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QoS Approach Based on RBF Neural Network and Fuzzy Method for Mobile Ad-hoc Networks

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***Abstract*-**This paper presents a novel QoS support approach for mobile ad hoc networks (MANET). The fuzzy logic is used for QoS management in two phases, first for traffic rate controlling, and then for packet accepting controlling. After using fuzzy logic we used Radial Basis Function Neural Networks (RBFNN), for QoS management. The results show that our new management methods (RBFNN QoS management) not only has a best tracking of fuzzy results, but also have a good classification of data that are gotten as feedbacks of mobile ad hoc networks(MANET).

Keywords- QoS management; fuzzy logic; Radial Basics Function neural networks; mobile ad hoc networks.

I. INTRODUCTION

Recent emergence of affordable, portable wireless communication and computation devices and concomitant improvements in the communication infrastructure, have resulted in the rapid growth of mobile wireless networks [1]. *Ad* hoc networks are the ultimate frontier in wireless communications. This technology allows network nodes to communicate directly to each other using wireless transceivers (possibly along multi hop paths) without the need for a fixed infrastructure. These networks are self-creating, self-organizing, and self-administrating that makes them have a dynamic topology. There are some issues about MANETs such as: Routing Medium (or channel) Access, Mobility Management, Security and Reliability, Power Management, Quality of Service (QoS). QoS is the Capability of a network to provide better services to selected network traffic. Need for QoS in MANETs is because of Bandwidth management, Resource management and application requirements. The most important QoS parameters are Throughput, Availability, delay, jitter (delay variance) and packet loss.

In this paper we focus on delay and packet loss as QoS parameters. QoS management is so difficult in ad hoc networks because of Limited resources availability, Bandwidth, battery life, processing capabilities, Insecure medium, Flow states change over time, No central control for coordination, Imprecise state information, Dynamic network topology, Hidden terminal problem and the other like these. Because these problems, the QoS issue is so challenging. But Because of the unique characteristics of the ad-hoc environment three models provide some good insight into the issues of QoS in MANETs. These models provide a comprehensive solutions, namely: SWAN [2], INSIGNIA [3] and FQMM[4]. SWAN proposes service distinction in stateless wireless ad hoc networks using distributed control algorithms and a rate control system at each node. The problem of SWAN becomes how to calculate the “threshold rate”, limiting any excessive delays that might be experienced. INSIGNIA is a lightweight QoS model with per flow granularity and reasonable performance for mobility. It uses bandwidth as the only QoS parameter, and allows local path redirection to recover from mobility situations [5]. INSIGNIA uses three levels of service: best effort, minimum, and maximum. Both SWAN and INSIGNIA are lacking the mechanism and the means to deal with extranet policy-driven QoS traffic. Both models apply bandwidth only to handle QoS requirements. FQMM is another approach combining the advantages of per-class granularity of DiffServ with the per-flow granularity of IntServ. It tries to preserve the per-flow granularity for a small portion of traffic in MANETs, given that a large amount of the traffic belongs to per aggregate of flows, that is, per-class granularity. FQMM offers a good solution for small and medium size ad hoc networks, but it is not suitable for large networks.

Recently, intelligent methods have been used in the area of ad hoc networks, aiming to get more flexible and adaptive models over the existing models. In this work we use two intelligent approaches, fuzzy and RBF neural network for QoS management in MANETs.

This paper is organized as follows: section II, we explain the fuzzy QoS. In section III, a new method for QoS management was proposed by using Radial Basis Function Neural Network (RBFNN). Section IV shows that new proposed method has a good tracking of the fuzzy results. Section V, forms conclusions.

II. FUZZY QOS MANAGEMENT

Fuzzy Logic was introduced in 1960 [6], [7], [8], by Lotfi A. Zadeh. Basically, Fuzzy Logic (FL) is a multi-valued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computer, in order to apply a more human-like way of thinking in the programming of computers [9]. A fuzzy logic system generally consists of three steps: fuzzification, rules evaluation, and defuzzification.

In this part first a fuzzy approach for QoS management was used, this approach has two contributions:
(1): a fuzzy approach, for best-effort traffic regulation rate, (2): a fuzzy approach for buffer management in order to have congestion control.

A. Fuzzy (1):

The feedback delay sensed from network, considered as input data for fuzzification and the traffic rate as output data. The feedback measurement represents the packet delay measured by the IEEE 802.11 MAC,Fig1,shows fuzzy modeling, and was obtained by using rules like bellow:

1. If measurement delay is increased, then traffic rate is decreased.
2. If measurement delay is medium, then traffic rate is medium.

B. Fuzzy (2):

The buffer level for accepting of packets was managed to have congestion control. Occupancy of buffer and admit number of packets were used as inputs and packet accepting rate as output for fuzzification step. Admit number was suggested as a parameter that shows priority of packets. In this way each packet has a higher admit number, it can be buffered sooner than the other packets. And the fuzzy rules are determined as bellow:

1. If occupancy is low and admit number is high, then accepting is increased.
2. If occupancy is medium and admit number is medium then accepting is medium.
3. If occupancy is low and admit number is high then accepting is increased.

After using rules like these, the QoS model shown in Fig. 2 was reached.

III. PROPOSED RBF NEURAL NETWORK

The RBFNN model consists of three layers; the input, hidden and output layers. The nodes within each layer are fully connected to the previous layer, as shown in Fig. 3. The input variables are assigned to a node in the input layer and pass directly to the hidden layer without weights. The hidden nodes or units contain the radial basis functions (RBF), also called transfer functions, and are similar to the sigmoid functions commonly used in the back propagation network models. They are represented by the bell shaped curve in the hidden nodes. Fig. 3 shows this architecture.

The signal propagation is introduced as follows. The input vector,

$$X(k) = [x_1, x_2, x_3]^T = [\Delta u(k), y_{out}(k), y_{out}(k-1)];$$

Where

$\Delta u(k)$, is the variation of the control input, i.e.

$$\Delta u(k) = u(k) - u(k-1);$$

$y_{out}(k)$, is the actual output of the system,

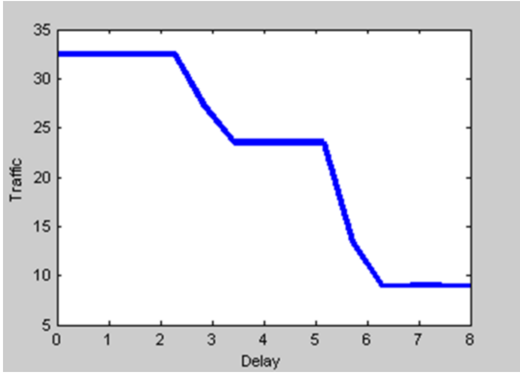

Fig. 1: fuzzy1, QoS modelling for traffic rate controlling.

k is the sampling/control index. The output of the hidden layer is

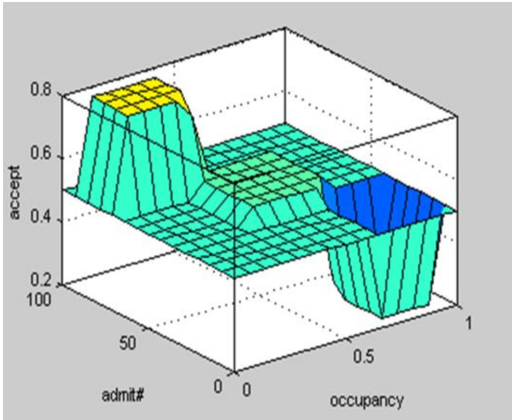

Fig. 2: fuzzy2, management of packet accepting

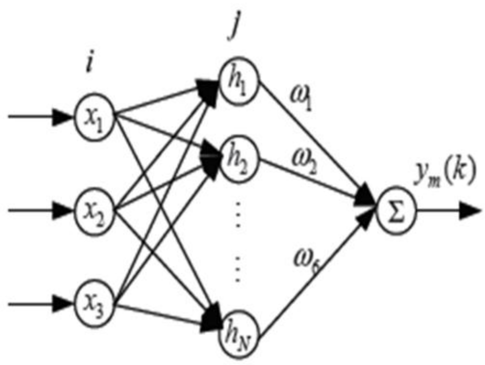

Fig. 3: RBFNN architecture

$$H = [h_j]^T .$$

$$h_j = \exp\left(-\frac{\left\|X - C_j\right\|^2}{2b_j^2}\right), j = 1, 2, ..., n;$$

Where,

$$C_j = [c_{j1}, c_{j2}, c_{j3}]^T ;$$

is the central vector of j th hidden neuron; bj is the basis-width vector. Then, we get the output of the RBF NN as

$$y_m(k) = W^T H(k);$$

$$W = [w_j]^T , j = 1, 2, ..., n.$$

The cost function of NN is governed by,

$$J_1 = \frac{1}{2}(y_{out}(k) - y_m(k))^2$$

Thus, the modified gradient descendent (MGD) method for training of the weights of RBF NNI iteratively is described as follows,

$$w_j(k) = w_j(k-1) + \eta(y_{out}(k) - y_m(k))h_j + \alpha(w_j(k-1) - w_j(k-2));$$

$$\Delta b_j = (y_{out}(k) - y_m(k))w_j h_j \left(\frac{\left\|X - C_j\right\|^2}{b_j^3}\right);$$

$$\Delta c_{ji} = (y_{out}(k) - y_m(k))w_j \frac{x_j - c_{ji}}{b_j^2}, i = 1, 2, 3;$$

$$c_{ji}(k) = c_{ji}(k-1) + \eta\Delta c_{ji} + \alpha(c_{ji}(k-1) - c_{ji}(k-2));$$

Where η is the learning rate, α is momentum operator.

According to the universal approximation ability of the RBF neural networks, it yields

$$\left\|y_{out}(k) - y(k)\right\| \langle \varepsilon,$$

Where, ε is a random small positive number.

Then, we get the Jacobian matrix of the system as,

$$\frac{\partial y_{out}(k)}{\partial \Delta u(k)} \approx \frac{\partial y_m(k)}{\partial \Delta u(k)} = \sum_{j=1}^{n} w_j h_j \frac{c_{ji} - \Delta u(k)}{b_j^2}.$$

Radial Basis Function neural network (RBFNN) is used as an alternative approach for QoS management..RBFNN was applied first, for traffic rate controlling and then for buffer management to have congestion control.

A. RBF1

RBF1 is for traffic rate controlling. The result was shown in Fig. 4.

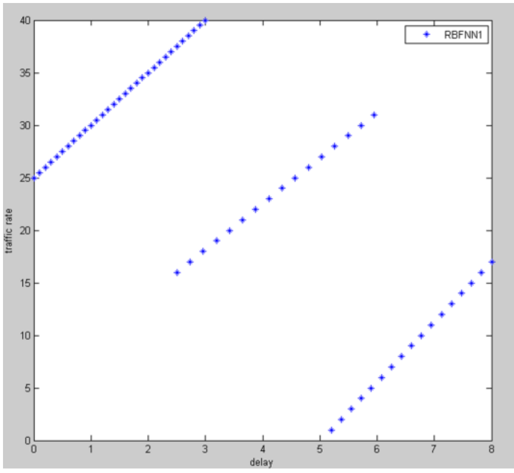

Fig. 4: Traffic rate controlling by RBF1

B. RBF2

RBF2 was used for buffer management. Fig. 5 reveals that the RBFNN approach has congestion controlling application, because it has a classification attribute in packet accepting by forming three separated groups.

IV. EXPRIMENTAL RESULTS

Fig.6 shows comparison between fuzzy approach and RBFNN approach for traffic rate controlling, and illustrates that our RBF method has a good tracking of fuzzy approach that we used and in [10] introduced.

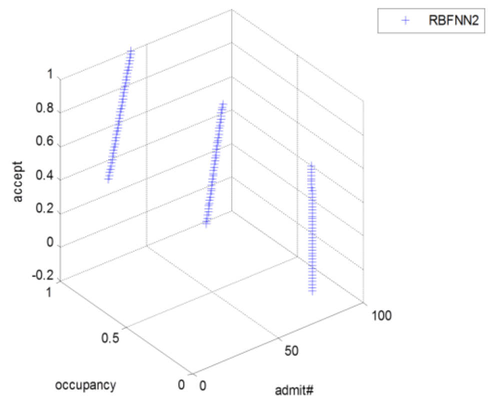

Fig. 5: RBF QoS management for packet accepting

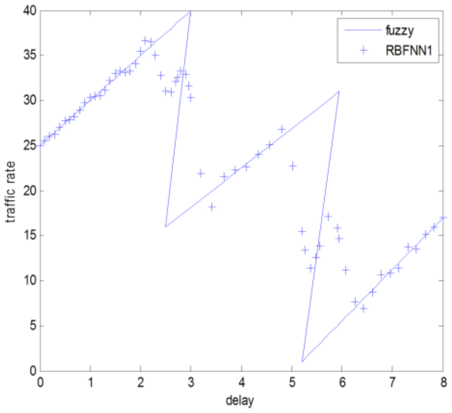

Fig. 6: Comparison result between fuzzy approach and RBFNN approach in phase1.

We apply another comparison between two approaches for packet accepting phase in Fig. 7. This comparison shows that the RBFNN method tracks the fuzzy approach and has an accurate classification of the input data in exact three classes similar to fuzzy rules.

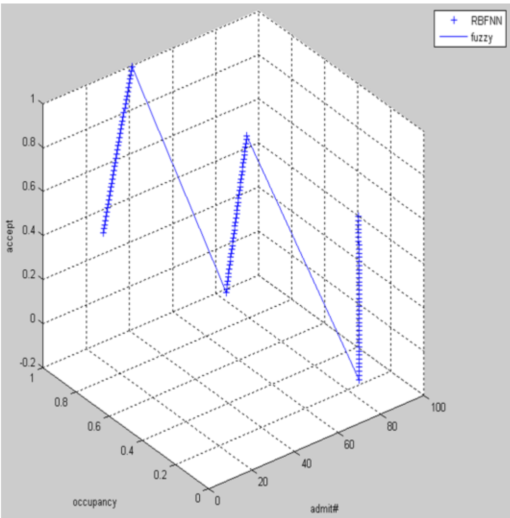

Fig. 7: comparison of fuzzy approach and RBFNN approach for packet accepting phase

V. CONCLUSION

In this paper the usage of RBFNN approach for QoS support in wireless ad hoc networks was explored. Fuzzy approach applied in two phases, aiming to control the traffic rate in phase A and improve congestion in packet accepting in phase B. Our RBFNN approach showed a good convergence to fuzzy approach and has a good classification attribute for congestion control in phase B. In phase B ,both in fuzzy approach and in RBFNN approach, another extra input parameter, the admit number was used that shows the priority of packets, despite of [10] that only consider the occupancy of buffer as input parameter for congestion control. With this assumption the congestion was modelled more perfect than the models as [10], and we introduced RBFNN approach for first time as a QoS method. Our experimental results show that this approach can be as useful as fuzzy approach.

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