Resource Dimensioning in WDM Networks under State-Based Routing Schemes

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***Abstract*— Network dimensioning for wavelength-routed WDM networks has been extensively studied to maximize connection acceptance rate while minimizing the total cost. However, Internet services are increasingly generating more demands that have high-bandwidth requirements with relatively short holding times. As globalization of companies or organizations becomes a new trend, the variety of Internet service demands, in space and time, creates a more variable and unpredictable traffic model for long term network provisioning. At the same time, upgrading backbone networks remains expensive and infrequent. It is important to be able to efficiently utilize precious network resources so that low call blocking is achieved while requiring fewer upgrades when the traffic model changes. There are two kinds of dimensioning problems. First, basic dimensioning allocates network resources for a newly built network. Second, incremental dimensioning allocates extra resources for an already built network without affecting currently available resources. Historically, routing and dimensioning problems are studied together as an optimization problem. However, as integrating multiple network layers into one control platform becomes a common trend, and as higher-layer traffic that currently utilize dynamic routing imposed on logical layers increases, it is essential to plan the underlying network based on dynamic routing schemes, such as open shortest path routing (SPF).**

In this paper, we study basic and incremental dimensioning for dynamic routed traffic. We propose a simulation based basic dimensioning approach and introduce two new incremental dimensioning techniques: MEAN and SD. We also introduce an evolutionary traffic model and traffic load computation criteria. Simulation results show that basic dimensioning effectively reduces the topological bottlenecks, rendering 7% less blocking compared to uniform allocation. With the evolutionary traffic model, SD incremental dimensioning shows advantages over the MEAN method on most practical networks. We also compare our results with fixed routing and dimensioning approaches, showing that dynamic approaches provide better network balance and utilization.

***Keywords* WDM networks, resource dimensioning, online routing, dynamic traffic.**

I. Introduction

With the use of wavelength-division multiplexing (WDM) technology, optical communication has been widely adopted by backbone networks providing high bandwidth and lower cost for long distance connections [1]. Due to the rapid growth of systems and applications that rely heavily on high data-rate communication, major network carriers have focused more on optical networks to support growing demands in a cost-efficient manner [2]. At the same time, the emergence of short term (a few hours to a week) applications that require high data rates, such as some types of financial transactions, high quality video delivery, and health care applications [3], has increased the dynamic variability of traffic. Building and upgrading optical networks in response to such short-term traffic changes is expensive and time consuming. For long-haul optical networks, installing new fibers often requires digging new conduits and/or laying submarine fibers, which adds costs over and above those of necessary hardware components[1]. To meet these emerging traffic patterns, optical networks should be provisioned so as to address both existing and expected future demands while simultaneously allowing robust adaptation to traffic fluctuations and unexpected future changes.

There are two types of network dimensioning. *Basic dimensioning* takes place when a company deploys a new network and allows for substantial flexibility in resource allocation. Basic dimensioning has similarities to physical topology design that both of them try to solve initial network resource allocation problem. However basic dimensioning is distinguished from physical topology design fundamentally. Physical topology design aims at creating a physical network layout from scratch. Fibre deployment cost, infrastructure cost and management cost sometimes are prior concerns to traffic demands. In contrary, basic dimensioning focuses on allocating fibres on a given physical topology based on traffic demands. Basic dimensioning becomes prevalent when majority network companies nowadays build their network via purchasing or renting fibres from few physical network infrastructure providers. In this case, allocating network capacity for their particular traffic demands is the most important design decision to be made. Basic dimensioning is rare once network companies are well-established. The second form of dimensioning, *incremental dimensioning*, occurs more frequently, and generally corresponds to cases in which a network company upgrades an existing network infrastructure to meet increased traffic demands. In this case, the original network is often already loaded with traffic. Removing already installed fibers or lasers is not economical in most cases, and disruptions

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[1] In practice, many extra fibers may be pre-installed to avoid physical reconstruction for future upgrades. However, transmitters/receivers still must be installed at the end nodes to drive the newly lit "dark" fibers.

may be forbidden by service-level agreements (SLAs) with some customers. There is often a limited budget for network upgrades as well, constraining the amount of extra resources that can be added. How to efficiently allocate extra resources on existing networks is an important problem, and is the focus of this paper.

In this paper, we study network dimensioning problem for online, state-based routing schemes. State-based schemes select routes based on the current network residual capacity rather than using a pre-selected (or fixed) route that depends only on the endpoints of the requested connection. The use of network state allows timely responses to traffic fluctuations with reduced blocking rates. We propose a simulation-based dimensioning scheme and compare it with an asymptotic model based on fixed routes. State-based routing schemes provide the most benefit when they are used in moderately loaded networks. We also propose two schemes for incremental dimensioning. Simulation results are presented for each scheme under evolving traffic patterns. We assume Poisson arrivals and departures for each connection. This assumption is appropriate for backbone traffic, where burstiness is smoothed through aggregation of the heterogeneous traffic imposed by virtual topologies running on top of the backbone. We also assume that the network is bidirectional. A connection request is initiated by a node pair either one of which servers as a source or a destination. Without loss of generality, we do not differentiate connection requests of opposite directions given that connections are bidirectional.

Our work focuses on the wavelength routed model where optical cross-connects (OXC) and optical fiber links are the main components of a WDM mesh network [4]. Connection requests are initiated by (arbitrary) node pairs in the network. Based on the routing policy and the current availability of wavelengths, the network either accepts or rejects each connection request. A request is rejected if insufficient resources are available to support the new connection, and no queuing of requests is assumed. Lightpaths are automatically set up and torn down by OXCs upon the acceptance and departure of connection requests. Each lightpath occupies a certain number of wavelengths on each link along its path until the connection terminates (leaves the network). We assume full wavelength conversion at all OXCs. The number of available wavelengths allocated on each link is the link capacity in WDM networks. We perform resource dimensioning for a WDM network by determining link capacities on the network topology using an estimated traffic matrix.

The remainder of the paper is organized as follows. Section II provides background on network dimensioning and discusses the benefits of studying dimensioning problems for online routing on WDM mesh networks. In Section III, we propose a simulation based basic dimensioning algorithm and introduce two incremental dimensioning approaches. We present simulation results for basic and incremental dimensioning in Section IV, and compare our dimensioning approach with an asymptotic optimization approach for fixed routing in Section V. Conclusions are provided in Section VI.

II. Motivations and Related Work

The goal of network dimensioning in WDM networks is to determine the number of wavelengths assigned to each link to meet the traffic demand and reduce cost [4]. In traditional approaches that has been studied extensively in circuit switching networks, routing and dimensioning problems are solved as a whole, and optimize fix routes which are assigned to each connection request. Capacity requirements are therefore determined by these fixed routes. Optical WDM networks are similar to traditional circuit switching networks in the sense that connection calls are made to setup a lightpath (circuit) for data transmission. However, they differ in many ways. First of all, setting up a connection in optical network is more expensive compared to electronic networks. Redirecting or preempting connections become undesirable as data loss per unit time is proportional to the network bandwidth. Network operators also are more reluctant to reject connections due to higher bandwidth demand of each connection and thus potential higher revenue. On the other hand, emergence of higher data-rate Internet applications increases the variance of traffic matrix over time, which makes networking planning more difficult. Finding efficient dimensioning algorithms for optical networks becomes a very practical research interest.

Under new optical network model, both simulation and modeling approaches to network planning on multiple layers have been studied in the literature [5]–[12]. Virtual logical layers that are built on top of physical WDM networks provide flexible routing and scheduling for the needs of different customers. Many logical layers can share one or more WDM lower-level networks. Some research also has been done on logical level optical network dimensioning and reconfiguration [11], [12]. Basically, they decide a logical demand for the underlying WDM network based on either a provisioned or measured traffic matrix. [11] proposed an online, logical topology reconfiguration based on live traffic measured on a daily basis. [9], [12] modeled routing and dimensioning as a cost optimization problem.

Similar approaches are applied on resource planning for the backbone WDM networks. Fixed routes satisfying optimal condition are assigned to each connection request according to its traffic demands. Nayak et al [4] proposed an asymptotic routing and dimensioning approach based on absorption probability analysis of a linear traffic growth model. [13] then proposed a time-dependent blocking probability approach that further reduces network capacity. Their work study transient network behavior starting from zero initial traffic, with the assumption that the network is periodically re-dimensioned and is able to be re-constructed in a timely manner responding traffic changes.

However, resource dimensioning for evolving traffic demands that are routed by dynamic algorithms, starting with non-zero initial state, receives more interest for well-established optical backbone networks with ongoing high data-rate connections. By using static optimization approach, the optimal condition may change when traffic pattern changes during the period when network is undergoing re-optimization and re-construction. It is difficult to evaluation the quality of optimal routing scheme under an unoptimized condition that the actual traffic matrix is different from the expected one. At the same time, integrating multiple network layers into one control structure is becoming a trend. GMPLS (Generalized Multi-protocol Label Switching) [14], for example, already provides signaling capability for explicit online routing for connection-oriented optical networks. It is a natural step for network carriers to begin seeking more flexible routing schemes that increase network utilization. Online, link-state based routing schemes that provide fast response to traffic variances and are capable of dynamic load balancing have been used by network carriers in supplement to the optimized paths [15]. As the impact of higher-layer traffic (which currently utilize dynamic routing) grows on logical layers, it would be beneficial to also plan the underlying network based on dynamic routing and dimensioning rather than fixed routing.

Incremental dimensioning proposed in this paper is a new dimensioning method to allocate additional capacities for evolving dynamic traffics that are routed by online routing algorithms, without interfering current traffic flows. Two online routing algorithms will be used for simulation. One is the shortest path first (SPF) on capacity residual graph. Another is the widest shortest path first (WSP) [16], [17]. For each connection request, SPF routing picks up a random shortest path amongst all current available shortest paths based on link states. WSP algorithm selects amongst the shortest paths with the widest bottleneck residual capacity. WSP provides better load balance then SPF, rendering lower blocking rate.

III. Network Dimensioning

In this section, we introduce algorithms for basic dimensioning and incremental dimensioning. Basic dimensioning allocates link capacities according to a provisioned traffic matrix and an average link capacity budget when the network begins operation. Incremental dimensioning determines the distribution of extra capacity according to a provisioned traffic matrix and the current network state when the network needs to be upgraded.

Table I summarizes the notations we use through this paper. For each connection request node pair $i \in R$, where R is the set of source-destination request pairs, λ_i is the arrival rate. μ_i is the expected holding time. r_i is the requested capacity for this connection. The Poisson arrival rate λ, departure rate μ and request bandwidth r, respectively may follow some distributions, such as uniform or Gaussian with a mean and variance. A traffic matrix is a sample over these specified distributions. E is the set of links. len_i^{SPF} represents the topological shortest path first (SPF) path length for request node pair i. And $\frac{\sum_i len_i^{SPF}}{|R|}$ is the average length of topological SPF paths on the network. For each link $l \in E$, C_l is the capacity on that link. $\sigma_l = \sqrt{C_l}$ is the statistical standard deviation. For dynamic traffic models, we define the offered network traffic load as

$$load = \frac{\mathsf{E}(\lambda)\mathsf{E}(r)\sum_i len_i^{SPF}}{\mathsf{E}(\mu)\sum_{l\in E} C_l} \tag{1}$$

TABLE I

Network definitions.

N	Set of nodes.
E	Set of links.
C_l	Current capacity of link $l \in E$.
B_l	Allocated capacity of link $l \in E$ as a result of basic dimensioning.
X_l	Allocated capacity of link $l \in E$ as a result of incremental dimensioning.
σ_l	Statistic standard deviation of link capacity B_l.
R	Set of all connection request pairs. $R \subseteq N \times N$.
r_i	Requested capacity of a node request pair $i \in R$.
λ_i	Poisson arrival rate per request pair i.
μ_i	Poisson departure rate per request pair i. The average holding time is $1/\mu_i$.
len_i^{SPF}	topological shortest path length for pair i.

where $\mathsf{E}(\cdot)$ is the expectation operator on some distribution.

Let $T = \{\lambda_i, \mu_i, r_i\}^{|R|}$ be one given traffic matrix that specifies the traffic requirements between all connection request pairs. In order to dimension the network for the average load of all possible traffic, the provisioned traffic matrix T should be normalized by the average load. Given that the arrival rate is proportional to the network load, normalization is done only on the arrival rate of each pair in the traffic matrix. Equation 2 shows the computation of normalized traffic matrix $T^{prj} = \{\lambda_i^{prj}, \mu_i, r_i\}^{|R|}$. For each connection i in T,

$$\lambda_i^{prj} = \lambda_i \frac{\mathsf{E}((\lambda)\mathsf{E}(r)\sum_i len_i^{SPF}}{\mathsf{E}(\mu)\sum_i \frac{r_i \lambda_i len_i^{SPF}}{\mu_i}} \tag{2}$$

Traffic matrix load normalization is important if only one projected traffic matrix is used during dimensioning. If the projected traffic matrix is somehow below the average load of the traffic distribution, the dimensioned network will tend to be overloaded when the actual traffic drifts away from the projection one. Otherwise, network resources are over provisioned due to a higher load traffic projection. However, if anticipated traffic used for dimensioning is from a large set of different traffic, the skew of load will not be as severe as in one matrix, so load normalization becomes optional. In this paper, we assume that the general distribution used to generate traffic matrices are known beforehand.

A. Basic Dimensioning

Provided a traffic matrix T^{prj} and a projected network load, the total capacity estimation $\sum_{l\in E} C_l$ can be computed by Equation 1. The goal of basic dimensioning is to eliminate these topological bottlenecks that gets saturated faster than other part of the network, contributing much more to blocking caused by connection requests that must go through the bottleneck. In our method, we first simulate the projected dynamic traffic by SPF routing with infinite networking resources until steady state. The stochastic system will surely converge into a steady state because our traffic load is finite. Discussions in Section IV and Figure 2 provides more details on determining the steady state of a system. For those network topologies that we use in this paper, see Figure 1, steady state is reached within 20,000 arrival requests. Then, we repeat the simulation to get the mean of used capacity on each link. B_l is the provisioned capacity for each link. Each time we repeat, depending on the level of estimation on future traffic, there can be a single projected traffic matrix or a set of traffic matrices. Note that the final total capacity may vary slightly (less than 1%) from the original estimation due to traffic matrix fluctuation. One may choose to simply "round off" each non-integer expected link capacity to a close integer, or "touch up" link capacity fairly to make total capacity equals to the estimation. The latter one guaranteed that provisioned capacity stochastically equals to 100% projected traffic load.

1: Set infinite available capacity on each link $C_l \leftarrow \infty \; \forall l \in E$
2: **while** System has not reached steady state **do**
3: Generate a new connection request j from traffic matrix T^{prj}.
4: Route j by shortest path first algorithm (SPF).
5: **end while**
6: $\widetilde{C}_l$ is the actually used network capacity of each link.
7: Repeat from Line 1 to get the distribution of $\widetilde{C}_l$, mean $\mathsf{E}_l(\widetilde{C}_l)$
8: Round mean capacity to integer $B_l \leftarrow \mathsf{E}_l(\widetilde{C}_l) \; \forall l \in E$ by "round off" or "touch up".
9: Compute statistic deviation $\sigma_l = \sqrt{B_l}$.

Algorithm 1: Basic dimensioning.

The actual network traffic may vary from the projected traffic in many ways. If all connection pairs keep the same ratio between the actual traffic pattern and the projected one, i.e. for each $i \in R$,

$$load\,ratio_i = \frac{r_i \lambda_i \mu_i^{prj}}{\mu_i r_i^{prj} \lambda_i^{prj}} \tag{3}$$

$load\,ratio_i$ stays the same for all connection pair i, the new traffic has the pattern as the projected one with different load. "Load ratio" is the ratio between actual load and projected load for all connection pairs. If a network is dimensioned with an envisioned 100% traffic load, the actual traffic is usually less in practice. If the actual traffic does not have the same load ratio compared to the projected one for each connection, there is a change in the traffic pattern. The level of change in the traffic pattern could be modeled as the level of "evolution" on the original traffic. Details of traffic evolution will be discussed in Section IV.

B. Incremental Dimensioning

In incremental dimensioning, extra capacity is allocated without any interference on established connections (and resources). This step is useful if the network is overprovisioned to some degree for future traffic variances, or during network upgrades when extra capacity budget needs to be allocated.

MEAN is the most basic incremental dimensioning method that proportionally increases each link capacity with the same over-provision ratio. Let X_l be the extra capacity allocated to each link l and C' be the total extra capacity to allocation. For each link l, MEAN calculates extra capacity as follows,

$$X_l = \frac{C' B_l}{\sum_l B_l} \tag{4}$$

Since our basic link capacity is dimensioned proportional to the projected network load, allocating extra capacity by MEAN is equivalent to increasing the projected load. If the actual network load is the same as projected load, i.e. load ratio equals one, the effective load ratio on an incremented network can be computed as

$$load\,ratio = \frac{\sum_l B_l}{\sum_l B_l + X_l} \tag{5}$$

Equation 5 generally can be applied to any incremental dimensioning methods that use Algorithm 1 for basic dimensioning.

The other scaling approach, SD, is proportional to the statistical standard deviation of each link capacity obtained from basic dimensioning (instead of the mean capacity). The idea behind SD is that link capacity with larger deviation tend to suffer more by traffic variances. It would be more effective to allocate extra capacity to these links rather than those with less traffic fluctuations. Extra capacity for SD is calculated as follows,

$$X_l = \frac{C' \sigma_l}{\sum_l \sigma_l} \tag{6}$$

, where $\sigma_l = \sqrt{B_l}$.

IV. Simulation Results

In this section, we present simulation results, which show that basic dimensioning and incremental dimensioning techniques are effective in provisioning network resources for dynamic traffic. We assume the network is connection oriented with full wavelength conversion capabilities at every node. We also assume that GMPLS like network control platform is available for explicit link-state based routing, providing signaling capabilities for setting up or tearing down a connection as well as updating real link state information. We further assume that request arrival rates and hold times for connections allow sufficient time for signaling such that all new connections are routed based on up-to-date information about residual capacity for all links in the network. Because the burstiness of traffic on WAN is usually well suppressed by huge amount of aggregate data, Poisson processes are used to model connection requests and hold times (arrivals and departures). In our simulations, the traffic pattern is determined by the arrival rate of each connection. Each connection requests a uniform 1 unit capacity and has the same departure rate. The departure rate is determined by the network load that is the product of the projected departure rate and the load ratio. In the incremental dimensioning experiments, actual traffic loads are set to be the same as the projected traffic load. The effective load ratio is the same as overprovisioning ratio as shown in Equation 5. We use three well-known networks for our experiments–NJ LATA, COST 239, and ARPANET. Unless stated otherwise, network references in this section refer to NJ LATA, the local access and transport area network for the state of New Jersey. The two dynamic online routing algorithms used are SPF and WSP.

The default parameters are specified as follows. The arrival rate of each connection is uniformly distributed between 1 to 10. The load ratio is 0.85 to the projected traffic load. Each connection request demands the same capacity and hold time. SPF and WSP are used respectively to route every

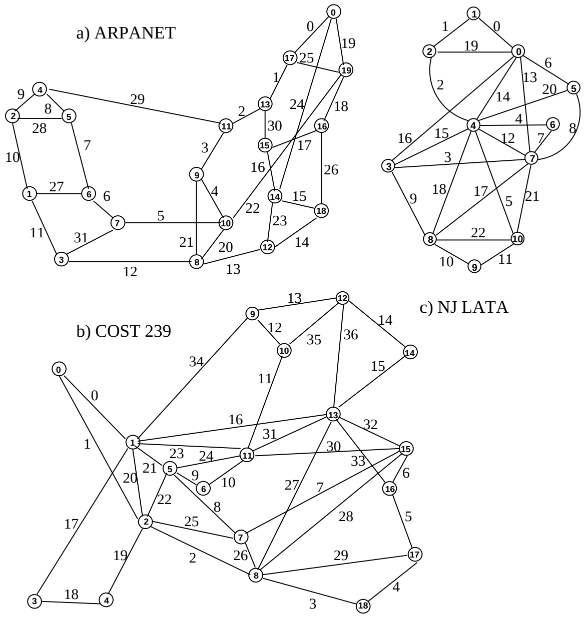

Fig. 1. Network topologies with link and node number.

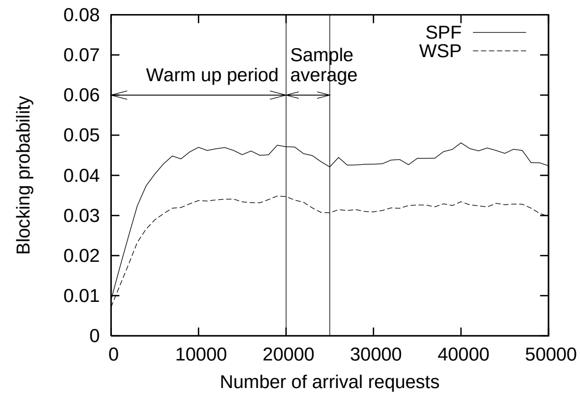

Fig. 2. Steady state performance on NJ LATA.

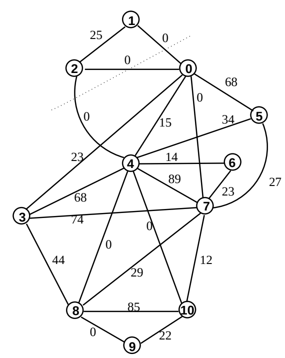

Fig. 3. A cut in NJ LATA after arrival of 1140 requests.

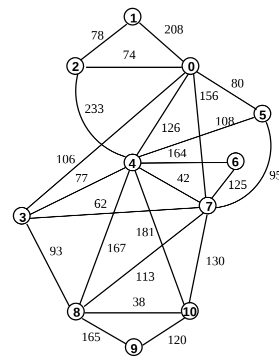

Fig. 4. NJ LATA network with balanced capacity.

requests. If there are no paths with enough capacity available, the request is rejected. Otherwise, a path is setup for this request and teared down after the hold time. No queuing is provided for rejected connections. Using basic dimensioning algorithm 1, the network is balanced with an average of 1000 randomly chosen fully loaded projected traffic matrices from the same uniform distribution. The blocking probability is obtained by averaging 100 runs of randomly chosen traffic also with the same distribution. For each round, the blocking rate is measured by sampling 5000 arrivals after running 20,000 warm up requests using the same routing algorithm. It is desirable to have more test samples to average. However the sample size that we choose in this paper is adequate to provide representative results for the system performance aspects that we intend to study.

Figure 2 illustrates the steady state of a dynamic network. The blocking probability for the jth request is the average blocking for the next 5000 arrivals. Steady states behavior is shown after 10,000 dynamic arrivals. Since it is a large dynamic system, some fluctuations are shown in the steady state. However, the range of fluctuations are less than 0.005 and fluctuation do not affect the relative results between routing algorithms. Even for larger networks, the system reaches steady state after 20,000 requests, at which point we measured the blocking probabilities.

A. Basic Dimensioning Performance

Algorithm 1 is very effective in reducing the topological bottleneck. For uniform link capacity allocation, Figure 3 demonstrates an example bottleneck cut consisting of three links—(1,0)(2,0)(2,4)—after running 1140 static requests. Figure 4 shows the balanced network capacity allocation after basic dimensioning by using simple "round off" method. The estimated network link capacity is 120 wavelengths per link. Figure 5 shows that blocking in an unbalanced network is about 7% larger compared to a balanced network. Notice that the total actual capacity on a balanced network is 2741, which is less than that of an unbalanced network (2760, 23 links $\times$ 120). In this case, the actual total capacity used is less than the estimated capacity. Figure 26 shows the basic dimensioning results of more networks with "touch up" method.

Figure 6 shows the distribution of blocking probability for each connection pair. Uni means that the traffic is simulated on a network with uniform basic capacity. BAL means that the network capacity has been balanced by basic dimensioning techniques. Both of them utilize the MEAN scaling method and the link state based SPF routing algorithm. Results show that the blocking probability across connection pairs are more balanced compared to the uniform capacity allocation, rendering lower overall blocking.

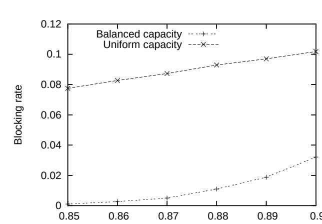

Fig. 5. Comparison of blocking on balanced and unbalanced networks with SPF routing

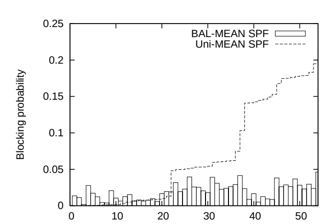

Fig. 6. Blocking distribution for individual connections.

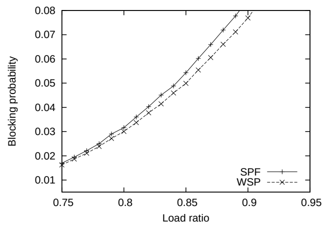

Fig. 7. Prj load 0.5.

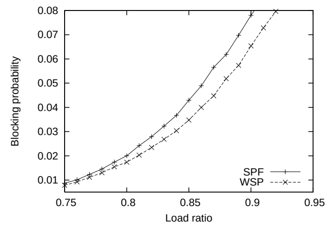

Fig. 10. Prj load 0.8.

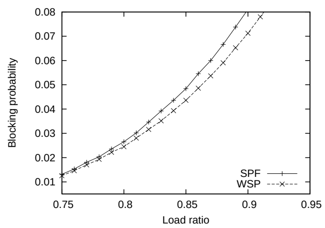

Fig. 8. Prj load 0.6.

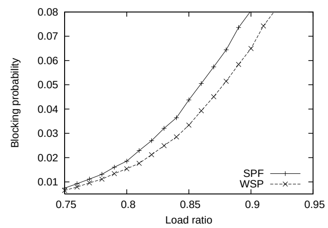

Fig. 11. Prj load 0.9.

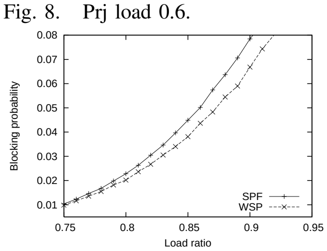

Fig. 9. Prj load 0.7.

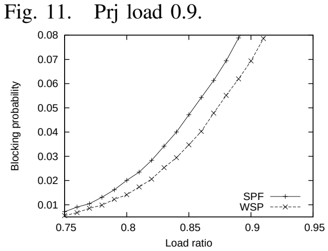

Fig. 12. Prj load 1.0.

Finally, the absolute projected traffic load does not affect the behavior of the network if the relative load ratio between projected and actual load stays the same. Figures 7-12 show that WSP routing always provides lower blocking compared to SPF regardless of projected traffic load. Without loss of generality, we use projected load of 100% during basic dimensioning for all other experiments.

B. Increment Dimensioning Performance

In this section, we compare two incremental dimensioning algorithms: MEAN and SD. As we have mentioned in the previous section, traffic can be changed in terms of load and patterns. If a traffic pattern changes when $r_i\lambda_i/\mu_i$ does not stay the same for each connection i, the traffic is considered to have evolved. Once we fix the demand and the departure rate for all connections, the only variable used in making changes to the traffic is the arrival rate. The arrival rate can be changed in two ways. First, the arrival rate changed, but the new value is obtained from the same distribution. This is the same as selecting many projected traffic in the default setting. Second, the arrival rate can be changed arbitrarily. Here, we focus on the first case. When the network is dimensioned with a single traffic, the actual traffic becomes different but stays under the same distribution.

Figures 13-15 show the comparison between MEAN and SD on traffic load. In the dimensioning stage, the network is basically dimensioned by the average of running many traffic with arrival rates are varying uniformly from 1 to 10 using Algorithm 1. Incremental dimensioning method, MEAN and SD, are applied respectively on each link with the same total

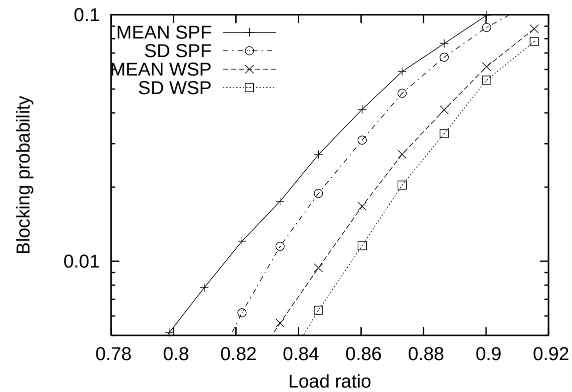

Fig. 13. Comparison of MEAN and SD on NJ LATA with various loads. The results are averaged over several different traffic.

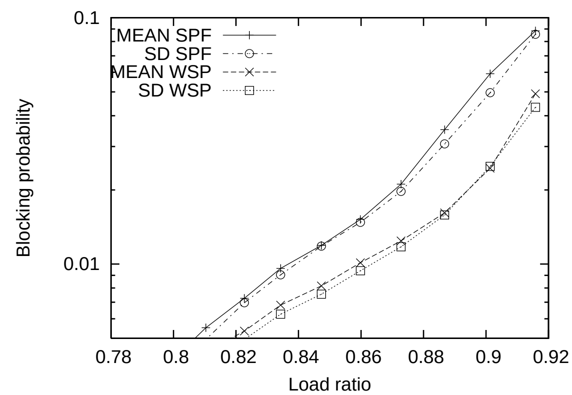

Fig. 14. Comparison of MEAN and SD on COST with various loads. The results are averaged over several different traffic.

extra capacity. In the testing stage, connection requests are generated by another random traffic matrix with the same uniform distribution. SPF and WSP algorithms are used to route connections until steady state. Then, the blocking probability of a traffic matrix is obtained. The final blocking result is computed by averaging 100 tests with random traffic matrices. Our results show that SD renders less blocking than MEAN on most networks. On NJ LATA, for example, SD provides 30% less blocking than MEAN with 0.86 load for SPF routing. The results also show that WSP in general provides better network load balance then SPF for either cases. SD shows advantage over MEAN regardless of the routing algorithms used. However, the level of advantage achieved depends on the topology.

For the remainder of this section, we will compare MEAN and SD under accountable traffic variances. First, we introduce the traffic pattern evolution model. Let T^{prj} denote the traffic projection matrix. Define ϵ be the traffic variance factor that measures the degree of evolution away from the original traffic. T' is another random matrix generated from the same distribution. The actual matrix T_ϵ, then, is the evolved traffic matrix from T^{prj} to T' by degree ϵ. T_ϵ is computed as,

$$T_\epsilon = (1-\epsilon)T^{prj} + \epsilon T' \qquad (7)$$

Note that the traffic projection matrix has been normalized

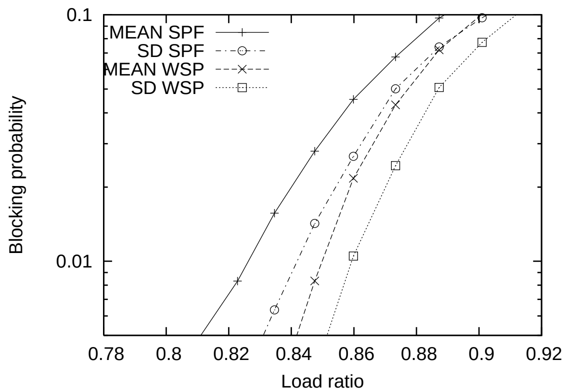

Fig. 15. Comparison of MEAN and SD on ARPANET with various loads. The results are averaged over several different traffic.

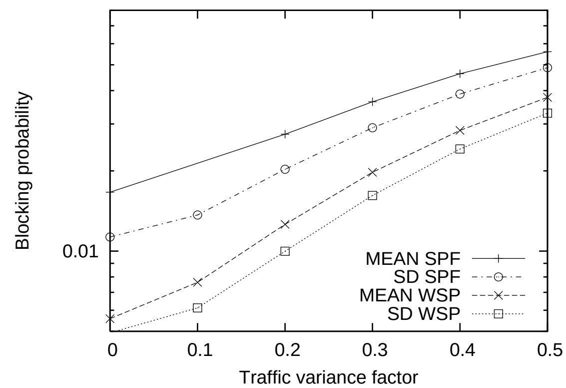

Fig. 16. Comparison on evolutionary traffic model on NJ LATA for uniform distribution. The results are averaged over several different traffic projections.

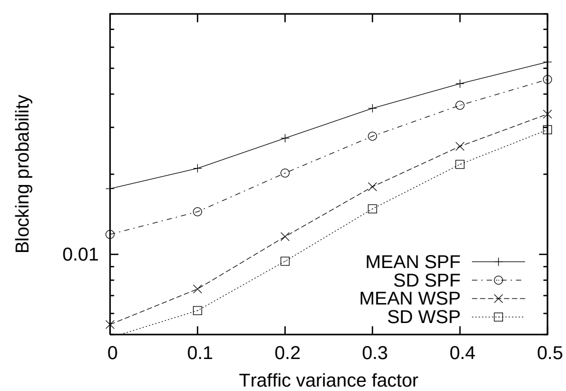

Fig. 17. Comparison on evolutionary traffic model on NJ LATA for Gaussian distribution. The results are averaged over several different traffic projections.

by Equation 2 according to the projected load. Therefore, the projected traffic load should agree with the average load of the actual traffic T'. In simulation, we will study three different arrival rate distributions with the same mean and variance: Uniform, Gaussian and Bimodal. Given a network dimensioned by one projected traffic matrix and fixed amount of extra capacity, steady state blocking rate is measured for a traffic T_ϵ that evolves from T^{prj} to a random traffic T' with degree ϵ. The average blocking for one traffic projection is computed by repeating experiments with 100 random T's. The entire experiment is again repeated for 100 randomly chosen projected traffic matrix Ts. Eventually the blocking rate is obtained by averaging the blocking rate of these different traffic projections. Figures 16-24 show the comparison between MEAN and SD over the evolutionary traffic model. The traffic variance factor ranges from 0 to 0.5 that the actual traffic is a mix of half projected traffic and half random traffic with the same type of distribution. Uniform distribution is the same as (1, 10) random pick. With the same mean and variance, we have a bimodal distribution, where only two end values are available for a random pick. For Gaussian distribution, we generate rates with the same mean and variance, but discard rates that are smaller than 1 or greater than 10. Effectively, the variance of rates generated by the Gaussian model is slightly smaller than those from uniform or bimodal. By picking up the same mean and variance, the uniform traffic tends to converge to Gaussian traffic when the sampling space is large. So the average result from uniform distribution is similar to Gaussian. However, the bimodal distribution presents a sharper fluctuation than uniform distribution, rendering a higher blocking probability on the same degree of traffic variance. For all three distributions, SD presents better provisioned networks compared to MEAN. Especially for ARPANET, which is more prone to topological bottlenecks (e.g. link 5, 12, 29), SD achieves about 50% less blocking for SPF compared to MEAN when uniform projected traffic has been changed by 50%.

V. Comparison with Fixed Routing and Dimensioning

In this section, we discuss fixed routing and dimensioning methods proposed by Nayak [4], and compare their approach with ours. Nayak et al analyzed the upper bound and lower bound of capacity needed to achieve a low absorption probability during a certain time interval. Their result is useful to model the time interval between network re-dimensioning and required capacity for each link to achieve low blocking during that interval. Absorption probability[2] for each link is the probability that a new connection arrives for this link when the link is full. Figure 25 shows the Markov model of a link with capacity N. The $N+1$ state is the absorption state.

However, in our model of long term dimensioning, we are only interested in the operating region where absorption probabilities are low, hence the capacity allocated for each link is high. They proposed an asymptotic optimal condition for dimensioning networks in this case. All connection requests are assigned a fixed route. A_{li} is the routing matrix for connection i and link l. Each connection has a time varying Poisson arrival rate $\lambda_i(t)$. Holding times follow a general distribution G. The capacity required on each link l during time $(0, T)$ is

$$B_j = \int_0^T G^c(T-\tau) \sum_{i \in R} A_{li} \lambda_i(\tau) d\tau \qquad (8)$$

where $G^c(t)$ is the complementary cumulative distribution function (CCDF). For the special case when arrival rate is

[2]Absorption probability and exhaustion probability are interchangeable in their papers.

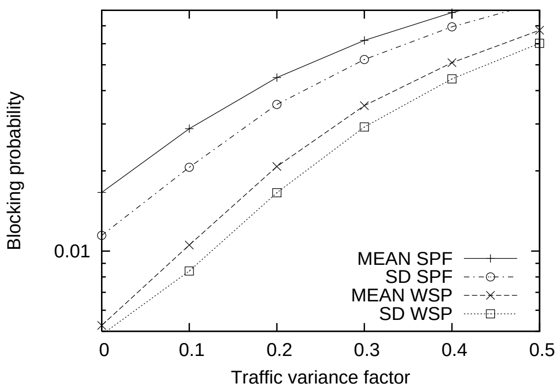

Fig. 18. Comparison on evolutionary traffic model on NJ LATA for bimodal distribution. The results are averaged over several different traffic projections.

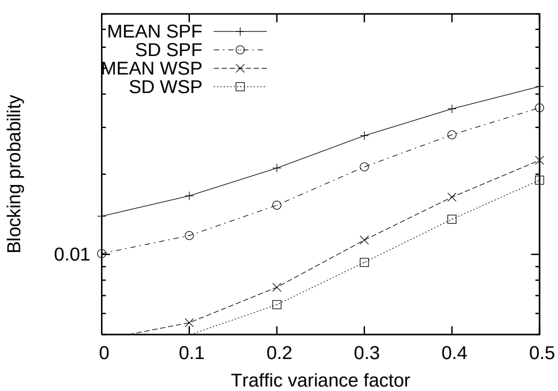

Fig. 19. Comparison on evolutionary traffic model on COST 239 for uniform distribution. The results are averaged over several different traffic projections.

a constant during time $(0, T)$ with demand r_i and Poisson departure with mean μ, Equation 8 becomes

$$B_j = \sum_{i \in R} A_{li} \lambda_i r_i \frac{1 - e^{-\mu T}}{\mu} \tag{9}$$

The average time horizon T for a system reaching steady states is computed by

$$T^{-1} = \mathsf{E}(\lambda)|R| \tag{10}$$

Given one projected traffic matrix T from uniform distribution (1, 10), the fixed routing and dimensioning method (ABS) will randomly assign a shortest path for each connection. This shortest path is also the fixed routing path. If any link on the fix assigned SPF for a request is full, the request is rejected. Figure 26 compares the link allocation of ABS and BAL (Algorithm 1 for dynamic routing and touch up method) with the same projected traffic pattern and 100% load (guaranteed by "touch up" method). The actual total capacity used is annotated along with the legend. For NJ LATA network, ABS uses 2759 wavelengths and BAL uses 2760. However, BAL uses less than ABS for COST. The differences is less than 0.05%, which means that they use the same amount of resources during basic dimensioning.

Equation 8 also shows that the allocation of link capacity is proportional to the increase in arrival rates. Equivalently, they use the MEAN approach to provision extra resources. For our algorithm, we use SD for incremental dimensioning.

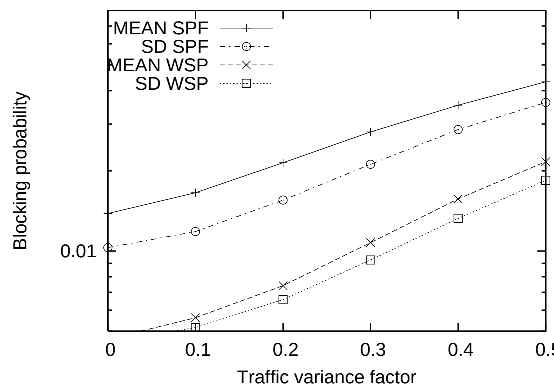

Fig. 20. Comparison on evolutionary traffic model on COST 239 for Gaussian distribution. The results are averaged over several different traffic projections.

Figures 28-30 show the blocking probability and network utilization for combinations of dimensioning method and routing algorithms. They use the same basic dimensioning result as in Figure 26. Given the same amount of extra capacity, ABS uses the MEAN incremental dimensioning and BAL uses the SD method. Only the same traffic pattern compared to the projected traffic is used during testing. Load ratio is computed by Equation 5. Utilization is the ratio between total average used capacity and total available capacity. FixSPF presents fixed routing pre-assigned by ABS. DynSPF is the same as link state dependent online SPF routing. WSP is an improved online SPF algorithm that utilize the widest channel. Results show that online routing and dimensioning algorithms present much lower blocking compared to fixed routing, especially when the network is less congested (less than 3% blocking). Higher utilization in dynamic routing means that better balance in using the resources is achieved. Even on ABS dimensioned networks (which are optimized for fixSPF), online WSP achieves a 50% less blocking compared to the fixSPF counterpart when the load is low. When the network load increases, online routing algorithms that use more resources tend to reject more connections. However, online algorithms can be designed to refrain from using excess resources when the network load is higher. Figure 27 shows the individual blocking rate for each connection. Dynamic routing and dimensioning method presents better balance amongst connections compared to fixed approaches.

VI. Conclusion

In this paper, we proposed resource dimensioning algorithms for WDM networks that balance link capacities for state-based routing algorithms. Due to the dynamic nature of state-based routing, we used simulation approach to find an effective balance in network resources given a projected traffic matrix (or matrices). Two stages of resource dimensioning are proposed: basic dimensioning and incremental dimensioning. Basic dimensioning algorithm aims at reducing topological bottlenecks. Simulation result shows that basic dimensioning effectively reduces 7% blocking rate compared to uniform allocation. For incremental dimensioning, MEAN algorithm that scales the network linearly and SD algorithm that scales

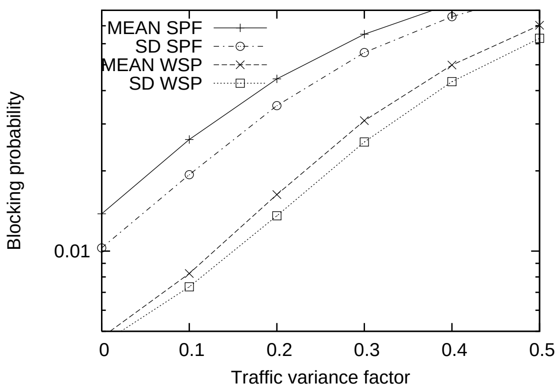

Fig. 21. Comparison on evolutionary traffic model on COST 239 for bimodal distribution. The results are averaged over several different traffic projections.

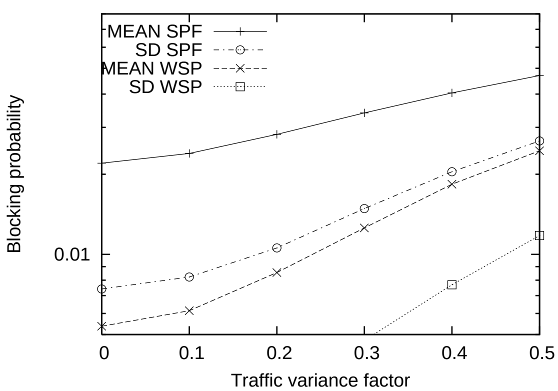

Fig. 22. Comparison on evolutionary traffic model on ARPANET for uniform distribution. The results are averaged over several different traffic projections.

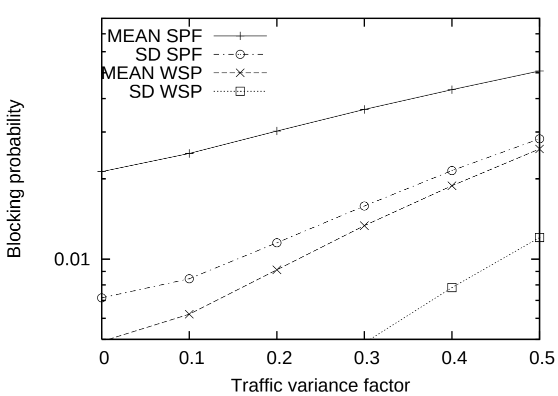

Fig. 23. Comparison on evolutionary traffic model on ARPANET for Gaussian distribution. The results are averaged over several different traffic projections.

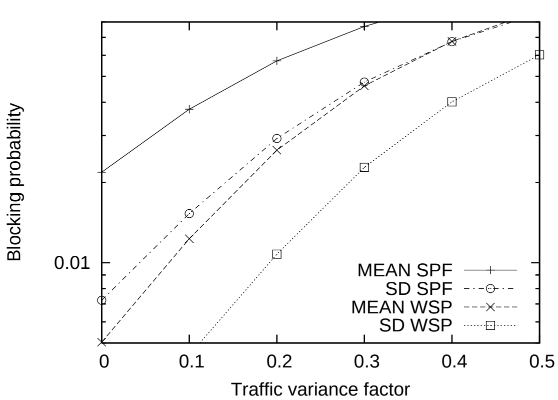

Fig. 24. Comparison on evolutionary traffic model on ARPANET for bimodal distribution. The results are averaged over several different traffic projections.

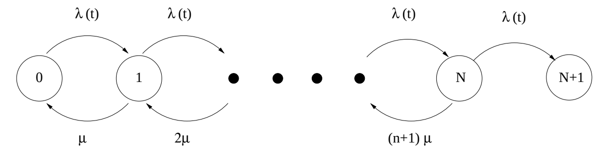

Fig. 25. Absorption Markov model for one link of maximum capacity N [4].

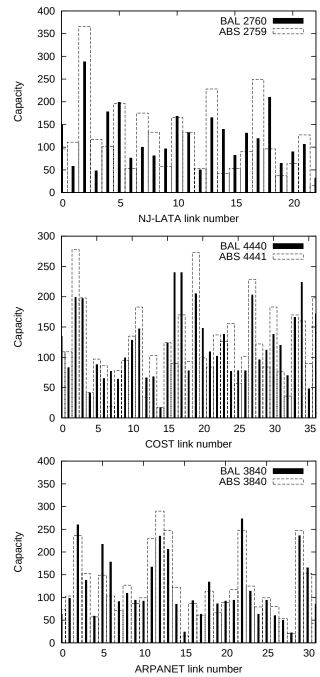

Fig. 26. Comparison of basic dimensioning methods.

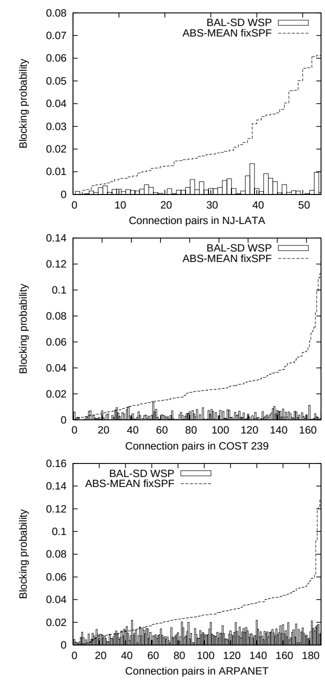

Fig. 27. Comparison of blocking distribution for individual connections.

the network by statistical standard deviation are propoesed. In addition, we proposed a traffic evolutionry model to emulate data traffic changes. Comparison of MEAN and SD are shown under various traffic loads and traffic patterns generated from uniform, Gaussian and bimodel distributions. Our results showed that SD outperforms MEAN in most situations, especially for networks that presents servere topological bottlenecks. Finally, we compared our basic dimensioning method with a fixed routing and dimensioning scheme. The results showed that dynamic routing and dimensioning provides better network balance when networks are moderately loaded.

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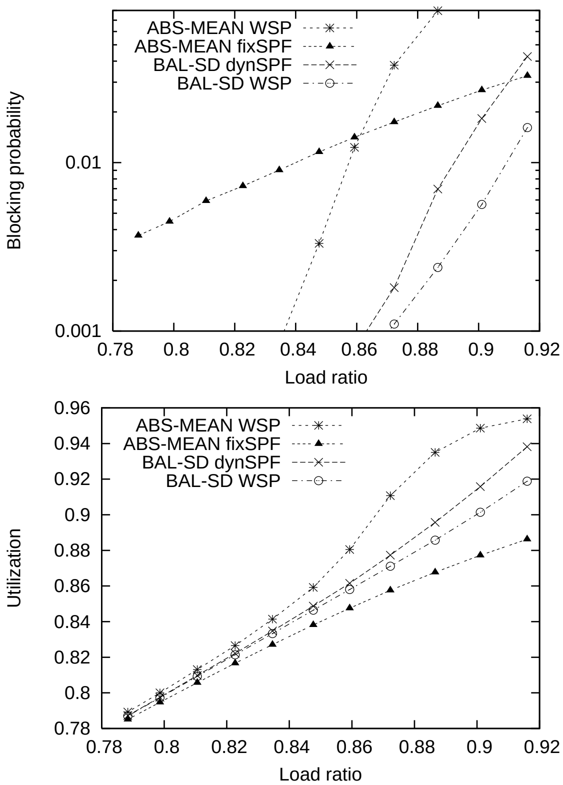

Fig. 28. Comparison of blocking and utilization for NJ_LATA.

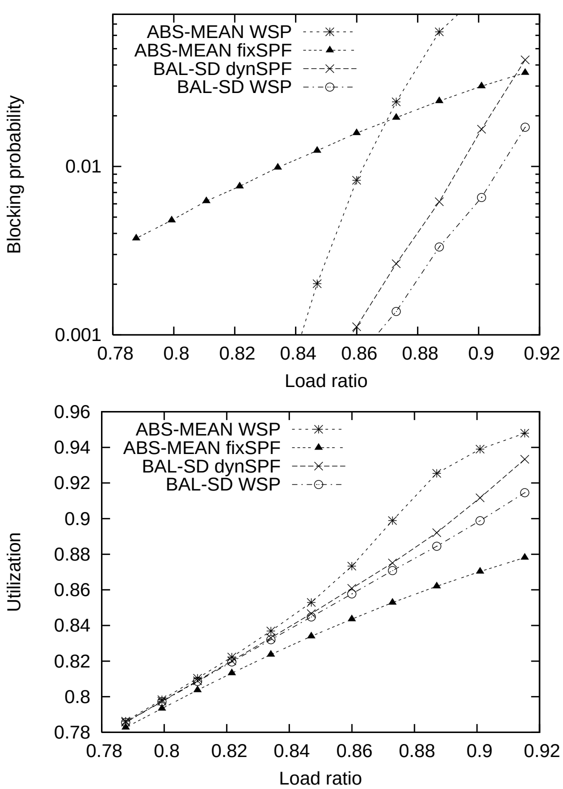

Fig. 29. Comparison of blocking and utilization for COST.

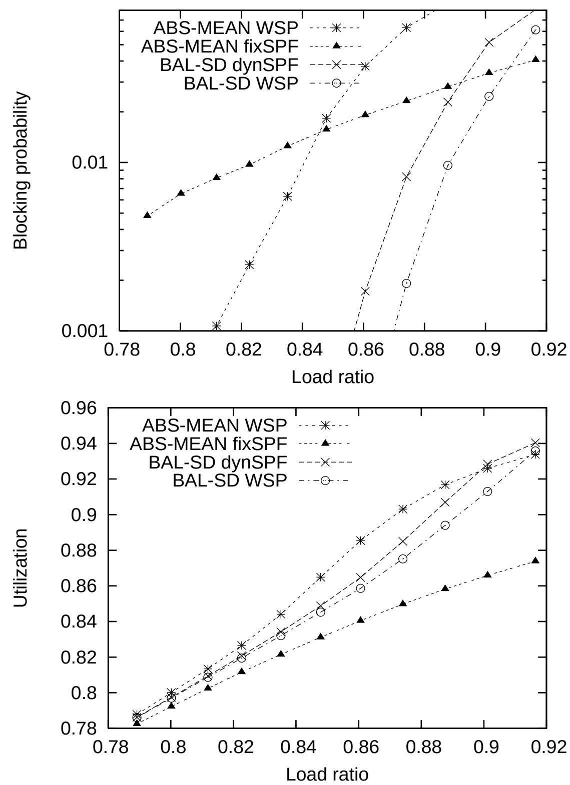

Fig. 30. Comparison of blocking and utilization for ARPANET.

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