Intelligent MANET System Model for Throughput Improvement & Prevention of Annomaly in MANET

Pankaj Kumar Sharma, Asho K. Sinha

Abstract: MANET is a self-configured network of devices in wireless linked network, in an arbitrary topology. Each node is an independent node, which can play a role of host, router & receiver. The connectivity is established by operating system hosted on participating nodes. Routing algorithm establishes routes and forwarding information as packets to and from source to sink station. Many routing techniques attempt to achieve optimal performance, however modifications are still required in existing routing protocols to improve the performance of MANET. An efficient MANET leads to fulfillment of three key performance metrics (PDR, AE2ED, and Overhead). There exist some predominant anomalies in Mobile Ad-hoc Network in terms of above performance metrics. Anomalies in MANET arise due to various environmental factors like variation in number of connections among participating nodes, mobility of nodes, pause time of node, rate of data packet forwarded by nodes and total density of nodes, adversely affecting its performance. In order to overcome some predominant anomalies, in this research a systematic approach has been used to develop an intelligent system model, which controls the performance adaptively.

Keywords- MANET, PDR, AE2ED, Overhead, Fuzz

I. INTRODUCTION

In MANET, there is a group of wireless stations which can be formed dynamically without pre-existing infrastructure. [3] MANET is a self-directed system where mobile stations are exposed to travel randomly and act as routers. The types of traffic in MANET are reasonably different from infrastructure oriented network, it includes: [4]. Therefore the routing protocols for wireless networks are different from the wired network protocols. Soldiers rely on situational awareness information in the battlefield as well as in emergency situations.[5-6].

II. STATE OF ART

Many researchers have discussed the issues of security in MANET such as S. Umamaheswari [2] emphasized on data communication mechanism between mobile nodes based on ACO approach, V. Venkata et. al. [1] proposed a model to replicate the properties of the resistant system. However a systematic method has not been attempted earlier to develop an intelligent model for MANET to control the performance under different environmental factors.

The relevance of present research work is for handling dynamic environment in MANET, which is originated by varying network conditions like number of connections, transferred packets, density of available active and inactive nodes, movement speed and halt time during the communication in MANET system.

However, these approaches are not useful to dynamic MANET, because variation in the mobility of nodes, varying number of active/in-active connections, variable pause time, variable data rate and frequently leaving or joining the network, results as highly dynamic network medium. A memory management scheme [9-17] was introduced. They did not test the scheme in the environments having higher number of nodes, high mobility, more applications, and more variations in flow of arrival rates 18]. The idea of reliability factor to determine reliable routes among the transitional nodes was introduced [19]. It was proposed a stateless approach to MANET especially when dealing with highly dynamic network. The approach was incapable to address the impact analysis process of the different parameters which determine the efficiency and overhead .A model for node mobility [16-19] was developed for modeling technique for performance analysis of MANET. They emphasized on fluid-flow based differential equation models performed for queuing analysis. They emphasized on modeling of queuing system. They did not address the effect of node mobility on MANET performance.

MANET can be modeled as a framework of Total System Intervention (TSI) and, can be shown how TSI helps after integration with model to understand the risks and opportunities. [19]

The system engineering & architecting [19] states that any problem statement in MANET may be defined more precisely and accurately. Complex systems can be developed using principles of system engineering & architecting. In network communication research, an increasing interest in designing the model for autonomic computing such as MANET [18].

The fuzzy controllers [17] introduced for multi-routing algorithm in MANET, so that the reconstructions of path in MANET may be reduced. Although, the controllers can be designed based on two methods [19]..

The state of the MANET may comprise of one or more input parameters and one or more output parameters. The controller controls the output parameters of the system.

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Fuzzy controllers have the deficiency of having the fixed fuzzy rules and can be used only in the static environment.

III. PROBLEM STATEMENT AND METHODOLOGY

Anomaly detection in MANET is difficult because of its dynamic nature. The conventional methods or models are not directly applied in MANET for overcoming the shortcomings. The objective of this thesis is to identify and possibly resolve the key issues in MANET which necessitates to develop an intelligent state variable model. The model controls the performance evaluation metrics. The development methodology of the model for controlling the MANET's behavior, comprises of state input-output variables. The proposed model for MANET is system is treated as a MIMO (Multi input Multi output) system.

IV. STATE SPACE CONTROLLER

Analysis of State space is considered with three types of variables (input variables, output variables and state variables) that may be involved in the dynamic system modeling. The system should contain the values of the inputs as $t >= t_1$. In a continuous time control system integration performs as memory, outputs of such integrators are treated as variables as internal state of system. Thus, output serve as state variables. Dynamics of the system are specified by state variables, which are similar to number of integrators [25-26]. Assuming that a multi-input and multi-output system involves in integrators. Assuming also that there are p inputs $u_1(t)$, $u_2(t)$, $u_3(t)$,…… $u_p(t)$ and q outputs $y_1(t)$,$y_2(t)$,…..$y_q(t)$ define the n state variable integrator's outputs; $x_1(t)$,$x_2(2)$………$x_n(t)$ then the system is depicted by,

For i=1, 2, 3……n Thus y_1 (t), y2 (t)…$y_q(t)$, may be given as,

$$y_j(t) = g_j(x_1, x_2, , x_n ; u_1(t), u_2(t), u_3(t) \dots u_p(t)) \dots (4.2)$$

$$\dot{x}_i(t) = f_i(x_1, x_2, \dots, x_n ; u_1(t), u_2(t), u_3(t), \dots u_p(t)) \dots\dots (4.1)$$

The equation (4.1) and (4.2) becomes as:

$$\dot{x}(t) = f(x,u,t) \dots\dots\dots\dots\dots\dots\dots\dots (4.3)$$

$$y(t) = g(x,u,t) \dots\dots\dots\dots\dots\dots\dots\dots (4.4)$$

The flow of equations (4.3) & (4.4) is shown in figure 2, let t=k+1, and t_0=k .

In the diagram, the function **g** is determined using ANFIS. This relates observed output Y_k with the state variables X_k. Each output is distributed into three clusters. If the output of MANET does not lie in the desired cluster then the fuzzy controller rules are designed using ANFIS. The system controller can be designed using the ANFIS scheme. The structure of the ANFIS is shown in Fig. 2. Inputs are modeled using Equations. 4.5 and 4.6:

$$e(k) = Y(k) - Y_D(k) \quad \dots\dots\dots\dots\dots (4.5)$$

$$\Delta e(k) = e(k) - e(k-1) \quad \dots\dots\dots\dots\dots (4.6)$$

Where k represents number of clusters, *Y(k)* is the observed output, $Y_D(k)$ is desired output, *e(k)* is the error and $\Delta e(k)$ error change. The module provides linguistic variables, inputs to the structure (rule-based). The rules (243) have been generated based on previous knowledge.

V. SYSTEM MODEL

According to RFC 2501 [1], the networking context must be considered in which the performance of protocol is measured. Network size (node density-ND), Network connectivity (maximum number of connections-MC), Topological rate of change (mobility speed-NM), Halt in rate of topological change (pause time-PT), Traffic patterns (data rate-NP): To predict the effectiveness of a protocol for adapting non-uniform traffic patterns.

The state variables of the MANET system model:

The state variables of MANET system model are defined as: $X(k) = [NP\ NC\ NP\ PT\ NM]^T$

The state output variables of the MANET system model are defined as: $Y(k) = [PDR\ AE2ED\ Overhead]^T$

Table. 1 Simulation Parameters [1]

Parameters	Value
Channel	Wireless Channel
Propagation	Two Ray
Interface	Wireless Phy
Mac Layer	IEEE 802.11
Queue	DropTail/PQ
Link Layer	LL
Antenna	Omni Directional Antenna
Queue length	50
RP	DSR
Time	100 sec
Nodes	12-111
Area	X=1000 m , y=1000 m
Speed	5-203 m/sec
Mobility Model	RPGM
Pause Time	5.0 -203.0 sec
Traffic Type	CBR
Packet Size	512 bytes
Rate	10 -505 packets/ sec

In this paper, the experimental data is generated using NS2.34 under the environmental conditions, shown in table 1. According to table the protocol for routing is used DSR; however any routing protocol can be chosen.

The simulation has been run for 100 seconds; however the simulation time may vary as per requirement. The simulated data is collected for

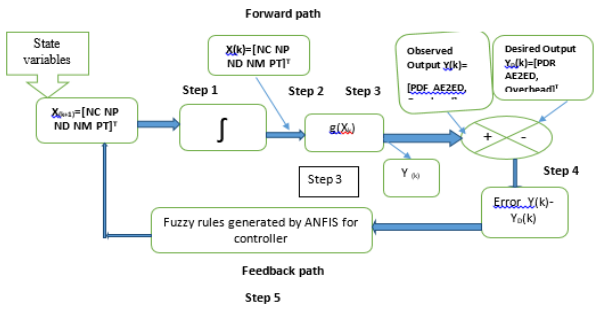

Fig. 1 Model formulation for MANET System

The system model for MANET has been formulated for addressing the anomalies, shown in figure 1. The state equation of the MANET system model is represented by X(k) & state model equations are discussed in equation 4.3 and equation 4.4. The output equation of the MANET system model is defined using Y(k), the model is applied to all three performance evaluation parameters (PDR, AE2ED & Overhead).

State output variables are:

- PDR, Overhead, Normalized Routing Load, AE2ED.

The system variables are defined as follows:

X (k+1) is state at k+1, X (k) is the state at k, Y (k) is observed output at k, g is the function, which is determined using ANFIS, Y_D (k) is the expected performance of MANET system model, ∫ (Integration function).

VI. CLASSIFICATION OF DATA SET

The simulated data obtained in table 1 , has been categorized based on the performance using k-means clustering algorithm. The goal of *this* clustering is to partition the data observed in MANET system model into k (*k=3)* groups. In the algorithm, the observations have been assigned to its closest group, usually using the sq Euclidean among the observation and the cluster centroid. The idea of clustering is to classify the operational data into different groups; one may be the higher performing group, medium performing group & lower performing groups. The training data set has been classified into three clusters for three state output variables PDR, AE2ED and NRL. Therefore in PDR,C1 is lower performing cluster, C2 is higher performing cluster and C3 is medium performing cluster. In AE2ED, C1 is lower performing,C2 is medium performing & C3 is higher performing cluster. Similarly, in Overhead, C1 is medium performing, C2 is higher performing and C3 is lower performing clusters Formulation of the system model The non-linear output models are implemented using ANFIS for each output separately. The model is divided into two parts forward path and feedback path. In this chapter the implementation of forward path is implemented, shown in figure 3. In forward path implementation, first the simulated data set of 100 observations is classified using k-means into three groups as discussed in Chapter 4. The figure 5.2 shows the MANET system model for PDR. The working of the model is as follows:

Step 1: In this paper, MANET model is simulated under 100 heterogeneous network conditions using NS2.34 network simulator and mobility generator tool (Bonnmotion 1.4). There are 100 observations obtained for three performance evaluation metrics (PDR, AE2ED & Overhead).

Step2: The whole dataset has been classified using k-means clustering algorithm into three broad clusters (lower, medium & higher), each based on performance metrics mentioned in step 1.

Step 3: The state of the MANET system model is defined by state vector X (k) comprising of five state variables: ND, NC, NP, PT & NM. The output vector Yk comprises of 3 output variables (PDR, Overhead & AE2ED)

Step 4: For training the model, simulated input/output dataset of 60 scenarios is used. The ANFIS generates 243 fuzzy rules using Gaussian membership function which maps the inputs to the outputs. To achieve the zero tolerance level of error, the model is trained & converged after 100 epochs.

Step 5: The model is validated by passing another input/output data set of 40 scenarios. The model is validated successfully at reasonably satisfactory level.

Step 6: The MANET is system has been described as a MIMO system, therefore requires design of controllers for each of the three outputs (PDR, AE2ED & Overhead). The controller adjusts the values of input variables for minimizing the difference between observed performance & actual performance. The controller controls the behavior of the mobile ad-hoc network intelligently in an adaptive .

MANET System model for PDR& Overhead

The developed ANFIS model structure with 5 input neurons and 1 output neuron along with 15 hidden layers (input membership function, rule base, membership function and aggregated output) is shown in Fig. 4. The hidden layers contains 243-243 neurons to deal with the problem (for selection of the proper rule base, because the rule base is written randomly in fuzzy, the neural network selects the right optimal rule base to fire).

The 5 input neurons, viz., the error and change in error, are given as input to the 1st hidden layer of the ANN as shown in Fig. 4. This 1st hidden layer deals with various input membership functions. In the 2nd and 3rd hidden layers, the set of 243 fuzzy rules is properly identified by training and the sets of optimal rules are selected. These sets of optimum rules are available at the 4th hidden layer. Out of the 243 rules, the optimal rules are fired here and the de-fuzzified output is obtained as the output neuron. The de-fuzzified output is further used to generate the firing pulse to be applied to the inverter bridge, which is further used to control the value of PDR or Delay or Ovehead.

After the simulation is run, the performance characteristics are observed on the respective scopes. The response curves of PDR, Delay, vs maximum number of active connections or node movement speed or pause time or data rate and node density respectively.

The simulation results showed that by using the neuro-fuzzy (ANFIS) control, that with the gradually decreasing values of input variable maximum number of connection from 66 to 38 and for the 243 rules.

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The PDR reaches its desired set value i.e 70%.

This shows the effectiveness of the designed neuro-fuzzy controller, which tries to increase the performance of the MANET, thus showing faster dynamism.

The PDR of MANET increases like a linear curve up to the desired value 70 % as shown in fig 2. Furthermore, it can also be observed that using the ANFIS control, the system stabilizes in a less time compared to the other methods.

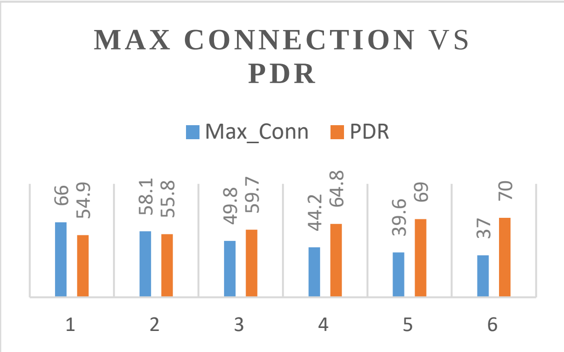

Fig. 2 The response curve of PDR with decreasing value of maximum number of connections while remaining rest of the input parameters as constant

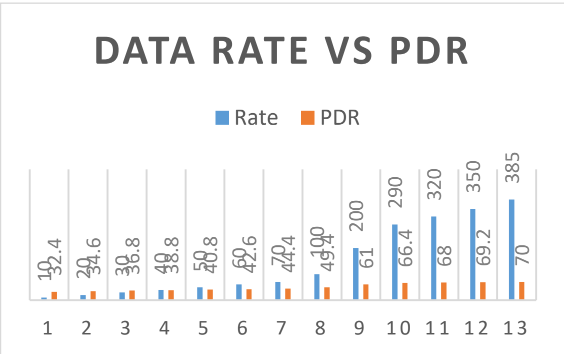

Fig. 3 The response curve of PDR with increasing value of data rate while remaining rest of the input parameters as constant

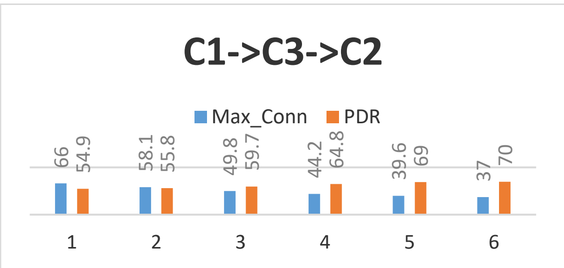

Fig. 4 Cluster transition of PDR vs Maximum connection

For training the model, simulated input/output dataset of 60 scenarios is used. The ANFIS generates 243 fuzzy rules using Gaussian membership function which maps the inputs to the outputs. To achieve the zero tolerance level of error, the model is trained & converged after 100 epochs. The model is validated by passing another input/output data set of 40 scenarios. The model is validated successfully at reasonably satisfactory level. The results are shown below:

Overhead:

Model type	:Sugeno
Data points	: 60
Epochs	: 107
Membership function	: Gaussian MF
Membership function type	: linear
Training optimization method	: hybrid
Converged value of RMS error	: 0.048

PDR:

Model type	:Sugeno
Data points	: 60
Epochs	:100
Membership function	: Gaussian MF
Membership function type : linear	
Training optimization method	: hybrid
Converged value of RMS error	:0.107

In summary, For training the model, set of simulated input/output data for 60 scenarios is passed. The ANFIS generates 243 fuzzy rules using Gaussian membership function which maps the inputs to the outputs. To achieve the zero tolerance level of error, the model is trained & converged after 100 epochs in Overhead controller model.

VII. CONCLUSION

The performance of MANET is affected by various anomalies exist in the MANET environment with respect to variation in - number of connections among participating nodes, mobility of nodes, pause time of node during mobility, rate of data packets forwarded by nodes & total density of nodes. So, the formulation of model for MANET system & designing of MANET controller is required to address these anomalies. To compare the behavior (PDR, AE2ED and Overhead) of MANET between stable & unstable state. In this paper, MANET model is simulated and behavior is compared under 100 heterogeneous network conditions using NS2.34 network simulator and mobility generator tool (Bonnmotion 1.4). There are 100 observations obtained for three performance evaluation metrics (PDR, AE2ED & Overhead). It is observed that the behavior of MANET is having uncertainty in which the performance is good or bad. It seems good in one but bad in others.

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