

# Effect of Adaptive Resource Allocation Methods on Performance Metrics in the Load Balanced RoF System

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## Abstract

This paper explores adaptive resource allocation methods to achieve efficient load balancing in Radio Frequency over Fiber (RoF) systems. As wireless data demand increases, RoF provides a promising solution by combining the high bandwidth of optical fiber with the flexibility of radio communication. A 30 GHz millimeter-wave RoF system is designed and simulated using OptiSystem, where key performance parameters such as received optical power, Q-factor, and Bit Error Rate (BER) are analyzed. The resulting dataset is used to train a Random Forest-based load balancing model that predicts optimal Remote Antenna Unit (RAU) assignments for improved throughput and signal integrity. Comparative evaluation shows that the proposed machine learning-based approach outperforms traditional methods, achieving higher accuracy, reduced latency, and better energy efficiency. The results highlight the potential of intelligent, data-driven resource allocation for enhancing the scalability and performance of next-generation RoF networks.

## 1. Introduction

The increasing demand for high-speed, flexible, and reliable wireless communication has driven the convergence of radio frequency (RF) and optical fiber technologies. As network traffic surges, issues like congestion and server overload become more critical. Grand View Research [1] projected that data center traffic would reach 9,965 exabytes by 2020, up from 4,515 exabytes in 2015. Additionally, SDN-based data center traffic was expected to rise from over 58% to more than 75% by 2020 [2]. Radio over Fiber (RoF) systems transmit RF signals via optical fiber, merging the high bandwidth and low attenuation of fiber optics with the mobility of wireless systems. This makes RoF essential for 5G, IoT, and smart healthcare applications [3]. Commonly used in fronthaul links, RoF connects base stations with centralized units [4]. A key challenge in RoF systems is load balancing distributing traffic efficiently across components like Remote Radio Heads (RRHs) and optical links to improve QoS, optimize resources, and maximize throughput [5]. Efficient resource allocation of bandwidth, memory, and processing power enables balanced loads, resulting in higher throughput and lower latency [6], [7].

Figure 1 shows a typical RoF architecture, where the Central Office (CO) centrally manages resources and user connections. This centralized view of all Remote Antenna Units (RAUs) allows for optimized network performance [8]. Recent studies have explored RoF in Wavelength Division Multiplexing (WDM) and Passive Optical Networks (PONs), as well as in 5G mobile fronthaul to improve speed and throughput [9]. Backhaul networks can be optical or wireless. In optical

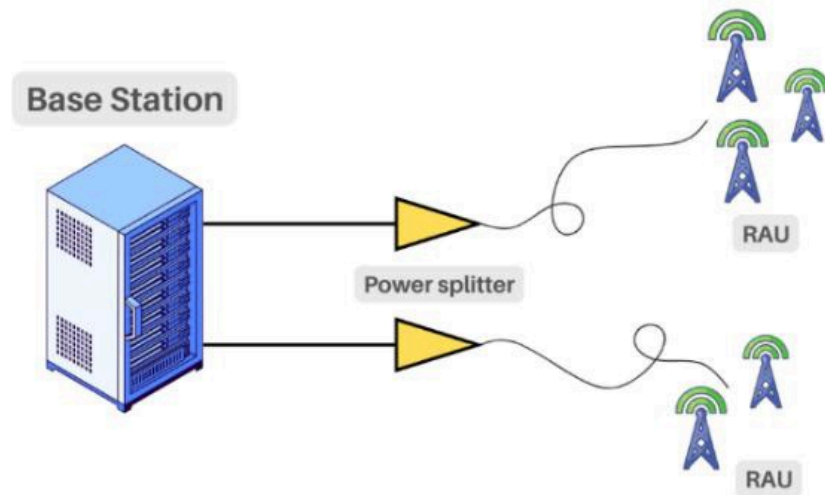


Figure 1: Radio over Fiber (RoF) Network.

backhaul, RF signals are generated at a central point, transmitted over fiber, and converted to wireless at the RRH [10]. This setup supports advanced features like beamforming and MIMO, and allows dynamic spectral allocation. RoF, offering speeds up to 30 Gb/s, is ideal for dense networks such as pico- and femto-cells. While wireless backhaul is simpler and cheaper to deploy, it is limited by spectrum scarcity, making optical backhaul preferable for high-capacity needs [10]. In dense networks, efficient radio resource allocation is vital for maintaining QoS. Machine Learning (ML) improves load balancing by enabling traffic prediction, better resource use, and enhanced scalability and performance [11]. Despite these advancements, two critical problems remain unaddressed in RoF-based wireless networks. First, uneven traffic distribution due to increasing user demand leads to performance degradation and user dissatisfaction [3]. Second, scalability and service diversity are constrained by limited resources. Although integrating cloud and edge computing architectures offers potential solutions, these limitations continue to hinder optimal network performance [11].

## 2. Literature Review

This section reviews four selected papers, comparing their objectives, network types, parameters, methodologies, outcomes, and limitations. Several studies address the number of Remote Radio Heads (RRHs), base stations, control units, and users in the Radio Access Network (RAN), aiming to enhance Quality of Service (QoS) in the growing 5G landscape. The focus is on load balancing and physical resource allocation in RoF-based networks.

M.Salhani and M. Liinajarja [12]

## 3. Design

Figure 2 presents the general architecture of the mmWave generator employing a cascaded modulation scheme, while Figure 3 illustrates the design of the proposed RoF system developed in OptiSystem 21.1. The system operates at the 30 GHz band, where a Central Station (CS) generates and distributes RF signals corresponding to IEEE 802.11ad channel allocations to multiple Remote Antenna Units (RAUs) through an optical fiber link. At the RAUs, the optical signals are converted back into electrical form, amplified, and transmitted wirelessly to serve end-user devices. The simulation framework is further utilized for dataset generation, as depicted in Figure 4, where extracted features such as received optical power, Signal-to-Interference-plus-Noise Ratio (SINR), throughput, and logarithmic Bit Error Rate (log BER) are collected. Figure 4 illustrates the workflow of the proposed Random Forest (RF) model used for load balancing in the RoF system. The dataset collected from OptiSystem simulations undergoes feature extraction and preprocessing before being divided into training (80%) and testing (20%) subsets. The trained RF model predicts

Table 1: Comparison table for physical resource allocation for radio access network.

| Existing Works     | M. Salhani and M. Liinaharja                                                                                                                                                                                                              | Oyama and Seyama [13]                                                                                                                      | Borges et al. [14]                                                                                        | T. H. Dahawi [15]                                                               |
|--------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| <b>Year</b>        | 2018                                                                                                                                                                                                                                      | 2021                                                                                                                                       | 2021                                                                                                      | 2021                                                                            |
| <b>Objective</b>   | To transfer extra users from small cells to macro-cells.                                                                                                                                                                                  | To solve the mobile traffic imbalance between cell caused by nonuniform user distribution.                                                 | Develop a fronthaul architecture integrating optical and wireless technologies to enhance 5G performance. | Provide a cost-effective architecture for integrated wired and wireless access. |
| <b>Network</b>     | Ultra Dense Network                                                                                                                                                                                                                       | O-RAN                                                                                                                                      | 5G NR with Optical and Wireless Integration                                                               | MIMO-RoF Passive Optical Network (PON)                                          |
| <b>Parameters</b>  | Load among access point (AP), user of small cells, users of macrocells.                                                                                                                                                                   | Transmission Power, Channel Bandwidth, RU antenna, Num of UE (user entity).                                                                | Throughput, latency, and spectral efficiency.                                                             | Cost, signal-to-noise ratio (SNR), and energy efficiency.                       |
| <b>Methodology</b> | It determines the overlap ping zone and then the best candid ate user to be handed over to another AP or transfer red to the BS based on four approaches-, worst zone, mixed, passive and active approach to balance the number of users. | It proposed two load balancing method that is CU/DU-RU connection algo-rithm and cell association algo-rithm using the PF utility concept. | Optical-wireless integration using wavelength division multiplexing (WDM).                                | MIMO-RoF technology with PON-based deployment.                                  |
| <b>Outcome</b>     | According to this work the passive approach with mixed approach is most efficient approach for balancing the users in the network.                                                                                                        | For CU/DU-RU connection algo-rithm, it improved the fairness of the UE throughput and has lower UE power consumption.                      | Increased network capacity and reliability.                                                               | Demonstrated improved cost efficiency and energy savings.                       |
| <b>Limitation</b>  | It considers the base stations are permanently available.                                                                                                                                                                                 | For PF-based, it decreases the received signal power from RU and has lower CDF throughput.                                                 | Implementation cost and complexity of WDM systems.                                                        | Signal degradation due to interference and longer transmission distances.       |

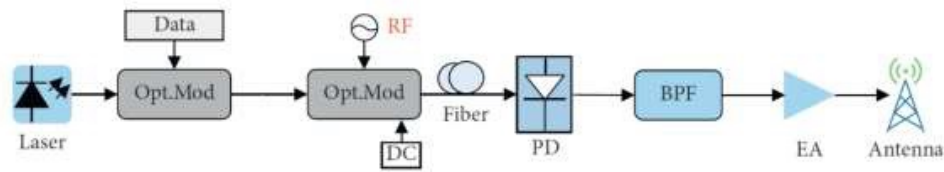


Figure 2: Architecture of mmWave generator using cascaded scheme.

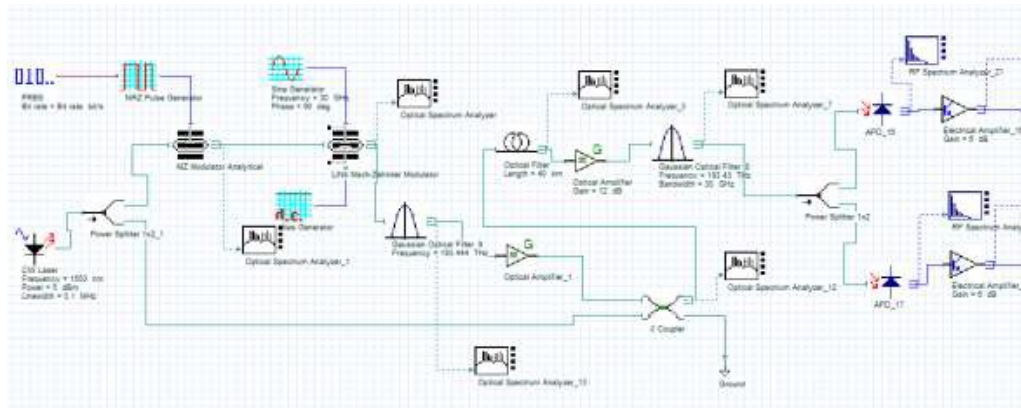


Figure 3: Simulation environment for RoF.

load distribution outcomes, which are then evaluated through performance metrics such as accuracy, Q-factor, and BER to assess the efficiency of the algorithm. These extracted parameters form the basis for training and evaluating the proposed Random Forest based load balancing model to assess system efficiency and decision performance.

Table 2 shows the dataset collected from the OptiSystem simulations of the 30 GHz mmWave RoF system. Each simulation run is identified by a unique `run_id`, with multiple RAUs (`rau_id`) operating under varying bandwidth configurations. The recorded parameters include received optical power (`rx_power`), Q-factor (`q_factor`), and logarithmic Bit Error Rate (`log_ber`), which serve as the primary features for machine learning input. The binary label `best` indicates the optimal RAU selection based on the highest signal quality and lowest bit error performance during each run. This dataset forms the foundation for training the Random Forest load balancing model, allowing it to learn the relationship between system parameters and optimal RAU assignment. By incorporating

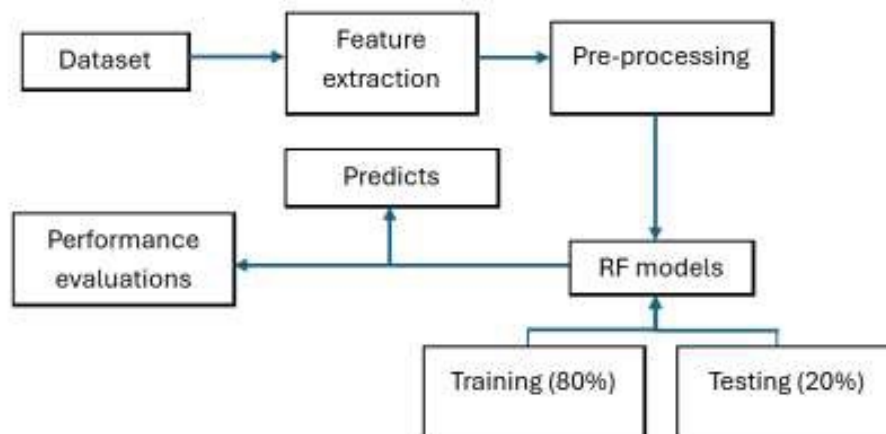


Figure 4: Workflow of load balancing using Random Forest models.

Table 2: Dataset collections from setup simulations.

| run_id | num_rau | rau_id | Band-<br>width<br>(GHz) | rx_power<br>(dBm) | q_factor | log_ber | best |
|--------|---------|--------|-------------------------|-------------------|----------|---------|------|
| 1      | 2       | 1      | 15                      | 0.28              | 8.53     | -17.22  | 1    |
| 1      | 2       | 2      | 15                      | 0.28              | 8.52     | -17.19  | 0    |
| 2      | 2       | 1      | 15                      | 0.31              | 8.49     | -17.22  | 1    |
| 2      | 2       | 2      | 8                       | -0.01             | 3.94     | -4.46   | 0    |
| 3      | 2       | 1      | 4                       | -0.55             | 0.00     | 0.00    | 0    |
| 3      | 2       | 2      | 8                       | 0.09              | 3.93     | -4.44   | 1    |
| 4      | 4       | 1      | 15                      | -5.59             | 8.56     | -17.23  | 0    |
| 4      | 4       | 2      | 15                      | -5.59             | 8.56     | -17.33  | 0    |
| 4      | 4       | 3      | 15                      | -5.59             | 8.54     | -17.26  | 0    |
| 4      | 4       | 4      | 15                      | -5.59             | 8.56     | -17.34  | 1    |
| 5      | 4       | 1      | 15                      | -5.70             | 8.51     | -17.14  | 0    |
| 5      | 4       | 2      | 8                       | -6.02             | 3.95     | -4.47   | 0    |
| 5      | 4       | 3      | 15                      | -5.70             | 8.54     | -17.26  | 1    |
| 5      | 4       | 4      | 8                       | -6.02             | 3.95     | -4.49   | 0    |

metrics such as Q-factor and log(BER), the model can effectively distinguish high-performance transmission links from degraded ones, enabling dynamic and intelligent load distribution across multiple RAUs.

## 4. Results and Discussion

As shown in Table 2, the simulated RoF system operating with a 5 dBm laser diode and a 40 km SMF link exhibits stable transmission performance across multiple RAU configurations. Higher bandwidth settings, particularly at 15 GHz, consistently produce stronger received power and higher Q-factor values ( $\approx 8.5$ ), with corresponding  $\log_{10}(\text{BER})$  around -17, indicating superior signal integrity. In contrast, lower bandwidth cases (4 - 8 GHz) experience notable degradation in Q-factor and BER due to increased dispersion and attenuation. Overall, the results confirm that the RoF link maintains reliable performance under long distance fiber transmission, forming a solid dataset foundation for the subsequent Random Forest-based load balancing analysis. The expected performance of the RF models should obtained 90% and above of accuracy.

## 5. Conclusion

This paper discuss resource allocation techniques using random forest algorithm in load-balanced RoF systems. The findings highlight that efficient allocation of spectrum, bandwidth, and processing resources significantly improves throughput, latency, and energy efficiency. Most reviewed methods use fixed strategies, but ML-based approaches show potential for adaptive load balancing. Future work should focus on low-complexity, real-time algorithms that integrate with SDN and edge computing to meet the demands of dense and dynamic network environments.

## References

- [1] "Software Defined Networking Market (2024 - 2030)." [Online]. Available: <https://www.grandviewresearch.com/industry-analysis/software-defined-networking-SDN-market-analysis>
- [2] K. Rupani, N. Punjabi, M. Shamdasani, and S. Chaudhari, "Algorithms for intelligent systems," in *Proceeding of International Conference on Computational Science and Applications*, J. C. Bansal, K. Deep, and A. K. Nagar, Eds.,

- Springer Singapore, 2020, ch. Dynamic load balancing in Software-Defined Networks using Machine Learning, pp. 283–292. doi: 10.1007/978-981-15-0790-8\_28.
- [3] T. Ishioka *et al.*, “Design and Prototype Implementation of Software-Defined Radio Over Fiber,” *IEEE Access*, vol. 9, pp. 72793–72807, 2021, doi: 10.1109/access.2021.3079915.
- [4] K. K. Qureshi, A. R. Qureshi, M. G. Magam, and L. Jamal, “Radio-over-fiber front-haul link design using optisystem,” *Journal of Optical Communications*, vol. 44, no. s1, pp. s1297–s1303, Aug. 2020, doi: 10.1515/joc-2020-0074.
- [5] I. Seremet and S. Causevic, “Advances of configuring Quality of Service (QoS) in Software Defined Networks (SDN) by using meter table,” in *2020 19th International Symposium INFOTEH-JAHORINA (INFOTEH)*, IEEE, Mar. 2020, pp. 1–5. doi: 10.1109/infoteh48170.2020.9066275.
- [6] K. Ramya, M. Sayeekumar, and G. M. Karthik, “Software Defined Networking Based Solution in Load Balancing for Media Transfer in Overlay Network,” *Journal of Computational and Theoretical Nanoscience*, vol. 17, no. 1, pp. 43–47, Jan. 2020, doi: 10.1166/jctn.2020.8627.
- [7] Y. Li, K. Satyanarayana, M. El-Hajjar, and L. Hanzo, “Analogue Radio Over Fiber Aided MIMO Design for the Learning Assisted Adaptive C-RAN Downlink,” *IEEE Access*, vol. 7, pp. 21359–21371, 2019, doi: 10.1109/access.2019.2897922.
- [8] K. Singh, A. Dixit, and V. K. Jain, “Hybrid Medium Access Control Protocol for Radio-Over-Fiber Networks,” *IEEE Access*, vol. 9, pp. 110889–110903, 2021, doi: 10.1109/access.2021.3103513.
- [9] J. He, J. Lee, S. Kandeepan, and K. Wang, “Machine Learning Techniques in Radio-over-Fiber Systems and Networks,” *Photonics*, vol. 7, no. 4, p. 105, Nov. 2020, doi: 10.3390/photonics7040105.
- [10] B. Post, S. Borst, and T. Koonen, “Load-Aware Sub-Band and Wavelength Allocation in Radio-over-Fiber Enabled Dense Wireless Pico-Cell Networks,” in *2018 IEEE International Conference on Communications (ICC)*, IEEE, May 2018, pp. 1–6. doi: 10.1109/icc.2018.8422379.
- [11] A. Rancea, I. Anghel, and T. Cioara, “Edge Computing in Healthcare: Innovations, Opportunities, and Challenges,” *Future Internet*, vol. 16, no. 9, p. 329, Sept. 2024, doi: 10.3390/fi16090329.
- [12] M. Salhani and M. Liinaharja, “Load Migration Mechanism in Ultra-Dense Networks,” in *Proceedings of the 2nd International Conference on Telecommunications and Communication Engineering*, in ICTCE 2018. ACM, Nov. 2018, pp. 268–274. doi: 10.1145/3291842.3291923.
- [13] T. Oyama and T. Seyama, “Load-Balancing Techniques for 5G Millimeter-Wave Distributed Antenna System,” in *2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*, IEEE, Apr. 2021, pp. 1–5. doi: 10.1109/vtc2021-spring51267.2021.9448953.
- [14] R. M. Borges *et al.*, “Integrating Optical and Wireless Techniques towards Novel Fronthaul and Access Architectures in a 5G NR Framework,” *Applied Sciences*, vol. 11, no. 11, p. 5048, May 2021, doi: 10.3390/app11115048.
- [15] T. H. Dahawi, Z. Yusoff, M. S. Salleh, and J. M. Senior, “Low-cost MIMO-RoF-PON architecture for next-generation integrated wired and wireless access networks,” *Journal of Optical Communications and Networking*, vol. 13, no. 3, p. 41, Jan. 2021, doi: 10.1364/jocn.413596.