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Introducing Artificial Intelligence to end-to-end service-oriented SATCOM systems

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Abstract

During the recent years, the satellites communications industry has been completely revolutionized due to the latest technological advances. A transformation from a static, mission-based paradigm into a completely dynamic environment has led to the necessity of reinventing, not only the space segment, but also the ground segment. Satellite payloads are now *softwarized*, providing unlimited configurability, almost only restricted by physical constraints. New technologies such as 5G/6G will imply the understanding between space networks and the terrestrial counterparts which, until now, derive from completely different paradigms. The development of algorithms and techniques based on Artificial Intelligence and, most important, the capability of using this technology in real time, is bringing up new opportunities, and new challenges. In this work, the authors firstly provide an introduction of the new paradigm in satellites communications, emphasizing the impact towards the ground segment necessities to accomplish the latest challenges. Then, the authors select different representative scenarios, related to ground segment operations, which are currently tackled manually. The necessity of finding alternative and efficient solutions to automate decisions leads to the research efforts towards the viability of the application of Artificial Intelligence in this sector. In this line, two of the selected scenarios are exposed in detail, while a simplified version is presented as a preliminary end-to-end system, developed in the framework of a research project. A third and more complex scenario is also proposed, introducing the roadmap envisioned for the current research line.

Keywords: Artificial Intelligence, autonomous operations, satellite communications, resources assignment, gateways diversity, traffic congestion

Acronyms/Abbreviations

Artificial Intelligence (AI)
Artificial-Intelligence-Powered Ground Segment Control for Flexible Payloads (ATRIA)
Field of view (FOV)
High power amplifier (HPA)
International Telecommunications Union (ITU)
Key Performance Indicator (KPI)
Low Earth orbit (LEO)
Machine-to-machine (M2M)
Machine Learning (ML)
Medium Earth orbit (MEO)
Network management system (NMS)
Radiofrequency (RF)
Satellite communications (SATCOM)
Service level agreement (SLA)

1. Introduction

Latest technologies such as software defined payloads, virtualization, Artificial Intelligence (AI) and 5G/6G, among others, are revolutionizing the satellite communications (SATCOM) industry. Missions are no longer fixed until satellites' end of life but, in contrast, they are completely dynamic to provide optimal responses to the changing user demands. Then, this is inexorably leading to the necessity of transforming, not only the ground systems, but also the way the space assets are operated. In this line, a SATCOM system shall be dynamically adaptable, not only to provide responses to explicit services requests, but also to provide reconfigurability capabilities as a response to the implicit traffic demand changes.

Due to the above, the increasing number of heterogeneous service requests within a dynamical context are leading to the necessity of managing enormous quantities of data, almost in real time. It is also worth mentioning other problematics or challenges which are the result of this changing context. On the one hand, the resources fragmentation due to the heterogeneity of the services and requests. On the other hand, the lack of a pre-defined mission which, instead, is substituted by dynamic missions’ constraints.

Moreover, and unfortunately, the quality of the service is not static, and can decrease due to external agents such as the weather conditions, traffic congestion, interferences, whilst the service level agreements (SLA) shall be accomplished. This may imply the necessity of modifying the configuration of the ground and space assets, even if it has not been requested by the user. In this case, the role of the AI would be twofold, first, anticipate a potential quality decrease and, second, conveniently react, easing the computation of an alternative configuration.

With this paradigm, technologies capable of dealing with huge amounts of data are required, such as AI. But first, two questions shall be considered: for which operations, and using which data we can tackle this. Along this work, the authors will provide an insight of different SATCOM scenarios in which AI will provide added value to the operations, bringing up responses to the previous questions, and exposing the results of their research and proposed future work. The total of proposed scenarios is three, and deal with the gateways’ diversity, the congestion awareness, and the dynamic and collaborative resources allocation. For the first two scenarios, the authors expose the problem to tackle in detail, and discuss some preliminary results using a simplified version, as a first approach. The third scenario, instead, is proposed and exposed from a descriptive perspective, being part of the roadmap of the current research line.

The work is structured as follows. Section 2 tackles the gateways’ diversity scenario. Section 3 is focused on the congestion awareness scenario. Section 4 proposes a new scenario to be studied, the dynamic and collaborative resources allocation scenario. Section 5 is dedicated for the results and discussion. Section 6 presents the conclusion of the work.

2. The gateways diversity scenario

This section provides an insight of the gateways’ diversity scenario. First, the scenario is stated. Then, applicability of AI algorithms is discussed.

2.1 Scenario definition

In a satellite communication network, the connection to the gateway is the most demanding one in terms of bandwidth, even though a gateway station can count with larger high-power amplifiers (HPAs) and antennas than the remote stations to increase the link margins, so that the link can be used with a better efficiency (bits/Hz). In addition, the bandwidth demand has led to the use of higher frequency bands for the feeder links due to the availability of larger frequency bandwidths foreseen by the International Telecommunications Union (ITU) regulations. The use of higher frequency bands increases the sensibility of the communication links to weather conditions. Moreover, adverse weather conditions decrease the link margins, even making then impractical. Specifically, for Ka or Q/V bands, meteorological effects have a tremendous impact on the communication link. Indeed, rain attenuation could decay the receive signal power strength from few dBs to dozens.

In this situation, *gateway diversity* is used to continue operations of the satellite network. In a geostationary scenario, N nominal gateways can be defined, while P redundant units can be used in case of adverse meteorological events, leading to a total of N+P gateway schema. Then, user beams are served by a unique gateway and, in case one of the gateways suffers from atmospheric fading, another idle gateway -redundant unit- can be used instead. A smarter schema of gateway diversity known as soft diversity [1] consist of moving part of the traffic from one gateway to another. Nevertheless, in the following paragraphs, the first approach will be used. In this line, it can be extracted that the switching from the nominal gateway to the redundant counterpart implies a time which is directly related to the downtime of the associated services. Although the original objective has always been minimizing this duration, what if downtime could be reduced up to zero? To do so, AI and Machine Learning (ML) algorithms will be the best allies.

2.2 AI/ML algorithms applicability

The main idea behind the goal of setting to zero the mentioned downtime is predicting the necessity of the gateway switch, the earlier, the better. If a correspondence between the meteorological conditions and the associated impact in the links has been analysed, AI/ML techniques can be applied to forecast the switching necessity, to optimally associate the user beams and channels to the gateways, accomplishing the expected service level agreements (SLAs) without interruption.

From the operator’s perspective, the goal is to smartly select the gateways to be used while being able of keeping the system capacity above a certain percentage of its clear sky capacity. This selection can only be done every discrete slot time due to operations restrictions. Indeed, once the decision of switching has been made, the system constrains to perform the switch shall be taken into consideration. The key point is that it is not only necessary to predict an outage in the short term, but it is also relevant the prediction of its duration. Then, gateway switching will only make sense if the predicted outage time is greater than the switching time. From the above, it can be extracted the required inputs to perform trainings, predictions, and validation of the AI/ML algorithms.

2.2.1 Trainings

With respect to the trainings, at first, two inputs are essential. On the one hand, weather information in the gateways' geographical locations. Ideally, weather stations placed near the gateways would provide accurate data towards rainfall, humidity, fog, temperature, etc. On the other hand, accurate measurements of the service quality at the geographical locations of the gateways, such as beacons levels, ideally, at different frequencies. At this point, additional information provided by the operator is required, such as the when to consider an outage of the service based on the values of the beacons' levels, to delimit its duration.

The correlation between the mentioned inputs is the key of the AI/ML algorithm to be implemented, providing a relationship between the adverse meteorological conditions and the duration of an outage. As previously mentioned, outages durations greater than the time required for a gateways' switching will most probably end up in a switching operation.

2.2.2 Predictions

Once the algorithm is trained, it is time to perform predictions. For this purpose, the input of the algorithm shall be already based on a prediction, in this case, of the meteorological conditions. As happened for the training phase, accuracy of the result is increased if the predictions of the weather data correspond to the geographical locations of the gateways under analysis or, at least, they are the closest possible. This may be complicated, as in case of using meteorological forecasts from third-party systems, the probability of having a measuring station close to the gateway under analysis may be low. Instead, these systems normally provide forecasts based on averages which are not much aligned with the reality.

2.2.3 Validation

This shall be tackled from different perspectives. As mentioned above, first, the accuracy of the meteorological forecasts shall be evaluated against the real measurements taken from the weather stations placed in the gateways' locations, as explained for the trainings. If these forecasts are not sufficiently accurate, the complete algorithm would not provide useful results. Instead, inhouse meteorological forecasts could be tackled based on the tendencies of the measured data in the stations. Assuming a sufficient accuracy of the meteorological forecasts, the algorithm can be validated by means of comparing the predicted beacons levels, hence, predicted outage duration with the real values.

At this point, the algorithm is completely functional, although the added value of its implementation shall be evaluated. The main objective is analysing whether the switching policy has been based on *correct* switches or not. In other words, have the AI/ML decisions (based on predictions) been better than the operator's decisions (based on real-time weather measurements)? To do so, historical data from the network management system (NMS) can be of great help. It is proposed the analysis of the total downtime measured before the AI/ML based system deployment. In this case, it shall consider the total switching time, plus -if applies-, the additional downtime before starting the switching, due to the unexpected meteorological conditions. This downtime shall be compared to its homologous when using the AI/ML algorithms, as it shall be considered false negative casuistic, i.e., non-predicted outages which end up with the interruption of the services.

3. The congestion awareness scenario

This section provides an insight of the congestion awareness scenario. As in the previous section, the scenario is first stated. Then, applicability of AI algorithms is discussed.

3.1 Scenario definition

One of the main concerns when planning the network resources is the potential collapse due to congestion. Even for resources not yet operational could be of interest to detect congestion, gaps and future needs of the satellite network. Thus, reducing and avoiding congestion problems by planning ahead based on a network forecast.

The proposed approach is to have a monitoring system that triggers periodically the planification of the network, moving traffic and/or SATCOM resources from gateways or regions with less traffic to hotspots, when a significant growth of certain requested services is detected, along with future predictable and planned events. The system shall support long term demand forecast. Such forecasts shall be computed based on several inputs, for instance, past and current network resources usage, the connection between service requests and resource allocation, and correlation between requested services and slot time in which they are to be served. To accomplish this, different heuristics and AI/ML algorithms are envisioned to be used. To improve the accuracy of the ML models, these shall consider the forecasted resources which are not yet operational but set as commissioned. The proposed solution ensures that the current resources are known, and the future necessities can be extracted to forecast future demands as an output of the AI/ML modules.

3.2 AI/ML algorithms applicability

Depending on seasonal events, in a short-term framework, some peaks in the total throughput may appear and the overall network can suffer from collapses. The result is a degradation on the targeted throughput. Currently, the monitoring of these effects is performed by human intervention by inspecting the throughput and observing sporadic increments of the network load. Despite it is possible to monitor the current throughput, performing a forecast of the throughput in a two-hours window is not a trivial task. Therefore, deploying latest advances on ML by analyzing historical data and monitoring in real-time the status of the congestion and the throughput allows to obtain a more refined forecast. Thanks to this, it is possible to anticipate potential outages caused by peaks of demands and mitigate the impact by redistributing the resources. For this purpose, considering stationary demands and traffic is required.

3.2.1 Trainings

The algorithms previously mentioned would require training datasets. The main idea is to extrapolate the demand based on collected traffic and optimize the available capacity distribution to attend such demand. This approach requires a dynamic allocation of resources based on a prediction that may be inaccurate, resulting in non-desirable results. Moreover, this circumstance can be relatively common in scenarios where the demand tends to be non-stationary, and some peaks may occur. To tackle this obstacle another approach based on a congestion indicator is followed.

The congestion indicator refers to the network status and may be an integer or float to provide continuity, instead of a binary indicator. Therefore, this indicator might be used for two purposes. On the one hand, when the indicator reaches high levels, to forecast the risk of congestion. On the other hand, when the congestion indicator remains at low levels, to analyse if certain resources may be being misused and an optimization process should be carried out. The targeted throughput can be adjusted depending on the network congestion indicator. Therefore, for higher congestion values, the allocation rate is decreased to reduce the network congestion. Hence, this problem can be formulated in terms of max-min approach; maximizing the throughput whilst the congestion is minimized.

A carefully defined and structured training datasets is critical to achieve a high performance and accurate ML models and to avoid biased outputs. These datasets shall include the data available that might impact the throughput of the system. As previously mentioned, historical data and current information shall be used to train the algorithm, as well as future assets already planned. These datasets shall incorporate data regarding the type of traffic, geographic location of the services, number of beams, capacity of the beams, time of the year and other variables that might impact the results. Moreover, if available, the training dataset shall include the historical data from situations where congestion problems were detected, and network throughput was impacted. The key is to train the ML algorithm in such a manner that the ML model is produced with the knowledge of the demand tendency and traffic patterns.

3.2.2 Predictions

In the short-medium term, the authors differentiate two situations. One situation closer to a medium-term prediction. Due to computation times, there might be some predictions that cannot be performed on real-time. Simultaneously, due to satellites payload configuration times, the output of those predictions may take time to be effectively applied to reconfigure the satellite. The ML models' output will trigger a major payload reconfiguration. This would correspond to predictions of the beam layout and frequency plan at a certain point in time and may be applied every one or two hours. The second situation would be based in short-term predictions. The outcome from the models would trigger a minor payload reconfiguration. This reconfiguration might be, for instance, a modification in the channels associated beams, a beam frequency modification, the increase of the beam size due to a temporary hotspot or resources reallocation between beams. These changes on the satellite may be applied in real time.

3.2.3 Validation

When the predictions from the AI/ML models have been produced, its accuracy shall be validated. The predictions shall be compared with the a posteriori data obtained from the network monitoring system when timestamps match. Thresholds shall be defined indicating how accurate were the predictions with respects to the real scenario.

Once the output data has been validated, this data shall be used as feedback to the algorithm to re-train it. This allows the system to keep updated to the new traffic patterns and tendencies while the training algorithm is enhanced. This way, new model versions could be deployed with improved performance. However, when tunning the algorithm and providing feedback, special care is required to avoid overfitting of the ML models.

The ML predictions shall be compared to the ones that would have been estimated with human intervention. As well as the decisions taken by the ML models and the operator decisions shall be analysed to obtain which of the techniques produced better results.

4. The dynamic and collaborative resource allocation scenario

This section provides an insight of the dynamic and collaborative resource allocation scenario. In contrast with the scenarios previously presented, this one is exposed from a descriptive perspective, as being part of the roadmap of the current research line. Then first, the scenario is stated in detail and, second, a discussion of the AI algorithms applicability to the problem is proposed.

4.1 Scenario definition and discussion

Traditional geostationary communication satellites, and satellite fleets, manage their preassigned radiofrequency (RF) resources and gateways in an independent way, not working as a collaborative group. The capacity to share their service areas, RF resources, as well as gateways and satellite resources, could lead to a better usage of spare assets, hence, a better service provision. It is proved in [2] that the system performance can be increased by dynamically adapting the resource allocation to the characteristics of the system, i.e., traffic requested by the terminal. In the geostationary case, traditionally, each satellite counts with their own resources to serve a certain demand. With the new software defined satellites as an enabler technology, it is possible to think in a better way to serve the demand in a certain area, by dynamic and collaborative manners of sharing resources. In the literature, it can be found projects such as CoRaSat [3], which have already introduced the idea of collaboratively sharing the RF resources.

The authors of the present work propose to study the specific case of collocated and close satellites in the geostationary arc (from the same operator), by extending the traditional problem of a single satellite, into a multi-node one, collaboratively considering the beam layout and the frequency allocation. This idea can also be extended to Medium-Earth Orbit (MEO) and Low-Earth Orbit (LEO). For the MEO and LEO, those cases with significant overlapping in the field of view (FOV) are of special interest in terms of the coordination of the resources' assignments, considering the criticality of providing service to hot areas. Besides, it shall also be considered the assignment of terminals to beams, frequency reuse, and the management of handovers, dealing with the resources' assignment in an optimal way for the whole fleet.

The planning of this collaborative resources allocation shall manage (a) a demand prediction problem, and (b) a resources allocation optimization. To accomplish this, the model of the complete problem shall consider different aspects, such as: visibility between satellite and ground stations, proper link budget computation -taking into account interferences and signal attenuation due to atmospheric effects-, the physical and RF resources constraints, plus all the ongoing or scheduled missions. Special attention shall be paid to the later in case of flexible or software defined payloads, which are conceived to provide heterogeneous services in dynamic contexts.

As described in the paragraph above, the planning of the collaborative resources' allocation is based on two fundamental pillars. The demand prediction problem is related to the already discussed congestion awareness scenario and can be tackled by means of extracting knowledge from traffic measurements. Nevertheless, the resources allocation optimization even represents a more complex challenge. Satellites and ground antennas are already evolving towards flexible, reconfigurable payloads, beam forming antennas and on-board digital transparent processors, but the ground segment software is lacking behind. It must be capable of handling that complexity in real-time in a combined and integrated fashion. While fulfilling the final user needs in a transparent way, without service interruption and optimally exploiting all the resources available. The resource allocation problem can be split in several optimization problems described below.

4.1.1 Allocating resources: beam layout

The problem to solve is setting the beams configuration to provide service to a series of terminals. Nowadays, the problem shall consider thousands of beams and hundreds of thousands of terminals. For that purpose, the beams allocation and the assignments between the beams and the terminals shall evolve over the time, considering dynamically changing necessities. To accomplish this, it shall be taken under consideration a combination between regular and irregular layouts [4] to serve the different densities of the terminals, even using non-orthogonal frequency plan schemas. If a blocking situation is detected related to the channels' allocation, then a reconfiguration of the beams shall be accordingly triggered.

The idea is to dynamically adapt the beams configuration in response to the service demands. The key problem is that although a reconfiguration of the beam layout may be required as a response to a specific service request, it shall not be treated individually. A new reconfiguration of a certain beam may be a feasible solution to tackle this specific problem, although, as a whole, this new configuration may not represent an optimum use of the resources.

4.1.2 Allocating resources: dynamic channels and frequency plan

It must support the design or re-optimization of carrier frequencies allocation plans, maximizing the fleet resource utilization and frequency reuse on one hand, meanwhile assigning the gateway the required bandwidth to serve the demand and doing the allocation of the gateways to the different beams in response to dynamic demand evolution and environmental changes. Also, the frequency plan for regular and irregular layouts shall be considered, together with the system constraints regarding bandwidth and power availability and the interference generated by the configuration.

4.2 AI/ML algorithms applicability and discussion

Regarding the beam layout some references [4] consider the distribution of the terminals evolve, although the services still accomplish with the expected SLA and business and technical rules, then a sub-optimum allocation of the resources is considered as valid, accomplishing the exit criteria. In the context of a satellite payload able to reconfigure its beam pattern in short time periods, we could consider the shift from the traditional fixed beams towards a dynamic beam pattern where we can assign terminals to beams and variate their radius.

The immediate benefit of this reconfigurability is the assignment of hotspot areas a dedicated beam with larger equivalent isotropic radiated power. Therefore, there is a trade-off between the potential number of beams and their radius imposed by the space segment solution. Yet, another relevant approach could be a multi-mission entity able to assign resources from different satellites to the same user. This would involve assuming multi-frequency terminals with re-pointing capabilities for certain scenarios. In this context, the problem's dimensionality is increased leading to an eventual large computational time.

The simple initial approach is to cluster users by their positions and demands. In that case, the radius could be optimized using a genetic algorithm given a set of system level KPIs. Later, we could try to learn the optimizer approach using imitation learning [5]. The main challenge in here is to understand the operator's key performance indicators (KPI) which in general is fuzzy. Depending on the time-to-react of the module, the obtained ML model may not be sufficiently quick and *ad hoc* heuristics could be required.

Regarding the dynamic frequency, it is triggered on demand when a new service request enters in the system or as a response to an event related to the update of a business or technical rule. It is mainly applicable to flexible payloads, in which the transponder concept defined for traditional satellites is no longer applicable. Instead, it can be considered the term of *virtual transponder*, which is not restricted to a fixed frequency interval. To allocate the frequency for a requested service, the main criterion to accomplish is satisfying the SLA, and then, optimizing the resources utilization. To do so, the proposed solution considers the applicable business and technical rules within the *request analysis* phase. Then algorithms capable of optimizing the frequency allocation, considering the above as heuristics, or the usage of AI/ML is also tentatively foreseen. Several problems need to be solved, as the allocation of beams to gateways, the allocation of frequency to beams or the allocation of carriers to channels.

It is easy to observe that the selection parameters have a strong influence not only on the assigning capacity resources to the beams, but also on the interference values. We expect that each gateway has a maximum total available bandwidth and its corresponding maximum number of transmitted carriers. In addition to this, the satellite payload may restrict the available options for designing the selection variables.

It is important to remark that there might be different refinement analysis of the mentioned mathematical model of a multi-gateway transmission. First, we may consider the attainable rates of DVB-S2X instead of Shannon capacity. The mentioned binary non-linear optimization is solved via genetic algorithms. Those algorithms are known to require large computational times. There are approaches based on deep learning to try to speed up certain operations. Still, it is unclear whether the efficient solutions can be obtained in short time periods. Yet, a relevant issue in here is the spectrum fragmentation due to the disjoint allocation of channels among beams. An important aspect of the channel allocator is to carefully select continuous spectrum chunks leading a higher user terminal communication performance.

5. Results and Discussion

Within the previous sections, different scenarios have been discussed in detail. These scenarios have been selected by the authors as interesting from different perspectives. On the one hand, they have been chosen because they are aligned with SATCOM operations, hence, with real problems. On the other hand, because AI based technologies have been found as a feasible approach to tackle such complex problems. Some research has been already tackled in this line by the authors and presented in different works, aiming to define a guidance or the first steps towards the massive use of AI/ML in SATCOM [6-8].

As already mentioned above, the authors have already been working towards the first two scenarios, by means of the implementation of a system capable of tackling a simplified version of the proposed problems. Part of this work has been tackled within the context of the H2020-ATRIA (Artificial-Intelligence-Powered Ground Segment Control for Flexible Payloads) project [9]. These simplified versions are explained below.

Focusing on the first described scenario, the one dealing with the gateways' diversity problem, a first approach has been studied. Fig**.** 1 represents the proposed schema, aligned with the description provided in the previous sections. External systems are composed of the satellites operator facilities (from which beacons levels and weather data coming from onsite stations can be retrieved) and third-party systems (capable of providing weather forecasts, or even real-time weather measurements). Ground segment is composed of the end-to-end SATCOM system (which would embed an AI/ML core to execute the algorithms), the satellite/payload control centre, and an NMS (from which historical operations can be accessed). The simplified version of the scenario considers the boxes of the cited schema presenting the wider border. Then, meteorological information has been reduced up to a unique key indicator based on the rainfall, as has been considered the one with the highest impact on the link performance. This information has been retrieved from third-party systems, due to the unavailability of onsite stations for this purpose. Interface with the satellite/payload control centre has not been currently implemented, instead, the flow ends up by the recommendation of performing or not a switching operation between gateways, resulting from the output of the AI/ML algorithms. As a result, the proposed ground segment tool incorporates an AI/ML core which has been trained with real data, and retrieves weather forecasts from third-party systems, plus beacons levels from the satellite operator. As explained in section 2.2.2, the retrieval of forecasted rainfall in the locations of the gateways triggers a prediction of the outage duration in the same locations, warning the operator to consider a gateway switch in the coming minutes. Some preliminary results have already been discussed in [10].

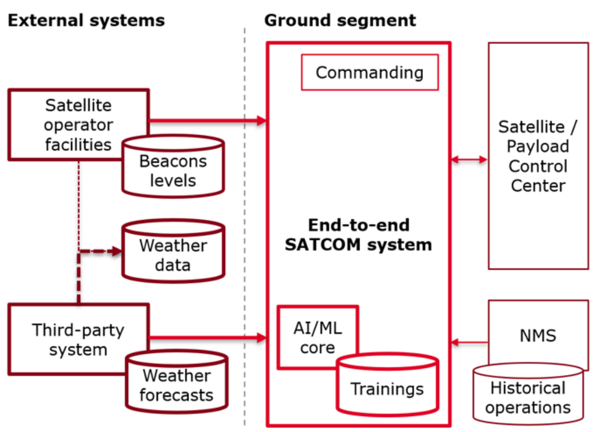

Fig. 1. Schematic of the proposed end-to-end SATCOM system for gateways' diversity scenario

Focusing on the second described scenario, the one dealing with the congestion awareness problem, a first approach has also been studied. In this case, Fig. **2** represents the complete system proposed in section 3. The main idea is analogous to what explained above for the first scenario, except for the different data coming from the external systems, which in this case is related to traffic and capacity per beam. The system has been trained with real data from the operators, containing measurements of traffic and capacity per beam, aggregated every five minutes. As explained in section 3.2.2, the retrieval of new aggregated information from the operator triggers a new prediction in the system, providing as result the forecasted congestion per beam, calculated from the capacity of the beam and the predicted traffic. The flow currently ends up at this level.

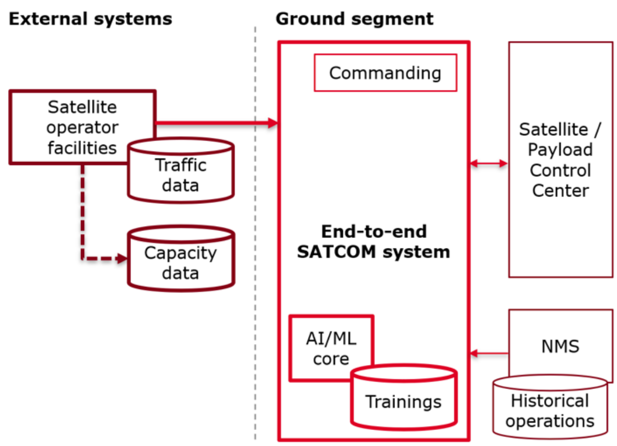

Fig. 2. Schematic of the proposed end-to-end SATCOM system for congestion awareness scenario

6. Conclusion

In this work, the authors provide an insight of three different operational scenarios susceptible to be managed by a system empowered with AI/ML technologies. The scenarios have been selected with the help of experts in the field of SATCOM operations, within the context of the ATRIA project. First, the scenarios are described, emphasizing the problematic to be tackled, and the consequences in the current operations. Then, the viability of applying AI/ML techniques is described, proposing the required input dataset to be considered for the training, prediction, and validation phases. Two of the proposed scenarios are then simplified and preliminary results from the ATRIA project are introduced. Representing these results a proof of concept of the system, it is envisioned the development of enhanced versions of the AI/ML algorithms, and new interfaces with the systems not currently included. Additionally, a third scenario is qualitatively presented and discussed, conforming the roadmap of the proposed SATCOM system.

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