

Machine learning-inspired intelligent optimization for smart radio resource management in satellite communication networks to improve quality of service

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Abstract. Satellite communication networks are seeing a significant surge in traffic requirements. Nevertheless, the rise in traffic requirements is inconsistent across the service region because of the unequal distribution of consumers and fluctuations in traffic requirements during the day. Variable payload designs solve this issue by enabling the uneven allocation of payload resources to match the traffic requirement of each beam. Optimization-based Radio Resource Management (ORRM) has demonstrated substantial efficiency improvements, but its high computational difficulty hinders its real-world deployment. This work explores the structure, execution, and uses of Machine Learning (ML) for resource allocation in satellite systems. The primary emphasis is on two systems: one that offers power, capacity, and beamwidth adaptability and provides temporal flexibility via beam hopping. The research examines and contrasts several ML methods suggested for these structures. The research determines whether training must be done online or offline depending on the features and needs of each ML method. The study analyzes the most suitable system structure and the pros and cons of each strategy.

1 Introduction to satellite communication and radio resource management

Satellite communications have grown significantly because of increased global connection needs [1]. Satellite communications are crucial in reducing the global connection gap by

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integrating terrestrial technologies like 6G and addressing the need to minimize the digital gap and achieve widespread coverage. The increasing need for traffic in satellite communications poses issues in efficiently allocating radio resources to fulfill Quality-of-Service (QoS) standards and minimize resource use [2].

Traditional satellite communication systems usually use static multi-beam setups with predetermined capacity and power distributions [3]. The systems cannot adjust to the changing traffic needs. Resources might be squandered, and user needs still need to be met. Software-defined carriers have arisen to address time-related and geographical fluctuations in demand, providing exceptional adaptability and versatility in Radio Resource Management (RRM) for satellite communications [4]. With the availability of cost-effective, flexible multi-beam payload technology, the issue of managing the inherent flexibility of the space sector emerged. RRM for multi-beam satellite systems has been a prominent area of study over the past 15 years, with a significant body of literature supporting this.

Machine Learning (ML) has emerged as a viable option for addressing computationally intensive optimization processes [5]. Because of the rapid growth in accessible data, ML has become a crucial technique in several aspects of wireless connections. ML is a valuable technique for speeding up intricate optimization processes in wireless communications. However, more research must be conducted on applying ML to satellite communications.

ML techniques have become a potential option for RRM in satellite communications, replacing traditional optimization methods [6]. ML-based methods can learn and forecast traffic trends, speed up complicated RRM algorithms, and enhance flexibility and adaptability in fixed optimization methods. Applying ML techniques on satellites is challenging due to high energy requirements that exceed existing capabilities.

The rest of the sections are as follows: Section 2 presents the relevant literature on RRM in satellite communications. The Optimization-based Radio Resource Management (ORRM) is formulated and examined in section 3. Section 4 discusses and assesses the simulation results of the suggested study. Concluding remarks and potential future research directions for RRM in satellite communications.

2 Related works

Alhashimi et al. suggested combining training and optimizing methods to solve mixed-integer concave programming problems in satellite RRM at satellite communications [7]. The intricate issue is divided into two categorization jobs and a power control challenge. One issue is tackled using a Deep Neural Network (DNN) technique, while the other is resolved by convex optimization. Cai et al. introduced a novel resource administration methodology for future Heterogeneous Satellite Networks (HSNs) to promote collaboration across separate satellite networks and optimize resource efficiency [8].

The research proposed using Deep Reinforcement Learning (DRL) methods to address the RRM problem by designing a realistic solution for the actual time, a single-channel allocation of resources issues. DRL designs rely on discretizing resources for distribution, while satellite resources like electricity are naturally continuous. Huang et al. investigated a DRL framework for energy distribution that uses ongoing, autonomous action areas, eliminating the requirement for discretization [9]. The approach could be better since specific demands still need to be met. Zhou et al. propose a new Dynamic Channel Assignment (DCA) technique, DRL-DCA, based on DRL for multi-beam satellite networks [10]. The findings demonstrated that this method achieve a reduced blocking likelihood compared to previous techniques, although it did not address the combined channel and energy distribution technique.

Zou et al. developed a game model to determine the best satellite communication strategy [11]. The authors propose a system for allocating bandwidth that can continuously assign

bandwidth to each beam. The suggested technique has helped manage bandwidth in scenarios with changing traffic patterns and extensive communication networks, all while maintaining reasonable commuting expenses. This strategy allows for working just a single resource on the satellite, posing a significant constraint when aiming for total adaptability in the multibeam satellite network.

The research examined the ML-based administration of resources in multi-beam satellite systems [12]. The authors discuss several ML algorithms used in systems with flexible authority connectivity and beamwidth and devices with beam-jumping capability. The research suggests combining training and optimizing strategies to solve a Mixed-Integer Convex Programmer issue in satellite RRM [13]. The problem is divided into categorization and power management optimization tasks, which are addressed using dual DNNs and convex optimizing techniques.

3 Proposed optimization-based radio resource management

The suggested ORRM architecture relies on training the offline ML model using a training dataset that characterizes the system's operation. It is possible to develop a model that controls satellite resources based on user link circumstances. Once the algorithm is trained, the ML might be placed on the satellite for interpretation. The design's primary benefit is reduced processing time due to the algorithm's pre-training. An additional stream, the demodulator, is necessary to examine real-time traffic requests, or an extra ML block for predicting onboard traffic might be added. This design heavily relies on the training information and algorithms utilized. This will result in increased sophistication and power requirements on boards. The traffic influence on the RRM's efficiency is impacted by significant shifts in the system, necessitating the need to retrain. This might result in higher costs and payload weight. The proposed ORRM architecture is shown in Fig. 1.

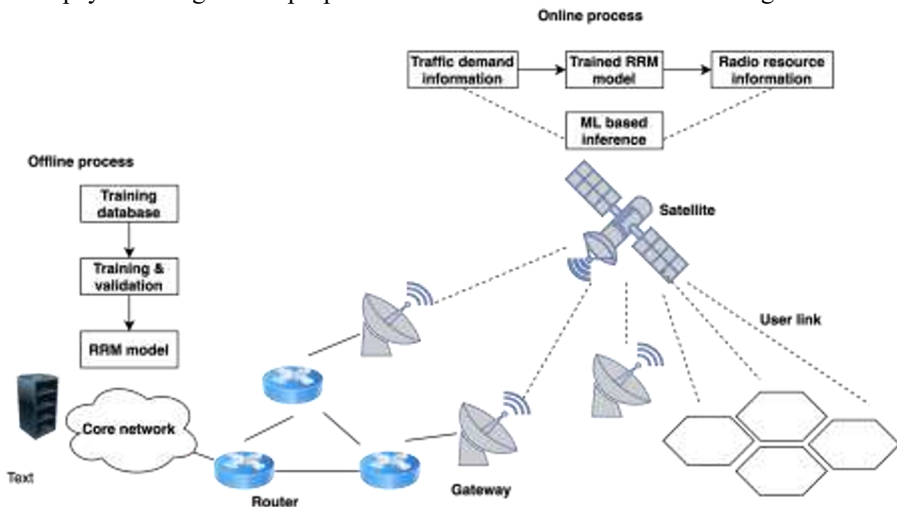


Fig. 1. The architecture of the proposed ORRM model

This method must be revised to the terrestrial standards and facilitate interaction among terrestrial and satellite networks. This technology optimally utilizes satellites and 5G networks, providing significant potential to enhance the utilization of resources and spectrum use. This method needs little changes to the terrestrial standards and facilitates connection among terrestrial and satellite networks. They provide a broadcasting service and interaction with continuous coverage throughout the day.

1. Satellites and small cell evolved Node Bs provide broadcasting services, ensuring continuous daily connectivity.
2. The macro-base stations consist of gNBs, providing extensive capacity and availability. It is tasked with covering burst services in areas outside the reach of the micro-base stations.
3. Micro-base stations provides comprehensive coverage in a concentrated limited region.
4. It is an advanced real-time spectrum detecting, forecasting, and distribution component. It does offline ML and testing. Spectrum detection identifies the accessible shared spectral for Dynamic Spectrum Utilization (DSU). The method uses virtual computation to get spectrum information predictively to fulfill spectrum resources and service needs.

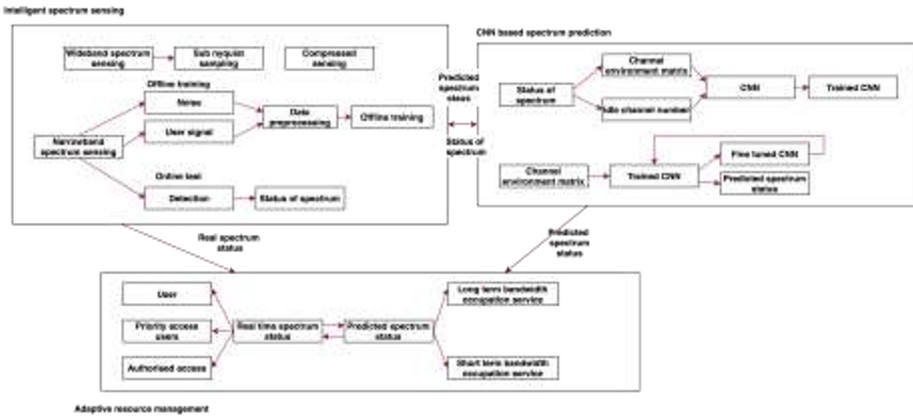


Fig. 2. The proposed RRM model of the ORRM

The depicted intelligent resource managing plan is seen in Figure 2. The ORRM collects, stores, evaluates, addresses, and disseminates data from satellite and terrestrial sources. The essential elements of pools consist of intelligent spectrum sensing, CNN-based spectrum prediction, and intelligent distribution of resources. The goal of the CNN with data preparation during offline training is to acquire improved features. Data preparation is used to increase features and enhance detection accuracy.

A CNN-based Signal Processor with fine-tuning is employed to enhance the extended delay of Interstellar Telecommunication Networks. The use of resources is adjusted based on the spectrum detection and forecasting results. The design maximizes performance using the convolutional layer's capacity to decrease parameter count and enable weight sharing. Performance is essential for comprehending complicated input information and facilitating quick, dependable categorization.

- Convolutional layers use convolution to map features and emphasize input qualities while preserving spatial connections.
- Recurrent Learning Unit (ReLU) layers introduce nonlinearity by replacing negative numbers with zero in the characteristics mappings.
- Pooling layers reduce feature sizes while maintaining significant data, efficiently summarizing the collected characteristics.
- The fully connected level utilizes these properties to differentiate between the categories specified in the initial training information.

3.1 CNN-based RRM scheme

The state space dimensionality grows tremendously because of random user motion at intervals t . The research provides a relational ORRM method that effectively addresses the problem of state space complexity and attains the best control strategy for RRM on/off switches. The study suggests including three concealed convolutional layers for the changing networking state-space feature. The concealed convolution layer consists of 64, 64, and 128 convolution filtering with input matrices of size $N \times N$, correspondingly. The input matrix includes the user's request, RRM on/off status, and capabilities. The research employs the Xavier standard initializer method for setting up every convolutional filtering. The result of the convolutional filtering is computed as:

$$O = \frac{I-K+2P}{S} + 1 \tag{1}$$

O indicates the convolutional filtering results, whereas I , K , P , and S denote the input dimensions, kernel size, quantity of paddings, and stride, accordingly. The research examines a kernel size of 2×2 for all concealed layers, assuming a cushioning value of 0 for all hidden layers, and sets the stride amount to 1 for all suppressed levels. The ORRM technique includes a convolutional level, pooling levels, and flattening and fully interconnected layers. The convolutional levels extract characteristics from the surrounding state space. Pooling levels are employed for down-sampling the retrieved features. The research uses a max filter to produce the highest value inside a particular area. To avoid excessive fitting in the neural network, the research applies dropouts to the result of the final max-pooling level with an expected value of $\beta = 0.25$. The final result of the last max-pooling level is transformed into a one-dimensional vector and then linked to a fully connected neural network of 100 neurons. The method carries out the training phase. The obtained state feature from the CNN is inputted into the ORRM to make decisions on switching on or off RRMs. The research establishes the state space $s(t)$, action space $a(t)$, and incentive function $K(t)$ for the issue.

State Space

At every single-phase t , the system records the state's characteristic, which includes the user data rate requirement $D_u(t)$, the on/off condition $v_r(t)$ of RRMs u , with a relational matrix connecting customers U and RRMs R . The relationship matrix is formed as $H \in R^{R \times H}$ and defined as:

$$H(t) = \begin{bmatrix} h_{11} & \cdots & h_{1n} \\ \vdots & \vdots & \vdots \\ h_{n1} & \cdots & h_{nn} \end{bmatrix} \tag{2}$$

The term h_{nn} represents the channel state characteristics between consumers and RRMs. The research combines all three attributes into a unified vector. The state space is as follows:

$$S(t) = [D_n(t), v_r(t), H(t)]^T \tag{3}$$

Action space

At every point t , the system determines the action depending on the RRMs on/off state, denoted as $a_r(t) \in \{0,1\}$. The research limited the agent to selecting actions depending on the current set of RRMs.

Reward

The reward determines whether to penalize or motivate the behaviors. Within the suggested structure, the reward is the goal function, which signifies the enhancement of energy efficiency and is expressed quantitatively as:

$$K(t) = EE(t) = \frac{\sum_{i=0}^N C_i(t)}{P_{tot}(t)} \tag{4}$$

The proposed ORRM in satellite communication networks, using ML, provides adaptability in power, capacity, beamwidth, and temporal flexibility via beam hopping.

4 Simulation and outcomes

The research examines the simulated environment and demonstrates the effectiveness of the ORRM method. A productivity review is conducted to optimize energy use, overall power utilization, and user quality of service satisfaction. The research addresses the user's request within the bandwidth range of 10 to 60 Mbps, with increments of 10 Mbps. The study examines a pair of situations to test the impact of adding additional RRM's on performance when agents cannot meet the user's QoS requirements. Every simulation went smoothly in the Python 3.7 surroundings. The agent undergoes 100 learning events to learn the surroundings and conduct, followed by competence evaluation based on 100 assessment experiences.

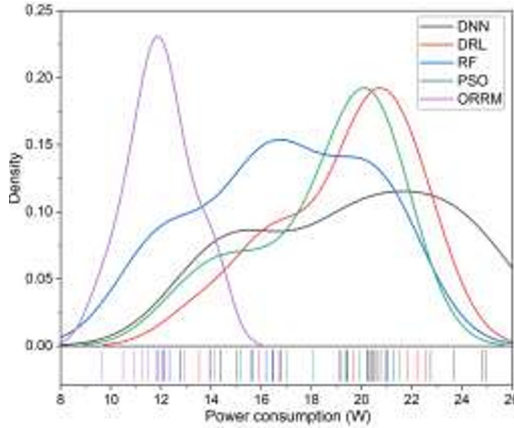


Fig. 3. Power consumption analysis

Fig. 3 depicts the power usage (W) for epochs ranging from 0 to 120. Power consumption is calculated as the amount of energy used during a specific period, and the findings reveal variations in consumption. Each method's findings show different levels of performance. The average power consumption values are as follows: DNN – 18.34, DRL – 18.78, Random Forest (RF) – 17.67, Particle Swarm Optimisation (PSO) – 18.61, and ORRM – 12.18. The ORRM approach surpasses other methods by continuously achieving a lower average power usage of 12.18, showcasing its efficiency in improving resource management for satellite communication systems.

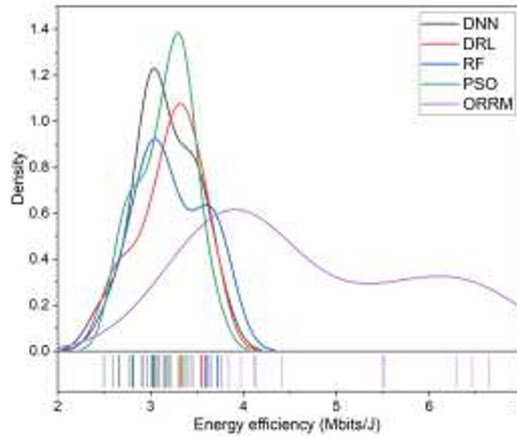


Fig. 4. Energy efficiency analysis

Figure 4 shows the energy efficiency (Mbits/J) throughout epochs ranging from 0 to 120. Energy efficiency is calculated by dividing the quantity of data delivered by the energy spent. Each method's findings show different levels of performance. The energy efficiency averages are as follows: DNN – 3.18, DRL – 3.26, RF – 3.24, PSO – 3.20, and ORRM – 4.71. The ORRM approach surpasses other methods by continuously achieving a higher mean energy efficiency of 4.71, demonstrating its efficacy in optimizing resource consumption and improving the network's energy effectiveness.

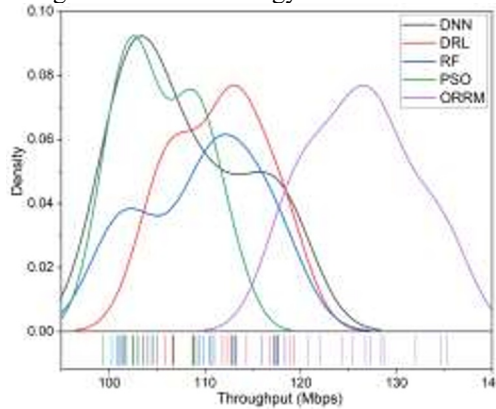


Fig. 5. Throughput analysis of different models

Fig. 5 shows the epoch's throughput (Mbps) ranging from 0 to 120. Throughput is calculated as the volume of data sent during a specific period. Each strategy has diverse performance outcomes. The average throughput values are as follows: DNN - 108.44, DRL - 111.72, RF - 111.22, PSO - 107.01, and ORRM - 125.62. The ORRM approach regularly outperforms other methods by achieving the most significant average throughput of 125.62, demonstrating its effectiveness in improving resource management and data transmission rates in satellite communication systems.

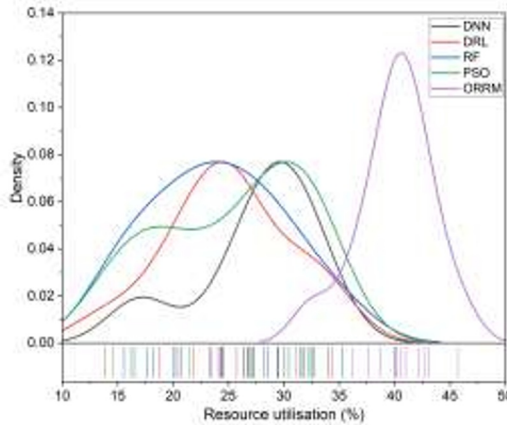


Fig. 6. Resource utilization analysis

Fig. 6 displays the percentage of resource use throughout epochs from 0 to 120. Resource utilization is calculated by determining the proportion of available resources used efficiently. Each method's findings show varied performance patterns. The average resource consumption for DNN is 26.92, DRL is 24.13, RF is 23.55, PSO is 24.53, and ORRM has the highest average of 39.83. The ORRM approach continuously beats other methods by reaching the most significant average resource utilization of 39.83%, showcasing its usefulness in optimizing resource consumption and improving efficiency in satellite communication systems.

5 Conclusion and findings

The space sector is increasingly interested in integrating ML into satellite communications networks as a possible alternative to sophisticated and time-consuming optimization methods used in the radio management of resources. The research primarily examined ML-based evaluation, explicitly focusing on the inherent characteristics of the models employed, their efficacy, and the additional delay caused by online or offline learning. Two distinct architectures are being considered for implementing the ML on Earth or aboard the satellite. This is determined by whether the training is done online or offline. The ORRM approach performs excellently in all categories, with a mean power consumption of 12.18 W, energy efficiency of 4.71 Mbits/J, throughput of 125.62 Mbps, and resource utilization of 39.83%. This advantage is accompanied by a rise in training duration, for ML is split between exploration and exploitation periods. Another benefit of CNN-based methods is that the training occurs live, meaning the CNN modeling is revised whenever there is a change in demand for traffic in the service region, resulting in an increased latency in the asset update reaction. This signifies a balance between the achieved productivity and the effectiveness of the execution.

Algorithms constructed using supervised learning are often learned offline. CNN-based techniques are proposed as a promising option for integrating onboard satellites. The research has found many Artificial Intelligence (AI) accelerations in the marketplace that are used for future application initiatives. The study determines the essential qualities that should be evaluated while selecting one.

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