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PRO-ACTIVE VIRTUAL TOPOLOGY RECONFIGURATION FOR IP-OVER-WDM NETWORKS WITH QOS PARAMETERS

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Abstract

Wavelength-division multiplexing (WDM) technology has emerged as a promising technology for backbone networks and Wide Area Networks (WAN) with Terabits per second bandwidth. IP-over-WDM networks i.e. Optical Internets will be the best choice for next generation Internets, due to its potential ability to meet rising demands of high bandwidth and low latency communication. Recently, Virtual Topology Reconfiguration of IP-over-WDM networks, has received greater attention among researchers. The approaches available in the literature for virtual topology reconfiguration are reactive type. In this paper, we have presented a novel approach of pro-active virtual topology reconfiguration for IP-over-WDM networks with Quality of Service (QoS) parameters and shown that this new approach achieves better QoS performance in terms of blocking probability, throughput and latency.

Keywords: *Lightpaths, Logical Topology, Pro-active, Traffic Engineering, QoS, Resource Management*

1. INTRODUCTION

The enormous growth of Internet dramatically increases the demand for data transmission capacity. In the last decade, WDM techniques and Optical fiber technologies together brought a revolution in high-speed communication networks, which are now able to meet the high bandwidth demands of current voice and data traffic. All optical WDM networks using wavelength routing are considered to be potential candidates for the next generation wide area backbone networks. In these types of networks, routing and switching are carried out in the optical domain instead of electronic domain. The traffic between various source-destination pairs can be routed over different wavelengths.

The Internet data traffic is expected to dominate voice traffic in the near future. With the Internet Protocol playing a dominant role in wide area networking technology and advancements in wavelength routed WDM technology to provide enormous bandwidth, the IP-over-WDM networks [1] become the right choice for the next generation Internet networks, which leverage the capabilities of the optical fiber, especially for wide area backbone networks. The IP-over-WDM network consists of a set of WDM links and hybrid nodes, each of which consists of electronic IP router part and Optical Cross Connect (OXC) part.

The future generation high-speed networks employing IP-over-WDM technology needs to be applied with the tool of traffic engineering for satisfying QoS requirements.

The set of all-optical communication channels (*lightpaths*) in the optical layer defines the virtual topology for the upper layer applications. Since the traffic demand of upper layer applications fluctuates from time to time, it is required to reconfigure the underlying virtual topology in the optical layer accordingly. However, the reconfiguration for the virtual topology is reluctantly disruptive to the network since some lightpaths should be torn down and some traffic has to be buffered or rerouted during the reconfiguration process. Therefore, it needs to have an efficient transition method to shift the current virtual topology to the new one so as to minimize the

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effect of the reconfiguration on the upper layer traffic Reconfiguration is a vital characteristic of WDM optical networks that allows network operators to rearrange the networks in response to the changing traffic demands, node failure, link failure, up-gradation of network, etc, to satisfy the QoS requirements.

This paper is organized as follows. Section 2 reviews the literature for traffic modeling. Section 3 descries the proposed work. Section 4 and 5 respectively presents traffic models and QoS models for virtual topology reconfiguration for IP-over-WDM networks. Section 6 validates the proposed traffic model. Section 7 analyses the results obtained using Poisson traffic and using self-similar traffic. Finally, section 8 concludes the paper.

2. RELATED WORK

In the literature, the virtual topology reconfiguration approaches have used pre-specified traffic patterns. As a general assumption, reconfiguration studies on WDM optical networks are based on the idea that the decision of reconfiguration is triggered by an event; hence the virtual topology reconfiguration is a reactive process.

The existing traffic models for the high-speed networks like IP-over-WDM networks are not suitable to describe real time traffic. Most of the traffic models described in the literature followed Poisson processes because such processes are mathematically tractable. The Poisson process made easier for analytical modeling and simulation studies of high-speed networks. However, the recent studies have shown that for both local area and wide area network traffic, the distribution of packet inter arrivals clearly differs from exponential. Such type of networks can be better modeled using statistically self-similar processes, which have much different theoretical properties than Poisson processes due to the fact that there is no natural length for a ``burst'' self-similar traffic, that is, traffic bursts appear on a wide range of time scales. In [8], Paxson and Floyd find that user initiated TCP session arrivals, such as remote login and file transfer, are well modeled as Poisson processes with fixed hourly rates, but that other connection arrivals deviate considerably from Poisson.

In the literature it has been often assumed that the burst arrival process is Poisson and the Erlang B formula has been used to calculate blocking probability. The authors [9] demonstrated that the traffic at the burst level is not Poisson and the distribution of burst size or burst inter-arrival time is definitely non-Poissonian, since the inter-arrival times between bursts are not independently and exponentially distributed. Hence, the Erlang B formula cannot be applied in such networks.

3. PROPOSED WORK

Today's internet traffic exhibits self-similarity phenomenon with long run dependence. The network-engineering problem for the future generation internet is to provide high QoS while maximizing network resources. The QoS can be viewed at the application or packet level, but QoS parameters are defined in terms of message delay, packet delay, queueing delay, blocking probability, throughput, etc. The previous research works show that self-similar network traffic can have a detrimental impact on network performance, including QoS parameters such as larger queueing delay and packet loss probability.

3.1. Proposed System Description

A reconfiguration algorithm needs to be realized with minimum disruption to the network and guarantee the QoS to the upper layers. The performance degradation of data transmission in the upper layers should be minimized. In our research work, it is proposed a new approach of pro-active virtual topology reconfiguration for IP-over-WDM networks with real time traffic modeling, considering QoS parameters, which is shown in fig 1. The virtual topology of the optical network is seen by the internet layer, which carries the IP packet traffic over this logical topology. The traffic

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monitor is observing the statistics about the dynamic traffic behavior and also observes QoS parameters for the carried traffic. Based on the current traffic behavior, the future traffic demands are modeled. The traffic modeling uses Gaussian distribution as it best represents the real time internet data traffic. The observed QoS metrics namely blocking probability, throughput and network delay are used to drive the reconfiguration stage based on preset threshold values. This process of traffic monitoring and QoS monitoring is a closed loop system so as to ensure QoS.

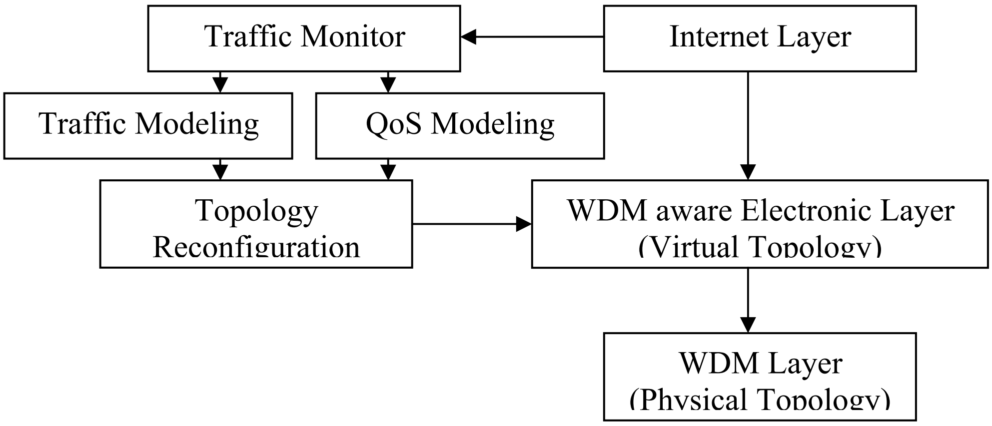

Fig 1. Schematic Diagram of VTR for IP/WDM Networks with QoS Parameters

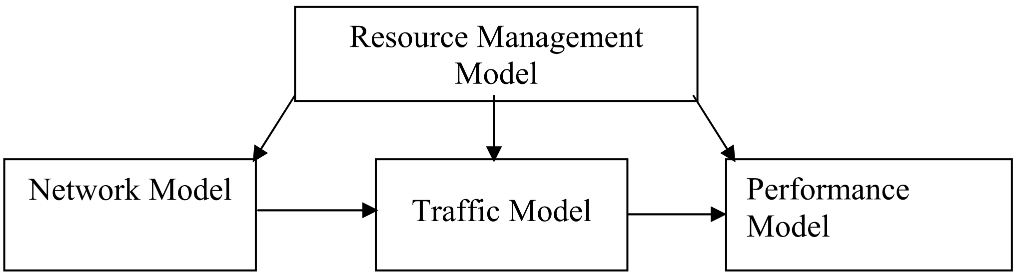

Fig 2. Resource Management Model

3.2. Network Model

We consider a network [6] of N nodes connected by bi-directional optical links forming an arbitrary physical topology. Each optical link supports w wavelengths, and each node is assumed to have T transmitters and R receivers. We assume that each node is equipped with an optical cross connect (OXC) with full wavelength conversion capability, so that a lightpath can be established between any node pair if resources are available along the path. Each OXC is connected to an edge device like an IP router, which can be a source, or a destination of packet traffic and which can provide routing for multi hop traffic passing by that node. Our network model considers network with an initial traffic matrix and reconfiguration decisions are based on traffic changes whenever such changes are necessary.

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3.3. Parameters

Listed below are the parameters used in the problem formulation.

i. Number of nodes in the network = N
ii. Number of wavelengths per fiber = w
iii. Capacity of each wavelength channel = C bits per sec
iv. Number of transceivers per node = R
v. Average Weighted Hop count for the Topology =*AWHT*

3.4. Notations

The following are the notations used in the problem formulation and in the algorithm.

i,j : end nodes
sd: source-destination pair

3.5. Variables

We define the variables used in the mathematical formulation.

i. Physical topology matrix P, where P_{mn} denotes the number of fiber links between nodes m and n.
ii. Traffic matrix T, where T_{ij} denotes the expected maximum rate of traffic flow from node i to node j, in bits per sec.
iii. Virtual Topology: The variable Vij denotes the number of lightpaths from node i to node j in the virtual topology. There may be multiple lightpath between the same source destination pair, if the traffic between nodes *i and j* is greater than a single lightpath's capacity (C).
iv. Wavelength Assignment matrix W, where Wij denotes the node to which the i^{th} node is connected on j^{th} wavelength.
v. Load matrix L, where Lij denotes the load on j^{th} wavelength channel of i^{th} node.
vi. Hop length matrix, H where Hij denotes the hop length for the lightpath between nodes i and j.If there are more than one lightpaths between two nodes then the hop length is the average of the two hop lengths.
vii. P^{ij}_{mn}, denotes the number of lightpaths between nodes *i and j* being routed through the fiber links between m and n.

3.6. QoS Parameters

The QoS parameters considered in this research work are blocking probability message delay and throughput. These parameters are defined as follows.

i. *Blocking Probability*:
Blocking probability of a network at a particular instant of time is defined as the ratio of number of traffic calls blocked to the total number of traffic requests.
ii. *Message Delay*:
Message delay in a network at a particular instant of time is defined as the average delay incurred for a message to travel from a source node to destination node.
iii. *Throughput*:
Throughput of a network is defined as the ratio of number of packets received at the destination node to the number of packets transmitted from the source node.

The traffic models and QoS models for the Poisson traffic as well as for Gaussian traffic are presented in the following section.

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4. TRAFFIC MODEL

A realistic Traffic model is a prerequisite for accurate performance evaluation. The traffic model consists of five layers: physical network, virtual network, call, burst, and packet layers. The different layers and their corresponding timing units are shown below.

Network layer	Timing
Physical network layer	Months
Virtual network layer	Days
Call layer	Seconds
Burst layer	mSecs
Packet layer	μSecs

The traffic models used for simulation of the VTR algorithm for IP over WDM network are:

i. Poisson -independent and identically distributed (i.i.d.) traffic model
ii. Poisson- traffic cluster model
iii. Gaussian Traffic model

4.1. Poisson iid model

The probability function of a random variable X which follows Poisson distribution is given by

$$P(X = x) = \frac{e^{-\lambda}\lambda^{x}}{x!}, \ 0 \le x \le \infty . \quad (1)$$

The important characteristics of Poisson process are:

i. The packet arrivals are Poisson distributed at a rate of λ
ii. The packet inter-arrival times are exponentially distributed
iii. Packet service rate is μ.
iv. Forward-recurrence time is exponentially distributed (i.e., memory less property)
v. Number of arrivals in non-overlapping time intervals are independent (i.e., independent-increments property), and it depends only on the length of the increment.

The independent and identically distributed (i.i.d) traffic model assumes uniform distribution between 0 and a maximum traffic density. The traffic matrix [5x5] generated using iid model is given below.

$$[T] = \begin{bmatrix} 0 & 7 & 38 & 3 & 24 \\ 1 & 0 & 2 & 22 & 47 \\ 12 & 10 & 0 & 3 & 4 \\ 3 & 14 & 1 & 0 & 2 \\ 44 & 1 & 32 & 13 & 0 \end{bmatrix}$$

4.2. Poisson Traffic cluster model

The traffic cluster is modeled by acting one particular node as source for a group of destination nodes or the particular node acting as destination for a group of source nodes. The particular node acting as source or destination for the group of nodes is called cluster head which depends upon the traffic pattern. In this model, the cluster size varies based on the number of nodes actively participate within the group of nodes. The example traffic matrix [5x5] generated using the traffic cluster model is given below.

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$$[T] = \begin{array}{|ccccc|} 0 & 1 & 2 & 3 & 40 \\ 1 & 0 & 2 & 3 & 40 \\ 20 & 10 & 0 & 30 & 40 \\ 3 & 4 & 1 & 0 & 20 \\ 4 & 1 & 2 & 3 & 00 \end{array}$$

In the above traffic matrix for the cluster heads are 3 and 4. Note that the traffic between sd pairs other than these two clusters are negligible.

4.3. Gaussian Traffic Model

A survey of internet traffic shows that it follows the property of self-similarity since it exhibits long-range dependence. Further, this self-similar traffic follows autocorrelation property and Gaussian distribution function. The Gaussian distribution is a continuous function, which approximates the exact binomial distribution of events. The general formula for the probability density function of the normal distribution is given by

$$f(x) = \frac{e^{-(x-\mu)^2/2\sigma^2}}{\sigma\sqrt{2\pi}} \quad , \tag{2}$$

where the parameter μ is the mean and σ is the standard deviation. The probability density function for the standard Gaussian distribution with mean μ = 0 and standard deviation σ =1 is given by ,

$$f(x) = \frac{e^{-x^2/2}}{\sqrt{2\pi}} \quad . \tag{3}$$

The self-similar phenomenon means that the traffic had similar statistical properties at a range of timescales: milliseconds, seconds, minutes, hours, even days and weeks. The merging of traffic streams, as in a statistical multiplexer, does not result in smoothing of traffic, in other words, burst data streams that are multiplexed tend to produce a bursty aggregate stream. Consequently, the traffic can be described by the mathematical property called, long-range dependence, which can be characterized that the correlation function of the traffic process is a heavy-tailed distribution. A stationery process is long range dependent if its autocorrelation function is infinite.

The self-similar traffic can be generated by using the Gaussian distribution and its property of long-range dependence on autocorrelation function. Most of the stochastic models for self-similar traffic are based on Fractional Brownian Motion [12][13].A self-similar process is a random process with a given scaling factor and self-similarity index, Hurst parameter *H*. The generation of self-similar traffic traces using Wavelet transform is described in the following section.

5. TRAFFIC PREDICTION MODEL

The traffic prediction can be done by linear model or non-linear model. But linear model suffers from inaccuracy and hence non-linear prediction models are preferred. The non-linear traffic prediction models include Wavelet transform model, neural network model, etc. The wavelet transform model for traffic prediction has better accuracy but it cannot be used to predict real time traffic since wavelet transfer does not have real time characteristics of the traffic. But neural network has the ability to train up from real time traffic trace and to predict the real-time traffic in advance. Thus the combination of Wavelet transforms model and neural network model solves the problem of real time traffic prediction with better accuracy. In the combined model of Wavelet Neural Network traffic prediction, the wavelet function is used in hidden layer of the neural network. The scale and translation parameters in wavelet model are represented as the weight value and threshold value respectively in neural network.

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Suppose that nonlinear time series transform function is $f(t) \in L^2(R)$ the wavelet transform is defined as,

$$\psi_{xy}(t) \geq |x|^{-1/2} \int_{-\infty}^{+\infty} f(t)\psi\left[\frac{t-y}{x}\right]dt . \tag{4}$$

Because the multiscaling functions have finite support, the approximation of any $f(t) \in L^2(R^d)$ is denoted as,

$$f_{P,Q}(x_1, x_2 \dots x_n) = \sum_{\sigma(d)\in\Gamma_n} \sum_{K_p \in J_M} C_{Q.K}^{\sigma(d)} \prod_{m=1}^{d} \phi_{P,k_m}^{\sigma_m}(x_m) \tag{5}$$

where, ***k= (k₁,k₂,...kₙ)***

$$\Gamma_n = \{\sigma_1 \oplus \sigma_2 \oplus \dots \sigma_n\}$$

$\phi_{P,k}^{i}(x) = 2^{P/2}\phi_i(2^P x - k); P, k \in \mathbf{Z}$ is the multi-resolution function to construct multiwavlets.

Since the equation has a linear-in-parameter structure which can be realized by a neural network, the coefficients C_{QK} can be represented as the weights of the neural network called wavelet neural network(WNN) for r=1, and multiwavelet neural network for r= 2. The proposed multi wavelet neural network (MWNN) is made of three layers: the input layer, the hidden layer, and the output layer. Suppose the support of φ(x1, x2,…xd) is $[0, u]^d$ and the support of the approximated function F is $[0, 1]^d$ then the number of nodes in the hidden layer must be $r(2M+u-1)^d$ and the set of threshold values should be $J_M = \{-u+1,\dots, 2M-1\}$.

5.1. Traffic Prediction Model Using Wavelet-Neural Network

The input layer of the neural network model consists of k inputs; each input has k values of the time series. There are n neurons on the hidden layer and the output layer consists of one neuron. The output neuron can give a k+1th time series prediction value. The weight value w_{ij}^m represents the scaling parameter in wavelet transform. This value is between neuron i on layer m-1 and neuron j on layer m.

Neural network has the ability to map any nonlinear and non-stationary function with high degree of accuracy. Radial basis function network is a single hidden layer feed forward neural network. Each node in the hidden layer has a parameter vector called as center. These centers are used to compare with network input and produce radically symmetrical response. These responses are scaled by connection weights of the output layer and then produce network output, where Gaussian basis function is used and given by

$$G = \sum_{i=1}^{n} w_i \exp\left[-\frac{\|(y-\mu_i)\|}{2\sigma_i}\right] , \tag{6}$$

where σ_i is the dimension of the influence field of the hidden layer neuron, y and μi are input and prototype vector respectively. The Recurrent Radial basis function network (RRBFN) considers the time as an internal representation and the non-stationary aspect of nonlinear function can be obtained by having self-connection on the input neuron of sigmoidal firing function and the recurrent weights are in the range [-1 , +1], with Gaussian distribution. This is a special case of locally recurrent, globally feed forward neural network. The RRBFN output for Gaussian basis function is given by

$$G(n) = \sum_{i=1}^{n} w_i \exp\left[-\frac{\sum_{j=1}^{m}(y^j - \mu_i^j)^2}{\sigma_i}\right], \tag{7}$$

where $G(.)$ is the predicted time series, n is the number of step prediction and j is the number of neurons in the input layer of RRBFN system, the architecture of RRBFN model is shown in Figure.

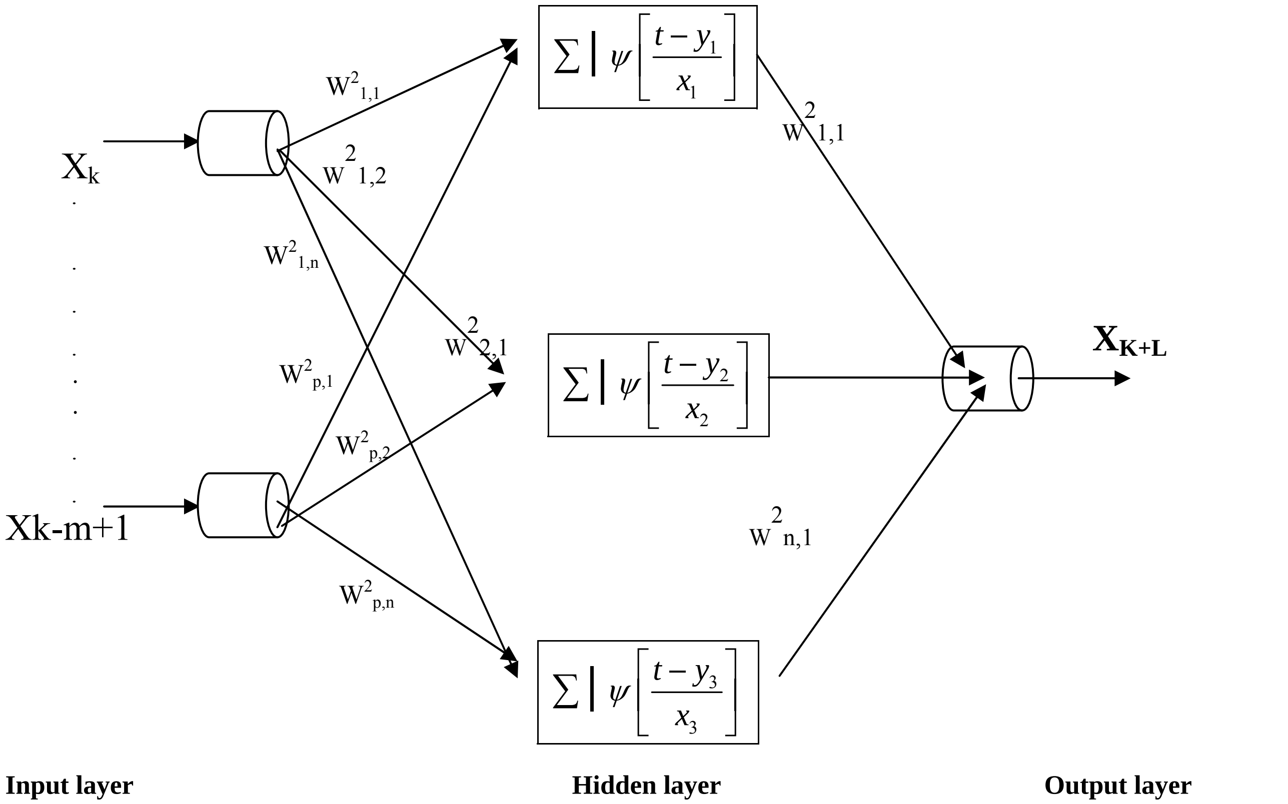

Fig 3. Wavelet Neural Network Traffic Model

The Recurrent neural network with standard gradient decent algorithms will provide better function approximation for a short time step. The RRBFN network has three layers: input, hidden and output. Here 300 neurons in the input layer with sigmiodal activation function and with the recurrent connections, the range of recurrent weights are -1 to +1. The hidden RBF layer has 175 neurons with RBF activation and output layer has single neuron with linear activation. Spectral radius is set to 0 and all the layer neurons have sigmoidal activation function.

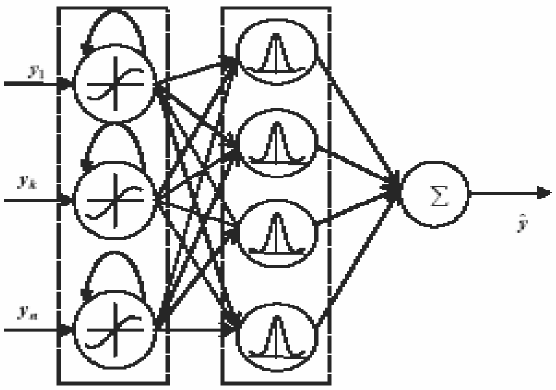

Fig 4. Architecture of RRBFN model for Traffic prediction

5.2. Traffic prediction with Wavelet Transform Model

Wavelet analysis of a time series with N data points ($N = 2^n$) can be easily expressed in complete binary tree form. The finest grain scaling coefficients are derived directly from empirical time series, using $C(k) = 2^{n/2}$ *Un,k. The Coarser-grained values are computed recursively upwards using the following expressions.

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$$Uj-1,k = 2^{-1/2}(Uj,2k + Uj,2k+1)$$
$$Wj-1,k = 2^{-1/2}(Uj,2k-Uj,2k+1)$$

Topmost scaling coefficient represents mean of empirical time series. Wavelet coefficients capture the behavioral properties of the time series. Suppose the initial empirical time series of interest has N = 8 observations in it as follows.

15 9 12 6 10 15 7 14 (mean = 11.0)

Wavelet transform can construct binary tree representation of the signal as follows.

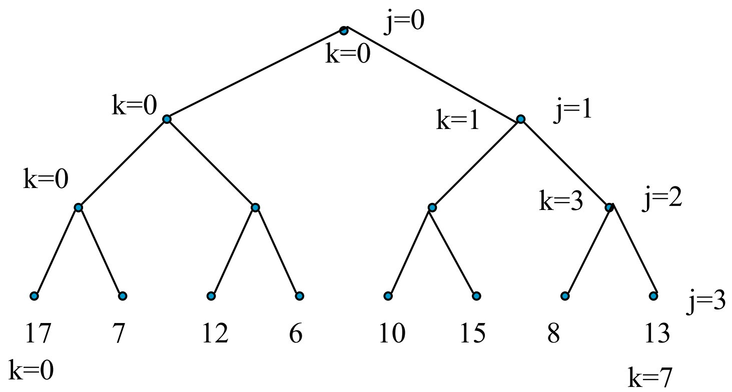

Fig 5 Binary Tree representation of Traffic Time series

The wavelength coefficients can be calculated as follows.

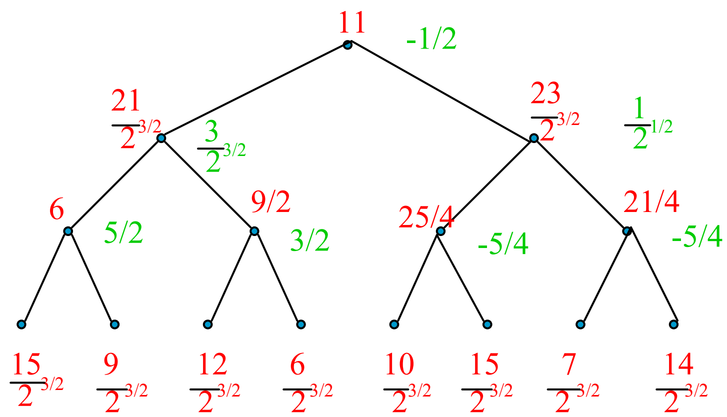

Fig 6 Wavelet Transform representation of Binary Tree

The original time series can be constructed exactly in a top-down approach using only the wavelet coefficients and mean.

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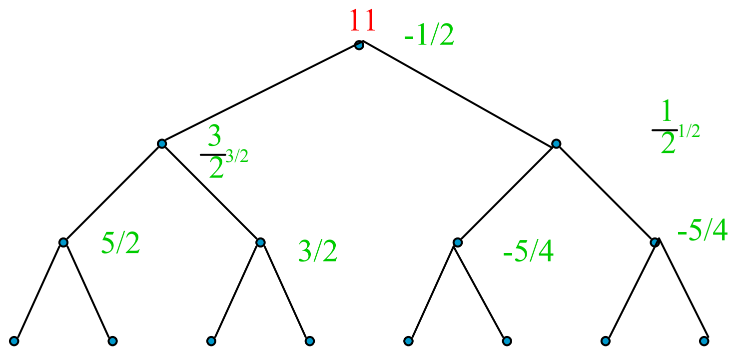

Fig 7 Wavelet Coefficients of Binary Tree

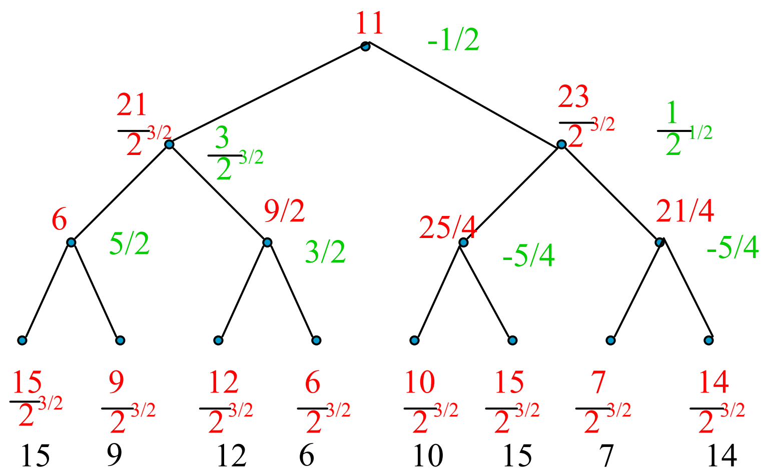

Fig 8 Constructing Traffic series using Wavelet coefficients and Mean

5.3. Wavelet-Based Traffic Model

The time series can be reconstructed exactly by using the existing wavelet coefficients, and the initial mean value. To generate something that "looks like" the original time series, it suffices to use Wj,k values from a similar distribution. Compute mean and variance of Wj,k's at each level of the binary tree as follows.

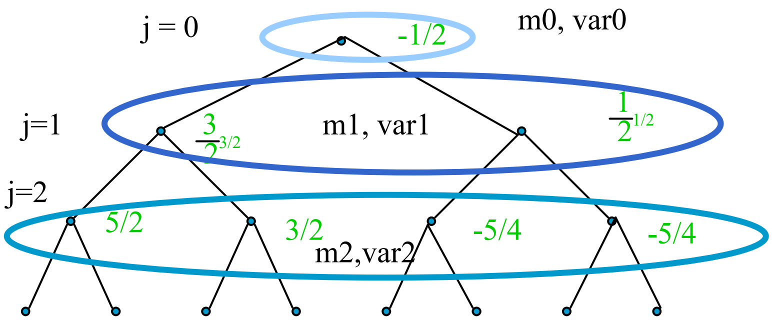

Fig 9 Computation of mean and variance of Binary Tree

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In compact representation, only the mean and variance of the wavelet coefficients at each level of the tree are sufficient rather than all the coefficients. Even more compact representation needs the variance needs to be stored since the mean of the wavelet coefficients tends to zero at each level of the tree. Define Aj,k is the normalized wavelet coefficient, Aj,k = Wj,k / Uj,k; Aj,k ≤ 1. By generating random Aj,k values from a specified distribution, one can generate synthetic time series with desired variance across many time scales. For traffic synthesis using the Multi Wavelet Model (MWM) approach, it is desired with "seeding" level j=5 of the binary tree with Gaussian values of desired mean and variance, and then applying the remaining traffic generation steps. Thus, Wavelets offer a flexible and powerful traffic modeling technique that is able to capture short-range and long-range traffic characteristics, including correlations in the time domain.

6. PERFORMANCE MODELS

The performance models can be described well by, QoS models.

6.1. For Poisson- i.i.d. Traffic Model

The independent and identically distributed (i.i.d) traffic model assumes uniform distribution between 0 and a maximum traffic density. It uses Erlang B traffic model with the following assumptions for modeling QoS parameters.

i. The packet arrivals are uniform and Poisson distributed at a rate of λ
ii. The packet inter-arrivals are exponentially distributed
iii. The packet service at a rate of μ
iv. Blocked calls are cleared

Following the above assumptions, the Erlang loss formula [12] is given by,

$$P_0 = \frac{A^C}{C!\sum_{n=0}^{C}\frac{A^n}{n!}} \quad , \tag{8}$$

which gives the blocking probability model for the IP-over-WDM network, where C is the channel capacity of one wavelength. Including the blocking due to reconfiguration, the total blocking probability is written as follows.

$$B = \frac{A^C}{C!\sum_{n=0}^{C}\frac{A^n}{n!}} + \left(1-\frac{l_d}{N}\right)^h\left(1-\frac{A^C}{C!\sum_{n=0}^{C}\frac{A^n}{n!}}\right)e^{t-t_0} \quad , \tag{9}$$

where A is the traffic load (λ/μ) in erlangs
C is the channel capacity of one wavelength.
N is the number of nodes in the network
l_d is the no.of lightpaths to be deleted or added
h is the number of hops between source and destination
t_0 is the initial time; t is the time at which reconfiguration is done

The latency of the network is delay incurred by the data packet from a source node to destination and is given by,

$$\text{Latency} = D_q + D_p + D_t + D_r + D_{rc} \quad , \tag{10}$$

where,

$$D_q\text{: Queuing delay} = \sum_{ij} \sum_{sd} T_{ij}^{sd} \frac{1}{\left(C - \sum_{sd} T_{ij}^{sd}\right)}, \tag{11}$$

where, T_{ij}^{sd} is the traffic demand between *sd* pair using link *ij*.

$$D_p\text{: Propagation delay} = \sum_{ij} T_{ij}^{sd} d_{ij} p_{ij} \ , \tag{12}$$

where,

d_{ij} is the distance between. end points *i and j*

p_{ij} is the physical link between end points *i and j*.

$$D_t\text{: Transmission delay} = \frac{packet\ length\ l}{channel\ bit\ rate\ r}, \tag{13}$$

$$D_r\text{: Processing delay} = \frac{1}{\left(\Re - \left(T_{sd} + X_i\right)\right)} \tag{14}$$

where,

$\Re$ is the processing capability of router in Mbps

T_{sd} is the traffic demand between a *sd* pair

X_i is the sum of traffic routed by router *i* except the traffic originating at the node *i*., and is given by,

$$X_i = \left[\sum_j T_{ji} + \sum_j T_{ij} + \sum_j T_{sd} \beta_{ij}^{sd} \right] - Tij, \tag{15}$$

D_{rc}: Reconfiguration delay .

6.2. For Traffic Cluster Model

Assuming the Poisson distribution for the uniform nature of the traffic and other assumption as made in the previous section, the QoS parameters will have the expressions as given earlier.

6.3. For Self-similar Traffic model

Considering the dynamic self-similar traffic, where lightpath requests arrive randomly to the network based on stochastic process, normal distribution. The following are the assumptions on the self similar traffic model used in our simulation study.

1) Calls arrivals are Gaussian process with a rate of λ.
2) Call holding times exponential with a mean of μ =0 and standard deviation σ =1.
3) Destinations are randomly generated with *normal traffic distribution (NTD).*
4) Calls that cannot be routed in the network are blocked and lost.
5) The capacity of the links, denoted by *C*, is the same for all the links in the network.

The simplest self similar model with long-range dependence is characterized by a single parameter called Hurst parameter. The blocking probability for a link using self similar traffic model is given by

$$P_b = \left[1 - (1 - \rho^w)^H\right], \tag{16}$$

where ρ probability for blocking for one wavelength link,

w is the number of wavelengths and

H is the number of hops in the particular link.

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The Blocking probability for the entire network is given in equation 3.5

Average delay encountered by a traffic burst is approximated in the equation 3.6

$$B = \frac{\sum_{s,d} A_{sd} P_b^{sd}}{\sum_{s,d} A_{sd}}, \tag{17}$$

where A is the traffic load; P_b is the blocking probability as given in 3.4.

The average delay for the traffic burst is approximated as,

$$Latency\ D = PD * MBS \sim c_m PD * MBS^{2-ß} \tag{18}$$

Where PD – Packet delay

MBS –Maximum Burst Size; C_m – Constant due to the tail component of the series

β is the tail component, $Tail\ ß = 1 + \alpha_0(\alpha - 1)$, where α_0, α- are power exponents

C_m is constant due to the Hurst Parameter $H=1-\lambda_g/\lambda_p$, *where* λ_g is the gaussian pulse amplitude

λ_p is the peak pulse amplitude. Alternatively, H=1-β/2 is called Hurst parameter.

Throughput of the network is defined as the total traffic load in the entire network which is given by

$$\text{Throughput } \tau = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} T_{ij} \ . \tag{19}$$

The utilization of the network is given by

$$\text{Utilisation } U = \frac{\textit{No. of WDM channels utilised}}{\textit{Total no. of WDM channels available}} \tag{20}$$

7. HEURISTIC ALGORITHMS

As the problem of VTR is computationally intractable and it is proved as NP hard with increasing N, it is proposed heuristic algorithms to solve VTR problem for larger N. In this section, we present heuristic algorithms for VTR driven by QoS parameters respectively blocking probability, network delay and throughput.

7.1. Proactive VTR Algorithm

The proactive VTR is composed of the following algorithms.

i. Blocking Parameter driven VTR Algorithm
ii. Differential Traffic Driven VTR Algorithm

7.1.1. Blocking Parameter Driven VTR

The blocking parameter driven VTR predicts the future traffic and estimates packet loss and hence the blocking probability. If the blocking parameter is greater than the threshold, VTR algorithm is called. This algorithm aims to reduce packet loss or blocking probability.

Input: Physical Topology; Current Virtual Topology, Traffic Demands
Output: Reconfigured Virtual Topology

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Algorithm:

for all sd pairs
*compute : WHT=T_{sd}*H_{sd};*
end for
sort sd pairs in non-increasing WHTs
for all sd pairs
compute shortest paths using all- pair shortest path algorithm
if no lightpath exists
if free wavelength available
if free transceiver available
establish lightpaths
else lightpaths deletion:
find different set of lightpaths to be deleted
sort lightpaths in non-decreasing order of load
delete the first lightpath in the set
establish lightpaths
if the topology is connected then break;
else continue
compute B for the new topology
if (B_{new}<B_{th})
if (N_{ch}< N_{th}) include the new topology in to VT set
else discard the new topology
end for
select the VT with min B

7.1.2. Differential VTR Algorithm

The differential traffic driven VTR computes the virtual topology based on the difference of the current traffic and future predicted traffic. If the differential traffic demand between a soured destination (*sd*) pair lies within a minimum range, then no new lightpath is established for the particular *sd* pair. The addition of new lightpaths will be done for the *sd* pairs having differential traffic higher than the minimum value. Thus, this approach reduces computation time for VTR and hence reduces the transition delay since it avoids unnecessary changes in the virtual topology.

Input: Physical Topology; Current Virtual Topology, Current Traffic Demands, Previous Traffic demands

Output: Reconfigured Virtual Topology

Algorithm:

1. *for all sd pairs, compute, differential traffic T^{diff}_{sd} = Abs($T_{sd}(t)$ - $T_{sd}(t-1)$)*
2. *for all sd pairs, compute, weighted hop count: WHT=T_{sd}*H_{sd};*
3. *Sort all sd pairs in non-increasing order of their differential weighted hop count DWHT = T^{diff}_{sd} * WHT*
4. *For the given VT, Compute AWHT=Sum(T_{sd}*H_{sd})/Sum(T_{sd})*
5. *For each sd pair from the sortedlist,compute shortest paths using all- pair shortest path algorithm*
6. *If no lightpath exists on the path found, check if free wavelength available and free transceiver available along the path.If yes, then establishes lightpaths. Else lightpaths deletion:*
7. *Find different set of lightpaths to be deleted; sort lightpaths in non-decreasing order of load delete the first lightpath in the set and establish lightpaths.*
8. *If the topology is connected then compute AWHT for the new topology*
   if ($AWHT_{new}$<$AWHT_{old}$) and
   if (Nch<limit)
   include the new topology in to VT set
   Else discard the new topology
9. *Repeat this procedure for all the sorted sd pairs*
10. *Select the VT with minAWHT*

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The flow diagram for the proactive VTR with QoS parameters is shown in fig 10.

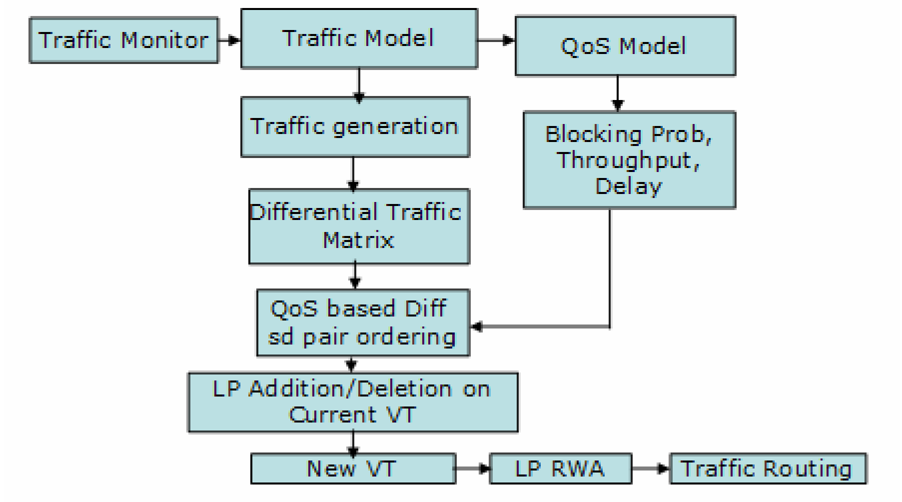

Fig 10 Flow diagram of Proactive VTR Algorithm

The devised proactive VTR heuristic algorithm has the following phases.

i. Traffic modeling
ii. QoS modeling
iii. Deletion of unused lightpaths
iv. Addition of new lightpaths to carry QoS Traffic
v. Routing and Wavelength Assignment for the lightpaths
vi. Traffic Routing for all source –destination (*sd*) pairs

The traffic modeling uses normal traffic distribution described in 4.3.. The traffic generation uses wavelt neural network model based traffic prediction as described in section 5.1. The QoS model monitors QoS parameters namely blocking probability, latency, throughput and utilization as described in section 6.3. Differential traffic matrix generation and QoS based sd pair ordering make use of the algorithms given in section 7.1.1 and 7.1.2 Lightpath addion and deletion are performed using these algorithms to yield new virtual topology after reconfiguration.

8. RESULTS AND DISCUSSION

8.1. Network Model

We consider a network of *N* nodes (B.Mukherjee et al., 1996) connected by bi-directional optical links forming an arbitrary physical topology. Each optical link supports *w* wavelengths, and each node is assumed to have *T* transmitters and *R* receivers. We assume that each node is equipped with an optical cross connect (OXC) with full wavelength conversion capability, so that a lightpath can be established between any node pair if resources are available along the path. Each OXC is connected to an edge device like an IP router, which can be a source, or a destination of packet traffic and which can provide routing for multi hop traffic passing by that node. Our network model considers network with an initial traffic matrix and reconfiguration decisions are based on traffic changes whenever such changes are necessary.

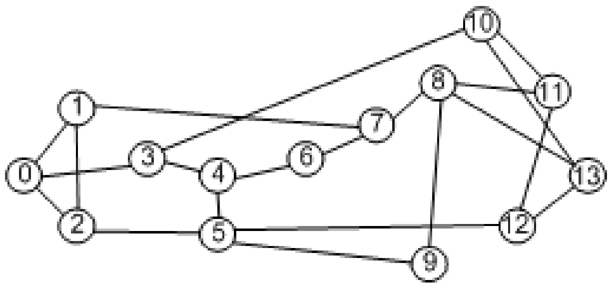

Fig 11. a) NSFNET with 14 nodes

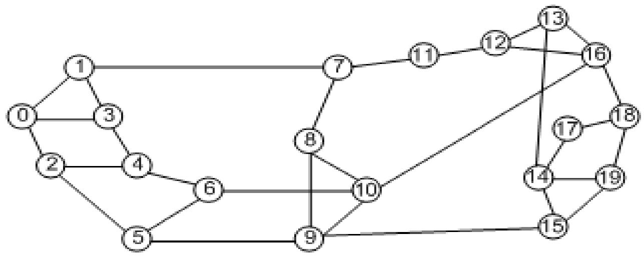

Fig 11. b) ARPANET with 20 nodes

8.2. Network Parameters for Simulation

i. Number of wavelengths per link, w =10
ii. Capacity of each wavelength C = 1 unit
iii. Packet arrival rate: 1024 pkts per sec
iv. Traffic Load = 10 to 100 Erlangs
v. Packet size = 512 bits
vi. Channel bit rate = 1Gbps
vii. Propagation delay = 1 μS
viii.Distance between nodes = 1 unit

8.3. Validation of Traffic Model

In this section, we validate the traffic model proposed. The Poisson traffic and Gaussian traffic are generated by using Java methods. The traffic estimates are compared with the real time traffic traces averaged over a period of an hour for the duration of 8 hours of a day. The generated traffic for iid Poisson model, traffic cluster model and for Gaussian traffic model are tabulated respectively in table 1, table 2 and table 3. It is observed from the table 1, the Poisson traffic model over estimates the future traffic and hence the error in the traffic computation is up to the maximum of 27.9 %. But with NTD, the estimated traffic values are very close to the real time traffic values and hence less error to the maximum of 3.4% only. Hence the new traffic model devised using NTD with Wavelet neural network model is validated using simulation. The simulation results for NSFNET and ARPANET show that the new model computes the future traffic values with high accuracy, which holds true for any other topologies.

Table 1 i.i.d Poisson traffic vs real time traffic

i.i.d traffic (Mbps)	55	51	53	56	52	48	40	33
Real-time traffic (Mbps)	43	42	44	44	45	40	34	28
Error %	27.9	21.4	20.45	27.45	15.5	20	17.6	17.85

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Table 2 Traffic cluster vs real time traffic

Traffic cluster (Mbps)	72	63	48	90	65	61	55	47
Real-time traffic (Mbps)	81	88	57	96	72	72	65	67
Error %	11.11	28.4	15.78	6.25	9.72	15.27	15.38	29.85

Table 3 Gaussian traffic vs real time traffic

Gaussian traffic (Mbps)	4.45	4.31	4.43	4.5	4.4	3.9	3.35	2.8
Real-time traffic (Mbps)	4.3	4.22	4.4	4.41	4.5	4.0	3.45	2.88
Error %	3.4	2.13	0.6	2.04	2.22	2.5	2.85	2.77

8.4. Evaluation of VTR Heuristics

The heuristic algorithms for VTR are implemented using **Java (**Sartaj Sahni, 2007) to generate dynamic virtual topologies. The generated virtual topologies are tested using **Hegons** for observing the traffic routing and blocking performance. The probability computation is done with using **MATLAB**. The performance of the devised heuristic for VTR with QoS is studied in terms of QoS parameters respectively Blocking probability, Latency and Throughput.

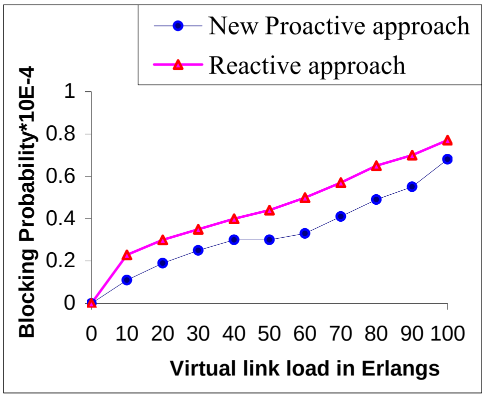

Fig 12 Blocking probability vs % Traffic load

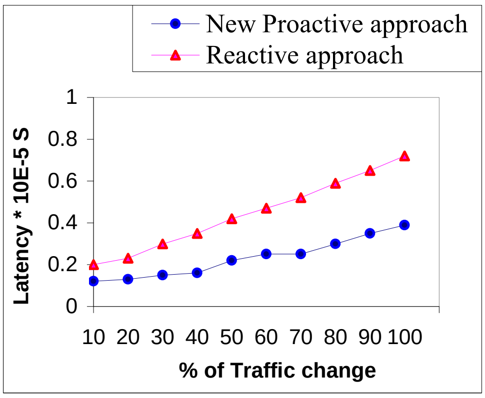

Fig 13 Latency vs % Traffic change

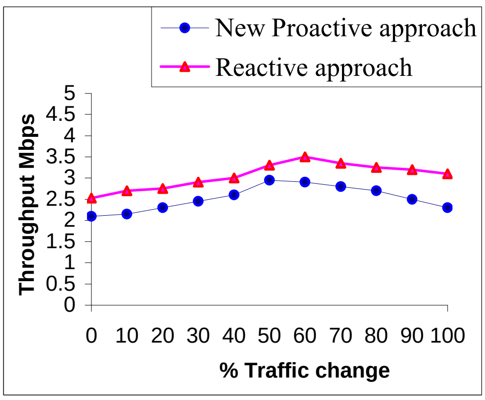

Fig 14 Throughput vs % Traffic change

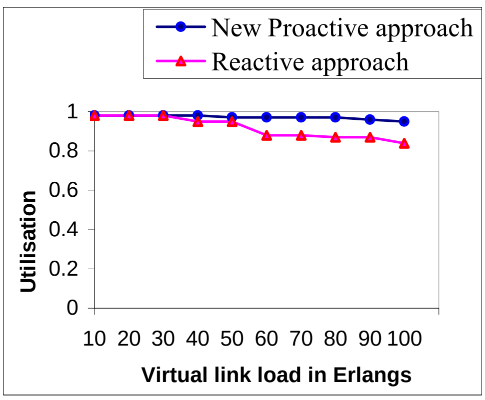

Fig 15 Utilisation vs Virtual link load

The blocking probability measured for different virtual load of the dynamic network for *i.i.d* traffic model is plotted in the fig. 12. From this graph, it is observed that the blocking probability is much less than the result obtained with reactive approach (Den-Rong, 2009). Thus the blocking rate

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of the proposed heuristic for the *i.i.d.* traffic model is considerably less than that of the existing approach. The network latency measured by varying percentage of change in traffic for dynamic network with gaussian traffic model is plotted in the fig. 13. From this graph, it is observed that the network latency is minimal compared to the reactive approach (Den-Rong, 2009).

The network throughput measured for various levels of traffic change for gaussian traffic model is plotted in the fig. 14. From this graph, it is observed that the network throughput of the proposed VTR heuristic for the gaussian traffic model is significantly better than that of the existing approach. The network utilisation measured for different virtual load of the dynamic network for the gaussian traffic model is plotted in the fig. 15. From this graph, it is observed that the network throughput of the proposed VTR heuristic for the new traffic model is significantly better than that of the existing approach.

8.5. Validation of QoS Model

Assuming the parameters listed in section 8.2, the QoS model devised in 6.3 is validated for the QoS parameters as follows. The analytical model described in section 6 has been used for theoretical evaluation of blocking probability, latency, throughput and utilization. The blocking probability values computed for increasing traffic loads and the corresponding simulated values are tabulated in table 4. Observe from this table 4, the blocking probability values computed are very close to the simulated one. Further, the network utilization computed using the analytical model and the corresponding simulated values are close to each other. The simulation results for NSFNET and ARPANET show that the new devised QoS model has better performance such as Blocking probability, latency, throughput and Utilization which hold true for any other network topologies.

Table 4. Traffic load vs blocking probability

Traffic Load *A* (Erlangs)	10	20	30	40	50	60	70	80	90	100
Blocking Probability *B* x10^{-4} (using analytical model)	0.10	0.16	0.22	0.27	0.29	0.31	0.38	0.46	0.51	0.65
Blocking Probability *B* x10^{-4} (using simulation)	0.11	0.19	0.25	0.3	0.3	0.33	0.41	0.49	0.55	0.68

Table 5. Traffic change vs latency

Traffic change (%)	10	20	30	40	50	60	70	80	90	100
Latency *D* x10^{-4} S (using 3.6)	0.096	0.10	0.12	0.135	0.18	0.21	0.22	0.255	0.27	0.293
Latency *D* x10^{-4} S (using proactive VTR)	0.12	0.13	0.15	0.16	0.22	0.25	0.25	0.3	0.35	0.39

Table 6. Traffic change vs Throughput

Traffic change (%)	10	20	30	40	50	60	70	80	90	100
Throughput in Mbps (using analytical model)	2.67	2.85	2.96	3.11	3.2	3.43	3.65	3.77	3.83	3.96
Throughput in Mbps (using simulation)	2.7	2.75	2.9	3	3.3	3.5	3.35	3.25	3.2	3.1

Table 7. Traffic load vs Utilisation

Traffic Load *A* (Erlangs)	10	20	30	40	50	60	70	80	90	100
Utilisation (using analytical model)	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.97
Utilisation (using simulation)	0.98	0.98	0.98	0.98	0.97	0.97	0.97	0.97	0.96	0.95

From the tables 4, 5, 6 and 7 observe that the QoS model and simulation results are correlating with analytical results in terms of blocking probability, latency, throughput and utilisation. Thus the devised QoS model for the IP-over-WDM networks is validated.

9. CONCLUSIONS AND FUTURE WORK

A survey of previous researches shows that the internet traffic cannot be best represented by using Poisson distribution. Instead, it exhibits self-similar property with long-range dependence on its auto correlation function. In this research work, an algorithm is proposed for the proactive Virtual Topology Reconfiguration with considering QoS parameters for Multihop IP-over-WDM optical networks with gaussian traffic model. The new traffic model uses wavelet neural network based traffic prediction. The Gaussian traffic model predicts the traffic with less than 3.4% of error. The proposed heuristic approach was validated for NSFNET with 14 nodes using simulation. The simulation results show that the new approach achieves better QoS in terms of blocking probability; throughput and latency for the proposed Gaussian traffic model for dynamic IP over WDM networks, compared to the existing reactive approaches (Den-Rong, 2008 and 2009). Thus Self similar traffic model predicts the real time traffic with better accuracy, compared to Markov model like Poisson traffic model. Further, the devised QoS model is also validated using simulation; the results are correlating with each other.

The future work includes devising VTR algorithms for Traffic Grooming capable GMPLS over IP-over-WDM networks, devising VTR algorithms for distributed GMPLS networks with QoS and implementing the algorithms for the above stated GMPLS networks using GLASS.

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