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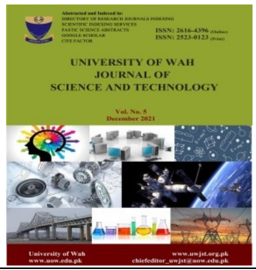

Artificial Intelligence Based Dynamic Wavelength Grouping for QoS in Optical Packet Switched Networks

Madeeha Kanwal[1], Farrukh Zeshan Khan[2], Rashid Amin[3], Syed M.Adnan[4] And Wakeel Ahmad[5]

***Abstract*—In Optical Packet Switching (OPS) networks wavelengths are shared on optical links and data packets are multiplexed statistically in all-optical domain. Quality of service covers management of resources and traffic control to deliver improved services to specific traffic classes. An Artificial Intelligence Based Dynamic Wavelength Grouping (AIDWG) scheme is proposed for OPS. In this scheme, available wavelengths are partitioned dynamically by Linear Regression Model (LRM) and allocated to traffic service classes at each network link. AIDWG tracks the load, blocking, wait time and utilization of each traffic class and schedules optical packets according to the assigned group of wavelengths. A discrete event-based network simulator IBKSim is used to examine the performance of National Science Foundation Network (NSFNet) topology. AIDWG beats its previous static version named as Static Wavelength Grouping (SWG) by a significant factor. Due to the flexibility, the proposed AIDWG technique gives good results upto 40% in comparison to SWG in terms of blocking and throughput even when the load share of one class is significantly less than other classes of traffic.**

***Index Terms*— Artificial intelligence, Quality of service, Dynamic wavelength grouping, Optical packet switching.**

I. INTRODUCTION

INTERNET traffic coming from multimedia, live streaming, medical imaging, online gaming, and critical applications doubles every three or four months [1]. Wavelength Division Multiplexing (WDM) has offered as a feasible choice for broadband transmission capability in continuously varying internet traffic scenarios [2]. Numerous technologies were advanced for data transfer over WDM, such as Optical Burst Switching (OBS), Optical Circuit Switching (OCS), and Optical Packet Switching (OPS). OPS is based on hop-by-hop optical packet delivery of numerous IP client packets. Optical packets build electrically at the edge nodes, however their buffering and routing at core nodes are done entirely at the optical layer. In its basic form, OPS has higher bandwidth, utilization, flexibility, scalability and Packet Loss Ratio (PLR) [3]. Because of its fine granularity, scalability and high throughput, OPS may be the most revolutionary technology for core networks. On the other hand, optical packet's contention is a severe issue in the core of OPS networks. Optical networks must adopt the dynamic conditions of the environment to fulfil Quality of Service (QoS) standards.

The fundamental goal of QoS is to offer precedence to certain types of traffic, such as dedicated bandwidth, throughput, and latency in real-time traffic. Furthermore, prioritizing one or more traffic types does not lead to the failure of other traffic types. QoS refers to a set of requirements that users must meet, such as how quickly data packets can be delivered, how much end-user has to wait for receiving, how much possibility of data loss, and so on. The advent of enormously adaptable networking principles and the deployment of improved transmission techniques have made the optical network's operation and design highly complex [4].

Artificial Intelligence (AI) and Machine Learning (ML) methods can capture such complicated dynamic system behaviour with comparatively simple supervised or unsupervised algorithms training to address drastic variations in traffic requirements regarding latency, capacity, and QoS. As a result, current optical networks are anticipated to operate at substantially higher utilization levels than in the past while maintaining the strict quality of service standards. AI allows network engineers to develop data-driven models in optimized, desirable, and effective network management and provisioning. It will enable automated optical networks fast driven and self-configured. Furthermore, flow classification applies flow-specific policies to already supplied services, such as handling packet priority, performing flow and congestion control, and ensuring adequate QoS to each flow [5]. In OPS networks, AI-based techniques are getting more attention from researchers to enhance the telecommunication

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network performance in switching, transmission, and network management [6]. Optical networks can learn on their own using AI approaches with "self-aware" of network state, control rules, and "self-managed" of network operation, particularly failure management.

This research paper proposes a new QoS provisioning scheme categorized as "Artificial Intelligence Based Dynamic Wavelength Grouping in Optical Packet Switched Networks(AIDWG-OPS)". This new scheme is based on LRM and predict value of wavelength group for each priority class traffic. QoS standards are achieved in OPS in terms of blocking probability and throughput by using the wavelength grouping scheme under the wavelength reservation scheme in **Error! Reference source not found.**. In wavelength grouping, a set of wavelengths is dedicated to a specific traffic class with different priorities. LP optical packets can only use specified wavelengths, whereas HP can use all wavelengths. Restricting wavelengths for lower service traffic classes can provide differential QoS, and an HP optical packet with a higher number of wavelengths can reduce the chance of packet failure. In the static wavelength grouping scheme, there are some constraints which are overcomed in this research. As a load of HP traffic is less than LP traffic or total load, the static wavelength set assigned to the HP traffic class is underutilized. In this scenario total blocking probability increase thus throughput decrease [7]. Wavelengths are grouped dynamically for each type of incoming traffic to resolve this issue [3]. But dynamic wavelength grouping is done on the base of the total shared load of LP traffic class. Still, it is not deciding by considering other parameters like utilization, waiting time, blocking probability, and throughput. In OPS, Therefore the solution to this problem is to implement AI for wavelength grouping through LRM. The presented algorithm analyzes four different parameters and distributes wavelengths among other classes of traffic. This analysis is based on topology NSFNet-32. The contributions of this research work are as follows:

- Created dataset from run time simulations
- Trained the LRM on dataset
- Test the model on new input data
- Developed and tested a novel technique. "AIDWGOPS. "
- Successfully attained QoS in OPS networks.
- On varying load conditions, the total blocking probability is reduced.
- The network throughput was significantly enhanced

The rest of paper is organised in the following manner. Section II presents the related work, describes QoS constraints and techniques in optical networks. Section III gives a comprehensive overview of the proposed AIDWG strategy. Section IV describes our simulation setup, whereas Section V discusses the experimental results and evaluates the concept. Finally, Section VI gives the conclusion.

II. Related Work

AI techniques are categorized in different subfields as expert system (ES), machine learning (ML), robotics, and distributed artificial intelligence (DA) [8]. In contrast to the above-outlined approaches, ML has been widely applied in optical networks regarding QoS provisioning. An agent is trained on a collection of input-output pairs and learns a mapping function from input to output in supervised learning [9].

Many studies have been conducted to ensure QoS in OPS networking[10]. QoS can be implemented at various stages of OPS like in the wavelength reservations scheme, drop-based scheme, and packet aggregation scheme. Figure 1 depicts some of the policies and strategies for QoS differentiation that have been developed. These existing techniques , which have been designed as proactive and reactive [11] approaches [12], attempt to solve the contention problem in OPS networks, and include the use of software techniques and additional hardware for provisioning of best QoS-capable environments, with the goal of optimizing the PLR and blocking with minimal delays and improved throughput even in high and varying traffic loads.

Other QoS schemes can be labeled in Scheduling based scheme(Merit-Based Scheme(MB) [13]), packet assembly [14] (Composite Packet Assembly (CPA) [15], and Non-Composite Packet Assembly (NCPA) [16]), drop-based schemes [17], routing based schemes [18-21], wavelength reservation schemes (Wavelength Access Restriction (WAR) [22], Wavelength Allocation(WA) [23], Additional Wavelengths (AWs) [24] and Wavelength Grouping [7, 25, 26]), supplementary resource reservation (Egress Coordination [27], Contention-Less Transmission [28] and Multi-Fiber Allocation [70]), and contention based schemes (Coded Packet Transport (CPT) Scheme [29],Use of Wavelength Converters (WCs) [30], Shared Packet loss Recovery Scheme(SPLR) [31] and Network Layer Packet Redundancy Scheme [32]); for their brief overview see also [16].

In order to reduce the BLP, reinforcement learning was used in the OBS network to determine the best path and wavelength. A Q-learning-based algorithm is proposed, selecting optimal wavelengths from the available wavelengths for burst transmission to reduce BLP in OBS [2]. An automatons OBS network has been developed for self-protection, self-optimization, and self-restoration. This automaton network has a learning module that gradually learns from the environment's feedback. The intelligence acquired by these automatons is utilized in making control decisions that significantly impact performance, and these decisions, in turn, have a considerable impact on the environment [33, 34]. Close loop-based cognitive Graphical Probabilistic Routing Model (GPRM) has been established for OBS networks to guarantee end-to-end QoS. This model builds a practical routing table for OBS routing without influencing end-to-end delay. This cognitive closed loop-based mechanism maximizes wavelength utilization and decreases BLP in OBS networks [35].

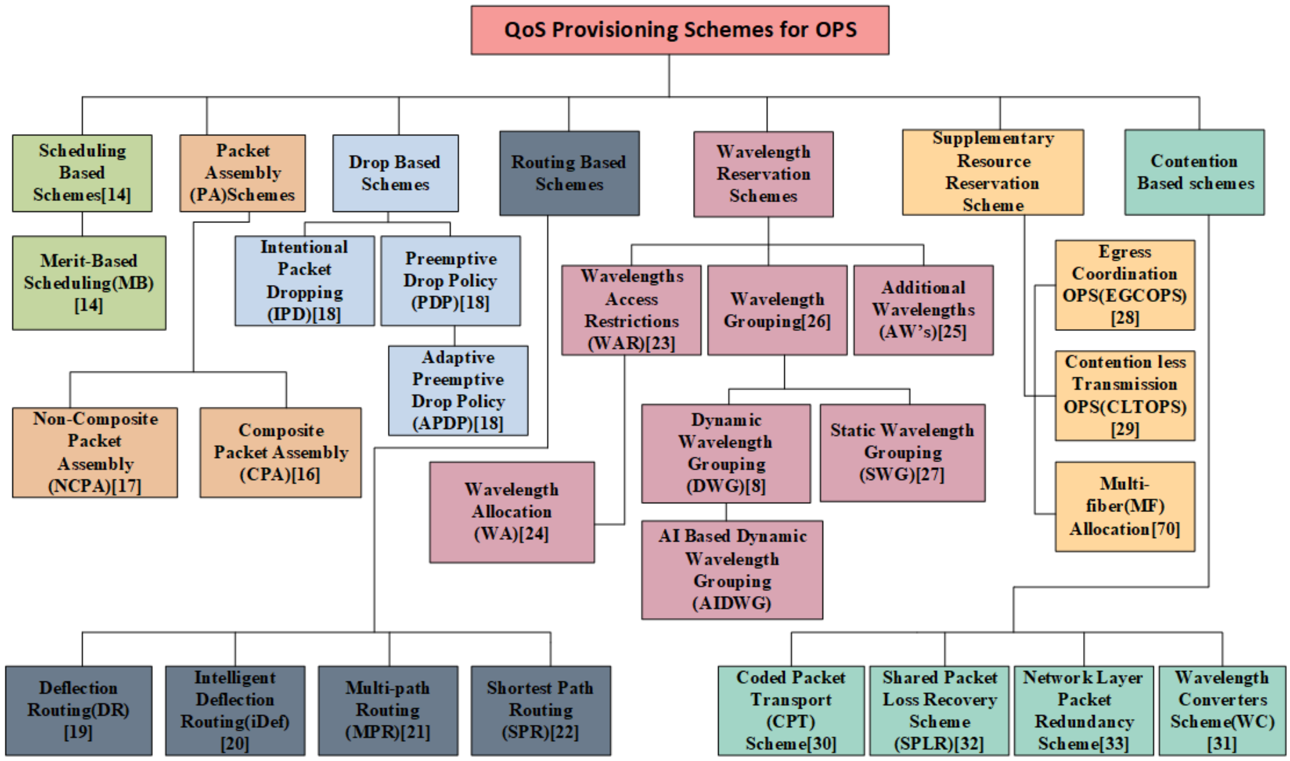


Figure 1. *Different QoS Techniques in Optical Networks*

III. Artificial Intelligence Based Dynamic Wavelength Grouping For QoS in OPS Networks

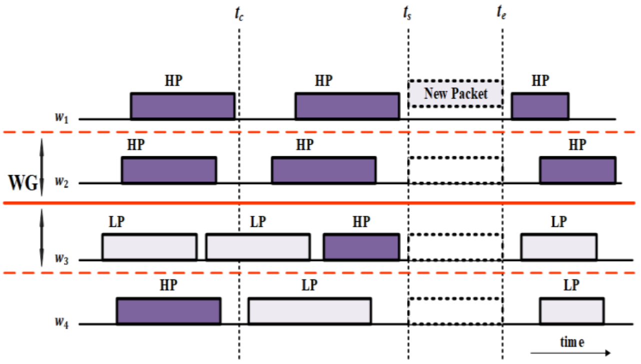
Limitations in the previous two versions of wavelength grouping (SWG, DWG) have been explained in the Introduction section. The algorithm proposed for SWG is not compatible with different arrival rates and dynamic traffic load. In SWG [7], the grouping of wavelengths is prefixed for each class of traffic. Let suppose 16 wavelengths are partitioned into 8-16 disjoint subgroups (8 for LP and 8 for HP), and each subgroup is assigned to a single priority class. If LP class traffic increase then this algorithm do not compete for extra resources. Thus total blocking probability increases and throughput decreases which refers to the unfair, inefficient, and inflexible wavelength partitioning behaviour towards QoS from a network performance perspective. DWG approach has been proposed as a solution for the above-highlighted problems of SWG. Any wavelength can carry optical packets of any priority class until the maximum count of reserved wavelengths for that priority traffic falls below a specific threshold. Additionally, optical packet of the HP traffic class may fill all possible wavelengths, potentially reducing packet losses caused by output port contention [3, 36].

Due to the above limitations and dynamic traffic nature, a more flexible and refined approach is proposed named "Artificial Intelligence Based Dynamic Wavelength Grouping (AIDWG)." AIDWG is the same as DWG, but linear regression model is used to decide wavelengths partitioning in disjoint subgroups at all switching nodes in the OPS network. The architecture of OPS is based on static routing rather than adaptive routing, so based on the physical distance or number of hops or some other fixed metric, one or more routes are determined in advance. For QoS traffic is distributed in the priority-based service classes where each class has a unique label P_ω. Also, P_ω is assigned by a wavelength set $w_{p\omega}$ out of total available wavelength w_{ti} at link h. The LRM is trained on the dataset and then based on the four parameters(load, blocking, waiting time, and utilization) value of $w_{p\omega}$ is calculated. The data set is based on the simulated values of the four parameters listed above. LRM take the current values of all four parameters and adjust the regression coefficients in order to give best wavelength group value and then according to the wavelength set optical packets are scheduled on available wavelengths. In our experiment, we looked at a network with traffic across two classes [ω Є (1, 0)] named as HP with ω = 1 and LP with ω = 0. As HP class optical packet is denoted by P_1 and LP class optical packet is addressed by P_0.

$$w_{p\omega} = \theta_0 + \theta_1 . L(P_1, P_0) + \theta_2 . BP_h^\omega + \theta_3 . WT_\omega^h + \theta_4 . UP_\omega^h \quad \textbf{(1)}$$

$$J = \frac{1}{n}\sum_{i=1}^{n}\left(pred\left(w_{p\omega}^i\right) - w_{p\omega}^i\right) \quad \textbf{(2)}$$

Where θ_0 is the intercept and $\theta_1, \theta_2, \theta_3$ *and* θ_4 are linear regression coefficients. It is critical to update the θ_n values to find the ideal weight that reduces the error between the predicted and actual value of $w_{p\omega}$. Cost function (J) given in Eq.2 is used to find the error and to update the values of θ_n we apply gradient descent on cost function by taking partial derivatives for each θ_n to achieve the best-fit line from Eq.1. BP_h^ω is the blocking probability, WT_ω^h is the Waiting time and UP_ω^h is the utilization for each P_ω traffic class on link h. Furthermore, calculated values of all parameters are sent to LRM. This model is already trained on the simulated dataset, and then according



to the given values of parameters, LRM provides a value of

Figure 2. *Scheduling through AIDWG using four Wavelengths*

$w_{p\omega}$ on a current link h from Eq.1.

Let suppose Eq.1 gives w_{p0} wavelengths for the transmission of P_0 optical packets on link h, then first w_{p0}= $(w_0, w_1, \ldots, w_{p0-1})$ wavelengths from w_{ti} and $w_{p0} < w_{t1}$ are arranged for P_0 optical packets. Thus P_0 optical packets can only use wavelengths from a specified set of wavelengths. HP optical packets can be scheduled on any wavelengths from total w_{t1}on link *h*. In this way, dynamic scheduling of optical packets is done on any available wavelength if there is a void length same as incoming optical packet length and w_{p0} are still less than w_{t1}. The scheduling module maintains the switching matrix, where it controls the transit packets competing with local packets of traffic for wavelengths utilization. To prevent the other traffic classes from being ignored and to maintain the network's QoS consistency despite the variable proportions of both classes in overall load, every switching node must ensure that the number of engaged wavelengths for P_0 does not exceed the w_{p0} preserved wavelengths.

TABLE 1
List of Notion Used

Symbols	Descriptions
ω	Priority classes
P_ω	Optical packets for ω priority
$w_{p\omega}$	Assigned set of wavelength for P_ω
w_{ti}	Number of wavelengths in link h
BP_h^ω	Blocking probability of packets on link *h*
WT_ω^h	Waiting time on each link *h*
UP_ω^h	Utilization of each wavelength set

Table.1 depicts the concepts used to calculate load for each class, blocking probability, waiting time, utilization, and network throughput. **Error! Reference source not found.** illustrates how AIDWG works in a scenario with two service classes and four wavelengths. At first, we suppose that two wavelengths ($w_3$and w_4) are available for P_0 class packets and P_1 has access to all four wavelengths (w_1, w_2, w_3 and w_4). At time t_c, P_0 optical packet can only schedule on w_3 and w_4 with the latest available unscheduled time[25, 37]. But after the first iteration, P_0 can also be schedule on w_1 and w_2 according to the value of w_{p0}. As a result of the dynamic behavior of AI-based wavelength grouping, wavelength partitioning changes over time with variations in QoS provisioned different parameters used in LRM, and assigned wavelengths for multiple service classes can vary.

IV. Simulation System and Setup

Using the discrete event-based IBKSim simulator [38], we performed simulation experiments to verify and analyze the results of the designed AIDWG scheme. AIDWG was simulated on popular network topology named as NSFNet network with nodes (n) =16 and links (h) = 25 represented in Figure 3.

We specified a threshold size of 1 Mbit and a threshold duration of 100s for assembling IP packets (generating from packet sources) into optical packets in assembly queues. A maximum of 10^3 optical packets can assemble in the FCFS dispatch queue. All intermediate node pairs have a uniform distribution of traffic. A control packet takes 10 μs to

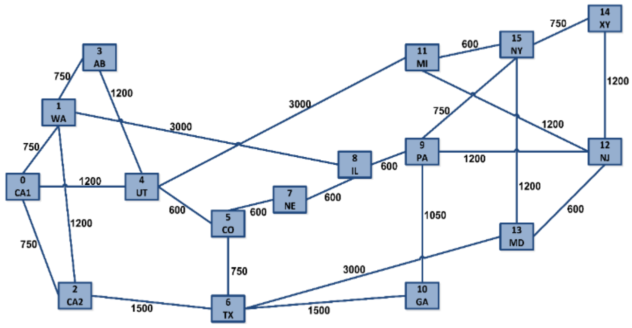


Figure 3. *NSFNet Topology*

process at each node, while the propagation delay is 5μs/km for each packet. The total time of simulation consists of 20 intervals and a warm-up interval, and the output accuracy is determined using a 95% confidence interval.

Each simulation interval generates 10^5 packets. We took an example of two priority classes where class 1 is HP traffic, and class 0 is LP traffic and then simulated this example with 16 wavelengths, each with a capacity of 10 Gbps. Further, scenario1 is based on the load share of each class in total load is simulated on NSFNet and evaluated the effect on QoS provisioning standards by load variation of different classes.

Configuration is designed so that at the start, HP traffic share began from 5% and then reached up to a maximum 50% share in total traffic load by the increment of 5% in each step. Likewise, started LP traffic share is 95% and reaches a minimum of 50% LP load share in total load by decrement of 5% in each step. After all was done, we arrived at a 50 percent HP and 50 percent LP configuration,.

V. Results and Discussion

AIDWG results are explained in terms of mean blocking probability, and total throughput at all network nodes. The proposed technique is evaluated and compared with the previous SWG scheme from **Error! Reference source not found.** to Figure 6.

Error! Reference source not found. indicates the mean blocking probability relevant to the average offered link load for HP and LP classes for SWG and AWDWG schemes in NSFNet topology. The wavelength grouping set is taken as 8-16 for SWG. We see that the mean blocking probability for HP traffic class is always less than LP class in both schemes and also HP traffic class blocking probability is less than HP blocking probability from SWG scheme. Because of the restricted wavelengths, More resources will be contributed by HP traffic packets and experience less Packet Loss Ratio (PLR) than LP packets. Smooth with a somehow curvy pattern shows a vast difference in probability of blocking for both classes (LP and HP), which assures QoS in terms of blocking probability.

TABLE 2
Simulation Parameters

Parameters	Values
size of packets	64 kbit
packet assembly threshold	time: 100 µs, length: 1 mbits
dispatch buffer capacity	103 packets
wavelength conversion	On each node available
link capacity	10 Gbps
total number of available wavelengths on each link	16
simulation intervals	20 intervals and a warm-up period
accuracy of results	95% confidence interval
Number of packets generated for each simulation interval	105
traffic classes of service	two-classes (HP: 1, LP: 0)

For AIDWG, blocking probability QoS is also shown with unfixed wavelength group with the same load configuration for HP and LP traffic classes. Wavelengths for each class are determined from LRM. The resultant curve is smoother and more carver. Furthermore, you can see a clear blocking difference between 0.4 to 0.6 load points. This difference tells us that AIDWG guarantees high

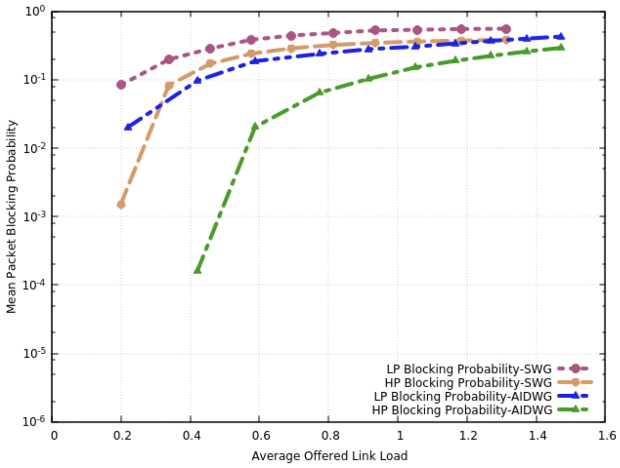
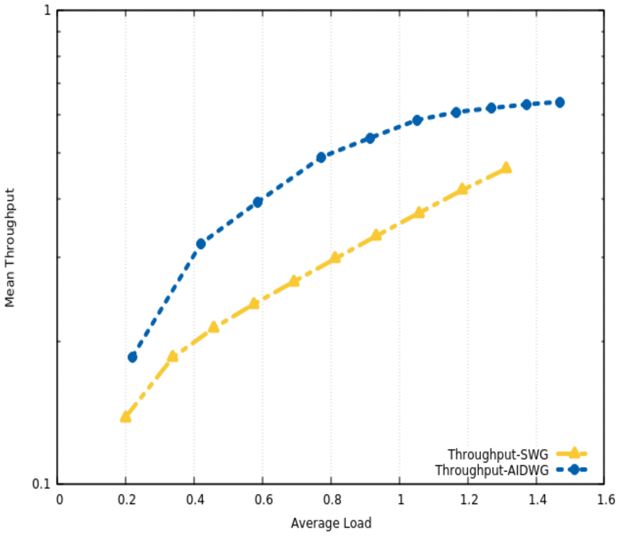


Figure 4. *Comparison between SWG and AIDWG in term of class-wise mean blocking probability and average load for NSFNet*

QoS services than SWG at each point of load. **Error! Reference source not found.Error! Reference source not found.** compared SWG and proposed AIDWG in terms of total blocking probability at each load point for NSFNet topology. The graph shows that at point 0.2, SWG



is giving very high blocking compared to AIDWG because HP load share is 5% and LP load share is 95%, and SWG is assigning 8-16 wavelengths which mean 8 for LP and remaining for HP. LP packets do not compete with HP to

Figure 5. *Comparison between SWG and AIDWG in term of average load and total blocking probability for NSFNet topology*

get more resources for large load share, so here PLR increases and thus blocking also increase in the SWG scheme. whereas proposed AIDWG scheme works using LRM, so it assigns wavelength group according to the current load situation by learning through an environment. Simulated values of laod,blocking,waiting time and utilization are sent to LRM and model give corresponsing set of wavelengths for LP class and remaining from total wavelengths are assigned to HP class traffic at each network node. At the equal load share, there is roughly a 50% difference between SWG and AIDWG because, at this point, SWG gives eight wavelengths to LP, whereas AIDWG gives value of wavelength set for LP according to updated model value.

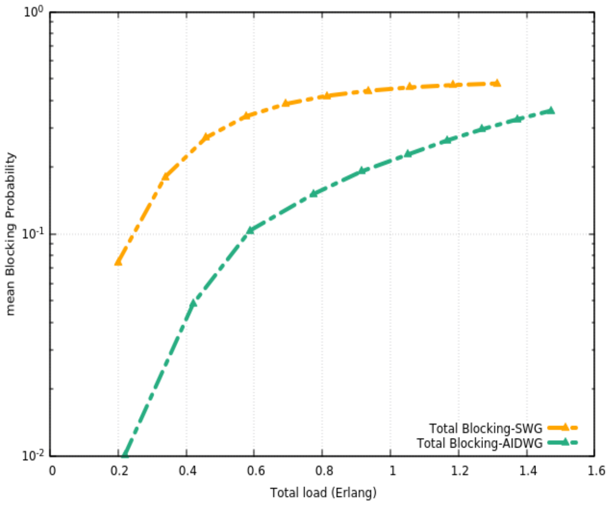


Figure 6. *Comparison between SWG and AIDWG in term of average load and mean throughput for NSFNet topology*

To check the efficiency and flexibility of proposed AIDWG in terms of QoS, Figure 6 indicates the mean throughput for NSFNet topology at each load point. At point 0.2, there is a minor difference between AIDWG throughput and SWG throughput. But as load increases, throughput is also increasing in both schemes. But from the Figure 6, we can see a clear difference at point 0.8, when HP traffic load share reached from 5% to 35% and LP load share is gone from 95% to 65% in total load, giving the idea that AIDWG is somehow extreme better technique than SWG.

Moreover, Throughput from SWG is linear and increasing sharply as load increase rather than according to each class load. However, throughput against the proposed AIDWG is linear and curvy and gradually increases with variation in each class's load.

Graphical analysis for both techniques shows that AIDWG improves QoS results in terms of blocking and Throughput. Also, the proposed scheme does not use extra resources like WAR for providing good QoS in real-time, interactive, and dynamic networks. Thus, from all the above discussion and results, we can say that AIDWG is a much better and flexible approach than all other schemes.

VI. Conclusion

AIDWG technique is proposed in this paper to give better QoS in fluctuating load-based OPS networks. Wavelength groups and other resources are dynamically partitioned and allocated to each traffic class by tracking the load, waiting time, blocking, and utilization in varying traffic loads. Wavelength group changes according to four parameters, and linear regression checks the best value for each type of load class. Dataset is prepared from multiple simulations. discrete-event-based simulation is evaluated in different load scenarios for each class to check the flexibility of DWG in terms of blocking and throughput. The graphical analysis shows a total improvement of roughly 30% and 40% in average blocking probability and network throughput of each class packet. AIDWG beats the old SWG scheme by allocating optimal partitioning of available wavelengths among different traffic load scenarios of HP and LP classes, guaranteeing QoS in terms of throughput and blocking. In the future, our target is to analyze the AIDWG with more parameters and improve the performance of the AI-based DWG technique in terms PLR.

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