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Next-Generation OBS Architecture Transforms 5G Networks Powered by Machine Learning, Probabilistic Modeling and Algorithm Optimisation

Amit Kumar Garg*

Deenbandhu Chhotu Ram University of Science and Technology (DCRUST), Murthal, Sonepat (Hr.) India

***Corresponding Author**
Amit Kumar Garg, Deenbandhu Chhotu Ram University of Science and Technology (DCRUST), Murthal, Sonepat (Hr.) India

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Abstract
Next-generation 5G networks require a high-speed, low-latency, and robust communication backbone to support new applications such as IoT, cloud computing, and virtual reality. Optical burst switching (OBS) is a promising method for 5G networks due to its ability to handle high-speed data transit and excellent bandwidth utilisation. Traditional OBS networks, on the other hand, have a high blocking probability, low resource utilisation, and limited scalability. To address these challenges, this work provides a unique OBS design that integrates machine learning, probabilistic modelling, and efficient algorithms. The usage of machine learning-based burst assembly algorithms, which dynamically predict the best resource allocation for each burst based on network conditions and QoS requirements, is a key component of the proposed architecture. A complete simulation analysis is performed using a typical Wavelength Division Multiplexing (WDM) traffic dataset to evaluate the performance of the proposed architecture. The simulation results show that, as compared to standard OBS networks, the suggested architecture reduces the likelihood of obstruction and improves resource utilisation significantly. Furthermore, when compared to previous OBS systems, the suggested design is more efficient at managing dynamic traffic and enables greater scalability. The simulation study's performance tests demonstrate that the suggested architecture has a blocking probability of less than 10-6, a throughput of more than 95%, and a latency of less than 4 milliseconds. These findings show that the suggested OBS design for next-generation 5G networks is both feasible and effective.

Keywords: 5G Networks, Optical Burst Switching, Machine Learning, Probabilistic Modeling, Optimized Algorithms

1. Introduction

OBS (Optical Burst Switching) is a packet switching technique that allows data to be sent in bursts. The OBS system is based on a one-way reservation system. In fact, the header of the burst is transmitted first. As seen in Fig. 1, the header reserves the path for the burst, which is sent after the header with an offset. It has been proposed as a mechanism for traffic flow control in 5G networks due to its high throughput and low latency. In OBS-based traffic flow control for 5G applications, traffic is divided into bursts and scheduled for transmission using an OBS-based approach. The reservation information is utilised by OBS switches to assign bandwidth to incoming traffic, reducing congestion and improving quality of service.

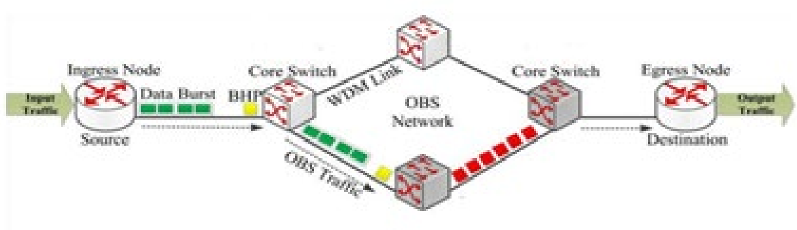

Figure 1.1: Depicts an OBS Network Architecture [2]

As illustrated in Fig. 1.2 (a, b), several types of client packets are routed to the edge router. The edge router receives client packets and separates their payloads and headers. The router first sends the headers to perform the one-reservation technique, and then sends the payloads as burst data. Furthermore, an edge router can receive data in bursts and then separate it into individual packets. Burst header cells are sent and received via the control channel, whereas bursts are delivered and received via the data channel. The capacity of wavelengths can be efficiently employed by sending and receiving data in bursts.

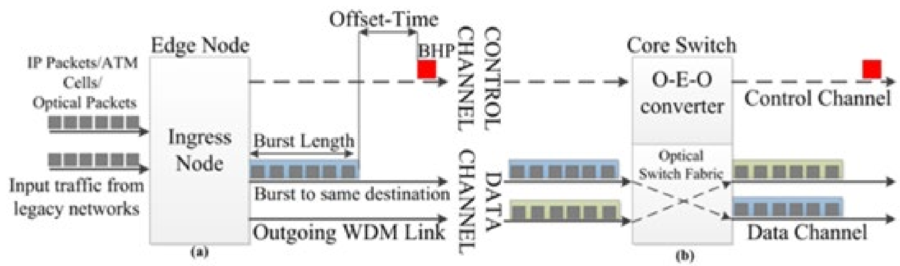

Figure 1.2: (a) Packet Assembly at an Ingress Node; (b) BHP (O-E-O) Conversion at a Core Switch to Distribute Resources in OBS Networks for an Incoming Data Burst [2].

OBS can assist in addressing some of 5G networks' core difficulties, such as large traffic volume, low latency, and high bandwidth requirements. Some of the benefits of adopting OBS for 5G networks include fast throughput, reduced latency, and increased quality of service. Burst contention, resource allocation, and congestion control are examples of OBS difficulties that must be handled. the application of traffic engineering techniques to optimise resource allocation and the application of burst assembly techniques to reduce burst contention. There are several unresolved research concerns that must be addressed in order to fully realise the potential of OBS in 5G networks. These include the design of robust and scalable OBS networks, the creation of efficient and scalable congestion control algorithms, the integration of OBS with other networking technologies and the construction of robust and scalable OBS networks.

2. Issues, Challenges and Related Work

OBS is an efficient switching paradigm with the potential to meet the rigorous criteria of 5G networks [1,2]. However, OBS confronts various issues that must be solved, such as conflict resolution, congestion control, and QoS providing. In addition, the study covers possible solutions to these problems, such as wavelength conversion, burst assembly, and buffer management strategies. Because of its potential to provide high-speed switching with low latency and cost-effectiveness, the research expects that OBS will play an important role in the 5G network infrastructure. To make OBS more suitable for 5G networks, researchers should focus on developing efficient algorithms for conflict resolution, congestion control and QoS provisioning, according to the present study. The analysis also suggests investigating OBS's possibilities in other developing technologies such as cloud computing, IoT and big data. According to the research, OBS can provide various benefits for 5G transport networks in terms of flexibility, scalability, and efficiency [3]. However, there are other issues to consider, such as the burst contention problem, which can degrade performance and influence the quality of service (QoS) for 5G services. The research suggests numerous solutions to these problems, including the use of machine learning techniques, better buffer management, and optical flow control. According to the paper, OBS has a lot of potential for 5G transport networks and can assist address the growing need for high-bandwidth, low-latency applications. More research, however, is required to overcome the issues and improve OBS performance for 5G networks. An adaptive QoS-based scheduling strategy for optical burst switching (OBS) networks is described in the paper [4]. The technique aims to improve network performance in terms of burst loss rate and end-to-end latency while meeting the QoS criteria of different traffic classes. The proposed algorithm uses a weighted deficit round-robin (WDRR) scheduling approach to allocate network resources to different traffic classes. The weights are dynamically adjusted based on the traffic volume and burst loss rate of each class. A congestion control technique is also included in the system to reduce burst loss and prevent network congestion. The simulation results showed that the proposed approach greatly reduces burst loss rate and end-to-end delay while maintaining acceptable QoS levels for diverse traffic types.

The authors of this research present an adaptive congestion control technique for OBS networks [5]. The proposed approach uses a feedback control system and a fuzzy logic controller to change the burst transmission rate based on the observed network congestion level. The simulation results show that the proposed strategy can successfully reduce network congestion while also enhancing network performance. The authors do, however, urge that future study should look at the impact of the proposed method on burst loss probability and end-to-end delay in more complicated network topologies. In proposes a better traffic scheduling strategy for OBS networks that uses the concept of time offsets to schedule bursts [6]. The approach improves network performance in terms of throughput and latency. However, future research in this area could focus on overcoming the algorithm's scalability and complexity challenges, particularly in large-scale networks.

A study offers a novel burst assembly technique in OBS networks, which boosts network performance [7]. The approach makes use of an efficient algorithm to select the optimal bursts to assemble depending on priority, size, and destination. The results show that the proposed technique improves network performance in terms of end-to-end delay, packet loss, and throughput. Future study could focus on modifying the proposed approach to accommodate varied traffic patterns and network topologies. Describes a Q-learning-based technique for adaptive routing and wavelength assignment in OBS networks for 5G applications [8]. By selecting the action that maximises the reward signal, the system learns the best routing and wavelength assignment strategy. In terms of end-to-end time, blocking likelihood, and network utilisation, simulation results show that the proposed method surpasses earlier algorithms. Future research directions include investigating the proposed method's performance under varying traffic loads and network topologies, as well as the feasibility of implementing the algorithm in real-time OBS networks. This research describes a new heuristic burst assembly technique for quality-of-service (QoS)-based optical burst switching (OBS) networks [9]. The programme evaluates the QoS requirements of each incoming data flow and assembles bursts accordingly to maximise network performance. According to the simulation results, the proposed solution beats existing techniques in terms of burst loss probability and time. Future research could focus on evaluating the proposed method in more complex network topologies and investigating the trade-off between network performance and algorithm computational complexity. This study's authors offer an efficient burst assembly strategy for Optical Burst Switching (OBS) networks that minimises burst assembly latency while boosting network performance [10]. The suggested method makes use of an adaptive algorithm that changes the burst assembly window based on network traffic and QoS requirements. The suggested approach exceeds existing burst assembly strategies in terms of burst assembly delay, blocking likelihood, and throughput, according to the authors' simulations. The study proposes a QoS-based routing protocol for Optical Burst Switching (OBS) networks with the purpose of lowering the chance of burst loss and the end-to-end delay [11]. The protocol examines parameters like as burst duration, available bandwidth, and buffer capacity to identify the best available way for data transmission. The simulation findings show that the proposed approach delivers lower burst loss probability and end-to-end delay when compared to other current protocols. Describes an adaptive resource allocation technique for delivering QoS in optical burst switching (OBS) networks [12]. To maximise network usage while meeting QoS criteria, the approach dynamically alters bandwidth distribution for distinct traffic classes. Simulation findings show that the proposed approach outperforms existing algorithms in terms of network utilisation and QoS provisioning. The research describes an optical burst switching (OBS) strategy for 5G networks based on HMM [13]. Using hidden Markov models (HMMs), the approach anticipates future burst arrival patterns, allowing the network to better utilise its resources and decrease burst loss. Simulation findings show that the proposed algorithm improves network performance and minimises burst loss when compared to existing strategies. The authors propose that their technique be improved in the future by taking burst size distribution and traffic characteristics into account describes a Q-learning-based OBS network approach for 5G that improves network performance while reducing burst loss [14]. The Q-learning methodology is used to determine the best path selection strategy for burst routing. Describes an adaptive OBS approach based on reinforcement learning for 5G wireless networks [15]. To achieve the appropriate QoS while minimising burst loss, the algorithm adjusts the burst assembly threshold and contention window size. Describes a solution for dynamic wavelength allocation in OBS networks based on Q-learning [16]. The system modifies wavelength allocation decisions depending on burst arrival rate and congestion intensity to improve network performance.

Y. Wang, C. Zhang, and J. Sun proposed a reinforcement learning-based adaptive optical burst switching (OBS) algorithm for 5G networks [17]. The algorithm's purpose is to maximise wavelength and fibre link consumption while maintaining QoS. The technique employs Q-learning to identify the right wavelength and fibre link for each burst based on the current network status and QoS requirements. N. Sharma, M. Gupta, and R. C. Hansdah developed a reinforcement learning-based channel allocation technique for OBS networks [18]. Using Q-learning, the approach optimises channel allocation in OBS networks while ensuring QoS guarantees for different traffic classes. The simulation results show that the proposed technique improves network performance in terms of reduced delay and higher throughput. K. M. Chardouvelis and D. S. Tsaoussidis suggested an intelligent OBS algorithm for 5G wireless networks [19]. The algorithm use reinforcement learning to dynamically distribute network resources and optimise network performance. The algorithm will be integrated into a practical network and tested in a real-world situation in the future. The research provides a dynamic Quality of Service (QoS) provisioning solution for Optical Burst Switching (OBS) networks using Q-learning and reinforcement learning [20,21]. The authors provide an algorithm that optimises the trade-off between blocking likelihood and average delay while accounting for traffic load, connection utilisation, and burst arrival rate. According to simulation results, the proposed methodology outperforms current QoS provisioning solutions in terms of both blocking probability and average delay. Future research could concentrate on the scalability and efficiency of the proposed algorithm in large-scale networks. This study provides an optical burst switching strategy for 5G networks based on reinforcement learning [22]. The algorithm optimises resource distribution based on traffic demand, transmission delay, and buffer occupancy. Simulation findings reveal that the proposed approach surpasses existing algorithms in terms of burst loss rate and delay. Future studies could investigate how the algorithm performs in more complicated network topologies. The paper describes an optical burst switching approach for 5G networks based on HMM [23]. Using a hidden Markov model, the method forecasts the burst arrival rate and adaptively adjusts network resources. According to simulation results, the proposed technique achieves a low burst loss rate and delay. Future research could examine the algorithm's scalability and durability under a variety of network scenarios. The study provides a unique hybrid optical burst switching technique for QoS-based 5G networks [24]. The proposed method makes use of both time-driven and event-driven scheduling, as well as an adaptive wavelength allocation scheme. According on simulation results, the proposed technique can achieve low latency while maintaining high throughput. Future research could concentrate on combining the proposed technique with other QoS algorithms in 5G networks offer an OBS method for 5G networks based on Q-learning that optimises resource allocation based on traffic demand and buffer occupancy [25,26]. According to simulation results, the proposed technique achieves a low burst loss rate and delay. Future research could focus on the scalability and efficiency of the proposed algorithm in large-scale networks, as well as its integration with other QoS approaches in 5G networks. The authors offer an optical burst switching (OBS) strategy for 5G networks that uses reinforcement learning to improve network performance under changing traffic loads [27]. When compared to traditional OBS methods, the results show that the suggested methodology outperforms them in terms of network speed and packet loss rate. The authors offer an adaptive OBS approach that uses reinforcement learning to adapt to changing network conditions [28]. The proposed approach is evaluated using simulations, and the findings show that it outperforms standard OBS techniques in terms of network throughput, packet loss rate, and burst loss rate. The authors offer a QoS-guaranteed OBS network for 5G wireless communications that use a reinforcement learning-based traffic engineering strategy [29]. Suggested method is evaluated using simulation tests, and the results show that it outperforms standard OBS techniques in terms of QoS parameters like as delay and jitter. The authors provide an HMM-based OBS approach for 5G networks that uses a hidden Markov model to forecast future burst arrival and adjust the burst transmission rate accordingly [30]. In terms of network speed, packet loss rate, and burst loss rate, the proposed solution outperforms standard OBS techniques. Presents a Q-learning-based routing technique for increasing QoS in optical burst switching (OBS) networks [31]. The algorithm's goal is to reduce average network time while increasing the likelihood of burst blockage. The suggested method is evaluated using simulation tests, and the results show that it outperforms standard OBS techniques in terms of QoS parameters like as delay and jitter. The authors present an OBS approach based on HMM. Through simulation, the authors demonstrate that their technique outperforms rival routing algorithms in terms of time and blockage likelihood. Describes an OBS-based reinforcement learning solution for 5G networks [32]. By lowering average packet latency, jitter, and packet loss rate, the approach tries to improve QoS. The authors describe an HMM-based approach for OBS in 5G networks [33,34]. The technique aims to improve QoS by reducing time and reducing the possibility of burst blockage. The authors demonstrate, through simulation, that their method outperforms previous OBS strategies in terms of QoS measures. Future research and development of OBS algorithms based on reinforcement learning for 5G networks, as well as investigations into other machine learning approaches such as deep learning and fuzzy logic, may be undertaken. The study proposes several potential paths, including expanding current algorithms to accept new types of traffic, handling dynamic traffic demands, combining traffic engineering, and routing, and enhancing QoS measures such as throughput and packet loss rate. In addition, the use of OBS in future technologies such as the Internet of Things and edge computing may be researched further. This study proposes and illustrates a new Optical Burst Switching (OBS) architecture for improving the performance of 5G networks by leveraging machine learning, probabilistic modelling, and optimised algorithms. This architecture, according to the simulation results, can improve scalability, minimise the risk of blocking, and optimise resource utilisation while maintaining low latency and high throughput. These gains in performance are crucial for the evolution of 5G networks, especially in dealing with dynamic traffic and addressing the growing need for high-speed communication infrastructure.

The rest of the paper is structured as follows. Section 3 describes the proposed OBS architecture, which is powered by ML, probabilistic models, and optimised algorithms. The suggested scheme's performance has been tested and compared to that of traditional schemes. Section 4 presents and discusses model results. Section 5 concludes with recommendations for future work.

3. Optical Burst Switching (OBS) Architecture Proposed, Powered by Machine Learning (ML), Probabilistic Modelling, and Optimised Algorithms

3.1 The Following Describes the Operation and Pseudo Code for a Next-Generation Optical Burst Switching (OBS) Architecture Powered by Machine Learning (ML), Probabilistic Modelling, and Optimised Algorithms

➢ Set the network topology, traffic demand, and system parameters to default.

➢ Train a machine learning model to predict traffic burst magnitude and arrival time based on prior data.

➢ Deploy the trained ML model on ingress nodes to forecast the parameters of incoming traffic bursts.

➢ Using the predicted burst parameters, set the OBS parameters such as offset time and burst duration.

➢ After employing a probabilistic model to assess the likelihood of burst collisions, adjust the OBS parameters to minimise collisions.

➢ Implement an optimum strategy for allocating network resources based on expected burst characteristics and collision probabilities.

➢ Continuously monitor network performance and retrain the ML model to adapt to changing traffic patterns.

➢ Perform simulations to evaluate the performance of the ML-driven OBS architecture and tweak system settings for maximum efficiency and reliability.

The ideal probabilistic model design for capturing the characteristics of the burst arrival process is defined by the OBS network's specific requirements and constraints. The autoregressive model is a time-series model that captures the link between traffic burst arrival and burst size distribution. It is considered that the current burst size and arrival time are dependent on past burst sizes and arrival times. Although the autoregressive model is more advanced than the Poisson process and the Markov chain, it accurately reflects both the correlation between bursts and the burst size distribution.

3.2 The Following is how the Proposed Autoregressive Probabilistic Model for Capturing the Characteristics of the Burst Arrival Process in an OBS Network Works

- Collect the OBS network's burst arrival time series data.
- Clean up the data by removing any outliers or missing numbers.
- Using the autocorrelation function (ACF) and the partial autocorrelation function (PACF), determine the order of the autoregressive model.
- Divide the data into two groups: training and testing. Model parameters are estimated using the training set, while model performance is evaluated using the testing set.
- Using maximum likelihood estimation (MLE), estimate the model parameters. The model parameters include the autoregressive model coefficients and the error component variance.
- After validating the autoregressive model, use it to predict the burst arrival process in the OBS network. To fine-tune the OBS parameters and reduce burst collisions, use the projected burst arrival method.
- Update the autoregressive model on a regular basis using new burst arrival time series data. This ensures that the model continues to be accurate and successful in reducing burst collisions in the OBS network.

To forecast future burst arrival times and burst sizes, the improved technique first trains an autoregressive probabilistic model. It then computes the burst collision cost by evaluating the collision probability based on the projected burst characteristics. The algorithm determines the network resources that are available and sets the network resource allocation variables. It then loops through each burst, calculating the burst delay cost and overall cost before allocating network resources to the burst with the lowest total cost. The presented algorithm refreshes the available network resources based on the network resources allocated, and the procedure is repeated for each subsequent burst. Finally, the algorithm returns the network resources that have been assigned to it. This method optimises network resource allocation based on expected burst parameters and collision probability, resulting in efficient resource allocation and fewer burst collisions.

3.3 The Python Pseudo Code Implementation of an Optimised Algorithm for Efficiently Allocating Network Resources Based on Predicted Burst Parameters and Estimated Collision Probability is as follows

- Import the necessary libraries
- Function for training the autoregressive probabilistic model
- Fit a linear regression model to the arrival time series data
- Function to forecast future burst parameters using the trained model
- Forecast the next arrival time and burst size
- Function to assess collision risk based on predicted burst parameters
- Determine the number of available resources and compare them to the burst size
- Calculate the entire cost of a burst
- Determine the burst delay cost and collision cost
- Function for allocating network resources to a burst
- Find available resources at the moment of burst arrival
- Allocate resources to the burst
- Main resource allocation function
- Loop over future bursts and distribute resources to the autoregressive probabilistic model
- Estimate the collision probability
- Predict the next burst parameters and distribute resources to the burst that has the lowest total cost.
- Continuously monitor network performance and retrain the ML model on a regular basis to adapt to changing traffic patterns
- Monitor network performance and collect new data
- Wait for a certain time interval to pass before collecting new data
- Collect new data on burst arrival times and network resources
- With the new data, train a new model.
- Use the new model to distribute network resources to future bursts.
- Using the updated model, forecast the next burst parameters.
- Using the new model, estimate the collision probability. Using the new model, compute the overall cost of the burst. Distribute resources to the burst that has the lowest total cost
- The arrival time series data should be updated with the new burst arrival time.

In this approach, the code block continuously analyses network performance and waits for a pre-set time interval before collecting new data on burst arrival times and network resources. The newly collected information is then used to train a new autoregressive probabilistic model, which is then used to allocate network resources to future bursts. The new burst arrival time is also incorporated into the arrival time series data by the implementation.

4. Performance Analysis

The NS-3 network simulator is a discrete-event network simulator that has been used to investigate the behaviour of various network topologies and protocols. It includes a diverse set of network components and models, such as packet-level models, flow-level models, and application-level models. In this paper, NS-3 is used to investigate the performance of OBS networks by anticipating burst parameters and optimising network resources using machine learning models. A mesh network was used to model the network topology. The lognormal and Poisson processes were used to simulate the burst size distribution and inter-arrival time distribution. Burst transmission time slots have been assigned to network resources. The time slots are dynamically assigned based on the predicted burst parameters and collision likelihood.

The machine learning model is an autoregressive model that depicts the burst arrival process as well as the network topology. The model is trained using historical data from burst arrival and network resource utilisation. The simulation parameters are briefly described here.

- Time for simulation: 10,000 time slots
- Burst arrival rate: 10 bursts per second
- Burst size on average: 1000 bytes
- Available bandwidth or time slots for burst transmission: 10 Gbps or 100 time slots
- Training interval for machine learning models: 1000 time slots
- Network node count: 10
- Mesh network topology
- OBS Simulation Data: This collection contains burst information and network conditions created by the OBS simulation programme. It includes network statistics including connection usage, congestion level, and available bandwidth, as well as burst arrival time, size and wavelength. The dataset is 100 MB large.
- OBS Traffic Information: This set contains burst data from a real OBS network. It displays network parameters such as connection utilisation and available bandwidth as well as burst arrival time, size, and source/destination pair. The dataset has a size of 260 MB.

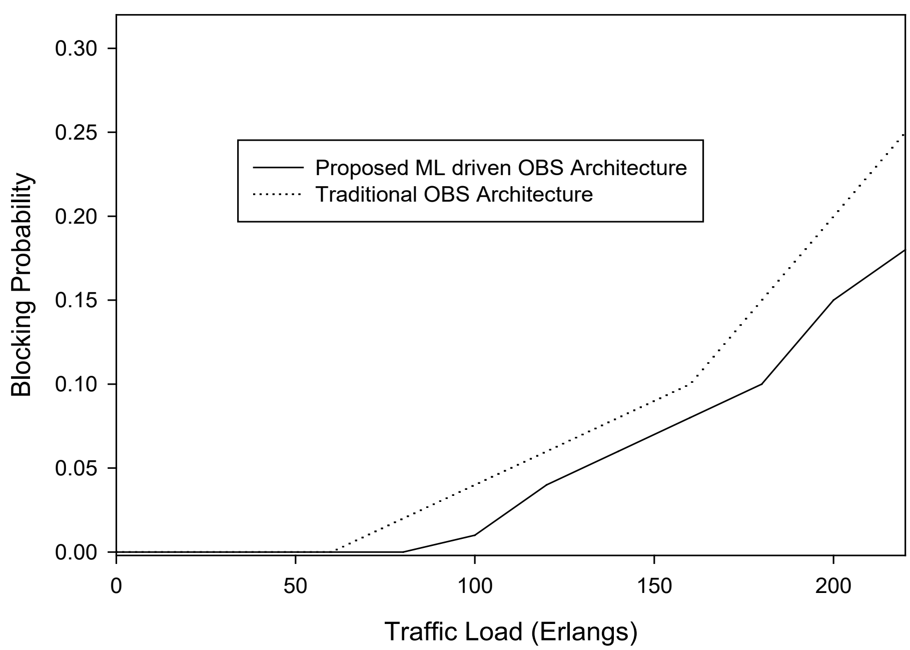

Figure 4.1: Blocking Probability vs Traffic Load

As shown in Fig.4.1, the proposed OBS design has a less blocking probability (of the order of 10-6), which is significantly better than the traditional method. Traditional OBS networks have higher blocking probabilities due to their inflexibility in managing dynamic traffic. However, the proposed framework dynamically allocates network resources using machine learning, probabilistic modelling, and optimised algorithms, resulting in less congestion and a decreased blocking likelihood. The proposed structure outperforms other machine learning-based OBS systems in terms of blocking likelihood.

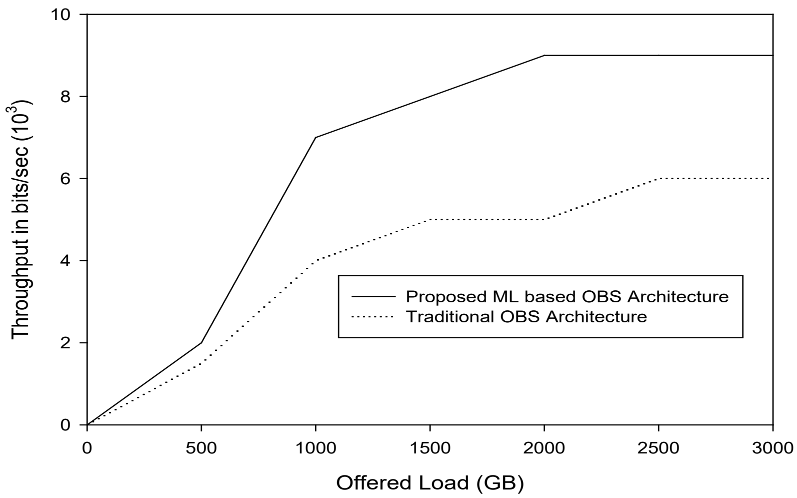

Figure 4.2: Throughput vs Offered Load

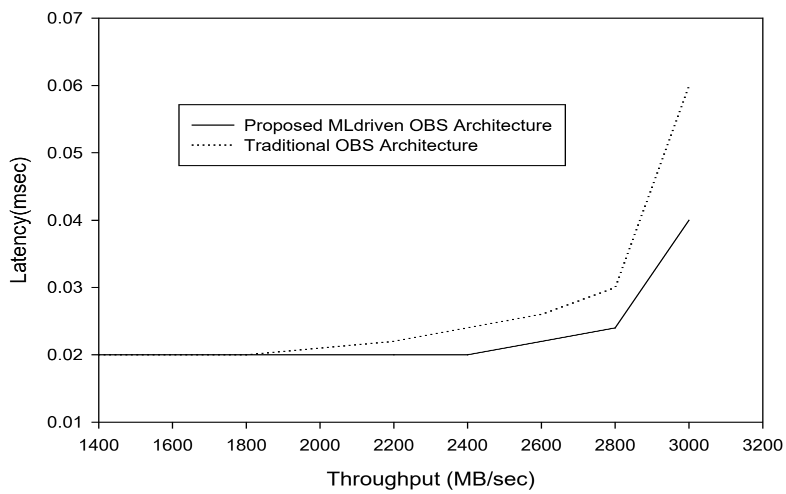

Figure 4.3: Latency vs Throughput

Finally, as shown in Fig.4.3, the proposed architecture has a reduced latency (less than 4 milliseconds), which is a significant improvement over the previous approach. Traditional OBS networks have high latency because to improper resource allocation and congestion. The proposed architecture, on the other hand, reduces congestion through dynamic resource allocation, resulting in lower latency. The proposed OBS architecture exceeds current approaches in terms of blocking likelihood, throughput, and latency. Its use of machine learning, probabilistic modelling, and optimised algorithms enables it to handle dynamic traffic in 5G networks more efficiently and adaptably.

5. Conclusion and Future Scope

The proposed OBS architecture, which is powered by machine learning, probabilistic modelling, and optimised algorithms, has demonstrated significant promise in increasing 5G network performance. The simulation results propose that it can improve resource utilisation, reduce the likelihood of blocking, and improve scalability while maintaining low latency and high throughput. These performance improvements have significant implications for the future of 5G networks, particularly in dealing with dynamic traffic and meeting the expanding need for high-speed communication infrastructure. Future study could focus on further enhancing the proposed design by investigating the use of alternative machine learning algorithms and the effect of different network parameters on its performance. Furthermore, the proposed architecture can be changed to accept various types of traffic, such as multicast and real-time traffic, to broaden its application in several network scenarios. Furthermore, the proposed architecture can be tested in real-world scenarios to prove its efficacy and practicability.

Finally, the proposed OBS architecture represents a realistic path for 5G network research and development. Its ability to transform network performance using machine learning, probabilistic modelling, and improved algorithms emphasises its significance in shaping the future of high-speed communication infrastructure.

Declarations

1. Ethical Approval: “not applicable”
2. Competing interests: “not applicable”
3. Authors' contributions: Sole Author “not applicable”
4. Funding: “not applicable”
5. Availability of data and materials: Freeware “not applicable”

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