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Decision Support System (DSS) For DSR in MANET Using Fuzzyfied ANN

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Abstract*— Mobile ad-hoc network technology has gained popularity in recent years by researchers on account of its flexibility, low cost and ease of deployment. The objective of this paper is to model the behavior of MANET for DSR protocol by considering some significant routing metrics. These metrics (packet delivery fraction, normalized routing load , average end-to- end delay etc.) have been generated by Network Simulator NS 2.34 tools and the node movement has been generated using Bonmotion 1.4.The MANET behavior for DSR protocol is hypothesized to be dependent on variables like node density, pause time , number of packets transferred , and the number of connection. In this paper the behavior of MANET is modeled using supervised learning algorithm i.e. Levenberg-Marquardt , which is a network training algorithm that updates weights and bias values for DSR (Dynamic Source Routing) protocol , The algorithm used in this paper is implemented on MATLAB 7.7 and the model is found to be satisfactory with the minimum error rate .

***Index Terms*— Ad hoc networks, Routing metrics, DSR, Fuzzy Logic, ANN etc.**

I. INTRODUCTION

In Mobile Ad Hoc Network (MANET) , A number of routing protocols have been developed and proposed [1, 2], that will help in route discovery and maintenance mechanisms for the mobile node to communicate with other nodes in MANET . The objective of all these protocols is to find the most reliable and feasible path. Since last few years, the research community has developed many routing protocols and submitted in the form of drafts to the group of Internet Engineering and Task Force Mobile Ad-hoc Networking (MANET) [7]. According to them the good protocols are the Optimized Link State Routing (OLSR), Zone Based Routing Protocol (ZRP),Temporally-Ordered Routing Algorithm (TORA) , the Ad-Hoc On demand Distance Vector (AODV) , the Destination-Sequenced Distance Vector (DSDV), the Dynamic Source Routing (DSR) and many more. Here is the brief overview of these protocols. Many research works have been compared for the different ad hoc routing protocols (OLSR, ZRP, TORA, DSDV, DSR, AODV etc. Johansson, et. al. [3]) under varying network scenarios. Packet Delivery Ratio (PDR) fraction, Normalized Routing Load and Average end-to-end delay are some prominent metrics used in the comparisons. Throughput and delay of the protocols Perkins,et. al. [4], focused on only comparing the two on-demand routing protocols i.e. DSR and AODV. Yang Cheng Hung, et. al. [5], focused on OLSR protocol compares only Node density versus speed. Thomas Staub, et. al. [6], focused on DSR and DSDV and find out that they did not supply any valid results in the hybrid situation. Similarly there are so many research works which have shown a number of comparisons on various routing protocols , analyze the performance of various protocols, there is still no such model or approach which can provide help in MANET area to compute the behavior of protocols using the formula or function , with the help of proposed model in this paper , DSR is the right protocol which shows satisfactory outcomes in most of the Mobile ad hoc network challenges. All these research works do not provide the methodology to find the sensitivity of performance metrics of MANET with respect to the input metrics. In this paper this issue has been resolved successfully. A lot of research has been done in MANET area, but still there is a gap to overcome the real environment challenges. The proposed model proposed in this paper will be able to shape out the behavior of MANET by using DSR protocol.

II. TOOLS & METHODOLOGY USED IN SIMULATIONS USING NS 2.34

In this paper we have used various tools such as network simulator version 2.34 (NS2.34) for getting the simulation results by writing and running the TCL script, applying the parameters in Table1,[7] in addition we have taken the help of traffic generation tool such as cbrgen.tcl and mobile movement scenario generation tool such as Bonmotion 1.4, after getting the results .Finally we have used the Fuzzy Inference System tool for testing the behavior of the scenario described in Table 1.

Table 1. SIMULATION PARAMETER

Simulation Parameters	
Routing Protocol	DSR
Mobility Model	RPGM
Simulation Time	100
Number of Nodes	10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150 ,160, 170
Simulation Area	x=800 m, y= 800 m
Speed	l=0.0 m/s, h= (5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60,

	65, 70, 75, 80, 85) m/s
Pause Time	3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27 ,29, 31, 33, 35
Traffic Type	CBR
Packet Size	512 bytes
Rate	(5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85) packets/sec
Number of Connections	10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90
Seed	1.0

III. FUZZY INFERENCE SYSTEM

A fuzzy engine includes the system rule base, input membership functions that fuzzify the input variables and the output variable. Fuzzification is a procedure where crisp input values are represented in terms of the membership function, of the fuzzy sets. The fuzzy logic controller triangular membership functions are defined over the range of the fuzzy input values and linguistically describe the variable's universe of discourse as shown in Figure 1. Following the fuzzification process the inference engine determines the fuzzy output using fuzzy rules that are in the form of if then rules. De-fuzzification is then used to translate the fuzzy output to a crisp value. To compute the output of this FIS given the inputs, one must go through six steps:

1. Determining a set of fuzzy rules
2. Fuzzifying the inputs using the input membership functions,
3. Combining the fuzzified inputs according to the fuzzy rules to establish a rule strength,
4. Finding the consequence of the rule by combining the rule strength and the output membership function,
5. Combining the consequences to get an output distribution, and
6. Defuzzifying the output distribution for computing the crisp output.

For implementation of the proposed model We have taken some results with the help of network simulator and consider those results as sample input and used these samples in FIS Editor toolbox and tuned out the DSR applying the fuzzy logic with the help of Fuzzy inference System and found that in which practical situations the DSR protocol performs poor, satisfactory and acceptable. A fuzzy inference system (FIS) is a system that uses fuzzy set theory to map inputs (node density, pause time, node mobility number of packets transferred, and the number of connection) to outputs (Packet Delivery Fraction, Normalized Routing Load and Normalized MAC Load) in the case of fuzzy classification). In this paper the Mamdani FIS is implemented for tuning the behavior of DSR. A fuzzy inference system (FIS) is a system that uses fuzzy set theory to map inputs like Node Density(ND), Pause Time(PT) , Node Mobility(NM), Number of Packets transferred(NP) , and the Number of Connection(NC) to outputs Packet Delivery Fraction(PDF) , Normalized Routing Load(NRL) and Normalized MAC Load(NML) in the case of fuzzy classification . In this paper the Mamdani FIS is taken for tuning DSR. The proposed Inference System is given in Figure. 1, combining the fuzzified inputs according to the fuzzy rules which are described in Figure. 4 to establish a rule strength and the sample crisp output is shown in Figure 2.

Table 2: Fuzzyfied Input output parameters

S. No	Inputs					Outputs		
	NC	NP	ND	NM	PT	PDF	NRL	AE2ED
1	LOW	LOW	LOW	LOW	LOW	P	G	G
2	LOW	MEDIUM	MEDIUM	LOW	MEDIUM	P	G	P
3	MEDIUM	MEDIUM	MEDIUM	MEDIUM	MEDIUM	S	G	G
4	HIGH	HIGH	MEDIUM	HIGH	HIGH	S	G	G

Where 'S' represents is satisfactory , 'G' represents Good and 'P' represents Poor Performance after implementation some observations are found and based upon some observations for tuning the DSR, table 2 is prepared and which is trained using neural network. Figure1 shows the implementation model of Fuzzy Inference System, model is operated on five input variables (NC-number of connections, NP- Number of packets, ND- Node Density, NM - Node Mobility, PT- Pause Time) and three output variable (PDF-Packet Delivery Function, NRL-Normalized Routing Load, NML-Normalized MAC Load). Table 1 shows the

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parameters and their fuzzy value, processed through FIS. Figure 2 shows the basic model structure for training the fuzzyfied inputs and outputs through neural network.

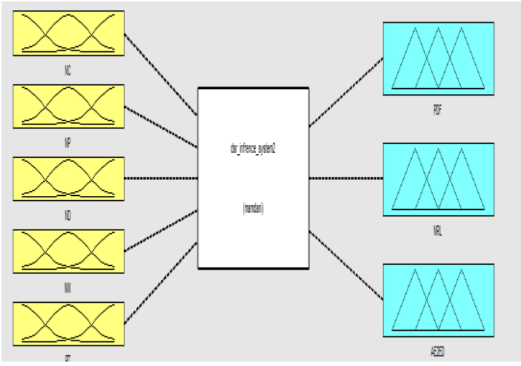

Fig 1. Fuzzy Inference System for DSR

IV. NEURAL NETWORKS

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. Model is trained through the neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Basic model structure is shown in figure 2..

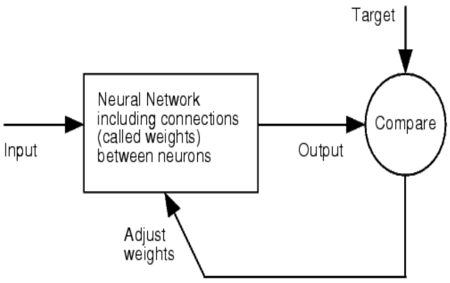

Fig 2. Basic Model Structure of Neural Network

Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector.

Training DSR using Neural Network

Fuzzy decision support system for DSR represents the validity of relationship between the inputs (No. of connection, No. of packets, Node density, Node mobility, & Pause time) & outputs (Packet delivery Ratio, Normalized routing load, Average end-2-end delay). In this paper, the Levenberg-Marquardt (LM) algorithm is used which is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions [8, 9]. It has become a standard technique for non-linear least-squares problems [10], widely adopted in a broad spectrum of disciplines. LM can be thought of as a combination of steepest descent and the Gauss-Newton method. After simulating the model using network simulator (section II.1), the obtained results are fuzzyfied using FIS (section II.2), for the validity of the results of section II.2, the result is trained using Levenberg Marquardt training algorithm. Hypothesized that in the present research work the outputs PDF (Packet delivery Ratio), NRL(Normalized routing load), AE2ED(Average end-2-end delay) depends on inputs NC (No. of connection), NP(No. of packets), ND(Node density), NM(Node mobility), & PT(Pause time) . the process of training is shown in Table 2 derived from Fuzzy Inference Engine used in section II.2. Table 2 representation of inputs and outputs to be trained, fter training using Levenberg Marquardt training algorithm , performance of outputs is observed that minimum MSE value for PDF found 3.48 x 10^{-12} at epoch 7 , for NRL .500 at epoch 4 and for AE2ED .500 at epoch 2. Sample output is shown in figure 3.

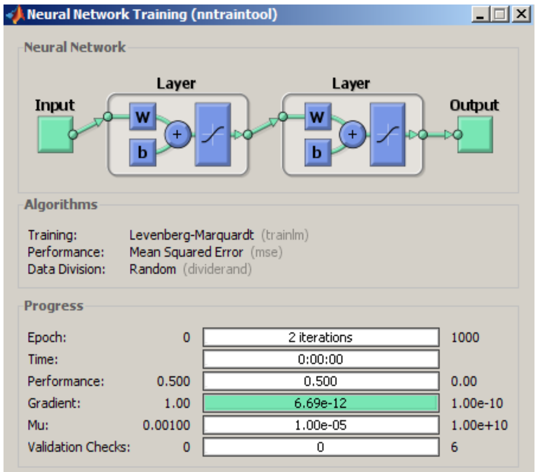

Fig 3 Sample Training Outputs

V. OVERVIEW OF SIMULATION RESULTS

The objective of the fuzzy Inference System is to reducing the overheads to decide that in which types of network conditions the protocol performs poor , satisfactory or acceptable , Figure 1 shows the strength of fuzzy rules, Figure 2 represents how the input metrics are strengthened by Fuzzy Inference System to relate the effect on output metrics, figure 3 describes the basic model of neural network, according to the model it is observed that which parameters are to be focused to increase the performance in terms of more packet delivery fraction with minimum routing load and delay, after applying the supervised learning algorithm on fuzzyfied input and output variables the behavior of MANET for DSR is

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satisfactory, result output after training using Levenberg Marquardt training algorithm is shown in Figure3.

VI. CONCLUSION

This paper proposes a fuzzy logic based decision as a scenario selection method. This facilitates the generation of effective results that shows the necessity for performing the appropriate model, in conjunction with this, MANET area research will be able to gain the advantages of the Fuzzy Inference system that provides some direction that how to target the challenges to achieve higher throughput at minimum cost and delay. By observing the model it can be found that which input parameters influences output parameters, it is concluded that either increasing the number of nodes or changing the speed of movement, it will degrade the performance of DSR protocol. By using the proposed model, if number of connection, number of packets , node density node mobility speed and pause time is increased with proper ratio then , performance of DSR can be enhanced , if performance of DSR is increased then MANET is able to have low signal loss, high energy nodes environment , that is MSE value is .5 which very near to zero.

REFERENCES

[1] E. M. Royer and S. B. Chai-Keong Toh, "A Review of Current Routing Protocols for Ad Hoc Mobile Wireless Networks", IEEE Personal Communications, April 1999, pp 46-55.

[2] M. Abolhasan, T. Wysocki and E. Dutkiewicz, "A review of routing protocols for mobile ad hoc networks", http:// www.elsevier.com/locate/adhoc, Ad Hoc Networks 2, 2004, pp 1-22.

[3] J. Broch, D.A. Maltz, D. B. Johnson, Y-C. Hu, and J. Jetcheva. A performance comparison of Multi-hop wireless ad-hoc networking routing protocols. In Proceedings of the 4th International Conference on Mobile Computing and Networking (ACM MOBICOM '98), October 1998, pages 85-97.

[4] Charles Perkins, Elizabeth Royer, Samir Das, and Mahesh Marina. Performance of two on-demand Routing Protocols for Ad-hoc Networks. IEEE Personal Communications, February 2001, pages 16-28.

[5] Yang Cheng Hung, Saleem Bhatti, & Daryl Parker titled on "Tuning OLSR" in The 17th annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC ' 06)[4].

[6] Thomas Staub, Computer Science Project, titled "Performance Comparison of MANET routing Protocols in Ad-hoc and Hybrid Networks" Computer Networks and Distributed Systems (RVS), Institute of Computer Science and Applied Mathematics (IAM), University of Berne, Switzerland, in February 2004.[5]

[7] [RFC 2501] S. Corson, J. Macker. Mobile Ad hoc Networking (MANET): Routing Protocol Performance Issues and Evaluation Considerations, January 1999.

[8] K. Levenberg. A Method for the Solution of Certain Non-linear Problems in Least Squares. Quarterly of Applied Mathematics, 2(2):164–168, Jul. 1944.

[9] D.W. Marquardt. An Algorithm for the Least-Squares Estimation of Nonlinear Parameters. SIAM Journal of Applied Mathematics, 11(2):431–441, Jun. 1963.

[10] H.D. Mittelmann. The Least Squares Problem. [Web page] http://plato.asu.edu/topics/problems/nlolsq.html, Jul. 2004. [Accessed on 4 Aug. 2004.].