# DERIVATIVE THRESHOLD ACTUATION FOR SINGLE PHASE WORMHOLE DETECTION WITH REDUCED FALSE ALARM RATE

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## ABSTRACT

*Communication in mobile Ad hoc networks is completed via multi-hop ways. Owing to the distributed specification and restricted resource of nodes, MANET is a lot prone to wormhole attacks i.e. wormhole attacks place severe threats to each Ad hoc routing protocol and a few security enhancements. Thus, so as to discover wormholes, totally different techniques are in use. In all those techniques fixation of threshold is merely by trial & error methodology or by random manner. Conjointly wormhole detection is in twin part by putting the nodes that is higher than the edge in a suspicious set, however predicting the node as a wormhole by using some other algorithms. Our aim in this paper is to deduce the traffic threshold level by derivational approach for identifying wormholes in a very single phase in relay network having dissimilar characteristics.*

## KEYWORDS

*MANET, wormhole, Traffic prediction, parametric threshold implication, derivational approach.*

## 1. INTRODUCTION

A mobile unintended network (MANET) could be a self configuration infrastructure less network with non centralized administration. A mobile Ad hoc or unintended network is an autonomous assortment of mobile devices (laptops, smart phones, sensors, etc.,)that communicate with one another over wireless links and collaborate in a distributed manner so as to produce the required network practically within the absence of a fixed infrastructure. Every device in a MANET is unengaged to move independently in any direction, and can amend its links to different devices often. This type of network, operating as a complete network or with one or multiple points of attachments to cellular networks or the web, paves the approach for variable new and exciting applications. Application scenarios embrace, however are not restricted to: emergency and rescue operations, conferences are field settings, automobile networks, personal networking, etc. In wormhole attack, malicious node receives knowledge packet at one point within the network and tunnels them to a different malicious node. The tunnel existing between two malicious nodes is named as a wormhole. The tunnel gets the information from one network and replicates to different network. A wormhole therefore permits an attacker to form two attacker controlled choke points which may be utilized by the attacker to degrade or analyze traffic at a desired point.

DOI : 10.5121/ijdps.2014.5303

TPIDS is a lightweight traffic prediction intrusion detection theme that tumbling the value of communication and energy by hastily detecting the behaviour of the intrusions. Some work has been done to wormhole attack in mobile unintended networks however it cause excessive false alarm rate. In this paper we are focusing on reducing warning rate by choosing optimum threshold value to save lots of wastage of energy and information measure of mobile nodes in sleuthing wormholes. The remaining components of this paper is organized as follows: section III provides traffic prediction supported ARMA, section IV provides experimental analysis and results, section V presents relation between attributes of the network and threshold values, section VI presents threshold selection, finally conclusion is conferred in section VII.

## 2. RELATED WORK

The discussion starts by Yu Bo’s paper, that relies on the discovery of multi-hop recognition theme to detect attacks caused by the selection of transmitting the irregular packet loss. In this theme, a region of the transmission path, nodes are going to be randomly selected for testing. Detection point is going to be generated for every incident packet to the upstream transmission methods, any node within the middle, if not adequately recognized package, can generate warning data of abnormal packet loss and to submit a multi-hop to the supply node. Here, we have considered ton choosing transmission attack is taken into account, that introduces larger communications and computing prices. Then khin sandar win [6] proposes solely an analysis of detecting wormhole attack in wireless network, simply by quoting the benefits and drawbacks not suggesting for the foremost economical one. Han zhijie[1] instructed traffic prediction methodology, however he didn’t decrease the false alarm rate whereas detecting wormholes. Faizal M.A.[2] offers regarding solely a way to verify threshold values by using SPC approach that are more necessary for detection of wormholes and conjointly to scale back false alarm rate within the MANET. This observation is finished on real time network traffic having the aim of distinguishing the typical connection created by the host or hosts to single victim among one second interval.

## 3. TRAFFIC PREDICTION BASED ON ARMA

The existing traffic prediction model includes Poisson model, Markov model, auto-regressive model where Poisson is not suitable for the flow characteristics of MANET. This paper gathers information from Markov model and enhances it in auto-regressive moving average model to predict MANET traffic and the specific prediction model which is shown below:

Each and every node in MANET has its own random variable sequence $X_0$ , $X_1$ , $X_2$... is used to denote the state of the node at the same time; different nodes can be in different modes. Assume $X_n = i$ that is nodes are in the operational mode $i$ when it is in time domain n and also assume that the entire state transition take place at the beginning of any time domain, each node has some fixed probability in the state $i$ .if the next state is $j$ , then this is denoted by $P_{ij.}$

$$P_{ij} = P\, X_{m+1} = j \mid X_m = i \qquad (1)$$

Where

$P_{ij}$ The probability of entering the state $j$ when a node is in the operational state $i$ .

The migration probability of second-order is defined as $P^2_{ij}$ that is, a node in the current state of *i* will enter the state *j* after having two state transitions. (i.e.)

$$P_{ij}^{(2)} = P \ \ X_{m+2} = j \mid X_m = i \qquad (2)$$

This can be calculated by the following formula:

$$P_{ij}^{(2)} = \sum_{k=1}^{M} P_{ik} P_{kj} \qquad (3)$$

The migration probability of n order is denoted as
which is taken from the chapman- kolomogorov equation: $P^{2}_{ij}$

$$P_{ij}^{n} = \sum_{k=1}^{M} P_{ik}^{(r)} P_{kj}^{(n-r)} \qquad (4)$$

Where
$\gamma$ can take any arbitrary values between 0 and n.
A further notation of Markov chain for probability is to use M*M matrix of P which is called as migration probability matrix. In this matrix, the element $P_{ij}$ represents the probability in the *i* th row and *j* th column.

$$\begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1M} \\ P_{21} & P_{22} & \cdots & P_{2M} \\ . & . & \cdots & \cdots \\ P_{M1} & . & . & P_{MM} \end{bmatrix} \qquad (5)$$

Here, $P^2$ can be calculated by P*P and in general, $P^{(m+n)}=P^{(m)}*P^{(n)}$ which is similar to
By migration probability matrix and the initial $X_0$ of each node, we can build the sequence while comparing energy consumption and mobility for the entire MANET. If a node travels from i$^{th}$ state to s$^{th}$ state, then the number of time domains the node remains in the s$^{th}$ state is given by:

$$\sum_{t=1}^{T} P_{is}^{(t)} \qquad (6)$$

Assuming that $B_S$ is the data transmissible data quantity of a node stays at state s. then after calculating the number of domains, the total data transmissible quantity is given by the formula:

$$B^{T} = \sum_{s=1}^{M}\left(\sum_{t=1}^{T} P_{is}^{(t)}\right) * B_{S} \qquad (7)$$

And also the data of each node in the time can be calculated by equation (7).the transmissible data quantity for the total number of nodes in a cluster is given by

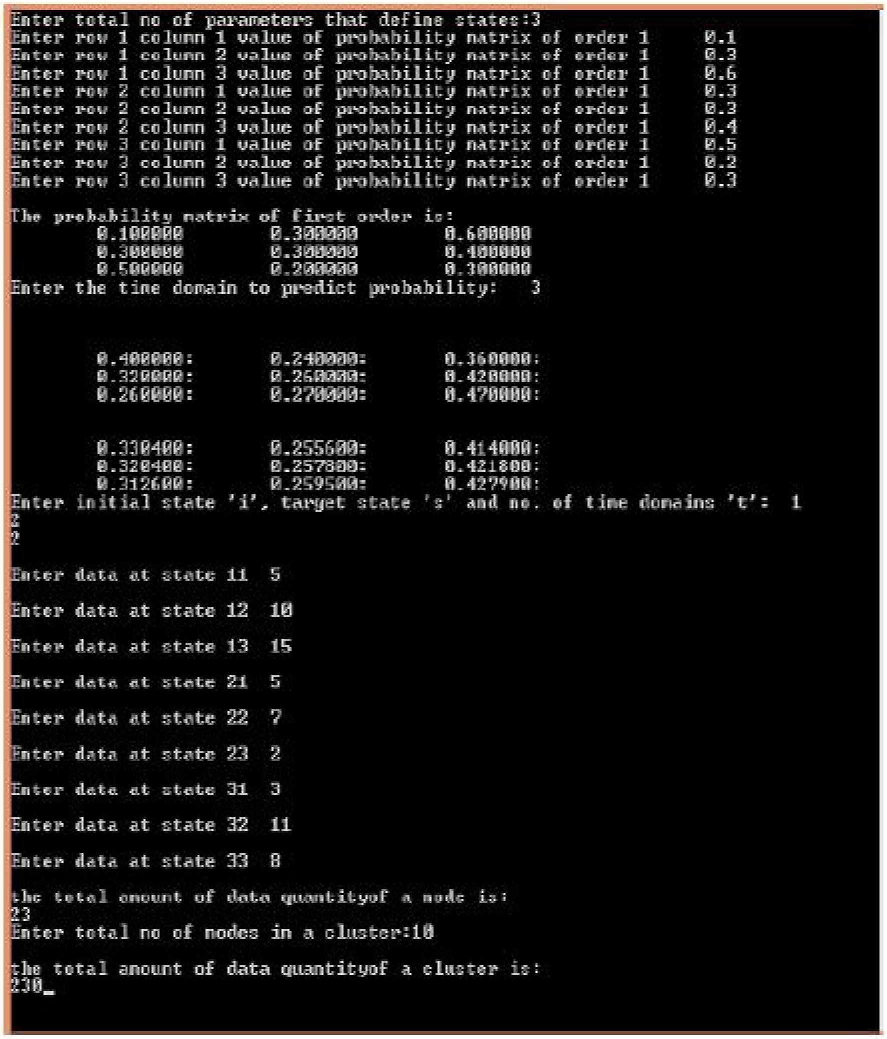
$$B_{total} = \sum_{C_{k-1}}^{C_{k-n}} \sum_{s=1}^{M}\left(\sum_{t=1}^{T} P_{is}^{(t)}\right) * B_{s} \qquad (8)$$

Where
$C_k$→ it is to represent $i^{th}$ node, in cluster $C_k$.
$P_{is}^{(t)}$→ is the probability from i th state migrating to the $s^{th}$ state.

## 4. EXPERIMENTAL ANALYSIS AND RESULTS

Generally, networks of nodes are created which generates its traffic randomly with specific direction and velocity. Using ARMA algorithm, traffic prediction for single node is found by equation (7) and also traffic prediction for cluster of different nodes is calculated by equation (8). Using intrusion detection system, detected traffic for each node is analyzed which results node with high traffic is finally concluded as wormhole. Further this paper focused on detecting anomalies caused by the invasion and leaving decision making and counter measures.

**SCREEN SHOT 1:**



```
Enter total no of parameters that define states:3
Enter row 1 column 1 value of probability matrix of order 1     0.1
Enter row 1 column 2 value of probability matrix of order 1     0.3
Enter row 1 column 3 value of probability matrix of order 1     0.6
Enter row 2 column 1 value of probability matrix of order 1     0.3
Enter row 2 column 2 value of probability matrix of order 1     0.3
Enter row 2 column 3 value of probability matrix of order 1     0.4
Enter row 3 column 1 value of probability matrix of order 1     0.5
Enter row 3 column 2 value of probability matrix of order 1     0.2
Enter row 3 column 3 value of probability matrix of order 1     0.3

The probability matrix of first order is:
        0.100000        0.300000        0.600000
        0.300000        0.300000        0.400000
        0.500000        0.200000        0.300000
Enter the time domain to predict probability:   3



        0.400000:       0.240000:       0.360000:
        0.320000:       0.260000:       0.420000:
        0.260000:       0.270000:       0.470000:


        0.330400:       0.255600:       0.414000:
        0.320400:       0.257800:       0.421800:
        0.312600:       0.259500:       0.427900:
Enter initial state 'i', target state 's' and no. of time domains 't':  1
2
2

Enter data at state 11  5

Enter data at state 12  10

Enter data at state 13  15

Enter data at state 21  5

Enter data at state 22  7

Enter data at state 23  2

Enter data at state 31  3

Enter data at state 32  11

Enter data at state 33  8

the total amount of data quantityof a node is:
23
Enter total no of nodes in a cluster:10

the total amount of data quantityof a cluster is:
230_
```

This screen capture shows the combined execution of both prediction data algorithm and the wormhole detection algorithm. Since the predicted data is got from the ARMA algorithm, it uses probability matrix i.e the probability of a nodes to go from state 'i' to state 'j' after time ‘t’ is shown in the above result.

In order to deduce the relation between the threshold and network attributes first we have to stumble on the relationship between the varying network characteristics and the normalized data. For this we reflect on the data present in each node, number of nodes, time instants etc.

Varying the network attributes like amount of data in nodes, number of nodes, number of time instants, the results have been simulated.

## 4.1. Analysis Using Data

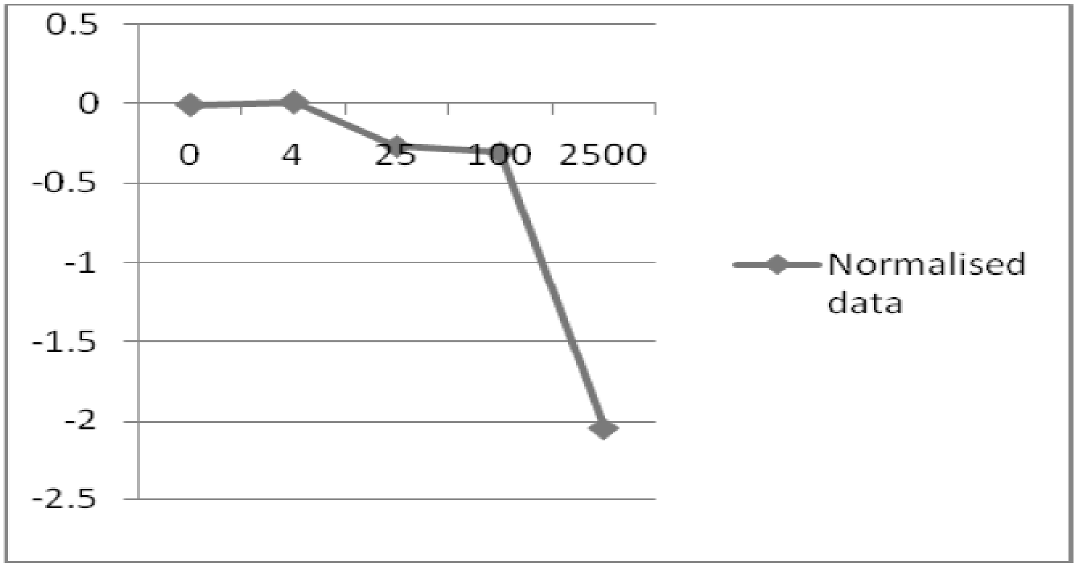
By varying the amount of data in each node in both prediction algorithm and wormhole detection algorithm, the total predicted data the actual data in the wormhole and the data in other nodes after certain number of transmissions is analyzed.

| S.NO | Data in each node | Predicted Data | Actual data in wormhole | Data in other nodes |
|---|---|---|---|---|
| 1 | 2,2,2 | 11.88001 | 12 | 5,3 |
| 2 | 2,4,6 | 28.20005 | 28 | 3,7 |
| 3 | 5,10,15 | 43.2000 | 55 | 6,16 |
| 4 | 20,30,40 | 129.60086 | 170 | 21,51 |
| 5 | 60,70,80 | 189.000031 | 410 | 61, 131 |
| 6 | 50,100, 150 | 180 | 550 | 51, 151 |

Table1.Analysis Using Data

This table (1) describes the relation between the predicted data and actual data in wormhole by varying the amount of data in each node. The inference is that data in wormhole is more than data in other nodes. More the increase in data in each node more will be the variation in predicted and the actual one. With this variation into concern the below graph is plotted.

Fig. 1 Variance Vs Normalized data



The Fig 1 is plotted against variance calculated from the amount of data in each node, and the normalized data calculated from the formula

$$\text{Normalized data} = \frac{\text{Predicted Data} - \text{Actual Data}}{\text{Predicted Data}} \qquad (9)$$

This graph infers that there is a diminishing relation between the amount of data in each node, and the normalized data which is above calculated.

### 4.2. Analysis Using Number of nodes

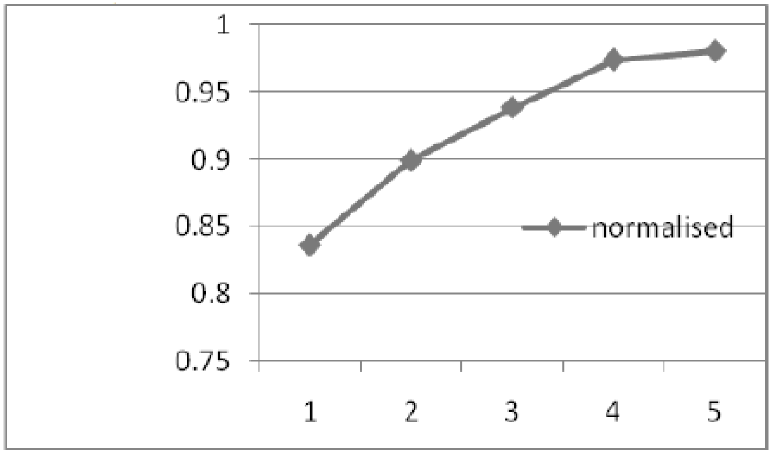
By varying the number of nodes in both prediction algorithm and wormhole detection algorithm, the total predicted data, the actual data in the wormhole and the data in other nodes after certain number of transmissions is analyzed.

Table 2.Analysis Using Number of nodes

| S. No | No. of nodes | Data in each node | Prediction data | Actual data in worm hole | Data in other nodes | No. of txm |
|---|---|---|---|---|---|---|
| 1 | 4 | 20,30,40,50 | 1783.5 | 291 | 22, 51,110 | 4 |
| 2 | 5 | 20,30,40,50,60 | 5723.22 | 391 | 22, 51, 91 | 5 |
| 3 | 6 | 20,30,40,50,60,70 | 9007.2 | 551 | 22,52,91,110,101 | 6 |
| 4 | 7 | 20,30,40,50,60,70,80 | 25278 | 651 | 22,51,91, 111 | 7 |
| 5 | 8 | 20,30,40,50,60, 70,80,90 | 33282 | 811 | 22,51,91,111,131 | 8 |
| 6 | 9 | 20,30,40,50,60 | 5116.4 | 991 | 22,51,91,111 | 9 |

This table 2 infers that while varying the number of nodes a suitable relation is formed between the predicted data and actual value of data from which a graph is plotted.

Fig. 2 No. of Nodes Vs Normalized data



This Fig. 2 infers that there is some linear relation between the varying nodes and the normalized value calculated from the above equation (9) by tagging the varying number of nodes in the X-axis.

## 4.3. Analysis Using Number of Time instants

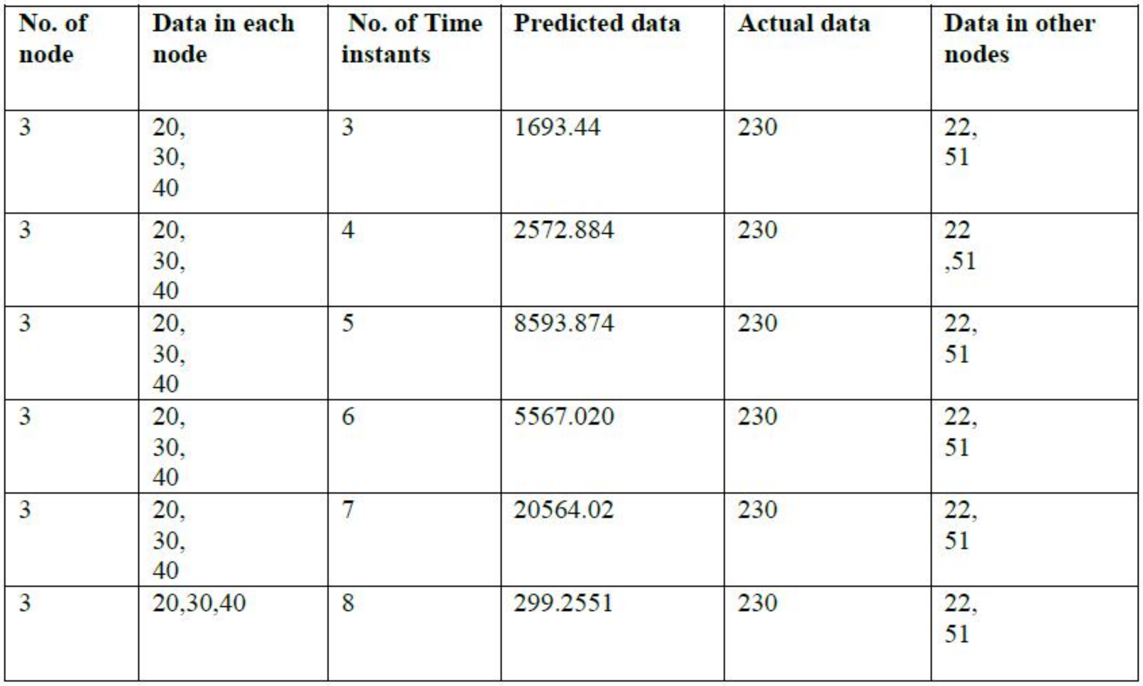
By varying the time instants in this table (3) a graph with some relation between the normalized data and the variable instants is plotted.

This fig (3) shows a decreasing relation on comparing the normalized data and the number of time instants by labelling them in the Y-axis and X- axis respectively.

The scenario of a Mobile Ad hoc network with a source node, destination node, route and wormholes is shaped in NS2 and the NAM output visualizes the node topology, connectivity, traffic or packet trace information carried out in MANET.

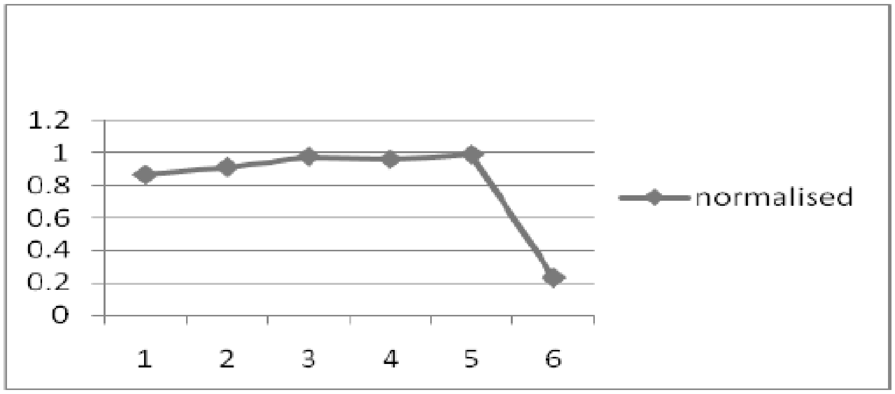
Comprehensive analysis of node.cc and its header files should be done, alterations should be made in NS2. Then by varying the parameters one by one threshold is deduced.

Table 3. Analysis using no. of Time Instants



| No. of node | Data in each node | No. of Time instants | Predicted data | Actual data | Data in other nodes |
|---|---|---|---|---|---|
| 3 | 20,<br>30,<br>40 | 3 | 1693.44 | 230 | 22,<br>51 |
| 3 | 20,<br>30,<br>40 | 4 | 2572.884 | 230 | 22<br>,51 |
| 3 | 20,<br>30,<br>40 | 5 | 8593.874 | 230 | 22,<br>51 |
| 3 | 20,<br>30,<br>40 | 6 | 5567.020 | 230 | 22,<br>51 |
| 3 | 20,<br>30,<br>40 | 7 | 20564.02 | 230 | 22,<br>51 |
| 3 | 20,30,40 | 8 | 299.2551 | 230 | 22,<br>51 |

Fig.3. No. of Time Instants Vs Normalized Data



## 5. RELATION BETWEEN NETWORK ATTRIBUTES AND THRESHOLD VALUES

Assume different threshold values and then experiment it with a network having characteristics like number of nodes, traffic intensity, node density and also wormhole density. And then, find false alarm rates for each assumed threshold values. The detection rate performance is highest for one threshold value for this network of certain parameters. The experiment is then repeated by varying the characteristics of the network and similar threshold values with best performance are obtained. Such threshold values of highest detection rate performance are found for each network with varying parameters. A mathematical relation is then deduced between the parameters of the network and such obtained threshold values. Based on this relation, an optimal threshold value with least false alarm rate can be selected for a network with any parameter set. This experiment is simulated in NS2 and the expected result would be in the form of a mathematical expression obtained by theoretical analysis.

## 6. THRESHOLD SELECTION

The normal and the abnormal traffic are differentiated using a threshold value. Thus suitable selection and the correct threshold value add an extra advantage for IDS to detect anomalies in the network. Selecting inaccurate threshold value will cause an excessive false alarm especially if the value is too low or if it is too high, it can cause the intrusion activity being considered as normal traffic. Most of the research does not propose a proper technique to identify the threshold technique. Here threshold is determined by dynamic techniques. Dynamic threshold technique requires prior knowledge of the network traffic before the threshold value can be selected.

## 7. CONCLUSION

In this paper, anomaly detection and security scheme based on Markov model is used by each node in MANET to predict traffic (TPIDS). All the above analysis shows that there exists a perceptible relation obtained by altering the network attributes, with this noticeable relation it is evident that there prevails an optimal threshold based on this relation. On deriving this relation wormhole detection can be ended in single phase. This relation is malleable to the protocol

DSDV which finds the wormhole by using shortest distance, hence in future work the optimal threshold for other routing protocols such as AODV etc can be deduced.

## REFERENCES

[1] C Han Zhijie, Wang Ruchuang: ‘Intrusion Detection for Wireless Sensor Network Based on Traffic Prediction Model’, 2012 International Conference on Solid State Devices and Materials Science.

[2] Faizal M. A., Mohd Zaki M., Shahrin S., Robiah Y, Siti Rahayu S., Nazrulazhar B.: ‘Threshold Verification Technique for Network Intrusion Detection System’, (IJCSIS) International Journal of Computer Science and Information Security,Vol. 2, No. 1, 2009.

[3] Ankita Gupta,Sanjay Prakash Ranga: ‘Wormhole Detection Methods In Manet’,International Journal Of Enterprise Computing And Business Systems(IJECBS), Vol. 2 Issue 2 July 2012.

[4] Moutushi Singh, Rupayan Das: ‘A Survey Of Different Techniques For Detection of Wormhole Attack In Wireless Sensor Network’ , International Journal of Scientific & Engineering Research Volume 3, Issue 10, October-2012 .

[5] Murad A. Rassam, M.A. Maarof and Anazida Zainal: ‘A Survey of Intrusion Detection Schemes in Wireless Sensor Networks’ American Journal of Applied Sciences, 2012.

[6] Khin Sandar Win, Pathein Gyi: ‘Analysis of Detecting Wormhole Attack in Wireless Networks’, World Academy of Science, Engineering and Technology , 2008.

[7] Lukman Sharif and Munir Ahmed, ‘The Wormhole Routing Attack in Wireless Sensor Networks (WSN)’, Journal of Information Processing Systems, Vol.6, No.2, June 2010.

[8] Jing Deng, Richard Han, and Shivakant Mishra, ‘Defending against Pathbased DoS Attacks in Wireless Sensor Networks’ SASN’05, November 7, 2005.

[9] Llker Demirkol, Fatih Alag¨oz,Hakan Delic, Cem Ersoy. Wireless Sensor Networks for IntrusionDetection:PacketTrafficModeling[EB/OL].www.cmpe.boun.edu.tr/~ilker/IlkerDE MIRKOL_COMML_ext_abstract . pdf.

[10] Onat I , Miri A. ‘An intrusion detection system for wireless sensor networks/Proceedings of the IEEE International Conference on Wireless and Mobile Computing’ , Networking and Communications (WiMOB’05) Mont real , Canada , 2005.

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