

An Analytical Model for QoS in Mobile Ad Hoc Network using Artificial Neural Network (ANN)

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Abstract— This study examines the challenge of predicting end-to-end packet delay in mobile ad hoc networks for Quality of Service (QoS) routing. Factors like node neighbors, interference, and medium access control impact delay unpredictability. We explore the potential of artificial neural networks to enhance accuracy in forecasting these delays, aiming to improve QoS within the dynamic Mobile Ad Hoc Network (MANET) context. We calculated delay using source-destination path length and average neighbors. Two models were built: Regression Neural Networks (RNN) and Radial Basis Function (RBF) networks. Using a network simulator, we gathered data sets for three routing protocols: AODV, DSDV, and DSR. These sets include delay, path length, and average neighbors. RNN outperformed RBF in predicting delay, as determined by various performance metrics.

Index Terms— Radial Bases Network, Regression Neural Network.

I. INTRODUCTION

Node mobility within network connections offers enhanced flexibility and adaptability. Moving nodes can form new connections, enabling efficient communication independent of fixed infrastructure. Mobility improves network resilience and connectivity. Considering factors like path frequency, average neighbors, and protocols, precise end-to-end delay prediction is crucial for routing QoS in MANETs. Reliable packet delay prediction is essential for effective routing QoS in Mobile Ad Hoc Networks [3]. This model expands from single-bounce packet delay decomposition to evaluating burst delays in spontaneous multi-bounce systems. Employing a restricted traffic multi-bouncing system, we've developed a model to estimate average packet delay. Leveraging artificial neural networks offers advantages: (i) Adaptability and non-parametric nature without stringent assumptions. (ii) Ability to uncover subtle data connections, even when less apparent or complex. (iii) Summarizing information effectively, a key attribute of neural networks [4]. In predicting specific events periodically, neural networks exhibit consistency even with impulsive input data. However, neural networks struggle with precise multivariate capacity (iv) and ambiguous relationships between limited input and outcomes (v). In this study, sum-recurrent NN and Radial Basis Function (RBF) networks are employed on existing experimental data for onset delays in specialized portable systems, employing various control methods [5]. This model predicts start-stop delays by combining two informative factors. Various models, such as Squared Error, Correlation Coefficient, and

Efficiency, are utilized to represent desired modules. The model's results contrast and analyze design quality based on criteria. Paths are defined as ordered link sets connecting sources. Path length equals shared links for a source-destination pair. QoS metrics in ad hoc networks include throughput, delay, and packet loss [6]. Delay, a vital QoS metric, in ad hoc networks comprises medium access and queuing delays. Predicting onset delay accurately is crucial for MANET QoS control. Numerical techniques for delay determination face challenges due to diverse system importance levels [9].

II. LITERATURE REVIEW

B. Davis, J. Broach, et al [10], Enhance the quality of service in MANETs by applying a cross-layer approach to the DYMO protocol. Furthermore, they believe that layered approaches are not appropriate for dynamic networks like Manets, as cross layer designs are shown to improve QoS significantly in mobile ad hoc networks.

III. PROPOSED SYSTEM

In comparison to the DSR, AODV performed better when compared to reactive routing protocols such as N. Garg 1, A. K et al [11]. In the discussion about QoS in MANET and optimizations on the cross layer, we focused on the importance of QoS. P. Kaur, D. Kaur, et al [12] ‘‘They used various mobility models, such as random-waypoint, uniform, grid, and various routing protocols to evaluate the performance of various routing protocols. In the Random way point mobility model, routing protocols perform better than other protocols. S. Chakrabarti and A. Mishra [13].

A, Venkataramana, et al. [14], published their review titled ‘‘Previously known as ‘‘QoS management and provisioning in mobile ad hoc networks’’, they mainly focused on the provisioning and management of QoS in mobile networks. Ad hoc networks. MANETs were analyzed using certain QoS models that provide architectures to provide QoS to mobile nodes. In our discussion, CEQMM (Complete and Efficient QoS Model for MANETs) is one such model which integrates IntServ and DiffServ attributes and also accounts for the dynamic topology and variable linking of mobile nodes present in mobile ad hoc networks.

A. Venkataramana, et al [15] to improve the reliability of packet delivery in case of node movement and route breaks, AODV-BR Backup Routing is proposed as a modified protocol version of AODV. There are multiple alternate routes in the mess configuration, and no extra overhead is involved in its construction. If data packets cannot be transmitted via the primary route, this alternate route is used. In situations where traffic load and mobility increase, AODV-BR routing protocol's performance decreases [16]. A fundamental goal of our proposed implementation is to improve the performance of wireless MANET networks, as they are characterized by a lack of infrastructure and a highly dynamic topology that changes nodes as they enter and leave the network due to broken routing links and packet loss. transactions, so it is necessary for the war to recalculate information about broken routing links [17]. Clustering and adaptive routing. Find the best path from the source to the stretch by overlaying the control message with a neural network. data computation. In order to predict start-stop delays, two input factors are mixed [18]. The prediction module must be exhibited through measures such as B. root mean square error, connection coefficient and efficiency were used. In addition, the criteria are used to select the most appropriate model structure, as a consequence of the model using network simulator, we used the trailing information (NS-2) [19]. Using Bonn-Motion programming, each flexible hub moves using random points way (RPW) in the design. Using the Random Point Way (RPW) development plan, 50 nodes were produced moving in a zone of 1200 meters’ and x 800 meters for 1000 seconds. nodes can reach a maximum speed $V_{\max}$ of 15m/s if they are configured properly. Hubs are always set so that the least speed $V_{\min}$ is 0.8 m/s. In the long run, one can observe that $V_{\min}$ is a set of positive incentive restrict common speed of a nodes at the end of the day, it turns out to zero [20].

TABLE-1 NUMERICAL INFORMATION SETS

Protocol	$V_{\min}$	$V_{\max}$	Destination	Source
DSDV	0.006054	0.073598	0.0367986	0.017986558
AODV	0.025480	0.087385	0.0412148	0.015335661
DSR	0.028903	0.07280	0.0382127	0.008765527

X- Distance, S- Source, $V_{\max}$ $M_{\max}$ Speed, $V_{\min}$ - Minimum speed. Every portable nodes uses IEEE 802.11 as a media access control layer with proper coordination. Control conventions include AODV, DSDV, and DSR. Nodes produce steady 1-packet/second traffic for 100 seconds. Network Simulator -2 handles the control bit rate. The ns-

2 test system simulates burst data transmission and collection. Meeting and transfer notifications are stored in a new follow-through design. AWK scripts analyze sequence records to extract starting delay and path length information.

IV. NEURAL NETWORK MODEL

In situations of uncertainty or system fluctuations, point predictions from neural networks (NN) hold limited value. Weighting coefficients and model construction are influenced by significant inputs, leading to potential drawbacks. Input variables can impact model structure, processing speed, and data redundancy. Excessive parameters in a model may result in overfitting to sample data, though not universally.

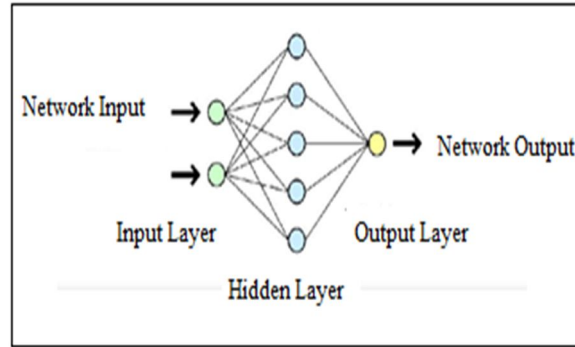


Fig.1 Neural Network

We only use the path length and number of adjacent nodes input variables of the path. As the queuing delay increases, increasing the length of the path causes more delay at every node. If maximum number of nodes on the path in MANET [20]. It is used for proximity functions and recognizing patterns. It uses a Gaussian potential function. The table below treats the square error root mean (SERM) as a multiple quadratic radial basis function. To evaluate and compare the suitability of different models, the following performance evaluation criteria are used: co-relation coefficient (R), "Coefficient Nash-Sutcliffe (E)". When the model starts to over fit, in hidden layers The number of nodes increases, thereby increasing the SERM.

The number of internal parameters adopts a neural network, and the network is a trial-and-error method. We can calculate this result using the following parameters. No. of epochs = 1.001, target = 00.002. Coefficient = 0.7

$$\phi(r) = (r_2 + c) \lambda_2$$

$$c = \text{true cost} \quad \lambda \in \mathbb{R}$$

$$\phi(r) = r$$

$$\phi(r) = r^2, \phi(r) = r^3$$

$$\phi(r) = \exp(-r^2)$$

it is a multilayer feed forward network. it consists of n number input neuron and n member output neuron. The density of the hidden layer is higher than that of the input layer, i.e. $n < m$. Weighted connections between hidden and input layers. Hyperbolic connection between input layer and hidden layer and the weighted node connections are hidden layer and output layers. Gaussian function

$$\phi(r) = \exp\{-r/2\sigma^2\} \quad \text{width parameter } \sigma > 0$$

Multi Quadric functions-

$$\phi(r) = \{r^2 + \sigma^2\}^{1/2} \quad \text{parameter } \sigma < 0$$

Multi quadratic functions generalized –

$$\phi(r) = \{r^2 + \sigma^2\}^\beta \quad \text{parameter } \sigma > \beta > 0$$

(i) Randomly select RBF centers from the training set. (ii) Selection of RBF centers by clustering. (iii) Orthogonal least squares for RBF network learning. RBN {radbas (n)=e-n2}. The weights are output layer are decisive. During this process, RBS centers are added by network is established, so all exercise samples are considered as applicants of a center, one means a squared error, and each given cos function is called for a new hidden unit.

IV. RESULT ANALYSIS

Different presentation assessment measures are used to determine the relevance and examine the different models: Agreement of index (AOI), Co-relation coefficient “(R), Coefficient Nash-Sutcliffe (E)”, and (SERM).

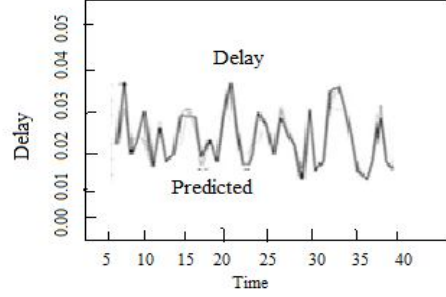


Fig-2 Predicted Delay for AODV Routing

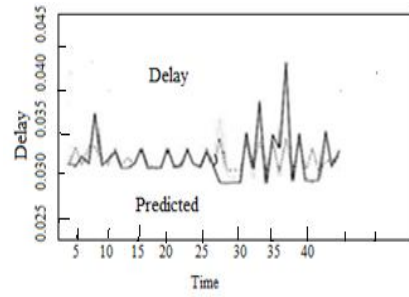


Fig-3 Predicted Delay for DSDV Routing

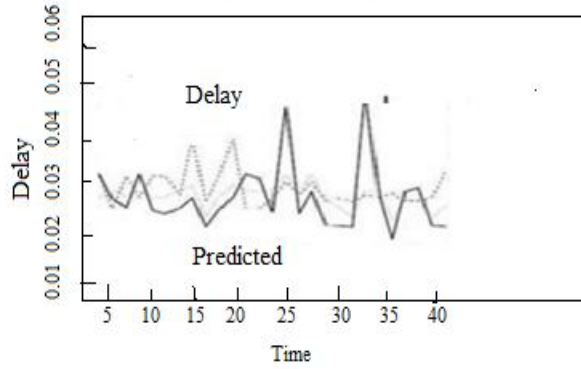


Fig-4 Predicted Delay for DSR Routing

Define the steps to determine the SERM and Absolute Mean Error (AME). According to condition 1 to 5, these two measures qualities.

$$R = \frac{\sum_{i=1}^n (O_i - O)(P_i - P)}{\sum_{i=1}^n (O_i - O)^2 \sum_{i=1}^n (P_i - P)^2} \quad (1)$$

$$E = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - O)^2} \quad (2)$$

$$AOI = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n [|P_i - O| + |O_i - O|]^2} \quad (3)$$

$$SERM = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2} \quad (4)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |O_i - P_i| \quad (5)$$

n data sets, P_i represents predicted delay of i^{th} time, O_i represents observed delay i^{th} time, * represents observed delay, and P represents difference in the period delay.

- $|R| \geq 0.8$: This indicates two sets of variables and solid associations
- $0.3 < |R| < 0.7$: there is two sets of variables and association between them
- $|R| \leq 0.2$: There is two groups of variables and weak association between them

A model using the Coefficient Nash-Sutcliffe (E) explains the basic helplessness problem. Its values range from -1 to +1. The Understanding Document (AOI) is a modification of Coefficients Nash – Sutcliffe. To denominator change is designed to refute differences in the mean target and mean observations. They were revealing inconsistencies as screwed-up terms were squared across the three bars. As the most important error measure, root mean square error ensures that the grotesque ordeals are given more care of the minor mistakes. RMSE to provide

measurable sign of model fault, similar to the sum of measurements. The RMSE view near to nil shows superior execution model. The mean absolute error (MAE) is not the square of the measurement, but is derived from an unmatched estimate of the confusion draw.

TABLE II. RNN-BASED DECENCY METHODS FOR VARIOUS INFORMATIONAL INDICES.

Protocol	R	E	AOI	SERM	MAE
DSDV	0.6263816	0.3670092	0.9999947	0.0020374	0.0003588
AODV	0.8713847	0.7400100	0.9999907	0.0027037	0.0003588
DSR	0.6034943	0.2790688	0.99995	0.002740	0.0004601

TABLE III. RBF-BASED DECENCY METHODS FOR VARIOUS INFORMATIONAL INDICES.

Protocol	R	E	AOI	SERM	MAE
DSDV	0.1445881	0.732575	0.9999617	0.0054934	0.0012993
AODV	0.9458817	0.8946922	0.9999962	0.0017207	0.0002746
DSR	0.0021966	0.3615913	0.9999724	0.0038145	0.0007153

R-Constant, E- Efficiency, Index of understanding (IOA) The real and expected delays of the explicit empowerment framework demonstrated using AODV leadership are shown in Figure 1. There are striking similarities between the predicted and actual properties of the two neural network models. It shows that using the DSDV Coordinating Show's unique naming framework delays authentication as well as the expected delay, Figure 2. Properties expected by RNN models that are close to true uniqueness will not yield good results anyway. The real offsets and design delays of oddly named frames with DSR coordination are shown in Figure 3. Neither model gave surprising results. Estimates of the execution score settings for the RNN and RBF models are shown in tables 2 & 3. For start-stop burst delays in spontaneous systems, Tables 2 and 3 show an advantage over the RNN model. RBF model outperforms the RNN in the estimation of the association constant R, efficiency E, AOI, SERM and MAE for the delay caused by the presence of AODV control. However, RNN approach have more suitable than the RBF framework. With exception of AODV, the connectivity coefficient R is below 0.2 for all other cases, indicating that the connectivity between the true and expected information indices is indeed very low. In fact, the productivity of even RBF organizations is very low for all but AODV. In fact, RBF organizations are not suitable for moving packets from beginning to end of the system using the AODV and DSR policy conventions. In spite of the fact that However, the revision between watched and genuine information was in the range of 0.6 as it were for the RNN model for DSDV and DSR steering conventions.

V. CONCLUSION

In modern times, we strive to find the true nature of neural frameworks to demonstrate a radical shift in data-mapping adaptive improvisation frameworks. For our reasons, we used two frameworks, Explicit RBF and Gausses Markvo found that the technique seems to be an unparalleled model of data admission. Typesetting delays can be reasonably controlled by using AODV in harmony with the RBF framework. A measure of how long the path is from the source to the destination and how many neighbors it has no matter which direction the route leads to the target known as path length and the average number of adjacent midpoints, we can determine the imprecise momentum of a packet. In the next security adventure, we will be able to determine a delay guarantee line in an exception-marked frame based on this deterministic delay.

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