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SPECTRALLY-EFFICIENT HYBRID OPTICAL WIRELESS ACCESS NETWORK WITH TRANSFER LEARNING APPROACH IN THE SCENARIO OF DIFFERENT FADING ENVIRONMENT

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Abstract

The next-generation technology had the vision to support services and cross-domain sharing in the upcoming 5G beyond technology-enabled networks. The rising requirement of increased bandwidth and resources are challenging the delivery of high-quality services while challenging the concept of green energy. This paper proposes a spectrally efficient and power-aware resource allocation scheme in Hybrid Optical Wireless Networks to wisely manage resource utilization in a spectrally efficient manner with minimal power consumption. The spectral efficiency of the power-aware scheme is evaluated in terms of Bit Error Rate (BER) and performance in terms of power consumption, throughput, latency, and balanced resource distribution in terms of Jain's Fairness Index. The proposed algorithm architecture uses enhanced machine learning to check how the network performs and trains the system using Artificial Neural Network with the credentials inspired by Levenberg's propagation model and further evaluated in Rician and Rayleigh fading channels. The simulation analysis demonstrated that with the optimal resource allocation the average throughput had reached 89% with reduced power consumption and network latency. The comparative analysis in terms of BER shows that the proposed work achieved minimal BER when evaluated using Rician and Rayleigh fading.

Keywords: Hybrid Optical Wireless Access Networks (HOWANs), Spectral Efficiency, Resource Allocation, Power Consumption, Throughput, Fading.

抽象的

下一代技术的愿景是在即将到来的 5G **中支持服**务和跨域共享，超越技术支持的网络。不断增长的带宽和资源需求正在挑战高质量服务的交付，同时挑战绿色能源的概念。本文提出了一种混合光无线网络中的频谱高效和功率感知资源分配方案，以以最小功耗的频谱高效方式明智地管理资源利用。功率感知方案的频谱效率根据误码率 (BER) **和根据** Jain **公平指数的功耗、吞吐量、延**迟和平衡资源分配方面的性能进行评估。所提出的算法架构使用增强的机器

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学习来检查网络如何使用人工神经网络执行和训练系统，其凭证受 Levenberg 传播模型的启发，并在 Rician 和 Rayleigh 衰落信道中进一步评估。仿真分析表明，通过优化资源分配，平均吞吐量已达到 89%，同时降低了功耗和网络延迟。 BER 方面的比较分析表明，当使用 Rician 和 Rayleigh 衰落进行评估时，所提出的工作实现了最小的 BER。

关键词：混合光无线接入网络 (HOWAN)、频谱效率、资源分配、功耗、吞吐量、衰落。

Introduction

The technical advancement had raised the demand for highly efficient and advanced network services to deploy various high demanding multimedia applications. This had led to the deployment of an open, flexible network that comprises heterogeneous devices involved in communication. Communication is usually is done through either wired, wireless, or a combination of the two. The last decade had witnessed an extensive evolution from 1G to 5G communication technology [1]. The rising popularity of multimedia technology further raises the demand for cross-domain services. Ultimately, it requires end-to-end management of resources for an efficient and quality service. The market trends had illustrated that the connection density is constantly rising and is expected to reach 100 billion connections within a 1 million sq. km area [2]. The critical analysis of the past and present market trends expects the 6G technology to enter the mobile communication market by the end of 2026 [3]. Owing to the explosion of data, deployment of various big data applications had led to the scarcity of spectrum leading to the necessity of spectrum efficient networks. This paves the path towards the merger of wireless network technology and optical network technologies to meet the expectations of high-quality demands in the near future. In this context, an access network is an integral part of a communication network that is aimed at delivering data from a central point to multiple endpoints.

1.1 Background of Network Technology

The features of the communication technology from the 1G to the 5G have attracted numerous applications and with time have evolved to meet the rising demands of society. Initially, communication technology was majorly concerned to serve the communication needs of society alone. At this stage, AMPS, TACS, and NMT were part of the initial communication system. However, over time analogy-based technology get revolutionized to a digital one and the need to maintain base stations also came into existence. The GPRS and GSM were the basis of this generation technology, however, they could not keep up with the rising network traffic observed in the early 20s. This was mainly due to the rise in multimedia-based applications. The audio-video streaming over online sites such as social networking and online gaming used to crowd the network. To address the rising demand for high-speed data transfer LTE enters into several events that lead to the rejuvenation of the communication technology under the name of LTE-Advanced (LTE-A). The current time is witnessing the beginning of massive MIMO-based architecture to overcome the challenges of the high-speed data transfer required by numerous applications. In the 5G vision, the network comprises both optical and wireless technology [4]. The key challenge here is deploying seamless and cost-effective modulation of radiofrequency and band signals using a single wavelength of an optical fibre. The wise combination of these two technologies followed by effective resource allocation using the latest access network had raised the research interests of the telecom industry.

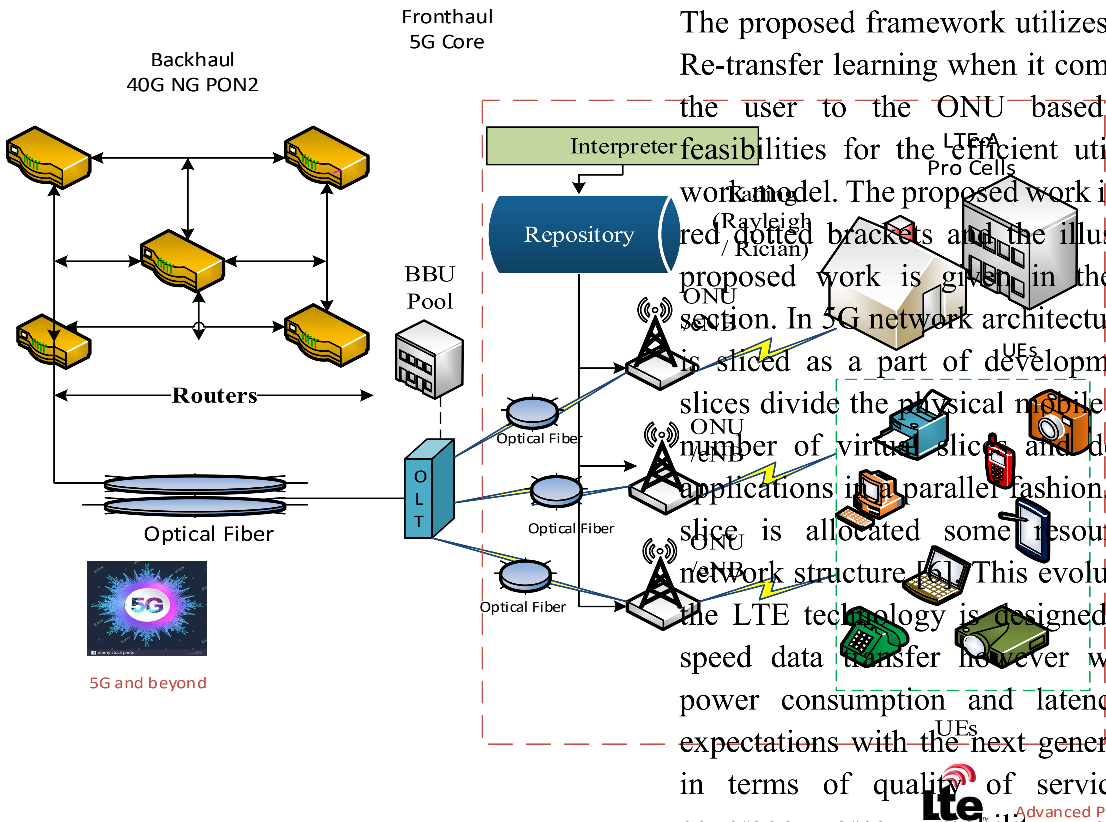


Figure 1: Proposed Architecture

The proposed framework is based on HOWAN architecture which contains 40G-NG-PON2 at the Backhaul and 5G at the front haul to support various LTE-Advanced (LTE-A) cells. The user equipment's are listed under LTE advanced pro network as shown in Figure 1. The advanced pro base stations along with the baseband units of cellular are placed at the right edge. The routers are connected to the OLT utilizing the optical fiber. The OLT is further connected to ONU/eNB using the fibers themselves. Utilizing such architecture will result in efficient gateway and bandwidth utilization and well as the enhancement of the signal strength. They represent the efficacy of proposed data communication; throughput is evaluated and is illustrated in the result section. The proposed framework utilizes the concept of Re-transfer learning when it comes to assigning the user to the ONU based on the best feasibilities for the efficient utilization of the work model. The proposed work is highlighted in red dotted brackets and the illustration for the proposed work is given in the methodology section. In 5G network architecture, the network is sliced as a part of development [5]. These slices divide the physical mobile network into a number of virtual slices and deploy different applications in a parallel fashion. As such, each slice is allocated some resources from the network structure [6]. This evolution is because the LTE technology is designed to offer high-speed data transfer however with challenged power consumption and latency. The rising expectations with the next generation networks in terms of quality of service, bandwidth, coverage area, mobility, and dynamics encourage the merger of two widely implemented technologies namely, optical and wireless technologies. As a result, the Hybrid Optical Wireless Networks offers to complement the features of individual technologies to exhibit the advanced network technology in a power-aware manner.

1.2 Hybrid Optical Access Network (HOWANs)

It has been established that wireless technologies exhibit a larger coverage area and are highly suitable for deploying long-distance communication with least compromising the quality of service (QoS). In contrast to this, optical technology offers wider bandwidth to support most of the advanced applications that require a network deployment in the form of hard lines which is practically costly. To complement and overcome the challenges of individual technologies HOWAN came into existence to integrate wireless and optical gateways.

The optical access networks summarized in Figure 2. Have been implemented globally to overcome the issues related to bandwidth. The PONs and AONs are the optical networks that are deployed using star topology. Among PONs, AONs, and point-to-point networks, PONs had been widely used due to relatively lower cost [7]. The Wavelength Division Multiplexed Passive Optical Networks (WDM-PONs) have been evolved to shown better adaptability with the rising bandwidth requirements. Other wireless versions that have been used by the end-users include Wireless Fidelity (WiFi) followed by Worldwide interoperability for Microwave Access (WiMAX), Long Term Evolution (LTE), and LTE-Advanced (LTE-A) [8].

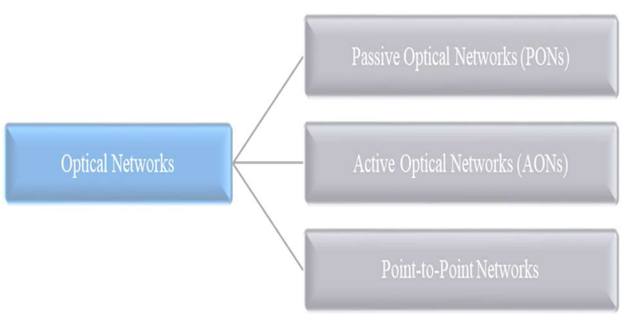


Figure 2: Optical Access Networks

The most essential aspect of the HOWAN is signal transmission. The communication using a wireless environment is highly unstable and multipath propagation is highly susceptible to fading effects. In the paper, mainly two models, namely, Rayleigh and Rician channels have been used to study the fading effects observed during communication using HOWAN. Fading is observed when the signal at the receiver end is a resultant of all the reflections and scattering effects. Multipath propagations usually result in fluctuation in the signal amplitude as well as phase difference due to the presence of reflectors within the communication path. When no LOS path exists between transmitter and receiver, the indirect path is used for the signal transfer and results in Rayleigh fading effect. However, when both LOS and non-LOS path exists, there is the possibility of the existence of both direct and scattered paths and results in Rician fading effect. As a result, the receiver experiences delay or phase shift. The Radio-over-Fiber (RoF) technology offers viable transmission of radio signals over the fiber-based infrastructure and has been widely used in HOWAN enabled systems [9-10]. In this context, this paper introduces a spectrally efficient and power-aware resource allocation scheme for efficient quality service in HOWANs. The interdependencies present in the heterogeneous network require a wiser investigation of power, bandwidth dynamics, and trade-off among users to maintain network performance. Recent years had witnessed the tremendous popularity of Machine Learning (ML) approaches to address the complex problems adjoining large-scale data communication using network technologies [11-12]. Therefore, this paper introduces the machine learning architecture is to wisely distribute the network resources in a spectrally efficient manner while maintaining a high Quality-of-Service delivered to users without compromising network performance. The work efficiency of the proposed work is evaluated in terms of Bit Error Rate (BER) and the performance is evaluated in terms of throughput, energy consumption, and network latency. The fairness of resource allocation in HOWAN is illustrated using Jain's Fairness index.

This paper is further divided into 5 sections with section 1 providing background and current status of network technology and attraction towards ML-based architecture. Section 2 discusses the existing work dedicated to the research in the field of hybrid optical networks. Section 3 summarizes the proposed methodology and algorithms implemented in the paper. Section 4 discusses the simulation analysis to justify the effectiveness of the proposed work. Section 5 finally concludes the paper with a list of references cited in the paper.

Literature Survey

The existing work of various researchers focusing on HOWAN and related technology are discussed in this section. These techniques have been implemented to address the rising challenges of dynamic access networks with the implantation of variable mechanisms to deploy quality service while satisfying the desired performance level. To achieve this, several published articles have been surveyed to analyze the current status of technical advances to meet the demands of present-day multimedia services and applications that required high-quality data transfer. PON and IEEE 802.16 were considered the most promising access technologies because they inhabit the flexibility feature from wireless technology and bandwidth feature from optical technology. In this context, a dynamic bandwidth allocation was proposed by Ou et al. in which convergence between Optical Network Unit (ONU) and 802.16 Base Station (BS) was investigated to reduce signaling overhead caused due to cascading bandwidth requests and responses [13]. A comprehensive study of the integrated mechanisms between WiFi/WiMAX and EPON/WDM-PON was conducted by Ghazisaidi and Maier while aiming at independent, unified connected, hybrid, unidirectional fiber ring and bidirectional fiber ring integrated architectures. The challenges adjoining the designing of future FiWi architectures using various algorithms and MAC protocols for RoF, FiWi, and radio and fiber networks had also been discussed [14]. The strategy of mixed programming had been formulated for virtual allocation challenges based on k-means clustering for partitioning access points into various clusters in HOWANs to achieve reduced overall wireless tele-traffic by utilization of optical technology [15].

The research activities related to FiWi network architecture were presented by Maier in which they investigated various network planning including reconfiguration to deploy quality service [16]. The survivability of FiWi in the age of wireless and optical technology was investigated by **Shaddad et al**. that had attracted the attention of the research community and led to the popularity of FiWi networks [17]. **Sarigiannidis et al**., 2015 had proposed a Dynamic Bandwidth Allocation (DBA) scheme in which 10 GB E-PON was integrated into the WiMAX networks as a predictive mechanism [18]. Later, the convergence between wireless and optical technologies had been used for alleviating the interdependencies while deploying an efficient bandwidth distribution of the mobile entities using Lagrange multipliers [19]. A low power relay selection algorithm based on k-means was proposed by **Hajjar et al**. that aimed at creating power-efficient small cells in LTE microcell in a multi-cell scenario. The analysis showed that the developed algorithm for relay selection based on the clustering mechanism improved the LTE capacity [20]. **Lagkas et al**. had proposed a resource allocation scheme for hybrid EPON and LTE-A Pro FiWi networks for the wireless domain. The scheme enabled allocation decisions based on multistage optimization in which optimization factors were directly related to bandwidth distribution, power consumption, and network traffic prioritization [11]. **Horvath et al**. had investigated the ONU activation process that is common for G-PON, E-PON, XG-PON, and NG-PON2. It was established that the shorter duration of the activation process is usually due to smaller frames in Ethernet-based PON for various variations in PONs. It was also observed that the speed of the activation process holds a key role in blackout scenarios in the optical units [21].

Liang et al. had proposed a reinforcement learning-based model to address the challenges present that are expected to challenge the Front haul 5G networks. The Q-learning model evaluated via simulation analysis in the TWDM-PON demonstrated low latency to satisfy the rising bandwidth demands of 5G Front haul networks [22]. **Pagare et al**. had investigated the N1 class Time and Wavelength Division Multiplexing (TWDM) NG-PON2 in the worst-case scenarios. The designed network was optimized in presence of both linear and non-linear impairments. The authors observed that in the presence of impairments 7 BER was observed with a quality factor of 5 for 10 GPS communication channels [23]. Later, the authors investigated the NG-PON2 network for the kerr effect, followed by wave mixing to analyze the effectiveness of HOWAN to deliver quality service with cost-effectiveness [24]. Some applications that rely on unsupervised learning in various types of wireless and associated networks are summarized in Table 1. More, recently, **Naik and De had** presented a comprehensive survey of ML applications involved at various stages in the network designing problem in HOWANs.

Table 1. Comparative analysis of ML inspired wireless and associated networks

Authors	**Implemented ML Technique**	**Network Model Used**	**Challenge Addressed**
Xia et al., 2012 [15]	K-means	Hybrid Network	Channel Allocation
Liang et al., 2016 [25]	K-means	MIMO	Spectral Efficiency
Hajjar et al., 2017 [20]	K-means	LTE	Relay Selection

Sarigiannidis et al., 2017 [26]	Machine Learning	10-Giga Bit-capable Passive Optical Network (XG-PON) and LTE	Network Configuration adjustment to manage traffic stream
Mostafa, 2017 [27]	RNN	MIMO	Interference Cancellation
Challita et al., 2018 [28]	Deep Learning	Long Term Evolution (LTE) Licensed Assisted Access LTE (LTE - LAA)	Overall resource management
Purushothaman and Nagarajan, 2021 [29]	DNN	massive-MIMO (m-MIMO)	Resource Allocation

The above discussion shows that the convergence between HOWAN and ML approaches will have an enormous positive impact in revolutionizing information technology. As such, it concludes that ML has proved to be a powerful tool to resolve the challenges present at developmental stages of HOWAN networks in a predictive manner. Now a day, the power, data transmission, efficiency, latency, cost, energy, etc. all need to be channelized while adapting to the challenges of rising traffic and network dynamics. The literature review illustrates how various unsupervised and supervised models have been adopted by researchers in recent years to address the challenges as listed in Table 1. In addition to this, few researchers had also integrated meta-heuristics in FiWi networks to optimize the challenges of bandwidth allocation [30]. Hence, the existing studies guides and motivates the authors for integrating machine learning architecture as a fruitful option to address the arising issues of network management due to the heterogeneous topology of the hybrid networks.

Proposed Methodology

The proposed methodology is divided into two segments namely the simulation environment formation and the training and classification architecture of the machine learning algorithm system. The core aim of this article is to enhance the overall spectral efficiency of hybrid optical wireless systems. To measure the efficiency of the hybrid network, there exist two different channels namely the Rayleigh fading channel and the Rician fading channel. To support the user requirements in the network and not to violate the Service Level Agreements (SLAs), resources are allocated to the providers. When it comes to the arrangement of a highly significant periodized scheduling order of data packets, energy efficacy becomes a foremost duty of the network scheduler to maintain the time limit of task completion.

Bandwidth distribution if performed in equal proportions results in a reduction of time delay and power consumption. Resource allocation and resource assignment problem has been one of the most centric problems in the world of Wireless Hybrid – Enabled Architectures. (Wireless Hybrid-EA). The entire work architecture can be illustrated using Figure 3. In the initial setup for processing, two different channels were set as mentioned earlier. Data packets on different priority orders are set to be sent through these channels.

The resource allocation mechanism is set to be running over a multi-resource allocation pattern and criteria followed by the machine learning architecture to divide the outcome of the channel. To divide the system output into different categories, a statistical machine learning approach is utilized. The utilization of machine learning is further segregated into two sub-steps namely the primary setup and the adjustment setup as shown in Figure 4. The primary setup contains the deployment of the ONU along with the user. The post-activity of the data transfer contains the collection of the data from the network. This process is termed data aggregation in the proposed work algorithm.

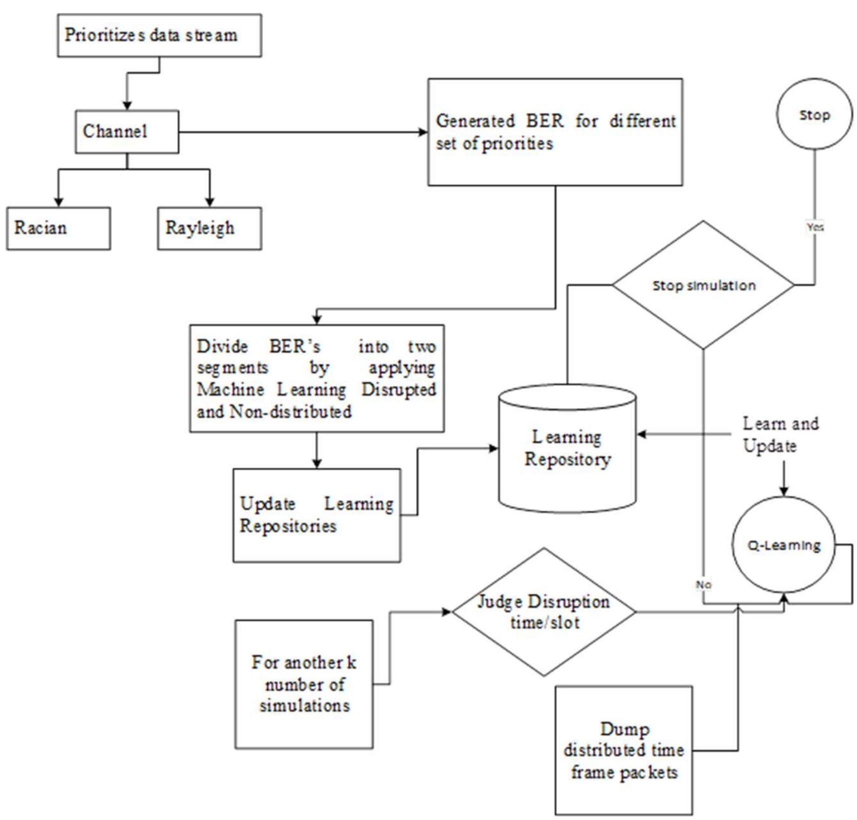


Figure 3: ML Utility work diagram

The purpose of the division of the aggregated data is to categorize the data based on the power spectral density and the consumed energy along with the throughput at the receiving end. To group the aggregated data, a K-means clustering algorithm is applied. K-means uses Euclidian distance to map 'k' number of centroids to the aggregated data. Mean Absolute Error (MAE) is calculated along with Standard Error (SE) and Standard Deviation (SD) is calculated using equations (1) (2) and (3). The overall error is calculated by adding all the errors in the lot.

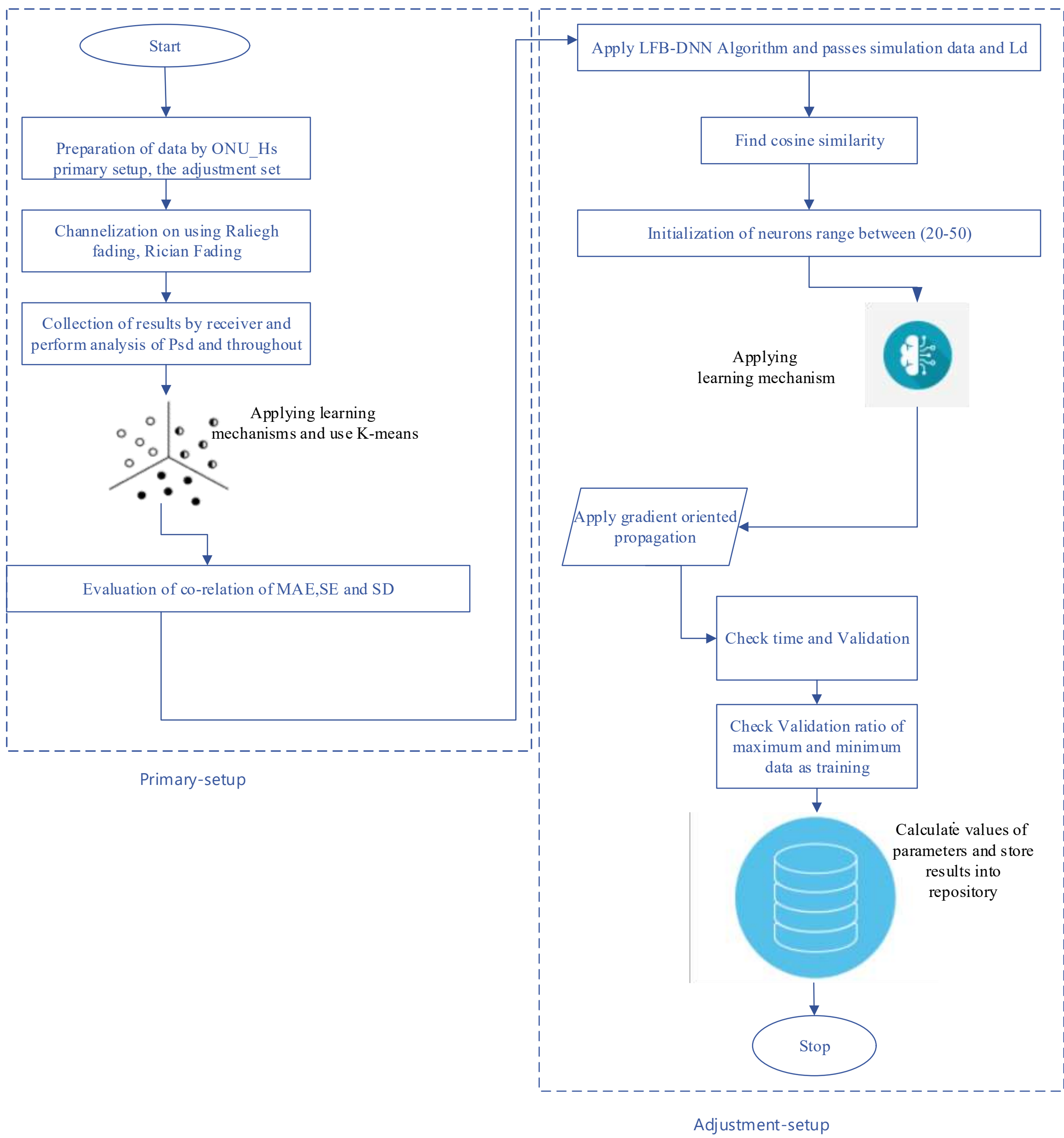


Figure 4: Workflow process of the proposed methodology using primary setup and adjustment set

$$\mathrm{MAE} = \frac{1}{2}\sum_{i=1}^{n}|x_i - x| \quad (1)$$

Where n = the number of errors.

$|x_i - x|$ = the Absolute errors

$$\sigma = \frac{\sqrt{\sum(x_i-\mu)^2}}{N}$$

(2)

σ= Population Standard Deviation.

N= Size of the Population.

μ = The population mean.

$$\mathrm{SE} = \frac{\sigma}{\sqrt{n}} \quad (3)$$

σ= Sample standard Deviation and n= number of samples.

$$f_{output} = f1 + f2 + f3 \quad (4)$$

If $f_{output}(1) < f_{output}(2)$, it denotes that the overall error in the first group is less than that of the second group and hence the first group will be labelled as the group whose performance is above the average performance of the entire network. This segment of time is considered to be the best time. The second portion trains the system based on the above-average and below-average class distribution. The mechanism is termed as a feedback mechanism for the proposed algorithm architecture. The performance of time frames is computed through the proposed algorithm by using two data transfers that are; ONU_H and ONU_L. ONU_L is the data that is transferred through ONUs and has low priority data packets and ONU_ H is the data that is transferred by the ONUs and contains high priority data packets. A total of 10,000 simulations has been done for the data aggregation work. In the proposed work, the simulation set is divided by utilizing ML that helps to avoid manual observations in the future. It is also used to neglect manual observations. It computed Bit Error Rate (BER) and Data Transfer Rate (DTR) or throughput in Mbps along with the energy consumed in mJ. For the division of processing the dataset learning mechanisms include iterative k-means with the enhancement.

The MATLAB simulation toolbox is used for the execution of the proposed algorithm and K-means is implemented as a ML from MATLAB. The data is divided by using the learning toolbox into three segments by applying a tag of {1, 2, 3} where 1 refers to low order and 3 refers to high order. For the labelling, it is important to find out the correlation between the distributed members. To compute the co-relation, after the "Critic" neutralization find the Mean Absolute Error (MAE) and Standard Error (SE) along with Standard Deviation (SD). There is also a transfer learning mechanism which is applied to the repository system in order to reduce the computation complexity of the final evaluation as shown in Figures 3 and 4. The transfer learning architecture uses biologically inspired neural networks. While considering configurations and algorithms of the network, researchers use terms borrowed from the principles of organizing brain activity. But on this, the analogy ends. Our knowledge of the work of the brain is so limited that there would be few precisely proven patterns for those who would like to be guided by them. The nervous system of the human, made from elements named neurons is of astounding complexity. Near 10^{11} neurons participate in approximately 10^{15} transmitting connections having a length of a meter or more. Commonly, every neuron includes multiple characteristics along with other body organs, however, it has distinctive capabilities: to transmit, process, and receive electrochemical signals with the nerve pathways that make the communiqué system of the mind.

Following are the pseudo code that describes the Algorithm

Working of LFB-DNN Algorithm

Input: SD – Simulation data, Labels, LD - Layer distribution

//Here Labels represents the different values of categories and layer distribution for the DNN.

1. Foreach$_1$ cl described in Labels // where cl is class label.
2. Compute the max correlation of category elements by finding the cosine similarities as described in Eq (5).
3. $Cos_{sim} = \frac{Ms_x.Ms_y}{||Ms_x||||Ms_y||} = \frac{\sum_{i=1}^{n} Ms_{x_i}.Ms_{y_i}}{\sqrt{\sum_{i=1}^{n} Ms_{x_i}^2} \times \sqrt{\sum_{i=1}^{n} Ms_{y_i}^2}}$ (5)
4. End For$_1$
5. Initialization of LFB-DNN according to a number of neurons between the {20-50} with the following 5G-EA credentials.
6. Apply feed-forward as a Learning Mechanism using weight variation including polynomial trade.
7. Apply Gradient Oriented as Propagation Type.
8. Use time and validation checks as stopping criteria.
9. The validation ratio {0.15, 0.20, and 0.25} consists maximum of 85% as training data and a minimum of 75% as training data.
10. Selection random sampling for test data.
11. Find out the data validation exhibiting the highest accuracy. The data is stored in the repository and apply to reinforce when the new values of simulation accuracy are encountered.
12. End Pseudo.

Results and Discussion

The results of the proposed algorithm are divided into two subsequent sections. The first section illustrates the results based on the machine learning architecture whereas the second part focuses on the illustration of the results which are attained through the transfer learning mechanism.
In order to illustrate the results, the following parameters have been computed and illustrated.

a) Power consumption: It is the total amount of power that is consumed to transfer the data from one end to another. The proposed algorithm architecture evaluates the performance in kW.
b) Jain's Fairness Index: It is the measure of fairness over any supplied data stream against the provided set of load. If there are three different priority structures and each priority structure is to be analysed, Jain's Fairness Index can be illustrated by using equation (6) which was earlier defined in [11].

$$\text{Jain's Fairness Index} = \frac{\sum_{i=1}^{pr1count}\sum_{j=1}^{pr2count}\sum_{k=1}^{pr3count}\int_{i=1}^{j} G}{n\times\int_{i=1}^{k} G_{ik}} \quad (6)$$

The simulation environment used for the deployment of the proposed architecture is summarized in Table 2.

Table 2. Simulation Parameter

Parameter	**Description**
Simulator	MATLAB 2016a
RAM	4 GB
Processor	Intel i5 core
Data Rate	1 to 10 Mbit per sec
Evaluation Parameters	Throughput, Power, and Latency
Machine Learning Architecture	Neural Network
40G-NGPON-2 upstream line rate	40 Gbps
LTE-Advanced Pro UE uplink rate	230 Mbps
LTE-Advanced Pro frame length	12 ms
UE buffer size per traffic stream	10 Mbps
Simulation time	40 s
Number of UEs per ONU/eNB (ki)	15
Number of ONUs/eNBs (i)	160
Number of traffic priorities per UE	3
Data generation rate per traffic stream	1 – 12 Mbps

Wireless transmission Power Per Bit	55, 110, 210 pW

The simulation scenarios considered in the study exhibited symmetric upstream and downstream rates of upto 12 GB/s as mentioned in table 2. The study was conducted by varying the traffic load that consists of three buffers having the 10 capacity of M bits and are further divided into three levels as illustrated in Table 3.

Table 3. Order levels based on traffic load.

Order 1	Lowest order traffic stream
Order 2	Medium order traffic stream
Order 3	Highest order traffic stream

The results are illustrated in such a fashion that it starts with the architecture of the previously implemented architecture system which includes Lagkas et al. [11] and the results with supported machine learning followed by the results with transfer learning. The results of the transfer learning will be better as compared to the results of the machine learning architecture system and normal traffic rotation policy. It is also observed that the performance varies post a load of 5 MB/s. The entire result frame is categorized and summarized in Table 4 and Table 5.

Table 4. Performance Analysis in terms of Jain's fairness, Throughput, and PDR

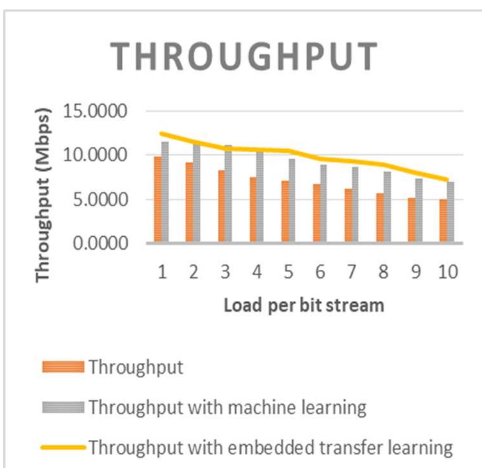
Load per bit stream	Jain's Fairness index normal [11]	With Machine Learning	With embedded transfer learning	Throughput [11]	Throughput with Machine Learning	Throughput with embedded transfer learning	PDR Normal [11]	PDR with Machine Learning	PDR with embedded transfer learning
1	0.9230	0.9250	0.9412	9.7768	11.5437	12.4436	0.7654	0.77123	0.78234
2	0.9230	0.9100	0.9311	9.1092	11.3200	11.5761	0.7522	0.6888	0.71351
3	0.9210	0.9145	0.9211	8.2468	11.0306	10.7840	0.7273	0.6181	0.6347

4	0.9011	0.9022	0.9216	7.4819	10.4349	10.5874	0.7241	0.5857	0.5540
5	0.9230	0.9250	0.9289	6.9931	9.5423	10.4792	0.7096	0.4956	0.5260
6	0.5789	0.6785	0.7722	6.6033	8.9044	9.5412	0.6935	0.4849	0.5121
7	0.5433	0.6432	0.6599	6.0972	8.6360	9.3311	0.5949	0.4724	0.4884
8	0.5211	0.6211	0.6422	5.6139	8.0714	8.8848	0.5673	0.4707	0.4529
9	0.5013	0.6015	0.6211	5.1468	7.3212	7.9925	0.5297	0.4386	0.4405
10	0.4911	0.5239	0.5523	4.9879	6.9356	7.2029	0.4503	0.4348	0.4112

Table 5. Performance Analysis in terms of Power ,and Latency

Load per bit stream	Power per bit [11]	Power per bit Machine Learning	Power with embedded transfer learning	Latency in seconds [11]	Latency with Machine Learning	Latency with embedded transfer learning
1	120.7760	115.6670	112.0000	1.8000	1.4000	1.2200
2	115.3155	105.2856	100.2913	1.0336	1.7280	1.5875
3	109.6978	97.5214	89.1557	1.0236	1.1532	1.9698
4	104.7498	90.5170	75.7646	1.5272	1.0957	1.7115
5	96.5413	87.6941	60.7115	4.1300	3.6700	3.0200
6	92.1205	84.5386	58.4364	6.7602	5.6925	5.6587
7	87.5017	75.0721	44.3823	9.6371	8.0093	8.2037
8	85.3230	67.6886	34.3088	12.1310	10.5884	10.4228
9	84.2976	63.2445	19.8321	14.9630	13.1854	12.6957
10	74.7221	58.3613	18.5232	17.5943	15.8716	14.8225

Table 4 gives a comparative analysis of various parameters namely Jain's Fairness, throughput, and PDR during three scenarios, namely, normal against existing work of Lagkas et al. [11], using machine learning, and using embedded transfer of learning. In similar context, the power and latency observed under the three scenarios is further summarized in Table 5 against respective variation in load per bit stream. Figure 5 shows a comparative analysis of three approaches in terms of various quality parameters. The throughput analysis shows that as the load per bit is increased during experimentation, a corresponding decrease in both throughput and PDR is observed. However, the overall power consumption decreases over the analysis. Jain's Fairness shows a better distribution of various resources during the processing with comparatively lower latency observed throughout the analysis over variation in the load per bit used for the experimentation. The proposed algorithm outcasts the existing machine learning mechanism which is discussed in the proposed methodology section significantly. The reason behind the significant improvement noted in the illustration is a result of the lower computation complexity of the proposed algorithm. The proposed algorithm uses re-enforcement which reduces the allocation time and more time is supplied to data communication. The raised PDR values demonstrate that not only injection rate is controlled but also the data flow is handled in parallel. In a similar passion, packet loss rate is found to increase as the load per bit stream is increased during experimentation.



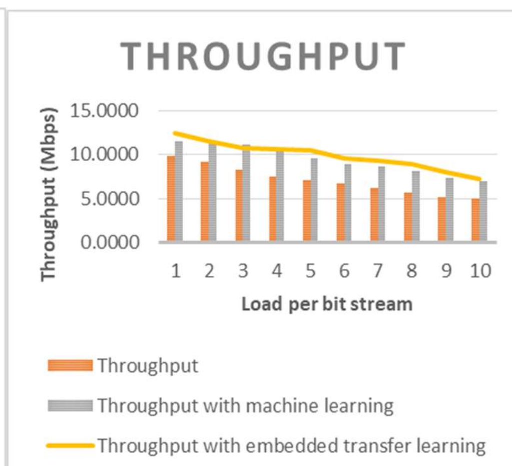


FIGURE 5: GRAPHICAL ILLUSTRATION OF THE COMPARATIVE PERFORMANCE ANALYSIS

The effectiveness of the proposed work is further evaluated while passing through two types of fading channels, namely, the Rayleigh and Rician channels. The BER analysis of the proposed works, when passed through Rayleigh fading channel, is illustrated in Figure 6. It is observed that using embedded transfer learning the overall minimal BER is observed in comparison to existing work and using machine learning. Similar, performance as illustrated in Figure 7 is observed when passed through the Rician channel. However, the overall BER increases with an increase in the load per bit, still the overall minimal BER is observed using embedded transfer learning.

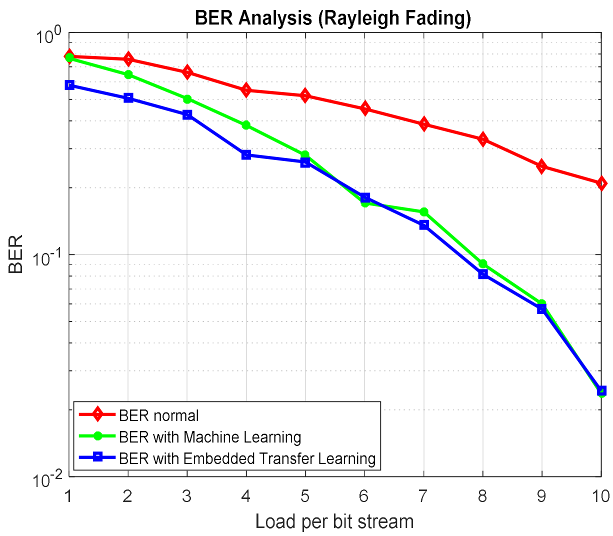


FIGURE 6: GRAPHICAL ANALYSIS OF BER IN RAYLEIGH CHANNEL

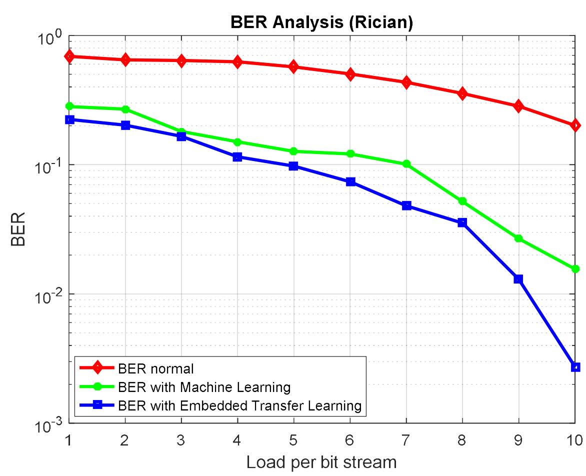


FIGURE 7: GRAPHICAL ANALYSIS OF BER IN RICIAN CHANNEL

Conclusion

The resource limitation and its wise use is the key feature to improve the performance of any architecture. The passing time has increased the number of applications and their adjoin demand for high-speed data transfer. This inevitably complexes the situation that requires the power, energy, and allocation of other types of resources. In this context, this paper has addressed the issue of effective resource allocation in LTE-enabled networks using an Artificial Neural Network. The simulation analysis in terms of power consumption, throughput, and latency followed by Jain's Fairness Index is evaluated to justify the improved resource allocation with the ML approach. Experimentation shows that the ML approach improved the network throughput to 89% at reduced power consumption while demonstrating minimal network latency. Another parameter used for the evaluation of the proposed work is BER that is analysed in both Rician and Rayleigh fading channels against variable load. In both scenarios, the proposed work using transfer learning outperformed the existing work and machine learning scenarios in term of BER used for the comparative analysis.

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