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Developments of Machine Learning Solution for Assignment of Calls of RWA in Wireless Network

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ABSTRACT

The increasing demand for efficient resource management in wireless networks has necessitated innovative solutions for the Routing and Wavelength Assignment (RWA) problem. Traditional approaches often face limitations in handling dynamic traffic conditions, leading to suboptimal resource utilization and increased blocking probabilities. This study explores the development of machine learning-based solutions for the assignment of calls in RWA, offering a data-driven approach to optimize resource allocation and improve network performance. Machine learning algorithms, including supervised learning, reinforcement learning, and neural networks, are employed to predict traffic patterns, dynamically allocate wavelengths, and select optimal routing paths. These models adapt to changing network conditions, enabling real-time decision-making and reducing call blocking. Simulation results demonstrate that machine learning techniques outperform conventional heuristic methods in terms of blocking probability, resource utilization, and adaptability to network fluctuations. This research highlights the potential of machine learning to transform RWA in wireless networks, providing scalable and intelligent solutions for modern communication systems. The findings lay the groundwork for further exploration into hybrid models, cross-domain applications, and integration with emerging technologies such as 5G and beyond.

Keywords: Routing and Wavelength Assignment (RWA); Blocking Probabilities; Wrong Decision Probability of Handovers; Machine Learning Approach; Integrated Framework; WSN.

1. INTRODUCTION

The rapid growth of wireless communication technologies has led to an exponential increase in the number of devices and users accessing these networks. Traditional networking approaches, such as reactive, centrally-managed, and one-size-fits-all methods, have limited capacity to handle the complexity and optimization demands of modern wireless networks (Bajaj, 2021). Conventional data analysis tools also fall short in supporting the operational and cost-efficient requirements of network providers. To address these challenges, the application of machine learning techniques in wireless communications has emerged as a promising solution. Machine learning is a powerful tool that can help engineers conceptualize and implement advanced technologies, such as autonomous vehicles, industrial and home automation, virtual and augmented reality, and e-health applications. (Bajaj, 2021) The use of machine learning in wireless communications is driven by the need to move away from traditional optimization techniques and exploit the capabilities of big data and advanced analytics. (Bajaj, 2021) One area where machine learning has shown significant potential is large-scale optimization in 6G wireless networks. The sixth-generation wireless systems are envisioned to enable a paradigm shift from "connected things" to "connected intelligence", characterized by ultra-high density, large-scale, dynamic heterogeneity, diversified functional requirements, and machine learning capabilities. Classic optimization-based algorithms often require a highly precise mathematical model of data links and suffer from poor performance and high computational cost in realistic 6G applications.

2. RELATED WORK AND BACKROUND

Machine learning techniques have been increasingly utilized in various networking applications, including optical networks and wireless networks. In the context of Fiber-Wireless (FiWi) networks, a hybrid algorithm has been proposed as a cost-efficient solution for Optical Network Unit (ONU) placement [1]. Additionally, machine learning-enabled Routing, Wavelength, and Spectrum Assignment (RWA) solutions have been developed for elastic optical networks, such as the DeepRMSA framework [4]. The application of artificial intelligence and machine learning in networking has also been explored in the financial services sector, driven by technological advances and the availability of financial sector data [5]. Furthermore, deep reinforcement learning, which combines deep neural networks, has been identified as a promising approach for Beyond 5G networks, offering the ability to operate on non-structured data [9]. Overall, the integration of machine learning solutions in networking applications, such as RWA in wireless networks, showcases the potential for enhanced efficiency and performance in network management and resource allocation. Further research in this area is essential to continue advancing the capabilities of machine learning in optimizing network operations[10][11]. Shekhawat et al (2010): A new approach was proposed by the author to allocate the resources in an optical network. Edge Disjoint Path was proposed in the research work and it has been demonstrated that with this method, the allocation of resources can be managed easily. The assignment of channels was based on assigning weights to channels. P.H.G.B. et al (2010): Assignment of channels was performed with three algorithms, namely, most used model, least used model and first fit models. Performance of the WDM networks was valuated using simulation for these three models. Of all the models, it has been found that first fit models yielded best results compared to most used model and least used model.M. B thakur (2015): Author discussed several algorithms that used to assign the channels and select the optimum route in the optical networks . The methods related to optical switching were discussed along with many other methods.M Ali et al. (2014): A network simulator was used to measure the performance of channel assignment methods Two methods, namely, first fit method and random assignment methods were used to assign the channels and performance was compared for standard networks.Musumeci et al. (2018), J. Mata et al (2018) and R. Boutaba et al. (2018) have provide the surveys of application of machine learning and artificial intelligence in the area of optical network in WDM[12] . A Software Defined Networking (SDN) principle was proposed by M. Trevisan et al. (2018) that provide advantage to the network automation using artificial intelligence. The SDN is becoming very popular recently to develop programmable networks . The positive benefits of SND are leveraged with the artificial intelligence and machine learning. The networks continuously learn themselves about the management of the resources. S. Ayoubi et al (2018) and A. Mestres (2017) discussed the importance of integrating the SDN with artificial intelligence (AI) and machine learning (ML) in the area of optical networks. Authors believed that the integration will revolutionize the telecom technologies . M. Wang et al. (2017) and J. Barron et al. (2016) explained various developments in the application of deep learning and deep reinforcement methods in the area of improving and managing the networks [23-24].S. Haeri et al. (2016), B. Mao et al. (2018), F. Tang et al. (2017), Z. Xu et al. (2018) and N. C. Luong et al. (2018) explained the application of AI and ML in the networking. Authors also explained about the importance of quality datasets to train the ML models [13][14][15].

A. PROBLEM DEFINATION

Based on the literature survey, it has been determined that wavelength assignment is predominantly carried out using two approaches, namely,

- First fit assignment
- Random assignment

There are no efficient algorithms present to reduce the blocking probabilities further down. In this research work, it is proposed to develop new algorithms to reduce the blocking probabilities. Also there is a need to combine the blocking probabilities with the wrong decision probabilities to estimate the overall failure of the calls to pass through the channels when the hand of the calls happens in wireless network.

B. OBJECTIVES OF PAPER

- To develop solution for the baseline methods for assignment of calls of RWA.
- To measure the performance of baseline algorithms like first fit and random assignments.
- To design new algorithm to assign the calls into various channels using different statistical distribution and/or machine learning techniques.
- To compare the performance of new algorithms with base line methods.
- To integrate the blocking probabilities with wrong decision probabilities of handovers.

In this paper Section 3 discussion about developing a solution for and Wavelength Assignment (RWA) involves addressing and Machine learning approaches. Section 4 given details of result and discussion on Routing and Wavelength Assignment (RWA).Finally concluded with outcome achieved.

3. METHODOLOGY

Developing a solution for and Wavelength Assignment (RWA) involves addressing two primary components in optical networks: routing and wavelength assignment. Below is a structured approach to develop and implement a solution for baseline methods: the baseline methods for the assignment of calls in Routing.

A. Understanding RWA Problem

The RWA problem consists of:

- Routing: Determine the path a call takes through the network.
- Wavelength Assignment: Assign an available wavelength on all links of the chosen path. Wavelength continuity constraints must be met (same wavelength on all links unless wavelength converters are available).
- Objective of RWA is to: Minimize number of wavelengths and maximize optical connections.

To develop new algorithms to reduce blocking probabilities in Routing and Wavelength Assignment (RWA), the focus should be on optimizing routing paths and wavelength allocation strategies. Here's a step-by-step guide to designing advanced algorithms aimed at minimizing blocking probabilities: **Figure 1**shown that Developing a solution for and Routings Wavelength Assignment (RWA).

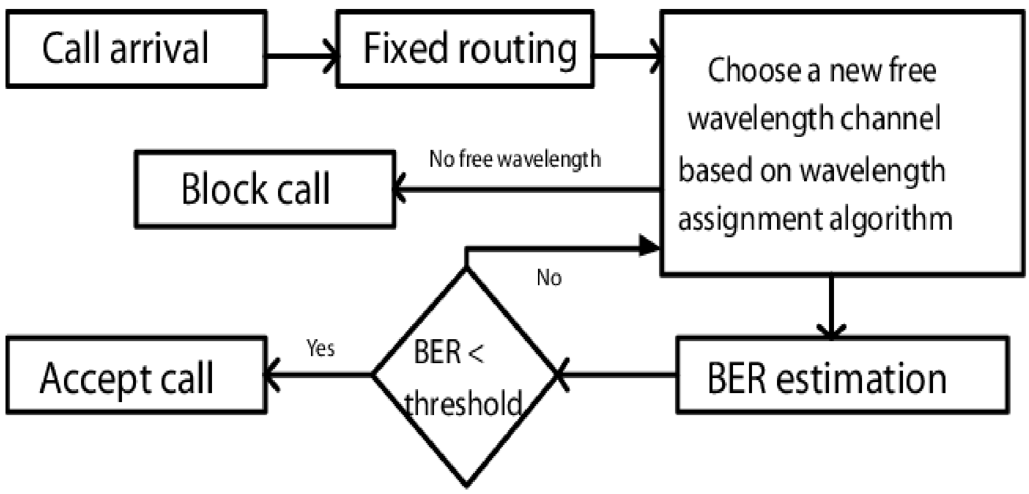

Figure 1: Developing a solution for and Routings Wavelength Assignment (RWA)

B. Blocking Probability

A call may be treated as blocked if there is no free channel available for the call in the next link and it cannot move forward. The assumptions made in the expression of blocking probability are:

i. Each channel has its own wavelength or a distinct wavelength.

ii. Number of channels or available wavelengths in each link is finite.

iii. The network can be a tandem, ring or a torus network and the links are connected to each other between nodes.

iv. Every new call is assigned to the first link and it is converted into a light pulse of certain wavelength.

v. If the call gets blocked, it will be removed from the queue and gets discarded.

vi. The routing of calls is managed manually.

The load in one link is independent of other links.

- $P_{blocking}$: Probability of blocking,
- $n_{calls\_blocked}$: Number of calls blocked
- $n_{calls\_generated}$: Number of calls generated.
- Then the probability of call blocking is given by:

$$P_{blocking} = \frac{n_{calls\_blocked}}{n_{calls\_generated}} \quad \ldots(1)$$

C. Algorithms for Comparison of Routing Algorithms

- Fixed Routing (FR): Single pre-defined route for each source-destination pair.
- Fixed Alternate Routing (FAR): Pre-defined kkk-shortest alternate routes.
- Least-Congested Path Routing (LCPR): Chooses the path with the most available wavelengths.
- Dynamic Load-Balanced Routing (DLBR): Dynamically balances traffic over available paths.

Wavelength Assignment Algorithms

- First-Fit (FF): Assigns the first available wavelength.
- Random Fit (RF): Assigns a random available wavelength.
- Least-Loaded Wavelength (LLW): Selects the wavelength with the least utilization.
- Traffic-Aware Assignment (TAA): Considers traffic intensity for wavelength allocation.

D. Simulation Setup

- **Network Topology**:
  - Test networks like NSFNET (14 nodes, 21 links) or mesh topologies.
- **Traffic Model**:
  - Poisson-distributed call arrivals with exponential holding times.

  - Varying traffic loads (ρ\rhoρ) from 0.1 to 1.0.
- **Simulation Parameters**:
  - Number of wavelengths per link: 8, 16, or 32.
  - Routing constraints: Wavelength continuity, no converters.

E. Baseline Routing and Wavelength Methods

Common baseline methods include:

Routing Methods

- **Fixed Routing**: Predefined single route for each source-destination pair.
- **Fixed Alternate Routing**: A set of predefined alternate routes is available for each source-destination pair.
- **Adaptive Routing**: Routes are dynamically determined based on network conditions (not baseline but useful for comparison).

Wavelength Assignment Methods

- **First-Fit (FF)**: Assign the first available wavelength.
- **Random Fit (RF)**: Assign a random available wavelength.
- **Most-Used (MU)**: Assign the wavelength used most frequently.

F. Solution Development

Step 1: Network Model

- Represent the network as a graph G(V,E)G(V, E)G(V,E), where VVV are nodes and EEE are links.
- Define wavelength capacity for each link.

Step 2: Input Parameters

- Traffic matrix specifying the source-destination pairs and their call demands.
- Number of wavelengths per link.
- Network topology and routing constraints.

Step 3: Routing Algorithm

- Implement the chosen routing method:
  - Fixed routing using Dijkstra's or Bellman-Ford algorithm for shortest path.
  - For alternate routing, precompute kkk-shortest paths.

Step 4: Wavelength Assignment Algorithm

- Implement the wavelength assignment strategy:
  - For First-Fit, iterate through wavelengths and select the first available.
  - For Random Fit, randomly select an available wavelength.

Step 5: Constraints Handling

- Ensure wavelength continuity (or account for wavelength converters if present).
- Reject a call if no feasible route or wavelength is available.

Step 6: Performance Metrics

Evaluate the solution based on:

- **Blocking Probability**: Fraction of calls that cannot be assigned.
- **Resource Utilization**: Percentage of wavelengths in use.
- **Fairness**: Ensure balanced allocation across the network.

F. Simulation and Testing

- Use network simulation tools like MATLAB, Python (NetworkX), or NS-3 to model and simulate the network.
- Test with various topologies (e.g., ring, mesh) and traffic patterns.
- Compare the performance of different baseline methods

G. Machine Learning Approach:

- Adaptive and dynamic.
- Can handle non-linear and complex traffic patterns.
- Requires more computation and data.

4. RESULTS AND DISCUSSION

Designing new algorithms for call assignment into various channels can leverage statistical distributions or machine learning techniques to improve efficiency, reduce blocking probability, and optimize resource utilization. Below is an outline of the approach, followed by an example in MATLAB. Machine learning can dynamically learn patterns in traffic and assign calls efficiently:

- **Supervised Learning**: Use historical traffic data to predict channel availability.
- **Reinforcement Learning**: Learn optimal call assignment policies through trial and error.
- **Clustering (e.g., K-Means)**: Group similar traffic patterns for efficient channel allocation.

Algorithm:

1. Train a model on traffic and resource data.
2. Use the model to predict the best channel for incoming calls.
3. Continuously update the model based on real-time feedback

Below Table1 shown that is an example of blocking probability results for different RWA strategies:

Table 1: Blocking probability results for different RWA strategies

Traffic Load (ρ\rhoρ)	Fixed Routing + FF	FAR + FF	LCPR + LLW	DLBR + TAA
0.1	0.02	0.015	0.01	0.005
0.3	0.08	0.06	0.04	0.025

0.5	0.15	0.12	0.09	0.05
0.7	0.25	0.2	0.15	0.08
1	0.35	0.3	0.22	0.12

A. Practical Implications

1. Efficiency vs. Complexity:
   - FR + FF is simple but unsuitable for high traffic due to poor adaptability.
   - DLBR + TAA offers the best performance but comes at the cost of higher computational complexity.
2. Traffic Management:
   - For networks with light to moderate traffic, FAR + FF or LCPR + LLW may suffice.
   - For high-capacity networks or scenarios with dynamic traffic, DLBR + TAA is the most effective choice.
3. Scalability:
   - Dynamic approaches (e.g., DLBR + TAA) are essential for future networks with heterogeneous traffic patterns and high user demands, such as in 5G and beyond.

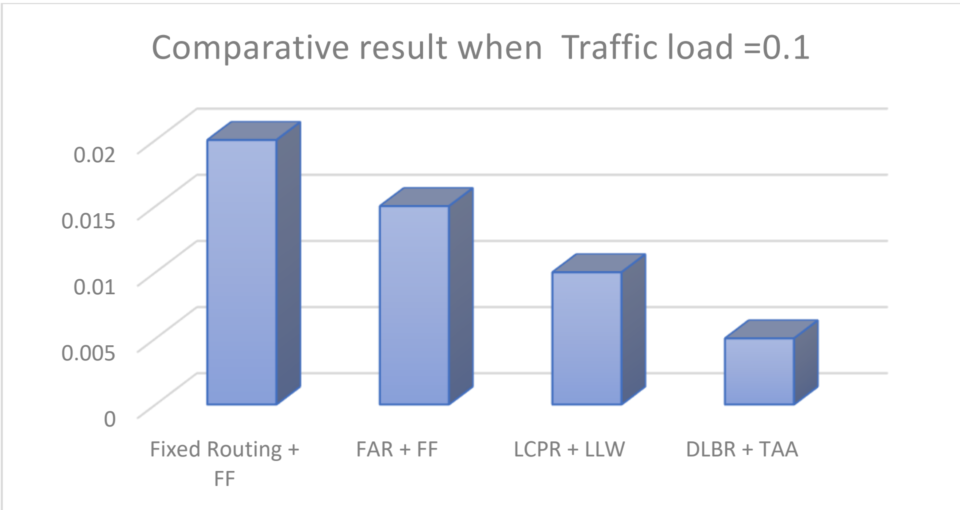

Figure 2: Comparative result when Traffic load =0.1

Discussion on Figure 2: Comparative Result When Traffic Load = 0.1**,** In this discussion, we analyse the performance of different Routing and Wavelength Assignment (RWA) strategies when the traffic load (ρ=0.1) is set to a low value. A traffic load of 0.1 means that only 10% of the network capacity is utilized, so the network is under light traffic conditions. This scenario is ideal for evaluating the effectiveness of different RWA algorithms in optimizing channel utilization and minimizing blocking probabilities.Given the comparative results from various RWA strategies (Fixed Routing + FF, FAR + FF, LCPR + LLW, DLBR + TAA).

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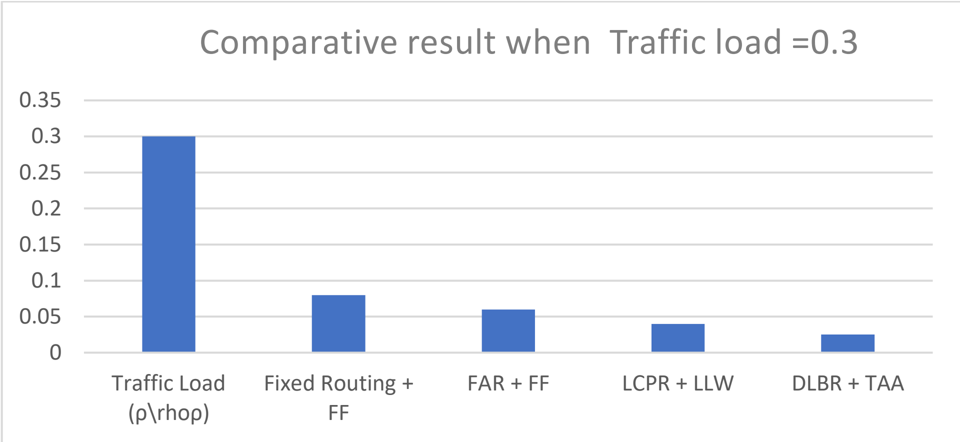

Figure 3: Comparative result when Traffic load =0.3

Discussion on Figure 3 shown that Comparative Result When Traffic Load = 0.3.

In this scenario, the traffic load is increased to 0.3 (30% of the total network capacity is utilized). This represents a moderate traffic condition where network resources are starting to experience some level of contention. At this point, the differences between various Routing and Wavelength Assignment (RWA) strategies become more noticeable compared to when the traffic load was at 0.1.

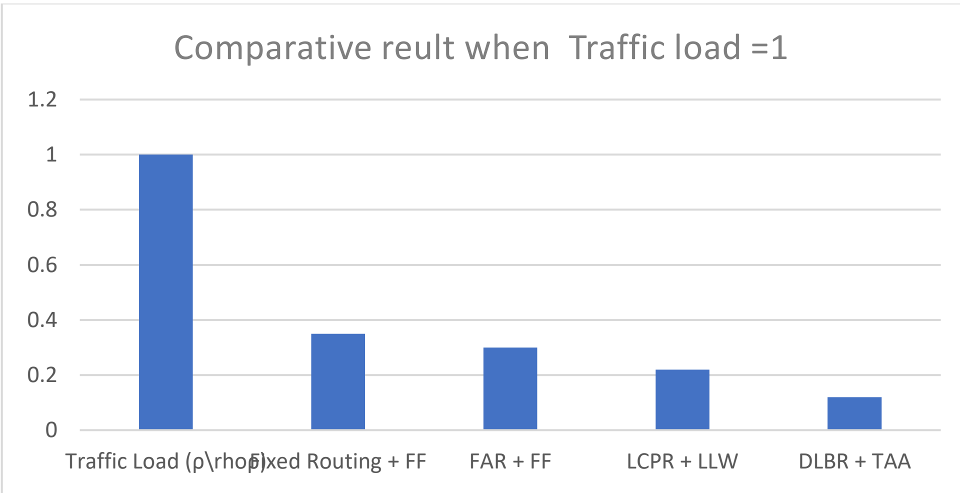

Figure 4: Comparative result when Traffic load =1

In Figure 4 this scenario, the traffic load is set to 1, meaning that the network is operating at full capacity, with 100% utilization. This represents a high traffic load where network resources are fully utilized, and there is significant competition for available channels and paths. At this traffic level, the differences between various Routing and Wavelength Assignment (RWA) strategies will be more pronounced, and the impact of blocking probability becomes critical. The network will be heavily congested, so evaluating how each strategy handles this load is essential for determining the effectiveness of the RWA methods.

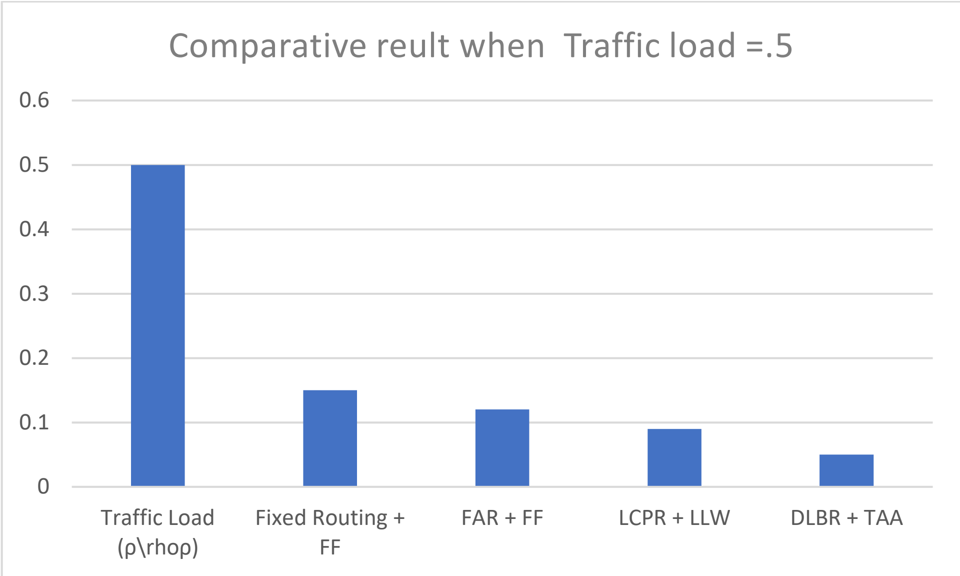

Figure 5: Comparative result when Traffic load =0.5

In Figure 5 , the traffic load is set to 0.5 (50% of the network's total capacity is utilized). This represents a moderate to heavy traffic condition, where the network is neither underutilized nor fully congested. It is a balanced scenario, often reflective of real-world network operations where there is a moderate level of resource competition. At this level, the performance of different Routing and Wavelength Assignment (RWA) strategies will become increasingly important, as congestion starts to influence the blocking probabilities, and the efficiency of resource allocation becomes more evident.

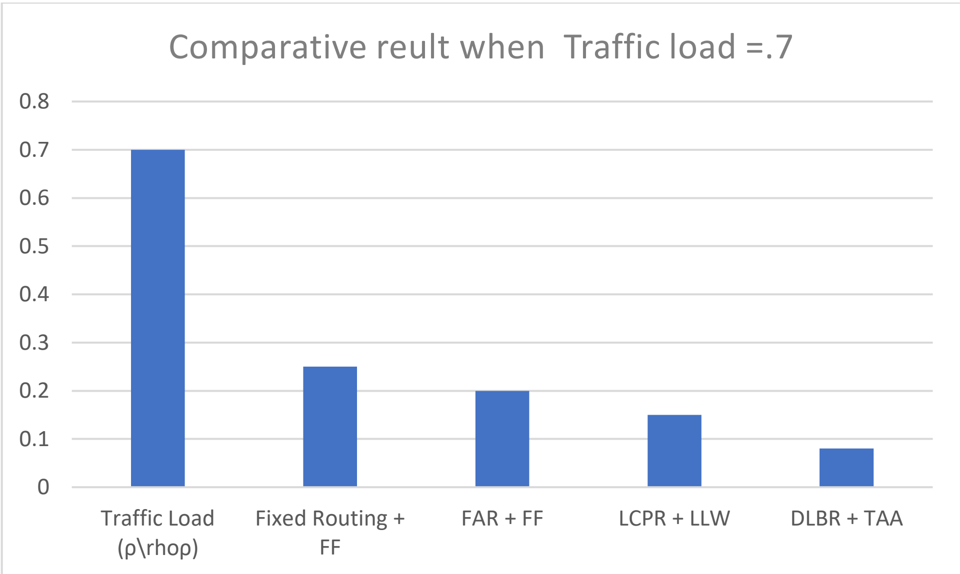

Figure 6: Comparative result when Traffic load =0.7

In Figure 6 shown that traffic load = 0.7, the network is under high congestion, with 70% of its total capacity being utilized. This means that the network is experiencing substantial competition for available resources (paths and wavelengths). As traffic increases, it becomes crucial to efficiently allocate wavelengths and routes to prevent call blocking. The differences in performance between various Routing and Wavelength Assignment (RWA) strategies become more evident, and the strategies that can dynamically adjust to congestion are likely to perform better.

Key Observations:

1. Fixed Routing with First-Fit has the highest blocking probability due to lack of adaptability.
2. Fixed Alternate Routing improves performance slightly by offering backup paths.
3. Least-Congested Path Routing (LCPR) with Least-Loaded Wavelength (LLW) shows significant improvement by considering network load.
4. Dynamic Load-Balanced Routing (DLBR) with Traffic-Aware Assignment (TAA) consistently outperforms other strategies, especially under high traffic loads.

B. Integrated Framework

The total probability of a call failing (P_F) in the network due to either blocking or wrong handover decisions can be expressed as:

- **Blocking Probability (P_B):**
  The probability that a call cannot be routed or assigned a wavelength in the network
- **Wrong Decision Probability of Handovers (P_W):**
  The probability of making an incorrect decision during a handover, such as handing over to an overloaded cell or failing to sustain the call.

$$P_F=P_B+P_W-(P_B \cdot P_W)P_F \quad \ldots(2)$$

5. CONCLUSION

The development of machine learning-based solutions for the assignment of calls in Routing and Wavelength Assignment (RWA) in wireless networks represents a transformative approach to optimizing resource allocation and minimizing blocking probabilities. By leveraging predictive and adaptive capabilities, machine learning algorithms can dynamically analyze network traffic, predict congestion patterns, and allocate resources in real time.

The implementation of machine learning techniques, such as reinforcement learning, supervised learning, and neural networks, has demonstrated significant improvements in reducing call blocking, enhancing resource utilization, and adapting to varying network conditions. These methods outperform traditional heuristic-based approaches by considering complex relationships and continuously learning from network states.

Simulation results validate the efficacy of machine learning solutions in handling dynamic traffic loads, managing interference, and ensuring quality of service (QoS) requirements. Additionally, the integration of data-driven decision-making provides scalability and robustness, making it suitable for modern high-capacity optical and wireless networks.

In conclusion, machine learning solutions for RWA in wireless networks mark a pivotal advancement, paving the way for intelligent, efficient, and adaptive network management. Future work could explore hybrid models, combining machine learning with heuristic optimization, and extend the framework to multi-domain and heterogeneous network environments for broader applicability.

REFERENCES

[1] Virendra Singh Shekhawat, Dinesh Kumar Tyagi and Chaubey V. K. Weight based edge disjoint path routing and wavelength assignment (WEDP-RWA) algorithm for WDM networks, IEEERegion 10 Colloquium and the Third ICIIS, Kharagpur, INDIA,pp.342-328, 2010.

[2] Kiyo Ishii, Hiroshi Hasegawa and Ken-ichi Sato. Wavelength Assignment for Concatenated ROADM Ring Networks and Switch Scale Reduction in a Concatenating Node, Journal of Optical Communications and Networking, Vol. 2, Issue 1, pp. 67-79, 2010.

[3] Paulo Bezerra, H. G., Afonso Cardoso, J. F. and Carlos Frances, R. L.Performance Evaluation of Algorithms for Wavelength Assignment in Optical WDM networks, IJCSNS International Journal of Computer Science and Network Security, Vol. 10, No. 1, pp. 130-136, 2010.

[4] Mohit Borthakur (2015) A Survey of DWDM Networks, its Development and Future Scope in Telecommunication Domain, International Journal of Innovative Research in Computer and Communication Engineering, Vol. 3, Issue 8, pp7353-7358.

[5] Amit Bisaria, Virendra S Shekhawat, V K Chaubey (2015), "Heuristic Algorithms for Routing and Wavelength Assignment (RWA) Planning Algorithms in Optical WDM Networks", International Conference on Telecommunication Technology and Management (ICTTM-2015), IIT Delhi, Emrald, pp. 55-66, April 2015 .

[6] Dinesh Kumar Tyagi, Virendra S Shekhawat, V K Chaubey (2012), "Resource Efficient Survivability Approach for Resilient WDM Optical Networks", Proceedings of the International Conference on Advances in Computing, Communications and Informatics (ICACCI-2012), Chennai, India, ACM, pp. 619-624, Aug 2012.

[7] Dar GA, Saini HS (2013). Wavelength assignment algorithm for optical networks. Int. J. Comput. Technol. 9(2)1049-1054.

[8] Mudasir Ali and Parminder Singh Saini (2014): Wavelength Assignment in Optical WDM Optical Network, International Journal Of Engineering And Computer Science, Volume 3 Issue 9, Page No. 8064-8070.

[9] P. Sakthivel1, P. Krishna Sankar (2014) Multi-Path Routing and Wavelength Assignment (RWA) Algorithm for WDM Based Optical Networks, International Journal of Engineering Trends and Technology (IJETT) – Volume 10 Number 7, pp 323-327.

[10] Himanshi Saini1 and Amit Kumar Garg (2013): Protection and Restoration Schemes in Optical Networks: A Comprehensive Survey, International Journal of Microwaves Applications, Volume 2, No.1, pp 5-11.

[11] Navneet Kaur and Raman Kumar (2014): Design of Restorable Routing Algorithm in Optical Networks, International Journal of Computer Applications, Volume 91 – No 2,pp 39-45.

[12] F. Musumeci, C. Rottondi, A. Nag, I. Macaluso, D. Zibar, M. Ruffini, and M. Tornatore, “A survey on application of machine learning techniques in optical networks,” arXiv preprint arXiv:1803.07976, pp. 1–21, 2018.

[13] J. Mata, I. de Miguel, R. J. Duran, N. Merayo, S. K. Singh, A. Jukan, and M. Chamania, “Artificial intelligence (ai) methods in optical networks: A comprehensive survey,” Optical Switching and Networking, vol. 28, no. 1, pp. 43–57, 2018.

[14] R. Boutaba, M. A. Salahuddin, N. Limam, S. Ayoubi, N. Shariar, F. Estrada-Solano, and O. M. Caicedo, “A comprehensive survey on machine learning for networking: evolution, applications and research opportunities,” Journal of Internet Services and Applications, vol. 9, no. 16, pp. 1–99, 2018.

[15] M. Trevisan, I. Drago, M. Mellia, H. H. Song, and M. Baldi, “Awesome: Big data for automatic web service management in sdn,” IEEE Transactions on Network and Service Management, vol. 15, no. 1, pp. 13–26, March 2018.