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ARTICLE TYPE

Supervised Machine Learning for Power and Bandwidth Management in VHTS Systems

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Abstract

In the near future, Very High Throughput Satellite (VHTS) systems are expected to have a high increase in traffic demand. However, this increase will not be uniform over the service area and will be also dynamic. A solution to this problem is given by flexible payload architectures; however, they require that resource management is performed autonomously and with low latency. In this paper we propose the use of Supervised Machine Learning, in particular a Classification algorithm using a Neural Network, to manage the resources available in flexible payload architectures. Use cases are presented to demonstrate the effectiveness of the proposed approach and a discussion is made on all the challenges that are presented.

KEYWORDS:
VHTS; Satellite Communications; Machine Learning; Flexible Payload; Dynamic Resources Management

1 | INTRODUCTION

Very High Throughput Satellite (VHTS) systems play a key role in complementing future terrestrial networks. In the near future, satellite communications are expected to provide capacities close to 1 Terabit/s [1,2]. The first generation of VHTS systems offered a uniform capacity per beam, however, traffic demands are non-uniformly distributed in the service area. This resulted in some beams not having the required capacity, while others have much more than required; hence, on one side there is a reduced satisfaction of traffic demands and, on the other side, in a waste of resources [3]. Therefore, one of the main challenges in designing future satellite broadband systems is the way to increase revenues for operators and simultaneously address unequal and dynamic traffic demands. Flexible payload is an optimal solution to meet changing traffic demand patterns [4]. In this sense, the design of a new generation of flexible satellite payloads is the subject of current research. Payload architectures must be able to allocate resources flexibly. In [5], the problem of resource allocation for VHTS is modeled as an objective function that minimizes the difference between the offered capacity and the required capacity. However, in order to meet traffic demands, a thorough analysis of payload architecture requirements and resource allocation methods in flexible payloads is necessary.

VHTS systems will provide Terabit connections using advanced flexible payloads, which will enable beam reorientation and reconfiguration, as well as individual beam power and bandwidth allocation. Thus, Dynamic Resource Management (DRM) techniques for SatComs (Satellite Communications) will be a key for operators [6]. While it may seem feasible to achieve a solution to this problem through optimization techniques, on a larger scale the number of resources to be managed, the limitations that come from the system and the infinite number of traffic demand situations

[0] **Abbreviations:** VHTS, Very High Throughput Satellite; DRM, Dynamic Resource Management; SatComs, Satellite Communications; AG-DPA, Assignment Game-based Dynamic Power Allocation; PPA; Proportional Power Allocation; ML, Machine Learning; AI, Artificial intelligence; NN, Neural Networks; TWTA, Traveling WaveTube Amplifiers; IBO, Input Back-off; BFN, Beam Forming Network; ModCod, Modulation and Codification; ACM, Adaptive Coding and Modulation

may result in a problem that cannot be solved with conventional techniques [4]. In order to solve this problem, the authors in [3] suggested an Assignment Game-based Dynamic Power Allocation (AG-DPA) to achieve a reduced suboptimal complexity in multibeam satellite systems. The authors compare the results obtained with a Proportional Power Allocation (PPA) algorithm, obtaining a remarkable advantage in terms of energy saving; however, the management of resources is still insufficient for the required demand. Most existing SatComs payloads do not offer any flexibility in terms of bandwidth or coverage. Instead, power flexibility can be achieved by modifying the working point of the on-board amplifier according to the transponder load. Recently, research interest has focused on the design of a new generation of flexible satellite payloads that allow DRM [7]. Currently one of the most studied challenges is how to allocate resources efficiently and autonomously according to the needs of traffic demand. As a result, interest in using Machine Learning (ML) algorithms in satellite communications has recently increased [8,9]. In this sense, there have been some technological advances in the use of ML on-board satellite communications, e.g., recently the NASA contribution to cognitive space communications [10]. In turn, some of these developments focus primarily on autonomous control and operations. The authors in [11] discuss why ML techniques should be used instead of traditional optimization techniques for resource allocation in satellite communications. The authors comment that when the number of communication resources and the selection of a particular set presents contradictory objectives, the use of traditional optimization techniques is limited. Some recent studies propose to solve the DRM problem using Reinforcement Learning techniques [8,9,12,13]. However, these techniques add an additional delay because the Payload controller training is done online.

In this paper we present a VHTS system that will respond to changes in traffic demand through modifying two payload communication resources: bandwidth and power for a limited number of beams. The proposed system trains the Payload control offline with a Supervised ML algorithm using a Neural Network. While in [14] the authors presented the preliminary results, in this paper the supervised learning approach has been extended including the background of Supervised Learning and a comparison between two different Neural Network architectures presented. The performance of these architectures in both training and resource management is evaluated. The main contributions of this work can be listed below:

- Supervised Learning algorithm is suggested and allows to implement off-line the system, thus avoiding the latency problems online process.
- In this paper, a comparison is made between two different Neural Network Architectures according to the performances.
- The cost function allows you to minimize the difference between the capacity offered and the capacity required while minimizing power and bandwidth consumption.

This paper is divided into six sections. Section 2 presents the background of Supervised Learning, Section 3 explains the definition of the problem and the payload architecture studied from a system approach. Section 4 introduces the rationale for managing resources using Supervised Learning techniques. In Section 5 the case study is explained, and the numerical results obtained through computer simulations are shown. Finally, the discussion and conclusions of the work are in Section 6.

2 | SUPERVISED LEARNING BACKGROUND

Artificial intelligence (AI) is the understanding deployed by machines. Research on AI is defined in computer science as the study of *intelligent agents*, i.e., any device that observes its environment and makes decisions that maximize its chances of success in some objective. Generally, the term *artificial intelligence* is applied when a machine imitates the *cognitive* functions that humans associate with other human minds, such as *learning* and *problem solving* [15]. ML is the study of algorithms that automatically improve through experience. It is considered a subset of AI. ML algorithms build a model based on sample data, known as *training data*, to make predictions or decisions without being explicitly programmed to do so. ML algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the necessary tasks [16].

In general, the different algorithms of the ML can be classified into three categories by their features: Supervised Learning, Unsupervised Learning and Reinforcement Learning [15]. Supervised learning is a technique for deducing a function from training data. Training data consists of pairs of objects: one component of the pair is the input data and the other is the desired results. The output of the function can be a numerical value (as in regression problems) or a class label (as in classification problems). The goal of supervised learning is to create a function capable of predicting the value corresponding to any valid input object after having seen a series of examples, the training data. To do this, one must generalize from the presented data to the previously unknown situations [17]. Supervised learning can generate two model types regression and classification supervised learning. Usually, it generates a function that transforms the input data into the desired results. Classification and regression algorithms are both popular methodologies for the ML when supervised learning techniques are used. However, the main difference is that the classification algorithms predict a *label* and the regression algorithms predict a quantity [16].

Neural Networks (NN) are a model inspired by the behaviour of the human brain. It consists of a set of nodes known as artificial neurons that are connected and transmit signals to each other. These signals are transmitted from input to output [18]. NN consists of three different layers as

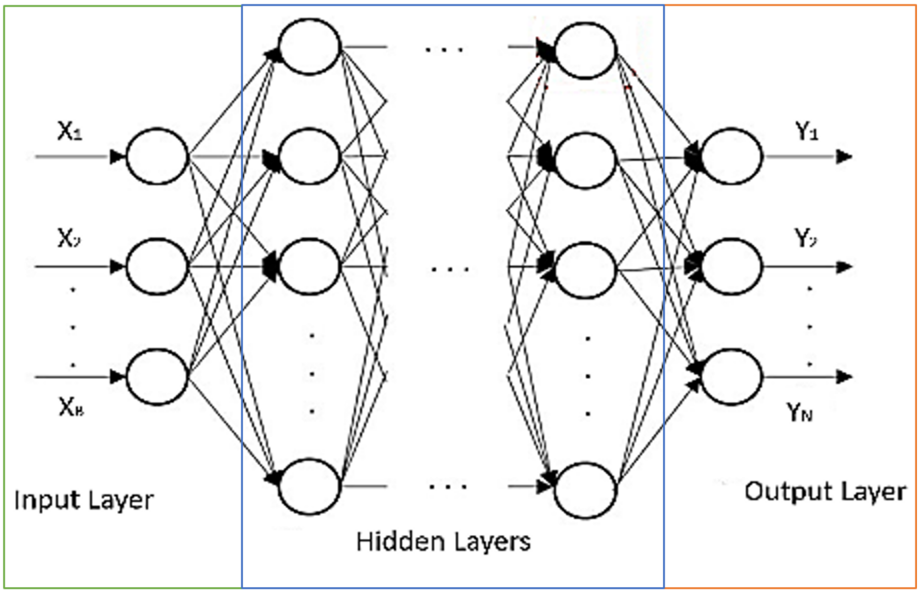

FIGURE 1 Generic Neural Network Architecture

shown in Figure 1. Input layer, where the input variables that can represent the characteristics of the system are located, is usually represented in vector form. Output layer, where the output variables stand, represents the information acquired given the input variables. The hidden layers are the location of the information that is propagated and analyzed to obtain an expected output. The training of a NN is performed through back-propagation, which consists of propagating the error between the desired output and the expected output from the last layer to the first, modifying the weights of the neural connections until the error is minimized [19].

3 | SYSTEM MODEL AND PROBLEM STATEMENT

This section presents the flexible payload architecture considered and mathematically defines the problem to be solved for the DRM.

3.1 | System Architecture

Authors in [20] defined promising flexible payload solutions. The authors explain that there is not any single solution, but that a set of key units has been defined to enable a range of payload response solutions to be proposed. In this sense, based on the flexible payload architectures proposed by the authors in [21], we study DRM in the architecture shown in Figure 2. In the considered architecture the bandwidth and power assigned in each beam are flexible. In that sense, the TWTA (Traveling Wave Tube Amplifiers) IBO (Input Back-off) is adaptable to obtain a flexible power allocation and BFN (Beam Forming Network) is used for the conformation of the beam which in this case is a fixed parameter.

If BW_c is the bandwidth per carrier, the flexible bandwidth assignment is based on assigning a certain number of carriers per beam. Thus, the bandwidth of the beam BW_b will be a product (i.e., $C_n \cdot BW_c$), where C_n is the number of carriers. The flexible payload must be able to separate the signals into frequency blocks and then rearrange them; this process requires a channelizer on board the satellite, as the authors mention in [21].

Under the proposed system, communication resources are managed in response to changes in traffic demand. The payload controller receives the input data from the gateways and user beams, generates optimal control through the Payload Control Center using a DRM. And finally it telecommands the power and bandwidth reallocation in each beam for the payload to switch its resource configuration.

3.2 | Link Budget

This subsection presents the link budget analysis used to derive the capacity offered by one beam. If we start from the general definition, the capacity offered by one beam can be written as:

$$C_b = BW_b \cdot SE_b \tag{1}$$

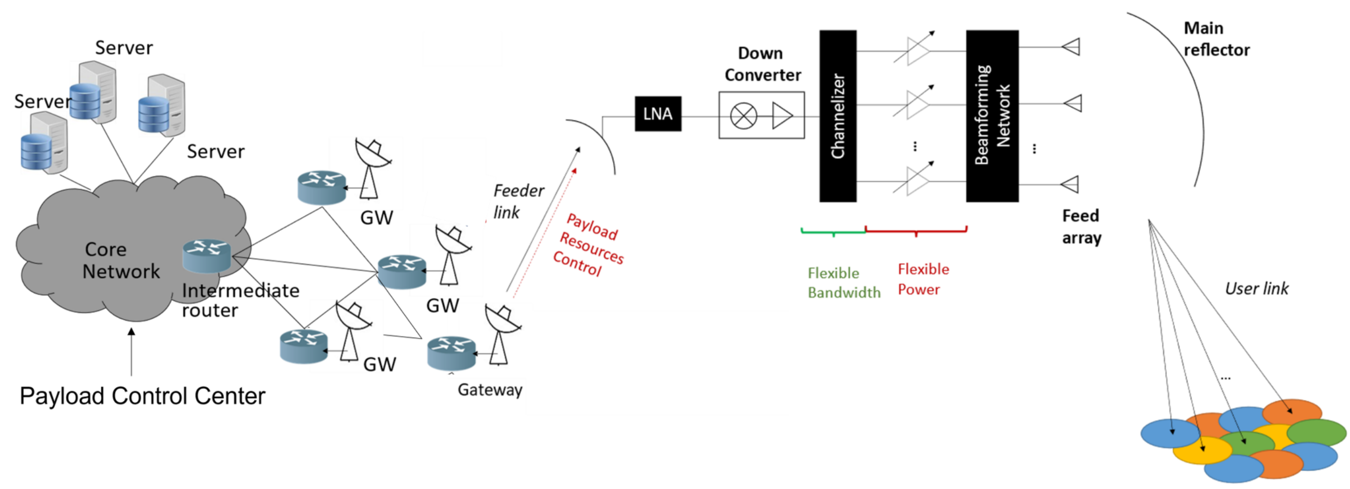

FIGURE 2 System Architecture: Flexible Payload and Resource Management.

where SE_b is the spectral efficiency of the ModCod (Modulation and Codification) of a reference commercial modem used to obtain the capacity of each beam, where we assume a specific Adaptive Coding and Modulation (ACM) scheme [22]. As observed in (1) the offered capacity depends on the bandwidth and spectral efficiency; the higher the bandwidth allocated in a beam the greater the capacity offered but the greater the spectral efficiency the greater the capacity can also be offered. Spectral efficiency (bps/Hz) depends on the $CINR_b$ (Carrier to Interference plus Noise Ratio in the b-th beam) [22], so increasing or decreasing the $CINR_b$ resort in increasing or decreasing the offered capacity, trough a proper function:

$$SE_b = f_1(CINR_b) \tag{2}$$

The variation of the spectral efficiency of each beam with the Carrier to Interference plus Noise Ratio ($CINR_b$) is modelled through a generic function $f_1(\cdot)$ as in [22]. The satellite is considered to have a bent pipe transponder architecture. The satellite gateway feeder link is not considered in the forward link because there are currently different technologies to guarantee the total link budget, such as ULPC (Uplink Power Control), and gateway diversity [23,24,25]; in this sense, the downlink link budget in the user link can be written as:

$$10^{\frac{-CINR_b}{10}} = 10^{\frac{-CIR_b}{10}} + 10^{\frac{-CNR_b}{10}} \tag{3}$$

where

$$CIR_b = P_b - I_b \tag{4}$$

$$I_b = \sum_{\varphi=1}^{\Phi} P_{co}(\varphi, \theta_b) \tag{5}$$

$$CNR_b = P_b + G_b + \frac{G}{T}_u - L_f - k - BW_b \tag{6}$$

where $CINR_b$, CIR_b (Carrier to Interference Ratio) and CNR_b (Carrier to Noise Ratio) are expressed in dB. CIR_b in (4) represents the ratio of the power allocated at b-th beam (P_b, in dBW) to the interference power at b-th beam (I_b, in dBW). The beam gain must be evaluated for the b-th beam in the service area and it depends on θ_b, which is the beamwidth, i.e., the 3 dB aperture angle of the b-th beam. The side-lobes of the satellite antenna pattern are taken into consideration only for the calculation of the co-channel interference due to spatially separated co-channel beams (the same color in the frequency plan). The co-channel interference power (I_b) is a function of the frequency reuse scheme and θ_b, and can be calculated, assuming the co-channel beams set in the system (5), where φ represents the φ-th interferer spot, Φ is the total number of interfering beams of the beam b, and P_{co} is the power level (in W) of φ-th interference inside the b-th beam. The traditional calculation of the CNR as a function of the power (P_b, in dBW) and bandwidth (BW_b, in dBHz) allocated to each beam is presented in (6). In the same equation G_b represents the gain in the main lobe of the $b-th$ beam, unlike [1], $\frac{G}{T}_u$ (in dB/K) represents the merit figure of the user terminal, L_f (in dB) the free space losses in clear sky conditions and k the Boltzmann constant (-228.6 dBW/(K·Hz)).

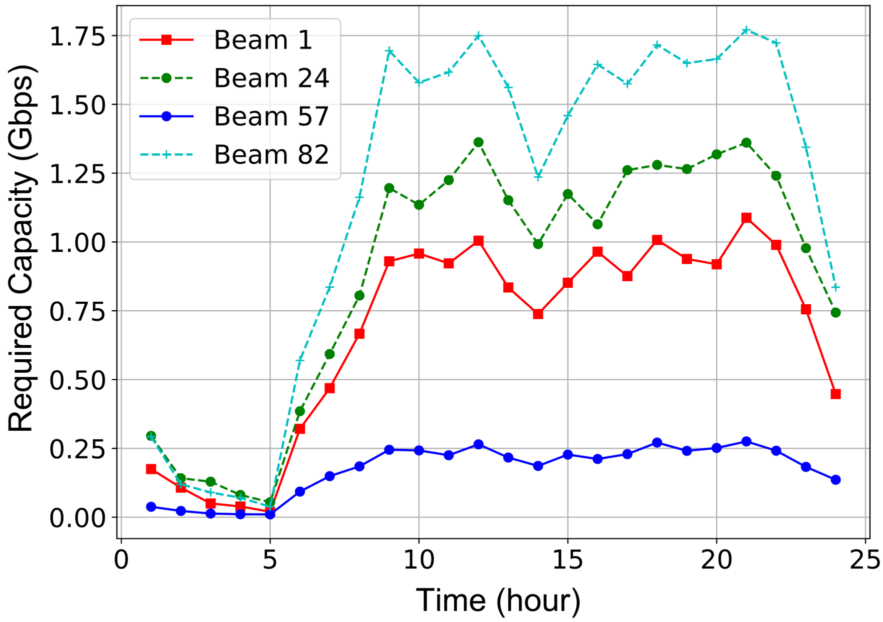

FIGURE 3 One-day cycle of traffic demand per beam

3.3 | Traffic Model

Garau et al. provided a traffic model that depicts realistic operational scenarios in [12]. The authors consider four different data sets that provide measurements for all beams and cover a sufficiently long time-window. These data were provided by SES S.A.; by exploiting these data sets, the authors aim to represent, first, the demand behavior during a typical daily operation cycle, and second, the unfrequented cases that could lead to major service failures if the algorithms do not provide adequate results. The reference model used by the authors represents the throughput demand in a typical commercial scenario, where a higher data rate is requested during specific time intervals of the day. On the other hand, we proposed a traffic model based mainly on the fact that the density of traffic demand per km2 depends on the throughput per user (in bps/user), the population density (in inhabitant/km2), the penetration rate (in user/inhabitant), and the concurrency rate that depends on the time of day [26] as shown in Figure3.

3.4 | Problem Statement

With the growing traffic demand in SatComs, the allocation of resources for each beam becomes key for traffic change over time. In a flexible multibeam satellite system, the beamforming antenna generates B beams over the coverage area. The offered capacity by b-th beam at the time t, $C_b(t)$ (in bps), must change as it depends on $R_b(t)$ (in bps), the required capacity in the b-th beam at the time t. We propose the optimization DRM problem for each time t that can be expressed as:

$$\min_{P_b(t), BW_b(t)} F_1$$

where

$$F_1 = \frac{\alpha}{B}\sum_{b=1}^{B}|C_b(t) - R_b(t)| + \frac{\beta}{B}\sum_{b=1}^{B}P_b(t) + \frac{\gamma}{B}\sum_{nc=1}^{N_c}\sum_{bc=1}^{B_c}BW_{bc}(t) \tag{7}$$

and

$$C_b(t) = f_2(P_b(t), BW_{bc}(t)) \tag{8}$$

subject to

$$\begin{cases} C_b(t) \geq R_b(t) & \text{if } P_b(t) < P_{max,b} \text{ and } BW_{bc}(t) < BW_{max,b} \\ C_b(t) = R_b(t) & \text{if } P_b(t) = P_{max,b} \text{ and } BW_{bc}(t) = BW_{max,b} \end{cases} \tag{9}$$

$$\sum_{b=1}^{B} P_b(t) \leq P_{max,T} \tag{10}$$

$$\sum_{bc=1}^{B_c} BW_{bc}(t) \leq BW_{max,c} \quad (11)$$

The cost function proposed in (7), aims to minimize three parameters for each time instant, t. The first parameter is the difference between the offered capacity and the required capacity, where α (in s/bit) is the correction factor that weights the difference in the cost function. The second parameter that is minimized is the total power (in W) used that is assigned to B beams, where β (in 1/W) is the correction factor that weighs the total power in the cost function. Finally, the third parameter that is minimized is the total bandwidth (in Hz) that is allocated to the beams of each color (B_c) within the frequency plan (N_c is the number of colors in the frequency plan), where γ (in 1/Hz or s) is the correction factor that weighs the total bandwidth assigned in each color of the frequency plan.

The capacity offered (8) in the b-th beam at time t, $C_b(t)$ is a function $f_2(\cdot)$ of the power allocated to the $b-th$ beam at time t, $P_b(t)$, as well as the bandwidth allocated to the b-th beam at time t, $BW_b(t)$. It is worth to be noticed that in (1), the general function of C_b is defined, however, the spectral efficiency depends on $CINR_b$ (2)-(6), so C_b can be rewritten as (8).

An important constraint is detailed in (9) imposing that the capacity offered must be greater than or equal to the capacity required for each beam, subject to the condition that the power and bandwidth assigned to b-th beam in time t ($P_b(t)$ and $BW_{bc}(t)$) are lower than the maximum allowed, respectively, for each beam ($P_{max,b}$ and $BW_{max,bc}$). Otherwise, the capacity offered in b-th beam will be the maximum possible. That is, if the capacity required in the b-th beam is greater than the system can provide, resources will be allocated to provide the maximum possible capacity offered, accepting that the cost function will be affected.

The other two important restrictions of the cost function are that the total power used $\sum_{b=1}^{B} P_b(t)$ must not be greater than the maximum power allowed ($P_{max,T}$), as in (10), and the total bandwidth allocated in each color of the frequency plan $\sum_{bc=1}^{B_c} BW_{bc}(t)$ must not be greater than the available bandwidth per color ($BW_{max,c}$), as in (11).

4 | SUPERVISED LEARNING FOR POWER AND BANDWIDTH MANAGEMENT

The suggested system manages communication resources in response to changes in traffic demand. The problem of power and bandwidth management presented in (5)-(11) has the drawback that the number of communication resources is reduced and the selection of a set of resources presents contradictory objectives, so the use of traditional optimization techniques is limited. In this sense, the contribution proposes the use of ML techniques for the management of payload resources on board a multibeam satellite with B user beams operating in Ka band. In the case presented, the system will respond to changes in traffic demand by modifying two communication resources: bandwidth and power for a limited number of beams. We will address the resolution of the DRM problem described in (7) using Supervise Learning, specifically using a Classification Algorithm.

Supervised algorithms require for its functioning training data and test data. Observations in the training set provide the experience used to learn by the algorithm. In supervised learning problems, each observation consists of one observed output variable and one or more observed inputs. Whereas test data is a set of observations used to evaluate model performance using some efficiency metrics such as accuracy [16]. Accuracy is a metric for measuring the performance of Neural Network training. Accuracy is defined as the ratio of the total number of times the correct resource configuration has been allocated ($RA_{correct}$) to the total number of times a resource configuration was allocated (RA_{total}) [17]:

$$Accuracy = \frac{RA_{correct}}{RA_{total}} \quad (12)$$

In this sense, training data are obtained using the cost function and constraints presented in (9)-(11), by approximating the variation of spectral efficiency with respect to the $CINR_b$ as explained in Section 3.

In order to generate the training data, a database is generated with possible capacity values required for each beam. For each of these possible combinations of required capacity in each beam, there is a label indicating the configuration of the resource allocation set that minimizes the cost function (7) and complies with the restrictions (8)-(11). The cost function implementing a Regularized Logistic Regression [17] to train the Neural Network (NN), especially using a Classification Algorithm, can be written as:

$$J(W) = -\frac{1}{m}\sum_{i=1}^{m}\left[Y^{(i)} \cdot \log \hat{Y}\left(X^{(i)}\right) + \left(1 - Y^{(i)}\right)\log\left(1 - \hat{Y}\left(X^{(i)}\right)\right)\right] + \frac{\lambda}{2m}\sum_{j=1}^{k} W_j^2 \quad (13)$$

where m represents the number of training samples, $X^{(i)}$ indicates the i-th training example with possible required capacities in each beam, $X^{(i)} = [X_1^{(i)}, X_2^{(i)}, ...X_B^{(i)}]$, $Y^{(i)}$ denotes the i-th configuration corresponding to $X^{(i)}$, $\hat{Y}(X^{(i)})$ is the configuration predicted for $X^{(i)}$, k is the order of Logistic Regression and λ is the regularization parameter to avoid overfitting. Logistic regression optimizes the log loss for all the observations in which it is trained, which is equivalent to optimizing the average cross entropy.

Figure 4 serves as a reference for understanding how the problem is addressed. The vector $X = [X_1, X_2, \ldots, X_B]$ represents the B (number of beams) inputs of the Neural Network. Vector $\hat{Y}$ represents the N outputs of the Neural Network, these outputs correspond to the set of resources

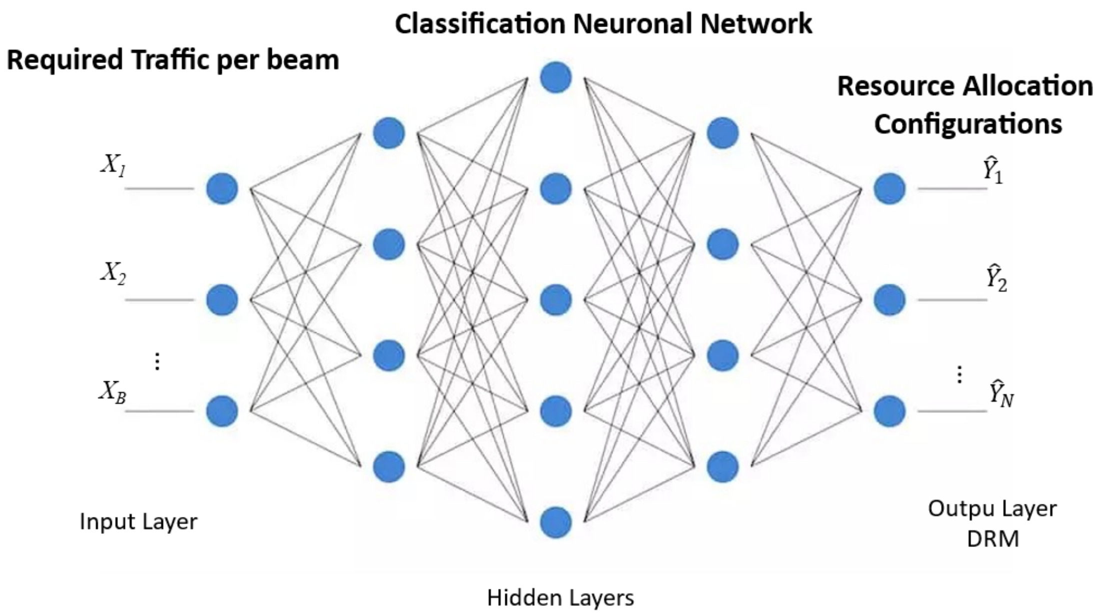

FIGURE 4 Neural Network to manage resources allocation

TABLE 1 Neural Network Architecture 1 and 2.

Layer	Architecture 1	Architecture 1	Activation function
	Size	Size	
Input	Number of beams	Number of beams	-
Hidden Layer 1	132	256	Sigmoid
Hidden Layer 2	132	128	Sigmoid
Hidden Layer 3	132	128	Sigmoid
Hidden Layer 4	132	32	Sigmoid
Hidden Layer 5	132	32	Sigmoid
Output	Total number of possible configurations	Total number of possible configurations	Softmax

allocated to the each of B beams. In a Neural Network, the activation function of a neuron defines the output of that neuron given an input or a set of inputs. This output is then used as an input for the next neuron and so on until a desired solution to the original problem is found.

Two neural network architectures are suggested and are presented in Table 1. Both architectures consist of the input layer of size $1 \times B$, 5 hidden layers and the output layer of size $1 \times N$. However, the first architecture contains the same number of neurons (132 neurons) and the second architecture has a different number of neurons in each hidden layer (256, 128, 128, 32 and 32 neurons respectively). The hidden layers of both architectures have the sigmoid function as activation and the output layer the softmax function.

The sigmoid function transforms the input values to a scale (0,1) as shown in the Figure 5, where high values have an asymptotic value of 1 and very low values have an asymptotic value of 0 [18]:

$$y = sigmoid(x) = \frac{1}{1+e^{-x}} \tag{14}$$

where x is the parameter to be evaluated in the sigmoid function and y is the result of the activation function.

The softmax function generates a vector that represents the probability distributions of a list of potential outcomes and is mathematically defined as [27]:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \tag{15}$$

The softmax takes a vector z of N possible configurations as input and normalizes it into a probability distribution consisting of N probabilities proportional to the exponential of the input numbers as shown in the Figure 5. That is, before applying softmax, some vector elements could be

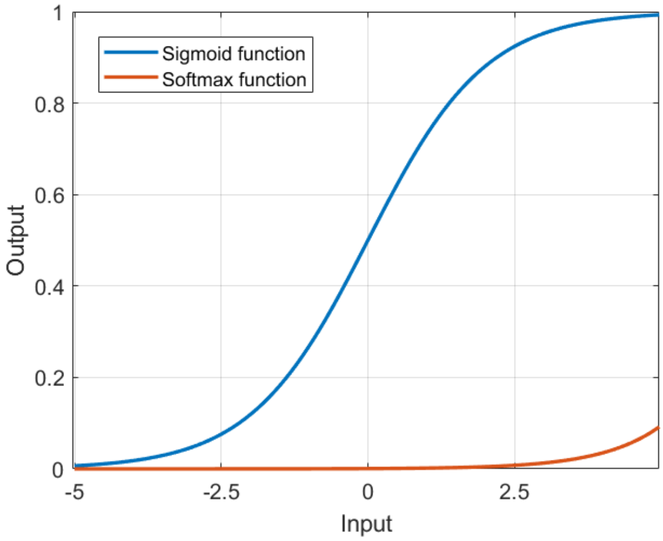

FIGURE 5 Behavior of activation functions in the neural network

negative or greater than one depending on the cost function; and it could not add up to 1; but after applying softmax, each element will be in the range of 0 to 1, and the elements will add up to 1, so that they can be interpreted as probabilities.

The resource management in the payload is carried out autonomously. The Neural Network training is done off-line. In other words, in resource management, the Neural Network represents only an intelligent switch for the payload that changes from one configuration to another every time instant, so the performance of the Neural Network during training is very important and it is also important to avoid overfitting, since this will depend on the management of resources.

The algorithm is separated into two stages, offline and online, and it is detailed in Figure 6. The first step is performed offline and consists of generating training data, i.e. possible values of required capacity in each beam as a function of daytime hours and then assigning labels to the training data that minimize the DRM cost function (7). Likewise the neural network architecture to be used must be defined and while the logarithmic losses are larger than the NN it is trained iteratively.

On the other hand, in the online stage, a vector with the traffic demand for each beam at time t is taken as input, and the DRM selects the optimal resource allocation based on the input data so that the Payload Control Center sends the resource reallocation configuration to the satellite through telecommand or signalling channel.

Two KPIs (Key Performance Indicator) are used to evaluate the performance of the DRM algorithm, with which an important trade-off can be observed. We define the first KPI as the Mean Difference of the DRM algorithm (in Mbps):

$$KPI_1 = \frac{1}{B\rho}\sum_{b=1}^{B}|C_b - R_b| \tag{16}$$

where ρ is the normalization parameter. Power savings is the second KPI[3], defined as

$$KPI_2 = \frac{P_{Total,UPA}}{P_{Total,Alg}} \tag{17}$$

where $P_{Total,UPA}$ is the total power of the payload when using uniform power allocation (UPA) and $P_{Total,Alg}$ is the total power of the payload when using power allocation using the proposed algorithm.

5 | NUMERICAL RESULTS

This section describes the payload architecture, the training data generation and the results obtained when power and bandwidth are managed with a Supervised Machine Learning algorithm.

SUPERVISED LEARNING ALGORITHM FOR POWER AND BANDWIDTH MANAGEMENT

Offline

1. Generate training data: Possible values of required capacity in each beam depending on the time day.
2. Assigning labels to training data that minimizes the DRM cost function:

$$\min_{P_b(t), BW_b(t)} F_1$$

$$F_1 = \frac{\alpha}{B}\sum_{b=1}^{B}|C_b(t) - R_b(t)| + \frac{\beta}{B}\sum_{b=1}^{B} P_b(t) + \frac{\gamma}{B}\sum_{nc=1}^{N_c}\sum_{b_c=1}^{B_c} BW_{bc}(t)$$

3. Defining the architecture of Neural Network
4. While log losses are higher than required:

$$J(W) = -\frac{1}{m}\sum_{i=1}^{m}\left[Y^{(i)}\log \hat{Y}(X^{(i)}) + (1 - Y^{(i)})\log\left(1 - \hat{Y}(X^{(i)})\right)\right] + \frac{\lambda}{2m}\sum_{j=1}^{k} W_j^{\,2}$$

   5. Training
   6. Testing

7. end While

Online

1. Input: Vector with the traffic demand by each beam in time t
2. DRM selects the optimal resource configuration depending to input data
3. Payload Control Center sends the resources re-allocation to the satellite via Telecommand.

FIGURE 6 Supervised Learning algorithm for resources management

5.1 | Payload Architecture

This paper studies the payload architecture shown in Figure 7 to evaluate resource management in a VHTS system using Supervised Learning. The architecture shows a flexible payload for 8 beams, the flexible parameters are the bandwidth corresponding to each beam (100, 200 or 250 MHz) and the power assigned to each beam (8, 10, 12 or 14 dBW). The beamwidth is fixed (0.65 degrees). The maximum power at each beam ($P_{max,b}$) can be 14 dBW. For its study we have as a restriction that the maximum power available to the payload ($P_{max,T}$) is 21.5 dBW. For example, a power assignment of 14 dBW per beam in all beams in a time slot is excluded because the total power required for this configuration would be 23 dBW, which would be outside the limitation. In the case of bandwidth, we assume that there are 4 colors in the frequency plan (N_c) and each color feeds 2 beams. We assume that the bandwidth available in each color ($BW_{max,c}$) is 500 MHz, so in this case there is no restriction because the maximum bandwidth that can have a beam ($BW_{max,b}$) in a time slot is 250 MHz and as there are only two beams per color will always be within the conditions allowed. The maximum bandwidth that can be assigned to each beam depends directly on the bandwidth of the user receivers and the number of users.

5.2 | Training Data

There are 12 possible resource allocation configurations per beam, as represented in Table 2. The allocation of resources of each beam is not independent, therefore not all combinations of resource allocation are possible; for this reason in the Neural Network training all those situations are discarded in which it is outside the constraints (e.g., that the total available power required is greater than 21.5 dBW).

In this sense, the minimum $CINR_b$ in each beam is 10.26 dB for this payload architecture and the maximum is 18.22 dB, which is equivalent to a range of 7.96 dB. And taking into account that the allocated bandwidth can be 100, 200 or 250 MHz, this corresponds to the range of offered

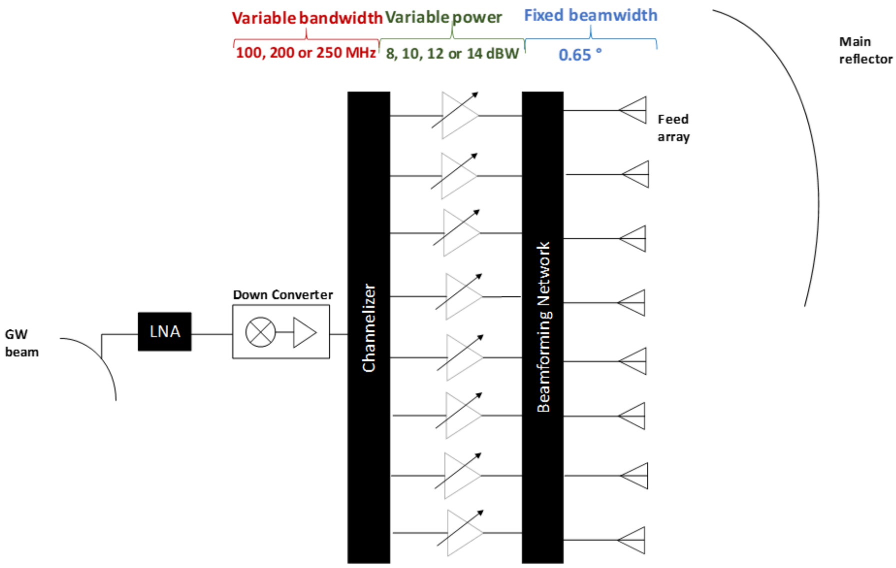

FIGURE 7 Flexible payload architecture for 8 beams

TABLE 2 Capacity Offered in one beam based on the Resources Allocated to the beam

Possible combinations for a single beam (Beamwidth = 0.65 °)				
BW [MHz]	**Power [dBW]**	**CINRb [dB]**	**S. E. [bps/Hz]**	**Capacity [Mbps]**
100	8	13.83	3.25	325.0
	10	15.46	3.55	355.1
	12	16.92	3.82	382.4
	14	18.20	4.06	405.9
200	8	11.15	2.76	551.2
	10	12.96	3.09	617.7
	12	14.65	3.40	680.4
	14	16.21	3.69	738.0
250	8	10.26	2.59	647.5
	10	12.09	2.93	732.3
	12	13.84	3.25	813.2
	14	15.47	3.55	888.6

capacity in each beam can have a variation of 563.6 Mbps, since the minimum throughput that can be offered in a beam is 325 Mbps and the maximum is 888.6 Mbps.

Table 2 shows the capacity offered in one beam as a function of the power and bandwidth allocated to that beam. It becomes clear that the allocation of bandwidth has a greater impact on the offered capacity. There is a trade-off, in that as the bandwidth increases, the $CINR_b$ reduces, resulting in a lower Spectral Efficiency and a lower level ModCod (Modulation and Coding); nevertheless, the capacity offered in the beam increases considerably.

5.3 | Training Performance

In the proposed system architecture, the trained Neural Network represents the intelligent switch that modifies the resources allocated in each beam depending on the required capacity. In the cost function (7) that we have used to generate the training data, we assume that α, β and γ are equal to one. 100,000 samples of B required traffics scenarios were generated for Neural Network training of which 70% was used for training and 30% for validation. Two Neural Network Architectures were used as described in Table 1 for $\lambda = 0.01$.

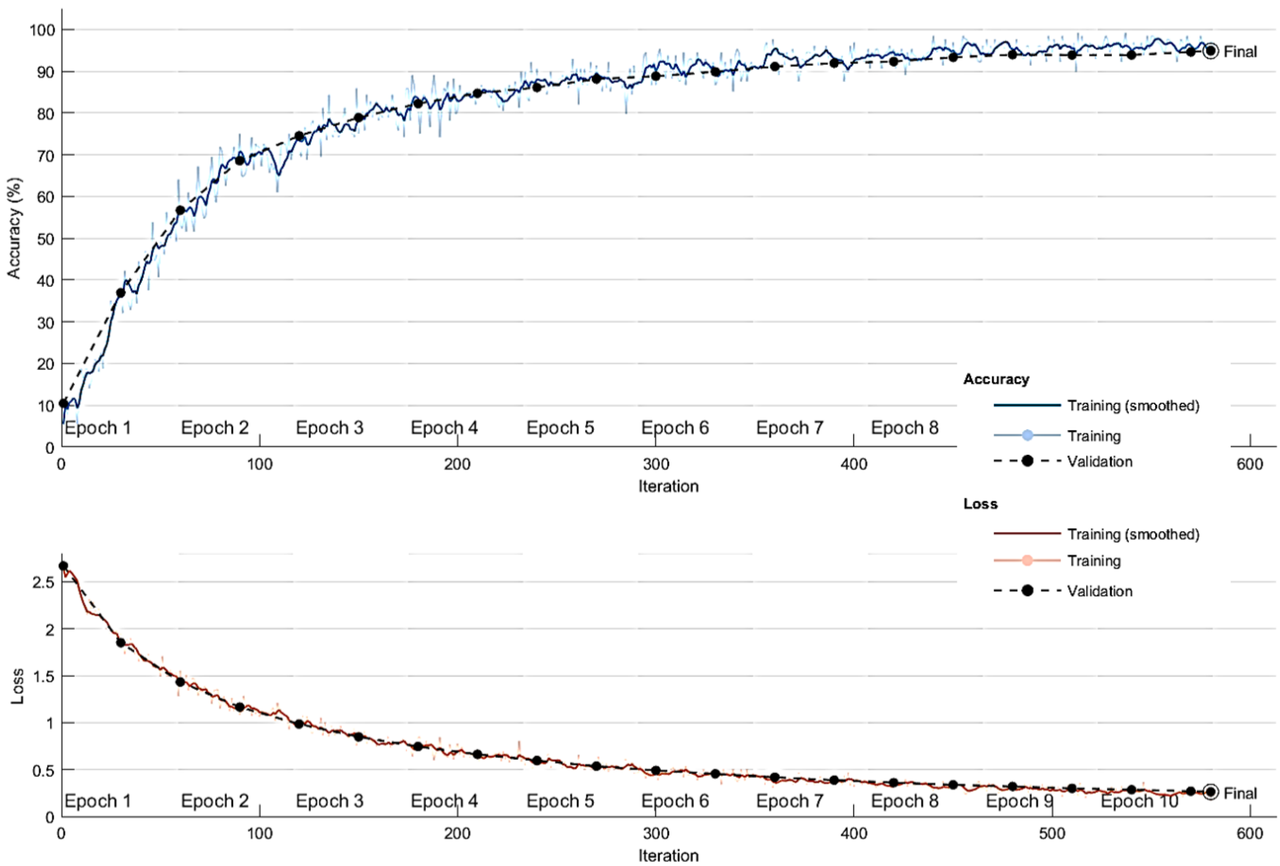

FIGURE 8 Training Progress: Log Loss and Accuracy. Neural Network Architecture 1.

Training was performed for 600 iterations and a final accuracy of 94.98% was obtained using a Neural Network with Architecture 1 and a final accuracy of 99.12% with Architecture 2. The log loss history and accuracy over the 600 iterations for Architecture 1 and 2 are shown in Figure 8 and 9, respectively, where the training and test performance is shown.

The Architecture 2 Neural Network has a better performance compared to Architecture 1. On the one hand, the Architecture 2 converges faster, it can be seen in Figure 9 that it takes less than 400 iterations to converge while for Architecture 1 after 600 iterations it still does not converge, as depicted in Figure 8. On the other hand, with Architecture 2, 4% more accuracy is obtained in both training and testing.

5.4 | Power and Bandwidth Management Performance

Figure 10 shows the performance of resource allocation management for a specific hour of the day (1:00 p.m.), assuming random values of traffic requirement on each beam for this hour. The figure shows the capacity offered and with the help of Table 2 it is possible to know the power and bandwidth assigned to each beam.

Using Architecture 1 (NN 1), the capacities offered are higher than those required for all beams and in each hour, except in two cases, one when the maximum possible power and bandwidth have already been assigned to the beam (Beam 3) and the other is in Beam 4, and in this case the constraint presented in (9) is not being met; this is because after 600 iterations of training the NN 1 has 94.98% accuracy (Figure 8). On the other hand, using Architecture 2 (NN 2), the capacities offered are higher than those required for all beams and in each hour, except when the maximum possible power and bandwidth have already been assigned to the beam (Beam 3). It is observed that with NN 2 it can offer a capacity following better the traffic demand because after 600 iterations an accuracy of 99.12% is obtained (Figure 9).

The resource allocation management is successfully performed for the required traffic. The difference between offered capacity and required capacity decreases compared to a traditional payload architecture (fixed power: 14 dBW, fixed bandwidth: 250 MHz) that meets all system constraints. This is shown in Figure 11(a), which presents an estimate of the average difference between offered capacity and required capacity for 48 consecutive hours. In particular, Figure 11(a) presents the performance comparison of a traditional payload and the case study payload where power and bandwidth allocation is managed by NN 1 and NN 2. In which it is observed that for both NN 1 and NN 2 the difference can be decreased

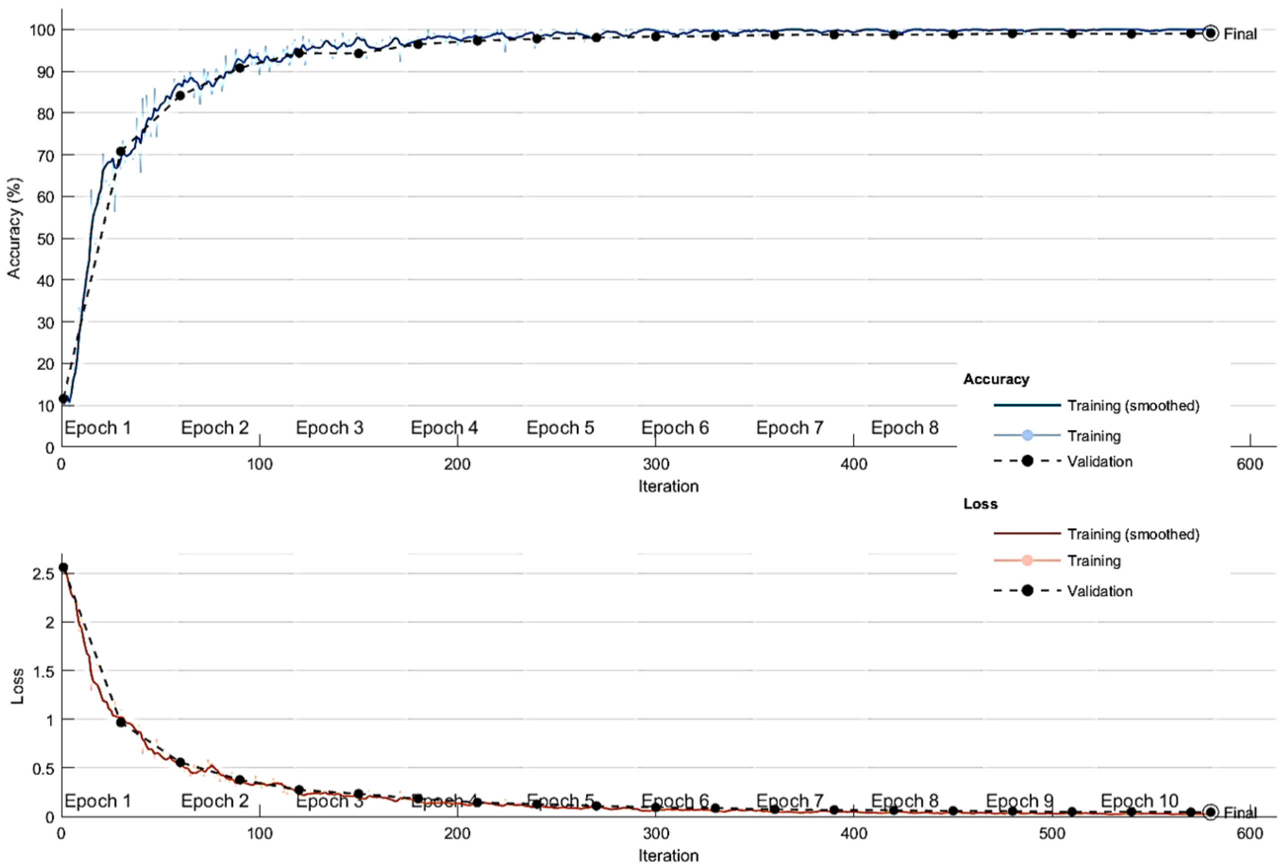

FIGURE 9 Training Progress: Log Loss and Accuracy. Neural Network Architecture 2.

up to 50 Mbps. On the other hand, Figure 11(b) represents the power savings obtained with NN 1 and NN 2 compared to a traditional payload where a fixed power is maintained at each time instant. It is observed that more than 50% of the power used for the studied architecture can be saved for both NN 1 and NN 2. This will allow savings in payload design cost.

5.5 | Discussions

The use of a Supervised Learning algorithm for resource allocation management in a flexible payload has the main advantage that the resource allocation is managed independently. In this work, we have specifically proposed to use a Neural Network using a classification algorithm, where the classes are all possible payload configurations complying with the resource allocation. The management of the payload resources is performed as an autonomous operation, but the main advantage of this methodology is that the management is performed with a low computational cost, since the training of the Neural Network is performed off-line. That is, the Neural Network represents only an intelligent switch for the payload that changes one or another configuration at every instant of time, so the performance of the Neural Network during training is very important for this methodology as well as it is also important to avoid overfitting, since it will depend on the correct management of the resources. In that sense, it has been demonstrated that for DRM better results are obtained using a Neural Network architecture with different numbers of neurons in each layer compared to a uniform architecture. However, this methodology has several challenges. One of them is that the number of classes is exponential as a function of the number of beams and possible variations in power, bandwidth and/or beamwidth. This significantly increases the computational cost during neural network training. However, the biggest challenge with this solution is that it cannot be applied to other types of flexible architectures such as beam hopping.

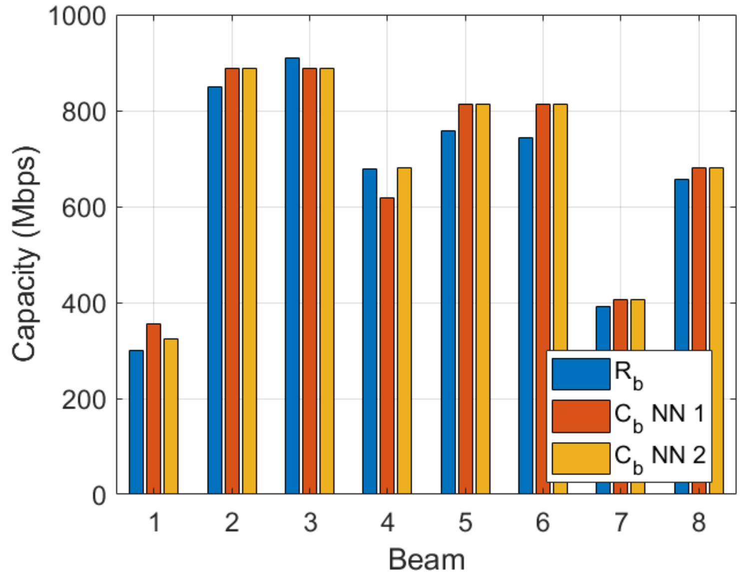

FIGURE 10 Performance of the Neural Network in the management of the allocation of resources at 1:00 p.m.

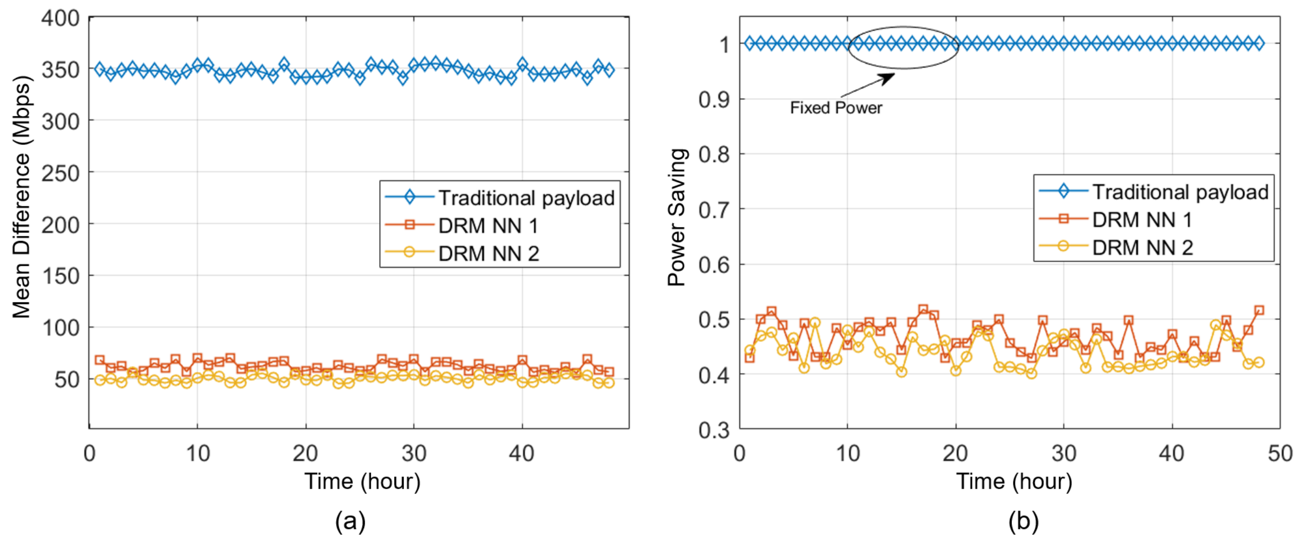

FIGURE 11 Mean Difference (in Mbps) and Power saving (dimensionless) comparison between a traditional payload and a payload with power and bandwidth management using NN 1 and NN 2 for 48 consecutive hours.

6 | CONCLUSIONS

This paper proposes the use of Classification Algorithms for resource management in a flexible payload architecture using Supervised Learning, where the classes are all possible resource allocation configurations of the payload excluding all those that do not meet the constraints. The training of the Machine Learning algorithm plays a very important role in the success of resource management, since the training is performed offline and is not updated once the payload is operational because once the Neural Network has obtained a correct training performance, it is able to generalize the learned knowledge and allocate resources when the traffic demand changes. As future work, the implementation of more robust classification algorithms such as Deep Convolutional Neural Networks is proposed [26] that allow characterizing the traffic demand in the service area and allocating resources. It is also proposed to implement the Reinforcement Learning algorithm to have a resource management that adapts to a dynamic environment. In addition, the impact of the lack of power accuracy in the payload on the system performance must be evaluated, in order to define which payload architecture is the most suitable.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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