

Machine Learning for Satellite Communications Operations

Miguel Ángel Vázquez, *Senior Member, IEEE*, Pol Henarejos, *Senior Member, IEEE*, Irene Pappalardo, Elena Grechi, Joan Fort, Juan Carlos Gil and Rocco Michele Lancellotti

Abstract—This paper introduces the application of machine learning (ML)-based procedures in real-world satellite communication operations. While the application of ML in image processing has led to unprecedented advantages in new services and products, the application of ML in wireless systems is still on its infancy. In particular, this paper focuses on the introduction ML-based mechanisms in satellite network operation centers such as interference detection, flexible payload configuration and congestion prediction. Three different use cases are described and the proposed ML models are introduced. All the models have been constructed using real data and considering current operations. As reported in the numerical results, the ML-based proposed techniques can improve a certain key performance indicator of each use case at least a 10%. In light of the results, the proposed techniques are useful in the process of automating satellite communication systems.

Index Terms— Satellite communications, machine learning, satellite operations.

I. INTRODUCTION

It may come as a surprise to realize that nowadays satellite communications still heavily depend on human expertise and manual operations. Satellite operator's network operations centers require strong human involvement, leading to a high operational expenditures (OPEX) and an implicit latency in human action which causes a degradation of quality-of-service (QoS). Indeed, ticket processing of incidents in the radiofrequency (RF) plane requires the intervention of human experts to provide a technical solution.

OPEX reduction will guide ground satellite segment system equipment. In this context, procedure automation of satellite communications operations will be a key element of future systems. As a matter

of fact, automation requires intelligent systems able to process certain inputs from satellite data and translate them into actions or into other data. There is a myriad of options for building these systems like knowledge-based ones where rules are conceived considering a domain-expert knowledge of the system [1].

However, motivated by the current data gathering processes of satellite systems and the explosion of cloud services for managing this data efficiently, in this paper we resort to data-driven techniques. Precisely, we consider the use of deep learning [2]. Deep learning is a field of machine learning (ML) which considers the optimization of cascaded linear and non-linear operations. Furthermore, deep learning presents tremendous potential whenever a large-scale amount of data can be used.

In this paper, three main current procedures of satellite communications operations are revisited; namely, interference detection, flexible payload configuration and congestion prediction. While interference detection requires raw in-phase and in-quadrature (IQ) samples of a transponder, congestion prediction is based on user rate demands historical data. Furthermore, flexible payload configuration both considers a theoretical model of the payload and certain rate demands over the coverage area.

The application of deep learning in the different use cases is introduced and the performance of the resulting system is described. For each procedure we show the benefits of automation based on the new ML-based techniques. Indeed, the proposed data-

This work is funded by the ARTES Future Preparation program of the European Space Agency under the contract No. 4000127265/19/UK/AB – Machine learning and artificial intelligence for satellite communications. The view expressed herein can in no way be taken to reflect the official opinion of the European Space Agency.

Furthermore, Pol Henarejos and Miguel Ángel Vázquez were supported by Catalan government under the grant 2017-SGR-01479 and by the Ministry of Science, Innovation and Universities of Spain under Project TERESA-TEC2017-9003-C3-1R (AEI/FEDER, UE).

Miguel Ángel Vázquez and Pol Henarejos are with Centre Tecnològic de Telecomunicacions de Catalunya, Av. Carl Friedrich Gauss 7 08860 – Castelldefels Barcelona (Spain). {mavazquez, phenarejos}@cttc.cat.

Irene Pappalardo and Rocco Michele Lancellotti are with Data Reply s.r.l., Via Castellanza, 11 - 20151 Milan, (Italy). {i.pappalardo, r.lancellotti}@reply.it

Elena Grechi is with Eutelsat, Rue Balard 70 - 75015 Paris, (France). egrechi@eutelsat.com.

Joan Fort is with Rheatech Ltd for European Space Agency (ESA) at the European Centre for Space Applications and Telecommunications (ECSAT), Fermi Ave OX11 0FD - Harwell, Didcot, (United Kingdom). joan.fort.alsina@esa.int

Juan Carlos Gil is with GMV Aerospace Isaac Newton, 11 - 28760 Tres Cantos, Madrid, (Spain). jcgil@gmv.com

driven techniques result into a potential substantial reduction of the operational costs of the control center. This cost trimming comes from the assistance information provided by the ML model which helps network operation center engineers in the decision-making process leading to a reduction of the event processing time. Note that quantitative cost analysis is out of the scope of this paper and the proposed ML models could potentially lead to cost reduction, but this is still a speculation.

To the best of authors knowledge, this is the first time the application ML in commercial satellite operation systems is introduced. Remarkably, other authors have addressed the problem of using ML in link-to-link design of scientific missions [3].

The remainder of the paper is as follows. Section II, III and IV describe interference detection, flexible payload configuration and congestion prediction use cases and its ML modelling. Section V concludes the paper.

II. INTERFERENCE DETECTION

A. Nowadays interference management in satellite control centers

To maintain a high QoS and user experience, interference is closely monitored and minimized in satellite networks. Interference detection is typically a task performed on a reactive mode instead of proactive. Given that in most of the cases, satellites simply relay signals coming from the Earth, interfering signals are present to a large extent in all frequency bands. The possibility to offload a purely human task such as power spectrum density check to an automated system, able to detect the presence of unwanted signals, is an exciting perspective in terms of improved spectral management and customer incident avoidance.

Most of the interferences present today are caused by human errors – either due to mispointed antenna (cross-polarization or adjacent satellite) or misconfigured equipment (noise introduction, intermodulation, etc.). These parameters cover 70-80% of all interference cases and are not related to terrestrial networks. If there are carrier overlaps, it implies a digital video broadcasting (DVB) carrier overlapping another DVB carrier or a satellite modem transmission, including very small aperture terminal (VSAT) traffic in time division multiple access (TDMA), for instance.

In order to mitigate them, there are several techniques that may help to reduce the levels of interferences. However, on many occasions, it is still difficult to cope with them. Currently, the only way to manage interference is by human intervention and performing an exhaustive analysis, that may take several days to solve the incidence. In other words, there are qualified personnel dedicated to detecting interferences by inspecting figures, such as the spectrum, abnormal error rates increase or degraded user experience.

B. Autoencoding for Interference Detection

For the aforementioned interference detection problem, we rely on an unsupervised ML model called autoencoder [4]. This technique allows to reproduce the inputs based on its previous training. If the inputs are similar to the training data set, the produced output maintains the same statistics. However, if the inputs are significantly different to the training, the produced output's statistics are completely different compared to the original. Hence, it is possible to detect signal perturbations that modify the original statistics by measuring the error between the input and output signals.

For our case, the autoencoder is composed by an encoding convolutional neural network (CNN) and a decoding CNN, stacked sequentially. The encoder compresses the data blocks and reduces the dimensionality of the input. The data is passed to the decoder, that increases the dimensions and restores the original dimension. The activation layer uses the hyperbolic tangent (tanh) function. CNN are specially indicated for fixed size inputs and they are capable to extract hidden patterns from the data. Our proposed autoencoding neural network (ANN) is composed by several convolutional and decimating layers, placed sequentially as depicted in Figure 1. A similar structure can be also used for decoding terrestrial signals **¡Error! No se encuentra el origen de la referencia..**

If the input signal does not contain any interference—and the statistics are not modified—the reconstructed signal is very close to the input. On the contrary, if the input signal contains interferences that modified the original statistics, the reconstructed signal is notably different. Hence, at the output of the model we compute the mean squared error (MSE) between the input and the output. This process is repeated for each L segment of the captured signal.

The set of MSE samples constitutes a signal, whose values are always positive and decrease if the input does not contain interference; and increase if the input contains interference. Moreover, this set also displays properties depending on the input's statistics. Thus, if the input's statistics are modified, this is reflected in the statistics of the MSE. This will be exploited by our approach.

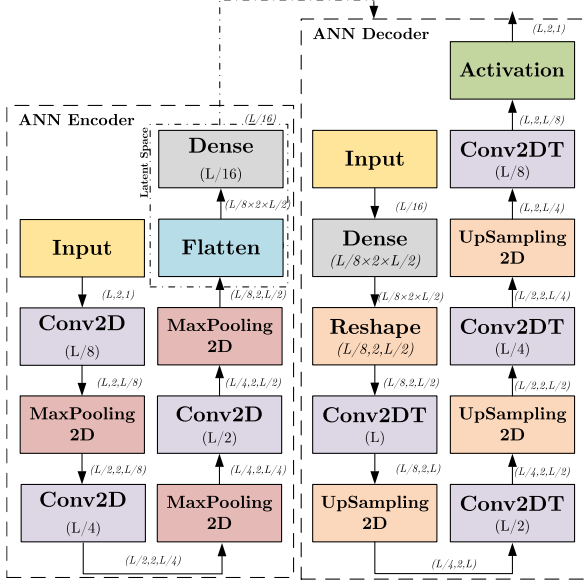


Fig. 1. Autoencoder using Convolutional neural network which is employed for interference detection. The triplets are the dimension of data between each layer.

As scoring methods we resort to different features of the resulting error; namely, sum of normalized moment deviation, S_1 , and the Pearson product-moment correlation coefficient between the MSE probability density function (PDF) with and without interference, S_2 [5].

To trigger the presence of interference, we use the previous scores to set the different thresholds, T_1 and T_2 . The first score, S_1 , defines the deviation between the statistics orders to the original.

We analyze different datasets, with and without interference and the results on the different scores. These datasets consist in several captures of different events (cross-polar interference, adjacent satellite interference,...) whose MSE output error is illustrated in Figure 2 with the MSE for the case we do not have any interference. As we expected, the resulting PDF is different for almost every event. By simple visual inspection, it is possible to advice the satellite operator that the signal is interfered at some location.

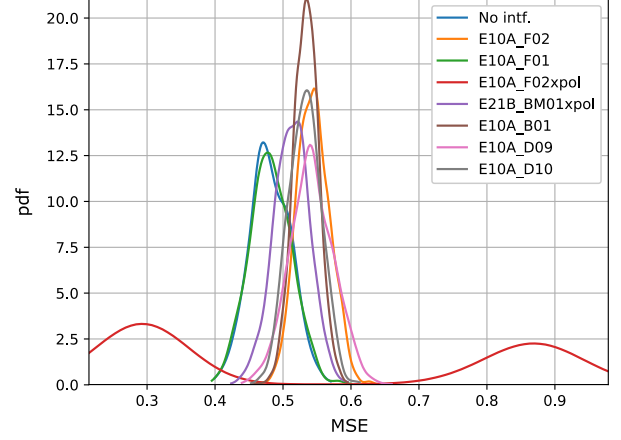


Fig. 2 Probability density function of the mean square error of between the input and output signals employed in the autoencoder. It is observable that different error statistics are obtained for each interference scenario. PDF and MSE values correspond to normalized RF signals and probability

The obtained performance of true positives is 81%, whereas the remaining 19% is caused by false positives. This is counterparted with the dataset without interferences, where the 98% are true negatives and the 2% are false negatives. It is important to remark that scoring values can be adjusted to modify these results. To our understanding, in the interference detection case, it is preferable to minimize false negatives, at expenses of false positives.

III. FLEXIBLE PAYLOAD OPTIMIZATION

A. Human-based Approach

Future satellites equipped with flexible payloads will allow their resources to be allocated in response to the temporal variations of the scenario such as dynamic traffic demands and undesired interference events. The satellite resources to be configured are the beam pattern, the transmit power and the frequency allocation. To the best of the author's knowledge, this configuration is expected to be performed by an operator using a graphical tool. That is, an operator will provide the Earth coordinates in order to modify the coverage of the satellite. Regarding the frequency and power allocation, the same idea is followed. Bearing this in mind, in the presence of an event, the operator shall compute manually the best resulting payload configuration. The idea behind the conceived ML model is to assist and, eventually, eliminate the human intervention in the payload re-configuration. This will reduce the

operational expenditures, reduce the time-to-react to system events leading to an increase of the customer QoS. As a general statement, the resulting ML model aims at providing a relevant payload configuration, which is able to assist the operator's job in producing a new payload configuration.

B. Optimization assisted via deep learning

The return link of a geostationary multibeam satellite system operating at Ku band in the presence of undesired interference is considered here. The satellite attends a total of N_u fixed satellite terminals. Each user terminal generates a traffic request of J_i bits/s for $i = 1, \dots, N_u$. Let h_i be the gain experienced by the transmitted signal of the i -th user terminal and received by the ground station.

For the return link, the satellite has available a set of N_{ch} subcarrier. We consider that each user terminal can only be served by a subset of frequency subcarriers (i.e. two different user terminals cannot use the same subcarrier). The return link transmission takes place in presence of an external interference at a certain geographical location. We consider that the interference transmit power is P_{int} and its equivalent channel is represented by h_i . The interference location is assumed known and the system designer can modify the satellite footprint in order to reject the received interference by a factor μ . This factor is assumed to be -6, -10, -15 and -18 dB. The interference bandwidth occupation is assumed to be a subset of the N_{ch} channels. As an example in Figure 3 we show different beampatterns for a $\mu = -15$ dB in a certain interference location.

The goal is to allocate resources such that each user terminal is offered a capacity (R_i) that is as close as possible to the requested capacity, J_i . In particular, we consider the optimization of the unmet capacity (UC) defined as the quadratic average difference between the requested capacity and the offered capacity. To sum up, the conceived model shall produce a mapping between user terminals and subcarriers given a scenario of h_i , J_i and the interference characteristics. Indeed, the ML model has as input the channel state information, the requested capacity and the interference power values over the different subcarriers. With this information, the model can compute the satellite configuration in terms of channel allocation (i.e. the mapping between subcarriers and user terminals).

Considering that the optimization is a large-scale integer programming problem, our first approach in solving the carrier allocation optimization problem is by employing a genetic algorithm (GA). For further details regarding this type of techniques, the reader can refer to [7]. It is important to emphasize how difficult the optimization is. The search space is determined by the number of available subcarriers and the number of users. With this, in order to solve the optimization problem, we shall evaluate a total number of $(N_u + 1)^{N_{ch}}$ solutions, leading to a huge search space dimension.

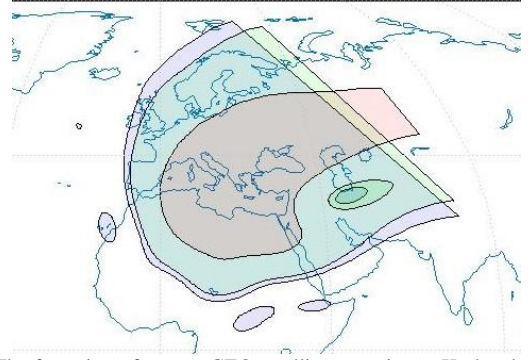


Fig. 3. The footprint refers to a GEO satellite operating at Ku band where an interference located in the middle-East is mitigated $\mu = -15$ dB. The different contours shows the minimum gain offered by the satellite. In particular the red contour shows 1.3 dB coverage, green shows -8.7 dB coverage and blue shows -13.1 dB coverage.

In order to reduce the computational complexity of the model, we consider the approach of assisting the GA with a certain knowledge learnt by a deep neural network (DNN). This philosophy reported in [8] has been utilized in other optimization techniques such as [9]. In here, our approach is to create a DNN able to generate efficient initial configurations so that the GA can provide efficient solutions in a short time period. Note that this differs to other approaches based on algorithm approximation techniques like [10] which aim to substitute the original optimization algorithm (in our case the GA) by a DNN.

The assessment of the model depicted in Figure 4 shows that the genetic algorithm model provides good solutions while the GA assisted via a DNN is able to obtain better results by using initial solutions from the DNN rather than pure random.

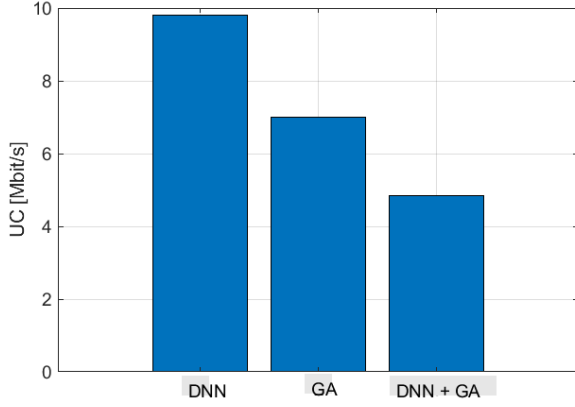


Fig. 4. This Figure shows in bars the resulting unmet capacity values in Megabits per second. This key performance indicator represents how different is the offered capacity with respect to the requested one. Three different techniques are included; namely, deep learning optimization, genetic algorithm and genetic algorithm assisted by deep learning. The latter shows the best performance.

IV. USER DEMAND CONGESTION PREDICTION

A. Congestion in Multibeam Satellite Systems

In satellite networks, the user distributions are unbalanced due to the geography and the population dispersion. As a result, some satellites have few traffic loads, while others face heavy traffic loads, which often lead to congestion events. We propose a ML-based method that predicts network loads and detects congested areas before they experience congestion. This is especially useful for detecting anomalous behaviors and predicting non-recurrent patterns in a strong non-linear scenario.

As of today, performance prediction is in general based on trend curves of the previous days. This does not allow either long term predictions or management of anomalous behaviors. By considering several additional factors (e.g., traffic

type), ML techniques can both extend the time frame on which the analysis is done and identify in quasi-real time irregular traffic patterns that unexpectedly affect the performance (e.g., release of software update or live events).

B. Clustering and Recurrent Neural Network for Congestion Prediction

The objective of this use case is twofold. Firstly, we characterize users by their traffic patterns, i.e., we want to cluster users based on their consumed services and on the timeslots when they are more active. By exploiting relevant trends of users belonging to the same network, we are able to provide additional insights to the specific area of interest. Secondly, we use ML forecasting techniques to predict network performance indicators, such as average download speed and fill factor index.

We investigate user's behavior from two different perspectives. The first is the consumed traffic typology, i.e., the used services, while the second refers to the time interval during the day when users mostly consumes their traffic, e.g., during a particular day timeslot or during the night. We identify 14 service categories, e.g., web browsing, social media, streaming protocols, etc., and 6 timeslots, i.e., morning, lunchtime, afternoon, dinner, evening, and night.

After scaling and dimensionality reduction using principal component analysis (PCA), we compare representation (t-SNE). As an example, we show a snapshot of this representation in Figure 5. We tested the hierarchical clustering, k-means, density-based spatial clustering applications with noise

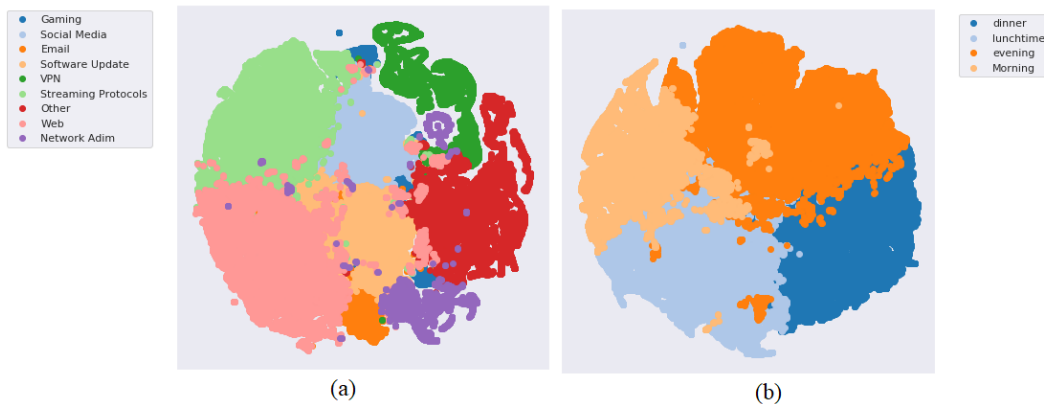


Fig. 5. Example of t-SNE representation of user clustering, based on the service group-driven fashion (a) and timeslot-driven fashion (b), respectively. It can be perceived well-defined and separable clusters for each of the two domain representations.

(DBSCAN), affinity propagation, and spectral clustering. several clustering algorithms by computing t-distributed stochastic neighbor embedding

Once the best cluster labelling is computed for each user and for both the service group and the timeslot dimensions, we move the focus to the network performance. Network performance indicators are considered in a time-series domain, together with other features coming from the clustering phase. Those are used to improve predictions with respect to a baseline scenario when no information about the user traffic patterns is provided.

For each identified cluster, we compute the time series of active users. We consider as *inactive* those users that switch on the modem but do not consume any active traffic during the day, thus being easily identified by an exploratory analysis on the download volume. Active users are instead users that exceed a specific download threshold and consume real traffic volume.

We consider a congested network and address the download speed forecasting. We compare three different forecasting algorithms, i.e., the recurrent neural network (RNN) with long short-term memory model (LSTM), the classic seasonal auto-regressive integrated moving average with exogenous regressors (SARIMAX), and Prophet algorithm from Facebook. We note that any other network performance metrics can be considered in the analysis since the model structure is highly flexible and easily customizable.

The available timeseries are split in train and test, with data from January 2019 to October 2019 for training and validation and on November 2019 for testing. Moreover, we consider the following scenarios: (1) The forecast of the download measured speed with no additional feature; (2) The forecast of the download measured speed with network capacity and download volume; (3) The forecast of the download measured speed with features derived from the clustering phase.

When computing predictions, different parameters are tuned according to the hyperparameters optimization activities within the validation dataset. The identified key performance indicators used to measure the model prediction capacity are percentage (scale-independent) errors, such as mean absolute percentage error (MAPE) in order to deal with different data rates within the network.

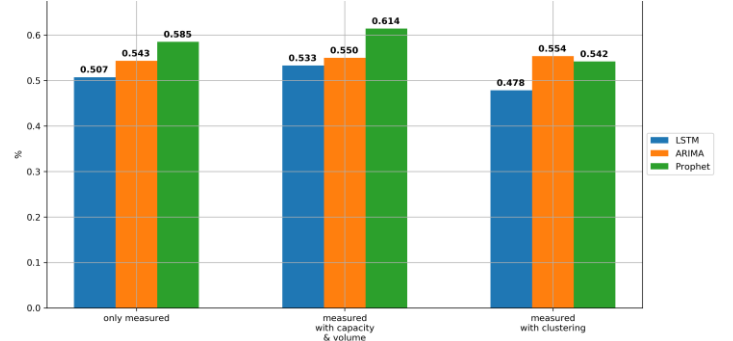


Fig. 6. Mean Absolute Percentage Error (MAPE) of the download speed forecast in the three considered scenarios.

As indicated in Fig. 6, we evaluate the download speed prediction when clustered active users time series are considered and compare this scenario with the one characterized by no clustering features. Generally, even though results are comparable, we recognize the LSTM to outperform the other algorithms. Moreover, the improvement of the clustering feature is moderate but evident. We believe that the similarity among the scenarios is due to the scarcity of the time depth and low data quality. We also use the Exponential Smoothing algorithm to compare the above performance with a naïve model. We prove that the gain in using any of the machine learning forecasting models is up to 10% on the MAPE indicator with respect to the baseline approach. We leave for future work the investigation of the model performance when a deeper dataset would be available as input.

The congestion prediction process is supposed to operate on a regular basis, even daily. A robust data cleaning and preparation should be performed to guarantee an adequate data quality and a strong data recovery in case of missing measurements. The algorithms developed for user classification and performance prediction can be deployed on the real network and run on dedicated machines.

V. CONCLUSIONS

This paper dealt with the problem of new ML-based data-driven techniques for enhancing current satellite communication operations. We show the potential of these techniques in relevant scenarios employing real-world data. The three procedures (interference detection, flexible payload configuration and congestion prediction) are initially validated in simulations using real data and its deployment into the legacy satellite control systems is feasible. All the

methods showed a good performance: i) the interference detector provides a false alarm probability lower to the current commercial techniques based on energy detection whose false alarm probability does not allow the detection of cross-polarization or adjacent satellite interferences; ii) the flexible payload optimization with deep learning is able to decrease the unmet capacity a 32% and iii) the forecasting method yields to a MAPE 10% reduction. The Deep learning techniques showed a great potential in the automatization of the mentioned operations.

ACKNOWLEDGEMENT

The authors would like to thank Tomás Navarro (ESA-ECSAT) for his constructive comments.

REFERENCES

- [1] R. N. Cronk, P. H. Callahan and L. Bernstein, "Rule-based expert systems for network management and operations: an introduction," in *IEEE Network*, vol. 2, no. 5, pp. 7-21, Sept. 1988.
- [2] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. Cambridge, MA: MIT press, 2016.
- [3] P. V. R. Ferreira *et al.*, "Reinforcement Learning for Satellite Communications: From LEO to Deep Space Operations," in *IEEE Communications Magazine*, vol. 57, no. 5, pp. 70-75, May 2019.
- [4] P. Henarejos, M. Á. Vázquez and A. I. Pérez-Neira, "Deep Learning For Experimental Hybrid Terrestrial and Satellite Interference Management," in *IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, Cannes, France, 2019, pp. 1-5.
- [5] P. Henarejos and M. Á. Vázquez, "Decoding 5G-NR Communications VIA Deep Learning," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Barcelona, Spain, 2020, pp. 3782-3786.
- [6] J. L. Rogers, and W. A. Nicewander, "Thirteen Ways to Look at the Correlation Coefficient," *The American Statistician*, vol. 42, no. 1, pp 59-66, Feb. 1988.
- [7] D. Whitley, "A genetic algorithm tutorial. Statistics and computing," *Statistics and Computing*, vol. 4, pp 65-85, Jun. 1994.
- [8] Y. Bengio, A. Lodi, and A. Prouvost, "Machine Learning for Combinatorial Optimization: a Methodological Tour d'Horizon," *arXiv preprint arXiv:1811.06128*, 2018.
- [9] E. B. Khalil, P. L. Bodic, L. Song, G. Nemhauser, and B. Dilkina, "Learning to Branch in Mixed Integer Programming," in *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence*, AAAI'16, pages 724-731, Phoenix, Arizona. AAAI Press.
- [10] 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, Oct. 2018.



Miguel Ángel Vázquez (SM'19) is senior research at CTTC. He received the Telecommunication Engineering degree, the Master's degree, and the Ph.D. (cum laude) degree from Universitat Politècnica de Catalunya (UPC), Barcelona, Spain, in 2009, 2012, and 2014, respectively. He also holds a degree in Computer Science from National Distance Education University. In parallel to his Ph.D.

studies, he worked as a research engineer at CTTC from January 2010.



Pol Henarejos (SM'20) is senior research at CTTC. He received the Telecommunication Engineering degree from the Telecommunication Engineering High School from Barcelona of Technical University of Catalonia in 2009. In 2012, he obtained the Master of Science in Research on Information and Communication Technologies. In 2017, he obtained the Ph.D. degree, distinction Cum Laude.



Irene Pappalardo is Data Scientist at Data Reply IT. She received both the B.Sc. and the M.Sc. degrees with honors in Telecommunication Engineering at the University of Padova in 2009 and 2012, respectively. In December 2016, she accomplished the second level master "Big Data in Business" at the University of Rome, Tor Vergata, that lets her start a new career as Data Scientist.



Elena Grechi is Head of Service Operations at Eutelsat. She obtained her Electronic Engineering degree at the University of Perugia in November 2014 after a brief stay in Brussels, Belgium for her degree thesis on "Directed diffusion routing algorithm for wireless sensor networks". In June 2015 she joined Eutelsat as "DVB, IP and systems engineer, occupying several positions in the company in the Deployment and Operations departments throughout the years.



Joan Fort Alsina is Flight Product Engineer at ESA. He received the Computer Engineering degree from the Technical University of Catalonia (EI FIB) and the Electrical Engineering degree from the French School of Civil Aviation (IENAC '00L) in 2003. He also obtained the Master of Science in Microwaves and Optical Telecommunications (DEA MOTO) from the Technical National Institute in Toulouse and later he received the M.S. in Space Studies from the International Space University in 2006.



Juan C. Gil Montoro is Marketing Product Manager for the GMV satellite control suite and GMV Satellite Control and Mission Planning PMO. He was born in Madrid, Spain in 1968. He received the B.S. and M.S. degrees in chemistry from the Universidad Complutense de Madrid, in 1990 and the Ph.D. degree in physical chemistry from the same University in 1997. In 1995 he joined GMV, an international conglomerate of companies where he has devoted the last 25 years in both technical and managerial roles in the area of satellite control.



Rocco Michele Lancellotti is senior data scientist at Data Reply IT. He received his PhD in Numerical Analysis from Polytechnic di Milano (Milan, Italy) at MOX Laboratory, Department of Mathematics. His research involved mathematical modelling and simulation of fluid-structure interaction cardiovascular problems, analysis, fitting, interpretation of experimental and numerical big data, and development of parallel efficient software for high performance computer architectures.