Learning to Optimize Satellite Flexible Payloads

Miguel Ángel Vázquez, *Senior Member*, *IEEE*, Pol Henarejos, *Senior Member*, *IEEE* and
Ana Pérez-Neira, *Fellow Member*, *IEEE*.

***Abstract*—This paper proposes an optimization technique for satellite systems with flexible payloads. Unlike current satellites whose per-beam capacity is fixed, forthcoming payloads will have bandwidth and power allocation reconfiguration capabilities allowing the operators to modify the offered capacity. Assuming a generic flexible payload architecture, this paper introduces an optimization technique that is able to provide an efficient bandwidth and power allocation that fulfil the user terminals rate requests. Furthermore, we introduce a deep learning regression algorithm able to reproduce the mapping of the proposed optimization technique with a very reduced computational complexity. By using the output of the optimization technique as ground truth, we design a deep neural network that behaves very similar to the optimization problem yet with a dramatically reduced computational time. Numerical results show the benefits of the proposed technique and in particular, we observe two order of magnitude computational time decrease when using the deep learning approach compared to the classical optimization technique yet preserving almost the same performance.**

Keywords*—*Satellite communications, deep learning, power control.

I. Introduction

Current commercial multibeam satellite systems present a fixed data-rate capacity at each beam. This fact strongly limits the operator exploitation margin as regional user data rate demands over a certain geographical area shall be predicted when the satellite is built and maintained over the satellite life which is generally about 15 years. Furthermore, mobile user terminals (UTs) such as vessels and airplanes lead to spatial temporal variations of the data-rate demands which might cause certain beams to saturate over a certain period.

In order to solve this problem, future satellite payloads will have reconfiguration capabilities. In particular, the on-board analogue infrastructure will allow modular spectrum channelization of each beam, providing a bandwidth and power control over the coverage area. Examples of future flexible payloads are Eutelsat Quantum and Inmarsat-6.

Although commercial flexible payloads are currently starting to be launched, academia has investigated them in the last fifteen years [1]–[4]. On the one hand, the works [1], [2] introduced the on board technology advances required for the creation of flexible payloads such as preliminary heuristic optimization methods. On the other hand, in [3] the authors assume an arbitrary payload architecture able to increase the flexibility of the allocation of power and bandwidth over the different beams and additional heuristic optimization methods. Finally, the work in [4] introduces a simulated annealing technique for solving a mixed integer linear program that models a particular flexible payload allocation optimization problem.

In contrast to the mentioned works, in this paper we introduce a new optimization approach that provides efficient solutions considering a generic flexible payload. In particular, we focus on minimizing the sum the users service level agreements (SLAs) violations, defined as the difference between the requested data rate and the offered one by the satellite operator. To the best of authors knowledge, the proposed approach is novel, and it certainly collapses the real problem of flexible satellite payload optimization. The resulting optimization problem is observed to be non-convex and, in order to solve it, we use the concave-convex procedure (CCP) [5]. Although CCP iterative method is able to yield an efficient solution, it requires solving a large number of convex problems, limiting its applicability in very short time-to-react events such as sudden requests of traffic demands. Remarkably, the CCP approach is ideal for large scale variations such as hourly data rate demands or planned new customers deployment.

Inspired by the recent results on deep learning for power allocation in different scenarios [6], [7], here we aim at using a deep neural network (DNN) for mimicking the CCP implementation over the conceived optimization problem. Concretely, we train a DNN with a plethora of channel realizations, data-rate user demands, and their corresponding efficient power allocation and we use this dataset as ground truth for designing a DNN. The numerical simulations show that the proposed DNN architecture can reproduce the power allocation efficient solutions of the CCP method. The conceived DNN is very attractive to the satellite industry as it is able to provide efficient power allocations with a dramatically low number of operations. A similar approach was carried out for satellite communications in [8], [9] considering other optimization problem and DNN approximation.

The rest of this work is organized as follows. Section 2 presents the power allocation problem for flexible payloads and introduces the use of the CCP method for solving it. The use of DNNs for power allocation is introduced in Section 3, showing how the training can be performed. Numerical results in Section 4 show the performance of the conceived DNNs for this optimization framework. Section 5 concludes.

II. System Model and Problem Statement

The system under consideration is a satellite forward link transmission with frequency-division multiple access. Perfect channel state information is assumed both at the transmitter (i.e. the satellite gateway) and the receivers (the satellite UTs).

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We consider a system with K feed elements (antennas) serving K users over M subcarriers. Note that a carrier can be occupied by one or more users.

We aim at finding a solution that guarantees the minimum rate constraints. In particular, we assume that the k-th user requires to transmit at least $\bar{R}_k$. Let $\mathbf{H} \in \mathbb{R}^{K \times K}$ be the channel gain matrix whose i, j entry (i.e. $h_{i,j}$) is the channel gain between the i-th transmit feed element and the j-th receiver. Note that this channel gain is assumed to be the same for all subcarriers $m = 1, \ldots, M$. This is due to the fixed satellite system channel characterization, which considers a flat frequency response over the available bandwidth. A schematic of the described scenario is depicted in Figure 1.

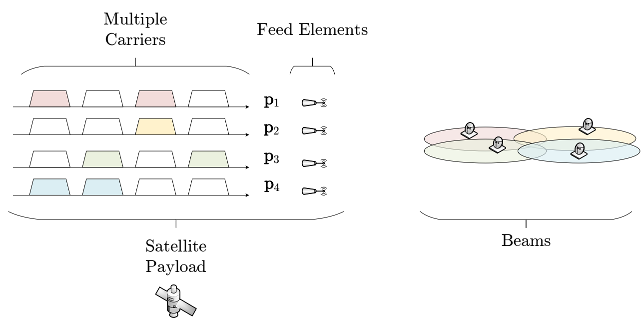

Fig. 1. Illustration of the system under investigation, here for a satellite with $M = K = 4$. Different colors refer to different user signals.

In this context, the optimization problem can be described as

$$\begin{aligned} & \underset{\{\mathbf{p}_k\}_{k=1}^K, \{s_k\}_{k=1}^K}{\text{minimize}} \quad \sum_{k=1}^{K} s_k \\ & \text{subject to} \\ & R_k \geq \bar{R}_k - s_k \quad \forall k, \\ & s_k \geq 0 \quad \forall k, \\ & \sum_{k=1}^{K} \mathbf{1}_M^T \mathbf{p}_k = P_{\max}, \end{aligned} \tag{1}$$

where

$$R_k = \sum_{m=1}^{M} \log_2 \left(1 + \frac{h_{k,k}^2 p_{k,m}}{\sum_{l \neq k} h_{k,l}^2 p_{l,m} + \sigma_{k,m}^2} \right), \tag{2}$$

where $\sigma_{k,m}^2$ is the additive white Gaussian noise power in the m-th band of the k-th user. For the sake of simplicity, we will consider that all satellite UTs have the same noise figure so that $\sigma_{k,m}^2 = \sigma^2$ for $k = 1, \ldots, K$ and $m = 1, \ldots, M$. Moreover,

$$\mathbf{p}_k = (p_{k,1}, \ldots, p_{k,M})^T \tag{3}$$

is the power allocation vector of the k-th user over the M carriers. We assume that $P_{\max}$ is the maximum available power at the satellite payload. Finally, s_k is the rate violation of the k-th user; that is, the difference between the offered rate, R_k, and the rate demand, $\bar{R}_k$.

It is important to remark that in here we opt to consider that the satellite is employing all the available power $P_{\max}$. As a general statement, this restriction naturally comes from the satellite payload radio-frequency design where the radiated power budget is designed considering a 15 years life cycle considering full power transmission. Indeed, in spacecraft satellite design, radiofrequency subsystem mass and power budget are designed considering worst-case scenario where the satellite continuously uses all available power. That is, our optimization approach is in line with general satellite mission designs. Of course, conceiving a power control algorithm capable of providing energy efficiency to the system while minimizing the user rate demands violation is of interest. However, in here our focus is the rate violation minimization. The study of energy efficiency algorithms is left for further work.

The optimization problem in (1) is a non-convex problem. Here, we aim at solving this problem with the CCP method [5]. This method is majorization-minization algorithm [10] that approximates the concave parts of the optimization problem by its first order Taylor expansion. Let us re-write the optimization problem (1) in standard form by considering the power minimization as objective function

$$\begin{aligned} & \underset{\{\mathbf{p}_k\}_{k=1}^K, \{s_k\}_{k=1}^K}{\text{minimize}} \quad \sum_{k=1}^{K} s_k \\ & \text{subject to} \\ & f_k(\mathbf{p}_k) + g_k(\mathbf{p}_k) + \bar{R}_k - s_k \leq 0 \quad \forall k, \\ & s_k \geq 0 \quad \forall k, \\ & \sum_{k=1}^{K} \mathbf{1}_M^T \mathbf{p}_k = P_{\max}, \end{aligned} \tag{4}$$

where

$$f_k(\mathbf{p}_k) = -\sum_{m=1}^{M} \log_2 \left(\sum_{l=1}^{K} h_{k,l}^2 p_{l,m} + \sigma^2 \right), \tag{5}$$

$$g_k(\mathbf{p}_k) = \sum_{m=1}^{M} \log_2 \left(\sum_{i \neq k}^{K} h_{k,i}^2 p_{i,m} + \sigma^2 \right). \tag{6}$$

Bearing in mind the CCP method, the concave parts of the optimization problem (i.e. $g_k(\mathbf{p}_k)$, $\forall k$) shall be sequentially approximated via its first order approximation at a given point $\mathbf{p}_k^{[t]}$ such as $g'_k(\mathbf{p}_k, \mathbf{p}_k^{[t]})$. That is, given a solution at the t-th iteration, the $(t+1)$-th is obtained via

$$\begin{aligned} & \underset{\{\mathbf{p}_k\}_{k=1}^K, \{s_k\}_{k=1}^K}{\text{minimize}} \quad \sum_{k=1}^{K} s_k \\ & \text{subject to} \\ & f_k(\mathbf{p}_k) + g'_k(\mathbf{p}_k, \mathbf{p}_k^{[t]}) + \bar{R}_k - s_k \leq 0 \quad \forall k, \\ & \sum_{k=1}^{K} \mathbf{1}_M^T \mathbf{p}_k = P_{\max}, \\ & s_m > 0 \quad \forall m \end{aligned} \tag{7}$$

where

$$g'_k(\mathbf{p}_k, \mathbf{p}_k^{[t]}) = g_k(\mathbf{p}_k^{[t]}) + \sum_{m=1}^{M} \frac{\sum_{i \neq k}^{K} h_{k,i}^2 \left(p_{i,m} - p_{i,m}^{[t]} \right)}{\sum_{i \neq k}^{K} h_{k,i}^2 p_{i,m}^{[t]} + \sigma^2}. \tag{8}$$

The CCP technique starts from a random feasible point $\{\mathbf{p}_k^{[0]}\}_{k=1}^K$ and it sequentially solves the optimization problem in (7). This sequence of optimization problems converges to a stationary point of the original optimization problem in (1) as reported in [5].

In light of the above result, a satellite network operations center could rely on CCP technique for hourly data rate demand variations, $\bar{R}_k$, as the resulting algorithm has a limited computational complexity of solving a sequence of convex problems via interior point methods. On the contrary, for short-term SLAs variation, a technique with a much lower computational complexity is required. In this context, we introduce the use of deep learning in the following Section. The main idea is to use the already proposed technique as ground truth data and design a DNN able to mimic its behaviour with a substantially lower complexity.

III. Optimization by Deep Learning

The conceived iterative algorithm CCP can be described as an unknown non-linear function. In particular, we can consider that the CCP method previously presented is an unknown mapping such that

$$\psi(\mathbf{d}) = \mathbf{y}, \tag{9}$$

where $\mathbf{d} = \left(h_{1,1}, \ldots, h_{K,K}, \bar{R}_1, \ldots, \bar{R}_K\right)^T$,

and $\mathbf{y} = \left(\mathbf{p}_1^T, \ldots, \mathbf{p}_K^T\right)^T$.

Note that we are not considering the whole solution of the optimization problem in (1) composed by $\{\mathbf{p}_k\}_{k=1}^K, \{s_k\}_{k=1}^K$, but only $\{\mathbf{p}_k\}_{k=1}^K$. This is because the output of interest is $\{\mathbf{p}_k\}_{k=1}^K$ and the resulting violation values can be obtained by computing the data rates considering $\{\mathbf{p}_k\}_{k=1}^K$.

In this Section, we aim at describing how a DNN could model the function $\psi(\cdot)$. In particular, bearing in mind that DNNs are universal function approximators [11], we train a fully connected feedforward DNN for being capable of learning the function $\psi(\cdot)$. For training convenience and as we describe in the following, we have used as data a normalized version of $\mathbf{y}$ such that $\mathbf{y}_{\text{normalized}} = \frac{1}{P_{\max}}\mathbf{y}$.

DNNs consists of a series of sequential operations generally coined as *layers*. Commonly, the first layer is coined as *input layer* and it fuels the input data into the network. For our case, the input layer has dimensions of $K^2 + K$ (i.e. the dimensions of $\mathbf{d}$). This data passes through L *hidden layers* and an *output layer*. Each of the layers have N_l neurons (i.e. processing units) for $l = 1, \ldots, L+1$. The output layer dimensions, N_{L+1}, are imposed by the dimensions of $\mathbf{y}$ which are KM.

The input data is sequentially processed by the different layers. Coining $\mathbf{x}_{l-1}$ the data input of the l-th layer and having $\mathbf{x}_0 = \mathbf{d}$, the output at the n-th neuron can be written as

$$[\mathbf{x}_l]_n = \mathcal{F}_{n,l}\left(\mathbf{w}_{n,l}^T \mathbf{x}_{l-1} + b_{n,l}\right), \tag{10}$$

where $\mathbf{w}_{n,l}$ and $b_{n,l}$ are the weights and the bias terms so as $\mathcal{F}_{n,l}(\cdot)$ is the activation function. In order to impose the sum-power constraint included in (1), we use as output activation function the *softmax* [12]

$$\mathcal{F}_{n,L+1}(\mathbf{x}_L) = \frac{e^{[\mathbf{x}_L]_n}}{\sum_{i=1}^{N_L} e^{[\mathbf{x}_L]_i}}. \tag{11}$$

TABLE I. Satellite System Specifications

Maximum radiated power ($P_{\max}$)	25.8 dBWatts
Channel bandwidth	500 MHz
Carrier frequency	20 GHz
Roll-off factor	0.2
UT receive antenna gain	42.2 dB
Satellite antenna radiation pattern	provided by ESA/ESTEC
Channel characteristics	path loss model in [13]
Number of beams	7
User data rate demands	Uniformly distributed

This activation function imposes that the sum of all elements of $\mathbf{x}_L$ is equal to one. This activation function naturally serves us to guarantee that the output of the DNN fulfils the available power budget constraint, $P_{\max}$ as the transmit power can be obtained with $\hat{\mathbf{p}} = P_{\max}\mathbf{x}_L$. For the other hidden layers, we have used the rectified linear units (ReLU) [12].

The DNN design is based on obtaining efficient weights and bias values for all neurons. This optimization relies on a set of Q pairs $\left\{\left(\mathbf{d}^{(q)}, \mathbf{y}_{\text{normalized}}^{(q)}\right)\right\}_{q=1}^{Q}$ where each pair corresponds to an input and output data of the CCP method over Q realizations.

Being $\mathbf{o}^{(q)}$ the output of the DNN for a certain input $\mathbf{d}^{(q)}$, in order to obtain efficient weighting and bias values, we optimize

$$\text{Total Loss}\left(\mathbf{W}, \mathbf{b}\right) = \frac{1}{Q}\sum_{q=1}^{Q} \mathcal{L}\left(\mathbf{o}^{(q)}, \mathbf{y}_{\text{normalized}}^{(q)}\right), \tag{12}$$

where $\mathbf{W}$ contains the DNN weights, $\mathbf{b}$ the bias values and $\mathcal{L}(\cdot,\cdot)$ denotes the loss function. The selection of the loss function is intrinsically related to the data and the final application. In recent results of deep learning for power allocation schemes, there is a common usage of the minimum squared error (MSE). This is the one we used here as well.

IV. Numerical Results

We consider a multibeam satellite system that serves $K = 7$ UTs. The path-loss model employed from [13] has been used considering the parameters described in Table I. The number of carriers, M has been set to 4, leading to a subcarrier bandwidth of 125 MHz. The data rate demands $\bar{R}_k$ is assumed uniformly distributed from 150 to 400 Mbit/s at each beam.

The dataset for every scenario has been obtained with 20000 realizations. The training of the DNN is done through the 80 % of the data set ($Q = 16000$). The remaining 20 % of the computed data set is used for validating the DNN design. All numerical results shown in the following corresponds to the results of this validation data set.

The considered DNN has $L = 4$ hidden layers. The training of DNN is performed considering stochastic gradient descent and the learning rate is governed by the Adam method [14]. Regularization is ensured by early stopping. In here we use the definition of regularization reported in Section 5.2.2 of [12] as any technique aiming to reduce the validation error. The reader can find more details of early stopping and other regularization techniques in Chapter 7 of [12].

Hyperparameter selection includes the number of units at each hidden layer and the learning rate. Sets of hyperparameter values are generated randomly and the preferred set is determined according to validation results [15]. The ranges of hyperparameters are as follows: number units of the hidden layers, $(150, 400)$, learning rate, $(10^{-3}, 10^{-2})$. For the considered dataset, 100 hyperparameter combinations are tried in a random search and we retain the best performing model.

Figure 2 shows the empirical cumulative distribution (CDF) of the sum of violation values (i.e. the objective function of the optimization problem in (1)) given the mentioned scenario. The blue curve indicates the results of the CCP procedure used as benchmark while the red one indicates the data rate for the DNN output. It can be observed that in both cases the DNN yields very close data rates to the ones with CCP. For the sake of completeness, we include in the Figure the violation values given a pure random power allocation which is shown to perform poorly compared to both of our proposed techniques.

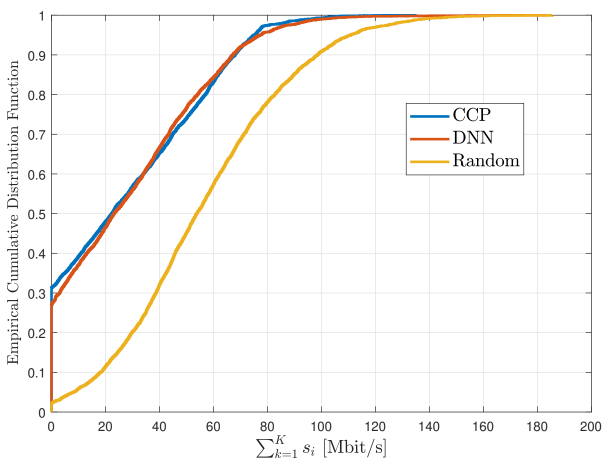

Fig. 2. Empirical CDF of the rate violation values ($\{s_k\}_{k=1}^{K}$) of the validation dataset.

Considering the average values, CCP yields to a sum violation of 28.07 Mbit/s while the DNN approach results in 28.53 Mbit/s. This very low difference between the ground truth (CCP) and the obtained model with DNN shows the potential of deep learning in mimicking flexible payload optimization techniques. In addition, the violation obtained via random power allocation is 56.59 Mbit/s.

We also evaluated the elapsed time of both techniques. For the CCP, we obtained an average computational time of 62.1 seconds while for the DNN the average elapsed time is 0.041 seconds. These two orders of magnitude reduction of the computational time enhances the potential of DNN in optimizing flexible payloads. These results have been obtained in the same personal computer using scripting programming languages.

V. Conclusions

This paper proposed an optimization framework able to tackle flexible payload configurations design. Given a set of required SLAs, the conceived technique based on the CCP was able to provide a carrier and power allocation in order to meet the data rate requests. We introduced a DNN design able to learn the described optimization leading to a solution with a very short computational time. The obtained technique is a promising tool for next generation satellite network operations centres where payload reconfiguration optimization will take place.

References

[1] P. Angeletti, D. Fernandez Prim, and R. Rinaldo, “Beam hopping in multi-beam broadband satellite systems: System performance and payload architecture analysis,” in *24th AIAA International Communications Satellite Systems Conference*, 2006, p. 5376.

[2] J. Lizarraga, P. Angeletti, N. Alagha, and M. Aloisio, “Multibeam satellites performance analysis in non-uniform traffic conditions,” in *Vacuum Electronics Conference (IVEC), 2013 IEEE 14th International*. IEEE, 2013, pp. 1–2.

[3] R. Alegre-Godoy, N. Alagha, and M. A. Vázquez-Castro, “Offered capacity optimization mechanisms for multi-beam satellite systems,” in *2012 IEEE International Conference on Communications (ICC)*, June 2012, pp. 3180–3184.

[4] G. Cocco, T. de Cola, M. Angelone, Z. Katona, and S. Erl, “Radio Resource Management Optimization of Flexible Satellite Payloads for DVB-S2 Systems,” *IEEE Transactions on Broadcasting*, vol. 64, no. 2, pp. 266–280, June 2018.

[5] A. L. Yuille and A. Rangarajan, “The concave-convex procedure,” *Neural computation*, vol. 15, no. 4, pp. 915–936, 2003.

[6] F. Liang, C. Shen, W. Yu, and F. Wu, “Towards Optimal Power Control via Ensembling Deep Neural Networks,” *IEEE Transactions on Communications*, vol. 68, no. 3, pp. 1760–1776, 2020.

[7] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, “Learning to Optimize: Training Deep Neural Networks for Interference Management,” *IEEE Transactions on Signal Processing*, vol. 66, no. 20, pp. 5438–5453, 2018.

[8] F. G. Ortiz-Gomez, L. Lei, E. Lagunas, R. Martinez, D. Tarchi, J. Querol, M. A. Salas-Natera, and S. Chatzinotas, “Machine Learning for Radio Resource Management in Multibeam GEO Satellite Systems,” *Electronics*, vol. 11, no. 7, 2022. [Online]. Available: https://www.mdpi.com/2079-9292/11/7/992

[9] F. G. Ortiz-Gómez, D. Tarchi, R. Martínez, A. Vanelli-Coralli, M. A. Salas-Natera, and S. Landeros-Ayala, “Supervised machine learning for power and bandwidth management in very high throughput satellite systems,” *International Journal of Satellite Communications and Networking*, 2021.

[10] Y. Sun, P. Babu, and D. P. Palomar, “Majorization-Minimization Algorithms in Signal Processing, Communications, and Machine Learning,” *IEEE Transactions on Signal Processing*, vol. 65, no. 3, pp. 794–816, 2017.

[11] K. Hornik, M. Stinchcombe, and H. White, “Multilayer feedforward networks are universal approximators,” *Neural networks*, vol. 2, no. 5, pp. 359–366, 1989.

[12] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.

[13] M. A. Vazquez, A. Perez-Neira, D. Christopoulos, S. Chatzinotas, B. Ottersten, P. Arapoglou, A. Ginesi, and G. Tarocco, “Precoding in Multibeam Satellite Communications: Present and Future Challenges,” *IEEE Wireless Communications*, vol. 23, no. 6, pp. 88–95, December 2016.

[14] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” *arXiv preprint arXiv:1412.6980*, 2014.

[15] J. Bergstra and Y. Bengio, “Random search for hyper-parameter optimization,” *Journal of machine learning research*, vol. 13, no. Feb, pp. 281–305, 2012.