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Model for MANET using Recurrent Neural Network & Extended Kalman Filter

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Abstract
In recent years there has been a growing concern by researchers in developing methods, techniques and algorithms for predicting the behaviour of various routing protocols in Mobile ad hoc network environment. The proposed work addresses the problem of predicting the behaviour of Mobile ad hoc network by considering state output variable such as Packet Delivery Ratio (PDR) is considered for evaluating the performance of MANET using recurrent neural network EKF (Extended Kalman Filter) algorithm. The state input variables such as Number of connections which shows the active connections, number of packets generated per unit time by any particular node, node density which shows the total nodes, speed of movement is the mobility speed of any particular node in a specified range & the pause time which shows the halt time of a node during its movement. The value of state output variable is observed using the network simulator for various network environmental conditions under DSR (Dynamic Source Routing Protocol). The proposed model has been tested on various simulated data sets is found to be quite satisfactory as compare with the conventional methods developed so far.

Keywords: DSR, PDR, MANET, EKF.

Introduction
A Mobile Ad-Hoc Network (MANET) is a self-configuring network of mobile nodes connected by wireless links, to form an arbitrary topology. The nodes are free to move randomly. Thus the network's wireless topology may be unpredictable and may change rapidly, minimal configuration, quick deployment and absence of a central governing authority make ad hoc networks suitable for emergency situations like natural disasters, military conflicts, emergency medical situations etc [1] [2]. Many
previous studies have used Random Waypoint as reference model [3] [4]. Dynamic Source Routing protocol is a reactive protocol i.e. it determines the proper route only when a packet needs to be forwarded. The node floods the network with a route-request and builds the required route from the responses it receives. DSR allows the network to be completely self-configuring without the need for any existing network infrastructure or administration. The DSR protocol is composed of two main mechanisms that work together to allow the discovery and maintenance of source routes in the ad hoc network. All aspects of protocol operate entirely on-demand allowing routing packet overhead of DSR to scale up automatically.[5] [6]

Hypotheses
It has been hypothesised that the MANET system can be defined by various state input variable X[k] consisting of five elements expressed by $X=[NC\ NP\ ND\ NM\ PT]^T$ where NC (Number of connections), NP (Number of packets generated), PT (Pause time), PDR (Packet Delivery Ratio), X (k+1) (State of MANET at (k+1)), X (k) (State of MANET at k), Y (k) (Observed Performance for MANET at k), F_{k+1} (weight matrix obtained from neural network)), μ (k) (exogenous variables), Y_D (k) (Desired output of MANET system), ∫ (Integration function),).

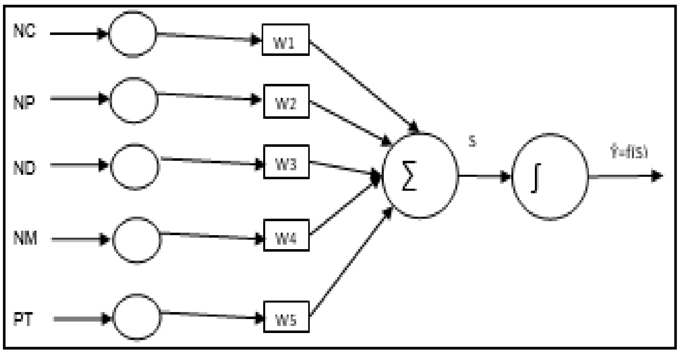
Proposed Model
The Kalman Filtering addresses the estimation of a state vector in a linear model of a dynamic system. However if, the model is nonlinear, the application of Kalman Filter may be extended through linearization procedure. The resulting filter is referred to as the Extended Kalman Filter(EKF)[7][8]. The architecture of Recurrent Neural Networks (RNN) used in this paper is shown in Figure 1.In order to apply EKF for estimating optimal weights of RNN (Recurrent Neural Network), weights of the network are interpreted as the transition matrix for the system's state. When EKF methods or any other sequential procedures are used to train networks with distributed representations, as in the case of multi-layered perceptron's recurrent neural networks, there is a tendency for the training procedure to concentrate on the most recently observed training patterns, to the detriment of training patterns that had been observed and processed

$$X_{k+1} = F_{k+1,k} X_k + W_k \quad (1)$$

$$Y_k = H_k X_k + V(k) \quad (2)$$

Equation (1) is known as the state equation , where $F_{k+1,}$ is the transition matrix causes for transition of the state X_k Xk+1.

The process noise W_k is assumed to be additive. Equation (2) is known as measurement equation, where Y_k is observable at time k and H_k is the measurement matrix. The measurement noise V_k is assumed to be additive. Here $X=[NC\ NP\ ND\ NM\ PT]^T$, and $F_{k+1} = [w1\ w2\ w3\ w4\ w5]^T$ is the weight vector containing weights associated with inputs, S is the summation of inputs multiplied by their corresponding as in equation(3):



Figuare 1: Architecture of Recurrent Neural Network

$$S=w1*NC+w2*NP+w3*ND+w4*NM+w5*PT \qquad (3)$$

The output Ŷ is computed by applying activation function on S. The activation function used in this paper is binary sigmoid function of the form as in equation (4):

$$\check{Y} = f(S) = \frac{1}{1+e^{-tS}]} \qquad (4)$$

In this paper the value of t is taken as 1. The measurement matrix H_k is p by r matrix of derivate of network outputs with respect to all the weights in the network where p is the number of outputs and r is the number of weights. Suppose that a measurement on a linear dynamical system, described by Eqs. (1) and (2), has been made at time k. The requirement is to use the information contained in the new measurement Yk to update the estimate of the unknown state Xk [9][10]

Table 1 shows the simulation input and output sets. For k=1,2,3......N , where N is the number of observations for machine learning.

$$\Gamma(k) =[C(k)P(k,k-1)C^t(k)+R(k)]^{-1} \qquad (5)$$

$$G(k) = P(k,k-1)C^T\ \Gamma(k) \qquad (6)$$

$$\alpha(k) =Y(k)-\check{Y}(k) \qquad (7)$$

$$\hat{W}(k+1|k) = \hat{W}(k|k-1) +G(k)\ \alpha(k) \qquad (8)$$

$$P(k+1,k = P(k,k-1) - G(k)C(k)P(k,k-1) \qquad (9)$$

Where P(k,k-1) is the error covariance matrix, G(k) is the Kalman gain, α(k) is the error between desired output Y(k) and estimated output Y̌(k), Ŵ(k+1|k) consists of estimated weights.

Results and Discussion

Fig 2 is showing the implementation with Recurrent Neural Network. The MANET is trained with recurrent neural network using Levenberg-Marquardt algorithm and performance is found satisfactory and the results are shown in Fig 3. Which shows the minimal error difference between observed PDR and Target PDR. Table 1 shows the set of simulation parameters , The proposed work is simulated using Refernce Point Group Mobility Model (RPGM)

Table 1: Simulation input and output

Simulation Parameters	
Routing Protocols	DSR
Mobility Model	RPGM
Network Activation Time	100 (s)
Number of Nodes	5-25
Simulation Area	x=1000 m, y= 1000 m
Speed	l=0.0 m/s, h= 5-25 m/s
Pause Time	3-11 (s)
Traffic Type	CBR
Packet Size	512 bytes
Rate	10.0 packets/sec to 30.0 packets/sec
Number of Connections	5-25
Seed	1.0

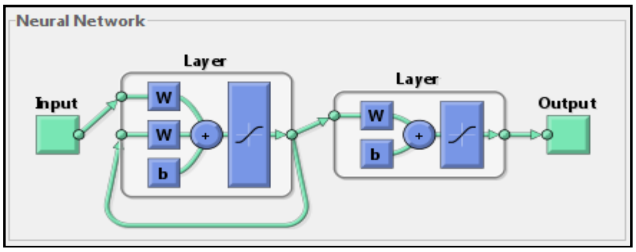


Figure 2: Recurrent Neural Network

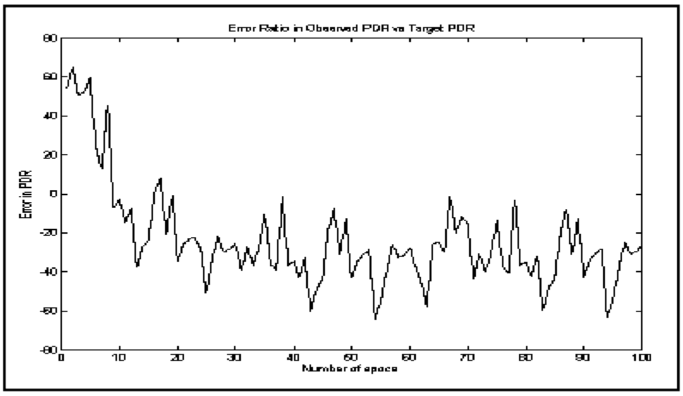


Figure 3: Performance evaluation using Levenberg-Marquardt algorithm

Conclusion

The algorithm implemented in this paper, comprises of state input variables such as Number of active connections, number of generated packets, node density which shows the total nodes, speed of movement of a node in a particular given range & the pause time which shows the halt of a node during its movement. The value of state output variable PDR has been observed using network simulator and trained using EKF algorithm and weights are updated using recurrent neural network. The model has been tested on various simulated data sets of input and output variables and is found to be quite satisfactory as compared with conventional. The can also be applied on other performance evaluation parameters like Overhead and delay and for any routing protocols.

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