Optical Network Modeling and Performance Using Random Graph Theory

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1 Introduction

The need for Internet traffic is increasing extremely quickly in the telecommunications world of today. The continuous expansion of data-centric applications has increased the requirement of higher bandwidth. Among various techniques, the key method that might be helpful when creating networks to meet the growing need for bandwidth is optical packet/burst switching. This technology is regarded as the future technology due to its high bandwidth utilization, low latency, and high throughput [1, 2]. Switches used in optical network implementation might be entirely optical or electrical in design. Switching's primary goal is to direct the packet to the proper destination port. The main challenge with an optical network is designing a switch and router configuration that can successfully conduct switching operations at high data speeds. Due to the infeasibility of optical processors, the present technology uses a blended method in which control operations are carried out by electronics while data propagates in the optical domain. This mix method is known as photonic packet switching technology. The control operations of big photonic packet switches in the photonic packet switching technology are likely to be handled by electronics, while packet routing and buffering are done optically [3, 4].

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B. K. Roy et al. (eds.), *Cryptology and Network Security with Machine Learning*,
Algorithms for Intelligent Systems, https://doi.org/10.1007/978-981-99-2229-1_8

A number of multinational companies are working on the highly demanding cloud computing. Network connectivity and dispersed computing resources are the two concepts that appear most frequently in descriptions of cloud computing. These two problems have drawn a lot of attention in recent years across a wide range of industries, concurrently with the Internet's enormous popularity and the increasing demands for processing enormous amounts of data, including the big data idea [5]. The concept of "big data" is used to describe the exponential rise in the amount of information that is available and utilized from a variety of sources.

The role of transport network is quite crucial component in the cloud computing concept because it connects disparate computer resources. The rapid growth of cloud computing necessitates a rigorous evaluation of the present network infrastructure from the standpoint of cloud computing demands. The demands of cloud environments cannot be effectively met by the present transport networks as per [6]. Three needs are specifically highlighted by the authors of [6] for transport networks that are cloud-ready.

- It must be flexible enough to provide the necessary capacity as needed.
- Multilayer-focused network administration.
- Cross-strata features that allow for cooperative resource optimization of the cloud-based application's resources and the connectivity-supporting underlying network.

Additionally, current networks are primarily designed to handle unicast (one-to-one) traffic, whereas various cloud computing applications generate novel traffic patterns like anycast (one-to-one-of-many) flows. When processing is subsequently concentrated in a limited number of locations (data centers), we may have a significant increase in the volume of traffic on network links around these locations, necessitating the use of high-capacity network technology.

The optical communication technology has the capacity to deal with cloud computing issues. This paper investigates the networking modeling using the random graph theory.

2 Related Works

In optical networks, nodes are connected via fiber links and data propagates on different wavelengths. At each node wavelengths are separated and passed through the switch and after dropping, buffering they again appear at the output of the switch where they are combined and pushed into the networks (Fig. 1) [7, 8]. Without wavelength conversion, the switching functionality cannot be fully achieved and the optical network's performance goes down as shown in [9, 10]. The light path maintains the same wavelength on all of the fiber links it uses if wavelength conversion is not possible; this leads to underutilized channel capacity. By allowing a link to utilize multiple wavelengths along its course, wavelength conversion enhances

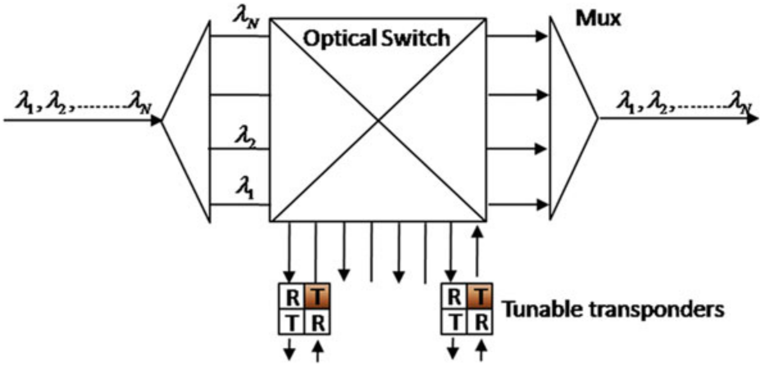


Fig. 1 Schematic representation of node design in optical networks

network blocking performance [6]. It is important to note that the cost of full wavelength conversion at each node is very high, therefore limited wavelength conversion is also considered [6].

Wavelength converters are only present in a small portion of nodes in these networks [11–14]. The optical switches are connected to create optical core networks. Numerous optical switch architectures have been presented in the past. There is a lot of competition among the data packets, so different strategies are utilized to reduce packet drop. A buffer-less switch architecture proposed by Proietti et al. delivers a negative acknowledgement to the sender in the event of contending packets and conducts retransmission for conflicting packets [15]. A large number of packets will be sent again due to the buffer-less design. The network will see more traffic as a result of packet retransmission and negative acknowledgment. The resolution of contention and streamlined traffic flow are both aided by packet buffering.

The concept of fiber delay lines (FDLs) was born as a result of the lack of optical RAM. By including a sequence of set length delays where data are kept for a brief period of time, optical FDL buffering prevents contention [16, 17] (Fig. 2). Storage in FDL is extremely constrained because of noise build-up. Due to FDL's bulky design, a high size buffer is not practical, and packets that cannot be held are ultimately destroyed. As a result, use of electronic data storage as a substitute strategy was proposed. Electronic buffering is a technique for managing congestion in which conflicting packets are buffered into a single shared electronic buffer [18, 19] (Fig. 3). Complex and power-hungry components are required for an electronic loopback buffer, as well as numerous optical and electrical conversions. For the resolution of optical packet contention, several researchers have also proposed a hybrid buffering approach. For short-term packet storage, an optical buffer is used, whereas for long-term packet storage, an electronic buffer is used [18, 19]. During full wavelength conversion, the blocking likelihood is reduced by buffering competing packets. In actual situations, switches are put in networks. Packets must be added or removed in order to increase the optical network system's connectivity.

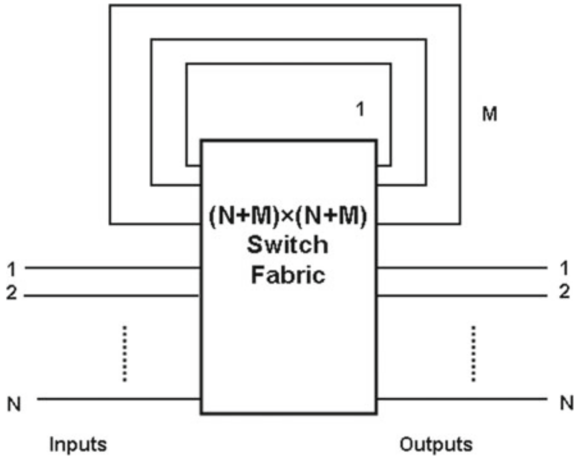


Fig. 2 Schematic representation of optical buffering using FDL

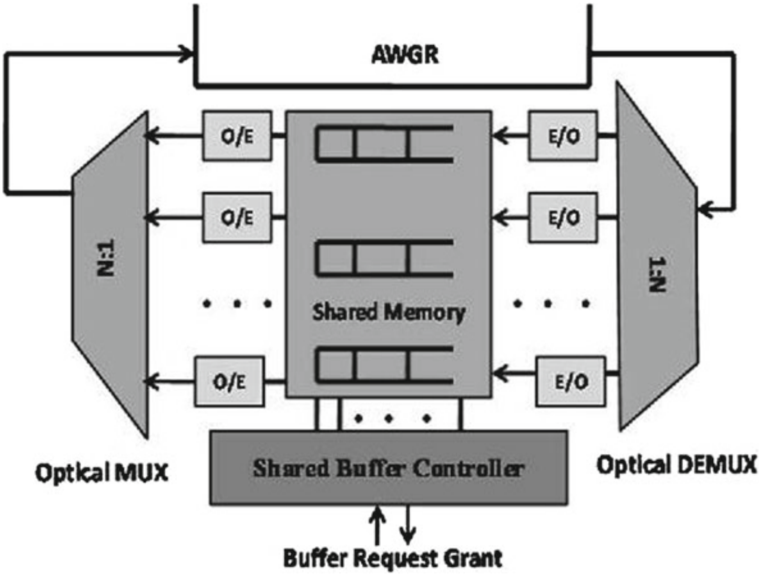


Fig. 3 Schematic representation of electronic buffering using FDL

The PLP of the switch is also examined under various loading and buffering circumstances. In the examination of blocking probability or PLP, load balancing is not taken into account. Using a load balancing approach can lower the likelihood of blocking and improve how network resources are utilized. By distributing traffic evenly over all of the network's links, load balancing prevents traffic jams on those links. By adopting load balancing, the number of wavelength converters deployed in the network can be decreased.

3 Random Graph Model

The random graph commonly regarded as the basic and oldest approach to modeling network behavior is Erds-Rényi model, [20, 21]. We make random distribution of 'n' nodes and add each node via an edge with probability 'α' in this model [22] $d = \frac{\log n}{\log \alpha (n-1)}$ is the normal geodesic distance is typically. For example, the average geodesic distance is 2 when $n = 10{,}000$ and $\alpha = 0.01$.

The given model proves to be ineffective because it is unrealistic for two nodes to link randomly in a real network. The following model was put out by Watts and Strogatz [23], who dispersed the nodes in a circle. In this model, each node is connected to both its closest and subsequent closest neighbors. Although this model is heavily clustered, it nevertheless deviates from small world features because on average a sizable number of nodes must be visited in order to link to random nodes. The authors suggested rewiring a few more wires linking some randomly picked nodes to shrink this globe. However, this model also misses a crucial aspect of actual networks.

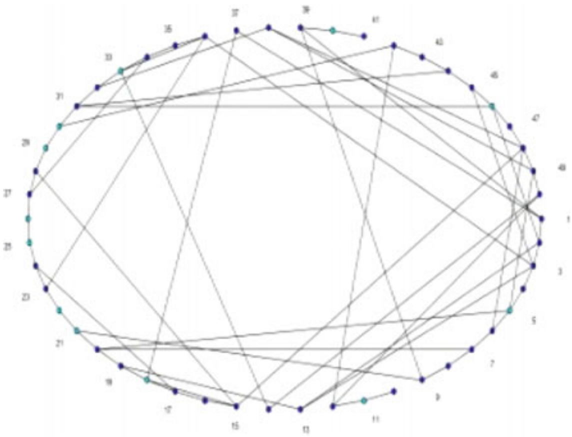
With 50 nodes and a rewiring probability of 0.2 or 0.5, respectively, the Erds-Rényi model is used in Fig. 4(a) and (b) to depict the network and linked nodes. Findings for 300 nodes are similarly displayed in Fig. 5(a) and (b) The greatest eccentricity of each graph vertex is known as the diameter of the graph. In other words, it is the distance along the longest, shortest path connecting any two graph nodes.

Figure 6 shows the relationship between diameter and node count for random graphs with $\alpha = 0$, Erds-Rényi model with $\alpha = 0$–1, and Watts and Strogatz with $\alpha = 1$. The graphic makes it evident that the diameter of a random graph rises linearly while it remains unchanged in the other two circumstances at a diameter value of 5–6.

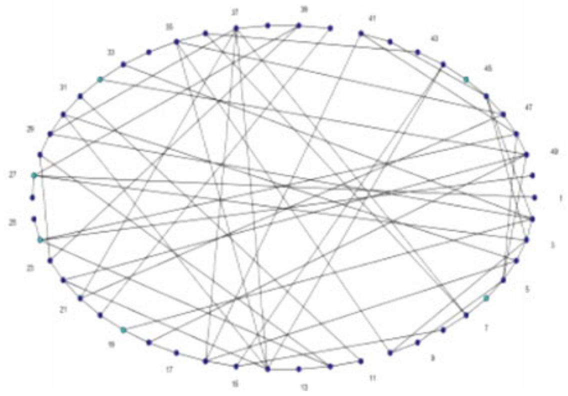
Figure 7 demonstrates how the number of nodes and the shortest path length interact in random networks, with $\alpha = 0$, Erds-Rényi model with $\alpha = 0$–1, and Watts and Strogatz with $\alpha = 1$. The graph demonstrates that the random graph's diameter increases linearly but in the other two circumstances, the dimension stays fixed at 4. Due to the fact that the diameter and shortest path between nodes would vary in a real-world network, neither of these models can adequately capture its features.

Barabási and Albert [24] presented an architecture based on two known facts about real networks: networks expand continually when new vertices are added, and these vertices connect specifically to locations that are now widely interconnected. A new node may link to a number of nodes in the current network at each time step in this approach, which assumes a modest number of nodes initially ($t = 0$). A node's degree determines how likely it is that new links will be added to it, therefore a node with a higher degree is more likely to do so.

Fig. 4 Schematic representation of random graph using Erdős-Rényi model, **a** $\alpha = 0.2$, **b** $\alpha = 0.5$



(a) α=0.2



(b) α=0.5

In a huge proportion of real networks, a normal approximation for the degree power-law exponent. The distribution of outward degree on the Internet is provided by

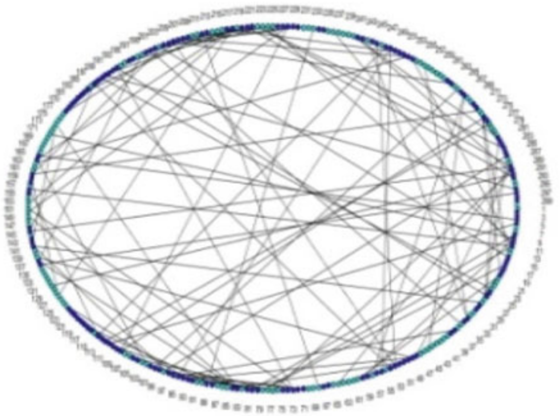
$$d(u) = au^{-\varsigma} 2.38 \leq \varsigma \leq 2.72 \tag{1}$$

The distribution of inward degree is represented as

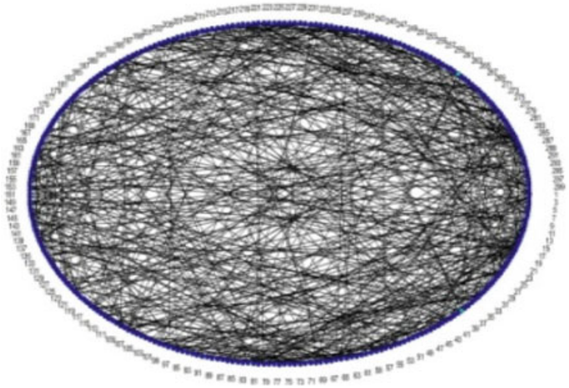
$$d(u) = au^{-\varsigma} \; \varsigma = 2.1 \tag{2}$$

The degree vs. fraction of nodes is plotted in Fig. 7. The figure makes it clear that nodes having a high degree are rare. A node having a degree of "1000" is highly improbable with a probability of 10^{-6}. The likelihood of an occurrence with a node degree of "10" is similarly extremely low (0.01). In real-time applications, more

Fig. 5 Schematic representation of random graph using Watts and Strogatz, **a** $\alpha = 0.2$, **b** $\alpha = 1$



(a) α=0.2



(b) α=1

incoming linkages than outgoing links have been observed. According to various values of, ζ the quantity of outbound links likewise fluctuates. Average degree is given by

$$\langle k \rangle = \sum_{k=1}^{\infty} k p(k) = \sum_{k=1}^{\infty} \frac{1}{k^{\gamma - 1}} \tag{3}$$

or

$$\langle k \rangle = 1 + \frac{1}{2^{\gamma - 1}} + \frac{1}{3^{\gamma - 1}} + \ldots + \ldots \tag{4}$$

The average node degree can be obtained by Eq. 4, for $\gamma = 2.1$ is 6.61, whereas the average node degrees for $\gamma = 2.38$–2.72 are 3.16 and 2.01, respectively. However,

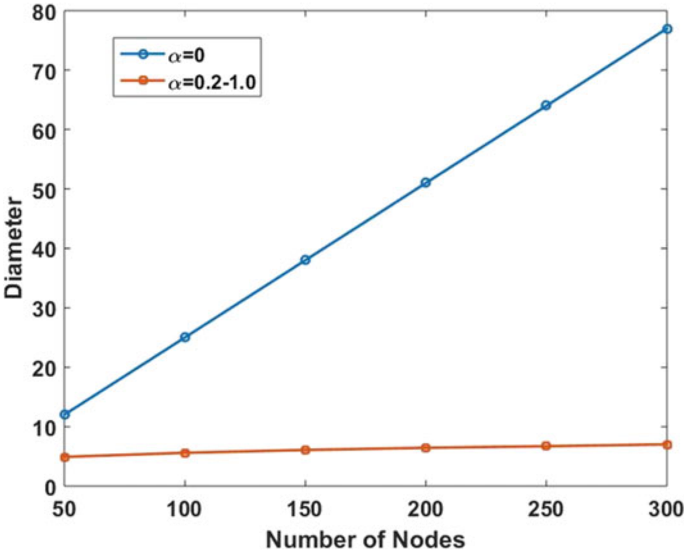


Fig. 6 Network diameter vs. number of deployed nodes for various random graph models

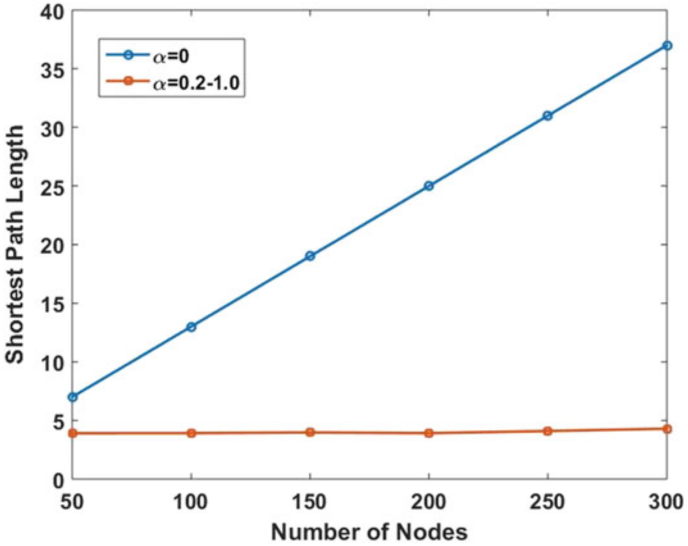


Fig. 7 Shortest path vs. number of deployed nodes for various random graph models

the Internet is generally a small world network (SSN) with an average degree of 4 and $\gamma = 2.2$ (Fig. 8).

The average shortest distance in the Leskovec et al., Web's experiment, which had 855,802 nodes, was 7, with a diameter of 21 [21].

As detailed above, the inward and outward degrees for networks lie between 2 and 4. Therefore various topologies are designed with minimum of 2 links and maximum of 4 links. In Fig. 9, USA, NSFNET topology is shown with 14 nodes and maximum node degree of 3. In Fig. 10, European Union, EON topology is shown with 28 nodes and maximum node degree of 5. These topologies are designed by considering various factors like geographical distance and wavelength routing criterion, etc.

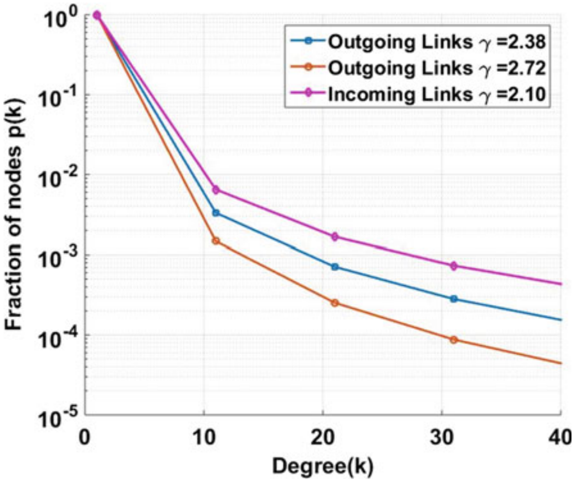


Fig. 8 Fractions of nodes vs. degree

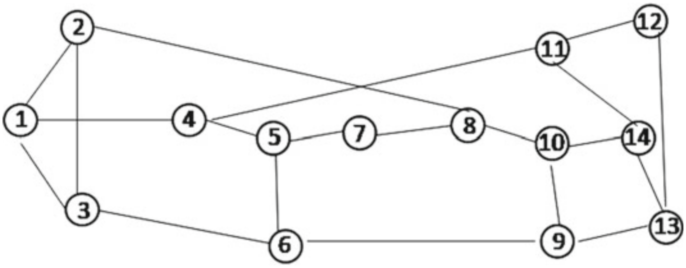


Fig. 9 Schematic of NSFNET topology (USA)

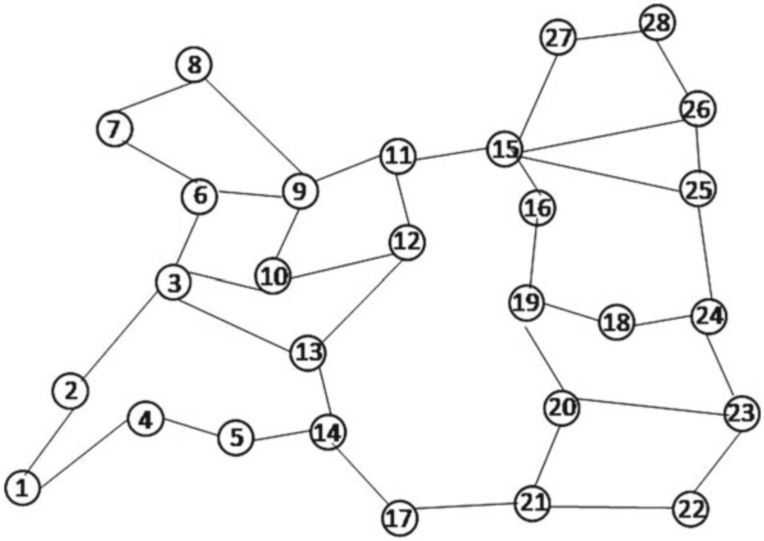


Fig. 10 Schematic of EON topology (European union)

4 Results

As already mentioned, a small-scale network has an average degree of 4, and hence we have to consider 4 input and 4 output links. The traffic model is considered to be random as detailed in [16]. Figure 11 plots PLP against load while varying the buffer from 0 to 16. Here, $B = 0$ makes it very evident that the switch is bufferless, meaning that the likelihood of packet loss is quite high. As a result, it can be concluded that intermediate switches require buffers and that even a little increase in buffer significantly lowers the likelihood of packet loss. Comparing results at the load of "0.6," the likelihood of a packet being lost for buffer-less switch is 0.21, and for the buffering of 4 packets is 1.4×10^{-3}, and the buffering of 16 packets is less than 10^{-6}. Hence, a buffer upgrade of 16 results in a 200,000 times improvement in packet loss efficiency.

Ultimately, various applications will necessitate varied packet loss rates as well as varying buffer sizes for various numbers of input links. If we require a packet loss probability of 10^{-4} at a load of "0.6," then maybe the necessary buffer for $N = 4$ is 6.

The maximum number of traversed nodes can increase to 21 as discussed above. As a result, overall packet loss will increase. Let on a node the packet loss is $\mathrm{P_L}$, then the throughput will be $(1 - \mathrm{P_L})$, and if data passes through "m" number of switches thus the overall throughput will be $(1 - \mathrm{P_L})^{\mathrm{m}}$. Thus, the final PLP after traversing through m node will be

$$P_L^m = \left[1 - (1 - P_L)^m\right] \tag{5}$$

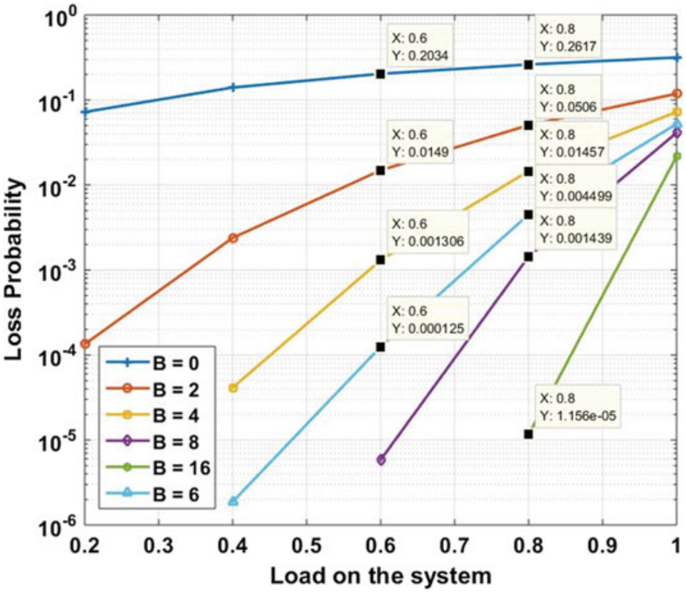


Fig. 11 Loss probability vs. load under varying buffer conditions

In Fig. 12, Effective loss probability vs. number of traversed switches is shown while considering PLP of a node as 10^{-3} and 10^{-4} respectively. It is clearly from the figure that the PLP nearly raises with the number of traversed nodes. For example, after traveling through the 10 nodes the effective PLP becomes 10 times. It can be understood from Eq. 5, as for the smaller value of P_L using the bi-nominal expansion the Eq. 5, can be written as

$$P_L^m = \left[1 - (1 - P_L)^m\right] = 1 - (1 - mP_L) = mP_L \tag{6}$$

The previous works deal with the packet loss performance of the individual switches. In this work packet loss performance of the cascaded switches is evaluated and it has been found that in the optical communication system where PLP is very less, the PLP of the cascaded switches rises linearly with the number of switches.

5 Conclusions

In the last several years, Internet usage has exploded. As a result, storage and heating issues are present with servers. Systems are switching from entirely electronic to hybrid technologies to deal with these problems. The design modeling of optical network is proposed by considering random graph theory. Various graph theory

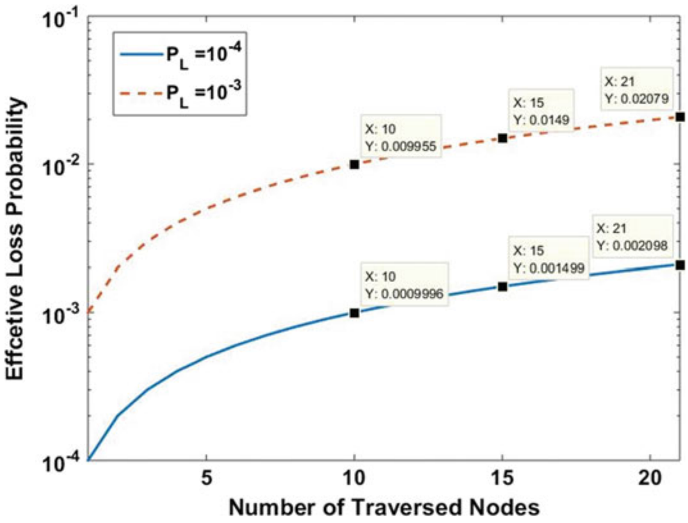


Fig. 12 Effective loss probability vs. number of traversed switches

models are discussed, and it has been found that the inward and outward degree in most of the nodes is 4. The number of cascaded switches is also evaluated. The simulation results are carried out to obtain the packet loss performance for an individual node and as well as for the cascade switches. It has been found that the PLP rises linearly with the number of cascaded switches.

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