuzzy technique (see Section 2.3.1). In the fuzzification step, a measured value (called crisp input) is converted into linguistic values (*low*, *medium* and *high* for bandwidth; *less*, *moderate* and *more* for packet loss rate) Each fuzzy set is associated with a membership function and is used to characterize how certain the crisp input belongs to the set. For a given crisp input, the membership function returns a real number in [0, 1]. The value closer to 1, more certain the input belongs to the set. A single crisp value can take more than one linguistic value; if the membership values overlap.

Inference and defuzzification: Since there are three linguistic values for bandwidth and packet loss rate, the total number of rules is 9. The rule-base is in a form called functional fuzzy system where each rule *i* is written as follows. Rule *'i':* IF bandwidth is *high* and packet loss rate is *less* THEN delay is *less*. The consequent part of if-then rules are optimized by fuzzy-Q learning (see Section 2.3.2). The decisions are based on the testing of all rules in FIS, thus rules are combined to make a decision. Aggregation combines output of rules as either *large* or *small* for the delay. To come up with single crisp output from FIS, centroid defuzzification is performed. Crisp output of the defuzzifier decides whether a node is QoS satisfied.

2.5. Intelligent Routing Agency

The agent based model shown in Figure 6 consists of User agency, DSR Agency QoS Agency and Common knowledge base. User agency has static agents (user manager agent (UMA). It accepts the multimedia application's QoS requirement in the form of delay. This agency triggers DSR and QoS agency. DSR agency comprises of static and mobile agents

(DSR manager agent (DMA), DSR agent (DSRA), and maintenance agent (MA)) to fetch all the multi-paths from source to destination and also to collect state information of intermediate nodes. The QoS agency comprises of static agents QoS manager agent (QMA), neuro-fuzzy agent (NFA), fuzzy QoS agent (QA) and fuzzy Q-learning agent (FQA). The agencies reside at each node. Knowledge base (KB) facilitates in storing and updating the information required for route computation and inter-agent communication. It comprises of information about multi-paths from source to destination, residual bandwidth, packet loss rate of all the intermediate nodes, etc. KB is read and updated by user Agency, QoS Agency and DSR Agency.

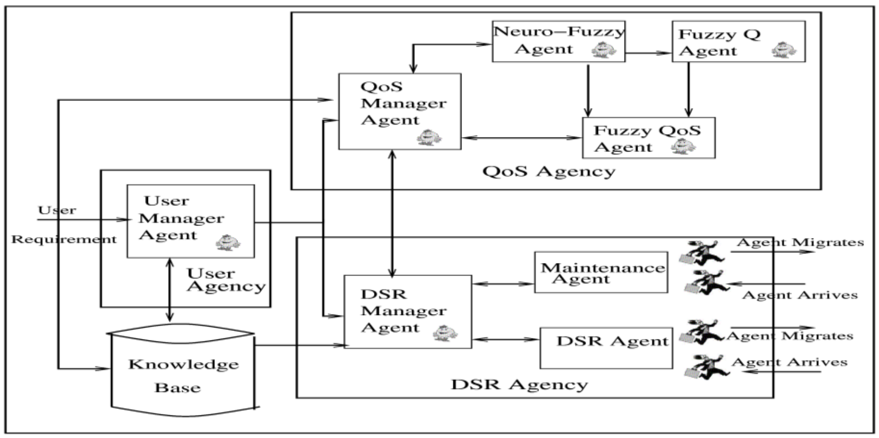

Figure 6. Agent based QoS Routing at Each Node

DSR agency components are explained as follows. ***DMA***: It is a static agent that has a role to play at the source node and intermediate node. It accepts destination node address from UMA and creates and co-ordinates with DSRA and MA of source node to obtain multi-paths between source and destination and also maintains the path.

DSRA**:** It is a mobile agent which initiates the route establishment process. It is triggered by the DMA. DSRA finds all multiple paths from source to destination and collects state information like bandwidth and packet loss rate of intermediate nodes (see Section 2.2) by using route request and route reply phases. DSRAs move in the network similar to RREQ and RREP packets of DSR. Later, they provide the multiple path information and state information to DMA.

MA**:** It is a mobile agent triggered by DMA whenever route failure occurs at intermediate nodes on the path. Patch up process is done as follows. (1) MA hosted by the intermediate node roams to collect the information about bandwidth and packet loss rate of the two hop neighbours of intermediate nodes and their connectivity and pass it to DMA and updates KB. Refer [18] for partial topology gathering by mobile agents during patch up process. MA collects information about only those neighbours who have lower mobility for better route lifetime. (2) DMA of intermediate node passes this information to source node DMA. (3) QoS agency at the source node finds nodes that satisfy QoS by applying FIS. (4) Source node DMA constructs a topology with QoS satisfied nodes and finds a patch up path between the intermediate nodes by using shortest path (Dijkstra algorithm) algorithm, and (5) DMA updates the path information from source to destination in KB by considering new intermediate nodes.

QoS agency performs the task of optimizing FIS and decides QoS nodes. It interacts with user agency and DSR agency during the process of QoS path identification. The agents in the QoS agency are explained as follows. ***QMA*:** It is a static agent that creates the other agents in the QoS agency. The agent interacts and communicates with other agents to optimize FIS as per requirements of a user. The agent collects the multi-paths from DMA and provides to FQA.

NFA: It is a static agent that performs the following tasks at the source node and is triggered by QMA. (1) It accepts user requirement for particular application from QMA. (2) Optimizes the membership functions of bandwidth, packet loss rate and delay by using neuro-fuzzy technique (Section 2.3.1), and (3) optimized values are used for further action by FQA. ***QA***: It is a static agent that performs the following tasks. (1) Receives fuzzy if-then rules and user requirement from QMA, (2) optimizes the fuzzy if-then consequent part by using fuzzy-Q learning technique (Section 2.3.2), and (3) optimized if-then rules are stored in FQA.

***QA*:** It is a static agent which performs the following tasks. (1) Receives all multi-paths from QMA and also the state information available on each of the intermediate node on the path. (2) It performs the task of fuzzy inference (Section 2.4) to decide QoS satisfaction. If QoS is satisfied, it considers the next node on the path for the verification until the last intermediate node on the path. If QoS is not met, it considers the next path that is available for QoS verification and (3) path met with satisfaction of QoS for all the nodes on the path is used to send the data packets.

2.6. Agent Interaction

Agent interaction diagram depicted in Figure 7 provides a detailed view of agents in finding QoS aware path for given source - destination pair and the user requirement. The numbers on the directed arcs denotes the sequence of interactions that takes place. Steps 2 and 3 are processed parallely.

1. UMA receives source address, destination address and QoS requirement.

2. DMA receives source and destination address from UMA.

    (a) DMA sends source and destination address to DSRA.

    (b) DSRA finds all multi-paths and sends back to DMA.

3. QMA receives source address, destination address and QoS requirement.

    (a) QMA sends delay requirement to NFA to optimize membership functions.

    (b) NFA replies optimized fuzzy membership functions to FQA and rules to QA.

    (c) QA replies inferred fuzzy rules to FQA.

4. DMA sends all multi-paths to QMA to select QoS paths.

5. FQA gets all multi-paths from QMA to decide whether node is QoS satisfied by using Optimized FIS.

6. FQA decides the QoS node; if satisfied, considers next node on the path for verification until last node, else gets next path available for verification. Transmits data on the QoS satisfied path.

7. DMA creates MA which periodically checks for the failure of any node or link failure.

8. MA brings information of failure of node or link and DMA repairs the route.

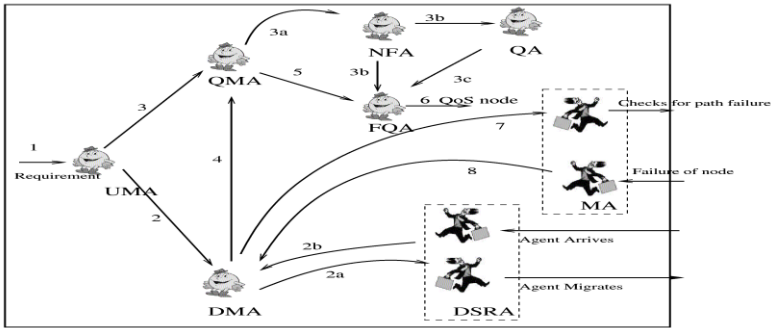

Figure 7. Agent Interaction Sequence Diagram

2.7. Limitations of the Proposed Work

The scheme has several limitations. (1) Performance depends on expert assistance for initial training; however it is one time process. (2) Security to mobile agents must be provided such that it should not compromise with neighbors. (3) Route discovery time needs further improvement, which may be done by predicting the communication requirements of the user and performing early training, (4) Some more inputs like hops, reliability, jitter and mobility can be added as fuzzy parameters and an ensemble neural network model may be used for discovering application specific membership functions. Further work can be carried out considering the limitations.

3. Simulation

The proposed scheme has been simulated in various network scenarios with 95% confidence interval by using C programming language to verify the performance and operation effectiveness. Simulation model for the MANET scenario consists of following models.

Network model: Mobile ad hoc network consists of a collection of N_{max} mobile nodes placed randomly in an area l x b m^2. The coverage area around each node has a bandwidth BW_{total} that is shared among its neighbors.

Propagation model: Free space propagation model is used with transmission range for each node as T_r for a single-hop distance. *Mobility model*: Mobility model uses random way point. The mobility of the nodes varies uniformly from M_{min} to M_{max}. Maximum number of nodes allowed for the movement is M_n within the area. Each host pauses at its current location for a period $P_{t,}$ the pause time, and the duration of the simulation time is S_t.

Channel model: Each wireless link is associated with a channel noise that consists of white noise (additive white Gaussian noise) and other channel interferences that defines the link quality. To access the channel, ad hoc nodes use CSMA/CA (802.11b) MAC layer standard protocol to avoid possible collisions and subsequent packet drops. We set queue length in MAC layer to be infinite to avoid packet dropping due to buffer overflow.

Traffic model: Constant bit rate traffic was generated by using fixed size packet, PKT_{size} bytes long. The packets are transmitted with BW_{trans}. For the traffic model, number of requests is R_{min} to R_{max} for simultaneous data sessions with source-destination pairs selected randomly. Different multimedia applications may require different delay which ranges from D_{min} to D_{max}. If Q_n number of nodes violate the QoS satisfaction, then path maintenance mechanism begins. New path discovery begins, if communication has elapsed for time of T_e.

Fuzzy and neuro-fuzzy model: Fuzzy linguistic variables considered are as follows. For bandwidth, '*low*' (*b0* to *b1*), '*medium'* (*b0* to *b2*) and '*high*' (*b1* to *b2*); for packet loss rate, '*less*' (*p0* to *p1*), '*moderate*' (*p0* to *p1*) and '*more*' (p0 to p1); for delay, *'small'* (d0 to d2) and '*large*' (d1 to d3). Learning constant for neuro-fuzzy model considered are; β as a constant, for fuzzy Q learning α is learning rate and γ is discount rate.

The proposed scheme is simulated using the following simulation inputs. l x b = 1000 m^2, BW_{total} = 10 Mbps, M_{min} = 0 m/s, M_{max}= 12 m/s, M_n = 0.25 percent of existing nodes, N_{max}= 100, P_t = 10 ms, S_t = 200 s, T_r = 225 m, R_{min} = 1, R_{max}= 30, PKT_{size} = 512 bytes, P_w = 100-500 mw, D_{min} = 100 ms, D_{max} = 150 ms, D_n= 0 to 225m, L= 1, α = 0.8, γ = 0.9, β = 0.3, *acceptable error* = 0.01, Q_n=2, T_e = 5 sec, *Bandwidth linguistic values are b0 to b1 = 0- 5 Mbps, b0 to b2 = 0-5 Mbps, b1 to b2 = 5 - 10 Mbps.* Packet loss rate linguistic values are *p0 to p1=0 - 5* percent, *p0 to p2 = 0 - 7* percent, *p1 to p2 = 5 - 10* percent and for delay linguistic values are, *d0 to d2 = 5- 100 ms*, *d1 to d3 = 50- 150 ms.*

The following performance metrics are used for evaluating the proposed scheme. *Acceptance ratio (AC):* It is the ratio of number of delay constrained QoS satisfied request to the number of user application request. R*oute discovery time (RDT):* It is the time needed for the source node to discover delay constrained QoS route to the destination. *Packet delivery latency (PDL):* It is defined as the average time taken to transmit a fixed number of packets from the source to destination. *Control overhead (CO):* It is defined as the ratio of the total number of control packets (or agents) to the total number of packets generated to perform communication. P*acket Delivery Ratio (PDR):* It is the ratio of the number of data packets delivered to the destination node to the number of data packets transmitted by the source node.

4. Result Analysis

In this section, we discuss various results obtained through simulation.

Acceptance ratio: Acceptance ratio is evaluated for various end-to-end delay requirements for multimedia applications for different number of nodes. Neuro-fuzzy DSR has more acceptance ratio compared to other two; because neuro-fuzzy DSR optimizes both input and output parameter membership functions and fuzzy rules according to end-to-end delay requirement to improve approximation accuracy to decide whether node is QoS satisfied. In fuzzy perfect DSR and FLQDSR, FIS are designed by the experts and are not optimized. Sometimes decision based on fuzzy inference may lead to wrong decision, hence acceptance ratio in FLQDSR and fuzzy perfect DSR is less. When number of nodes are increased from 20 to 40, acceptance ratio increases because number of nodes available are more and hence finds more nodes satisfying QoS.

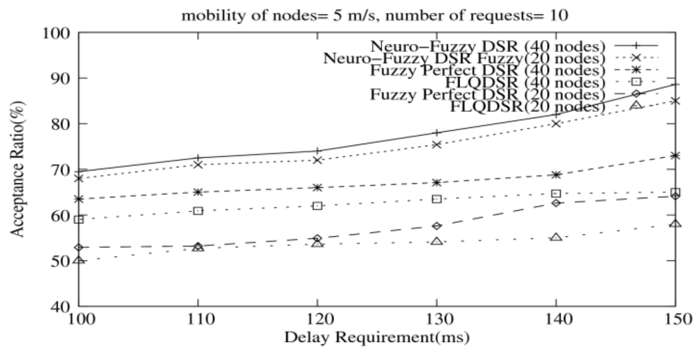

Figure 8. Acceptance Ratio Vs. Delay Requirement

As shown in Figure 9 acceptance ratio is high in neuro-Fuzzy DSR with increase in the number of nodes, since more number of QoS intermediate nodes are existing.

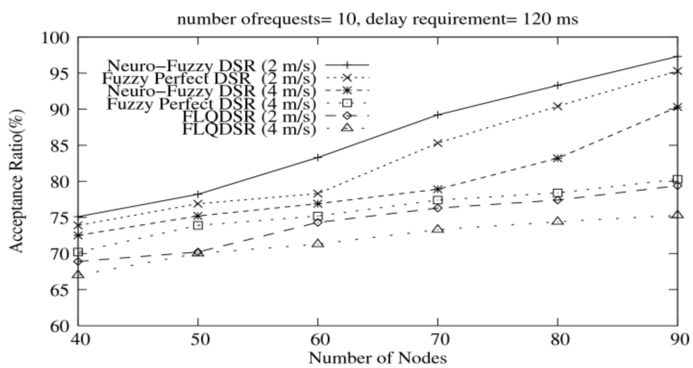

Figure 9. Acceptance Ratio Vs. Number of nodes

Route discovery time : Route discovery time includes the total time required to (1) find a number of multi-paths available between source and destination (2) to fine tune FIS and (3) to find delay constrained QoS satisfied paths between a pair of hosts.

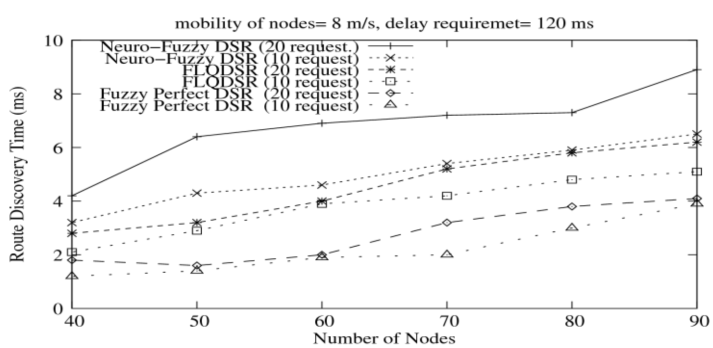

Figure 10. Route Discovery Time Vs. Number of nodes

We observe from Figure 10 that route discovery time is more in Neuro-Fuzzy DSR than FLQDSR with respect to increase in number of nodes since, in neuro-fuzzy DSR, it learns to optimize FIS according to user requirement. Neuro-fuzzy system some times require more training process to achieve a higher level of accuracy based on the membership function and learning process, hence RDT is more. Route discovery time increases with increase in number of nodes in neuro-fuzzy DSR because as the number of nodes increase, agents need to communicate with more number of intermediate nodes between a pair of hosts to establish a path.

Packet delivery latency: PDL for lower mobility values is less in all protocols as shown in Figure 11. But, as the mobility increases, fuzzy perfect DSR has link stability mechanism and neuro-fuzzy DSR has mobile agent mechanism to maintain the path whenever link or node fails with increase in mobility of the nodes. FLQDSR uses the DSR path maintenance which discovers the path again if not possible with a local recovery, hence more number of packets are lost and PDL increases exponentially with respect to the increase in mobility of the nodes.

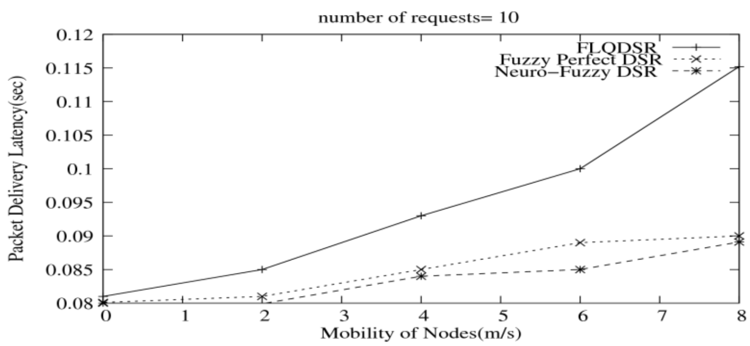

Figure 11. Packet Delivery Latency Vs. Mobility of Nodes

Control Overheads: Control overhead includes the number of packets (or agents) needed to establish path and to recover the failed links or the nodes. Control overhead increases with the increase in number of nodes and increase in mobility as shown in Figure 12. Neuro-fuzzy DSR uses delay constrained QoS path, thus probability of activating new route discovery process reduces and mobile agents recover the link or node failure. FLQDSR control overhead is more as it rediscovers the path when there is node or link failure due to mobility of nodes.

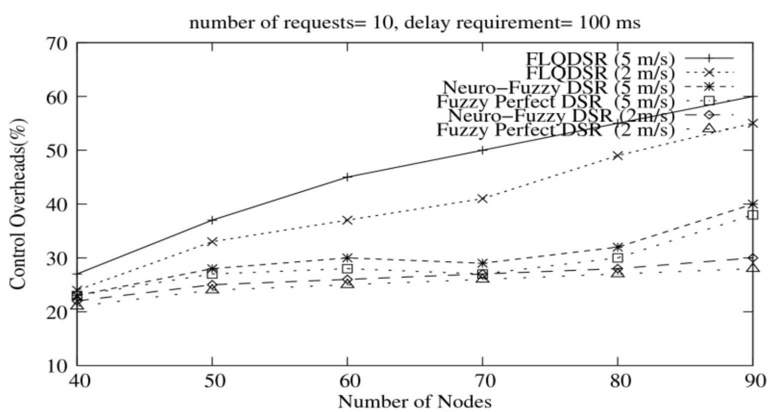

Figure 12. Control Overheads Vs. Number of Nodes

Packet Delivery Ratio: Packet delivery ratio increases as the number of nodes and request increases as shown in Figure 13. Dropping of packet is well controlled by neuro-fuzzy DSR by mobile agent MA. MA offers path information to the visited intermediate nodes which may be used by the source to find alternate QoS nodes. In Fuzzy perfect, it delivers the packet on the more stable route knowing the life time which makes less number of packets to be dropped compared to FLQDSR. FLQDSR, it maintains the path similar to the DSR protocol, hence PDR is less comparatively.

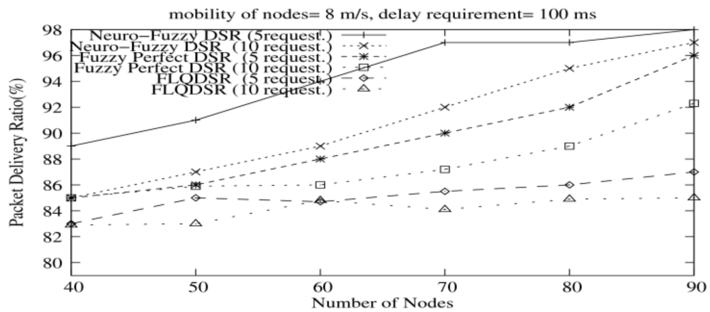

Figure 13. Packet Delivery Ratio Vs. Number of Nodes

5. Conclusions

This paper proposed an agent based delay constrained QoS unicast routing protocol for mobile ad hoc networks. We extended DSR protocol to find all the multi-paths and state information from source to destination. Fuzzy inference technique decides whether nodes on the path satisfy required delay. As decision is made by FIS and is dependent on the fuzzy membership functions and if-then rules; membership functions and if-then rules are optimized employing software agents. The proposed scheme effectively routes data packets to destination even in case of high mobility and link/node failures and has got good flexibility and adaptability. It improved the performance in terms of acceptance ratio, packet delivery ratio and latency.

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Authors

Vijayashree Budyal completed her B. E in Electronics and Communication Engineering and M.E. from Karnataka University Dharwad, India. She is pursuing her Ph.D in the area of Mobile Ad hoc Networks (MANETs). Presently, she is working as Faculty in Department of Electronics and Communication Engineering, Basaveshwar Engineering College, Bagalkot, Karnataka, India. She has published 8 national and international conference papers. Her area of interest are wireless networks, mobile ad hoc networks, and artificial intelligence. She is a member of IETE India.

Sunilkumar S. Manvi received M.E. degree in Electronics from the University of Visvesvaraya College of Engineering, Bangalore and Ph.D degree in Electrical Communication Engineering, Indian Institute of Science, Bangalore, India. He is currently working as Dean (R&D), Professor and Head of Department of Electronics and Communication Engineering, Reva Institute of Technology and Management, Bangalore, India. He is involved in research of Agent based applications in Multimedia Communications, Grid computing, Vehicular Ad-hoc networks, E-commerce and Mobile computing. He has published about 130 papers in national and international conferences and 70 papers in national and international journals. He has published 3 books. He is a Fellow IETE (FIETE, India), Fellow IE (FIE, India) and member ISTE (MISTE, India), senior member of IEEE (SMIEEE, USA), He has been listed in Marqui's Whos Who in the World.