# AI for Zero-Touch Management of Satellite Networks in B5G and 6G Infrastructures

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### Abstract
Satellite Communication (SatCom) networks are become more and more integrated with the terrestrial telecommunication infrastructure. In this paper, we shows the current status of the still ongoing European Space Agency (ESA) project "Data-driven Network Controller Orchestration for Real time Network Management - ANChOR". In particular, we propose a Long Short-Term Memory (LSTM)-based methodology to drive the dynamic selection of the optimal satellite gateway station, which will be performed by combining different kinds of information (i.e. traffic profile, network and weather conditions). Some preliminary results on the real world dataset shows the effectiveness of the proposed approach.

### Keywords
satellite-terrestrial Integrated networks, data management and orchestration, AI/ML resource allocation, smart satellite gateway selection

## 1. Introduction

Non Terrestrial Networks (NTN), and in particular Satellite Communication (SatCom) networks, are becoming more and more integrated with the terrestrial telecommunication infrastructure. This is the main aim that a lot of researchers and research activities have been achieving since the past few years. A concrete example is the 5G ongoing standardization activity within The Third Generation Partnership Project (3GPP) [1]. The ongoing Release-17 works are including efforts towards the definition of Internet of Things (IoT) over NTN and New Radio (NR) over

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NTN solutions[1]. The planned Release-18 works are still including standardization activities on NTN to further define Radio Layer 2 and Layer 3 details to allow solutions where non-terrestrial nodes can operate in the Radio Access Network (RAN)[2]. Numerous are the advantages that NTN can bring to the terrestrial networks [2]. Foster network spread, bringing connectivity to large currently un-served or under-served areas, offer backup links in case of non-normal conditions, such as outages or faults of the primary terrestrial infrastructure, and offload the terrestrial network offering additional connections to the users to address traffic peaks on the terrestrial network and preserve the performance of specific loss or delay-sensitive flows are just a few of them. However, several challenges and open issues are still to be properly investigated and fixed to allow seamless integration between terrestrial and non-terrestrial networks [3, 4], such as the definition of proper random access procedures, timing advance strategies, and hand-over managing policies, despite the considerable amount of research and development effort already done [5].

The employment of Artificial Intelligence (AI) and Machine Learning (ML) principles and related solutions is another important pillar of the communication network evolution [6]. It is evident looking again to the 3GPP Release-18 planned content list which includes the “AI/ML for Next Generation RAN (NG-RAN)”, “AI/ML – Air interface”, and “AI/ML study, Multimedia codecs, systems and services” topics and more generally to the huge amount of research contributions in the literature, which also includes studies and solutions to employ AL/ML techniques in NTNs [7]. Radio resource management, mobility management, and non-terrestrial/terrestrial network integration are just a few examples of the aspects that AI/ML solutions can help improve. However, due to the challenges and open issues still to investigate and address [8], the full integration of AI/ML strategies in communication networks have been considered, especially from the standardization viewpoint, as a matter of 6G or Beyond 5G (B5G) network evolution instead of 5G network consolidation. This is also reflected, as a consequence, in satellite-terrestrial integrated systems [9].

This paper shows the current status of the still ongoing European Space Agency (ESA) project “Data-driven Network Controller and Orchestrator for Real-time Network Management – ANChOR”[10], which aims to provide a further contribution towards the real integration of satellites into the 5G era and beyond. In particular, we will focus on describing one of the considered scenarios, the related network architecture, and the system prototype under development (Section 2), the AI-based method employed to drive the dynamic selection of the optimal satellite gateway station (Section 3) and the current and preliminary obtained results (Sections 4 and 5). Finally, conclusions are drawn in Section 6.

## 2. Anchor Architecture

### 2.1. Use case for hybrid terrestrial/satellite backhaul in 5G network

The ANChOR architecture has been designed to support a variety of Use Cases (UC) for the integration of satellite networks in 5G infrastructures, as initially presented in [11] (see Figure

[1]https://www.3gpp.org/release-17
[2]https://www.3gpp.org/release18

1). This paper addresses the architectural aspects to enable a particular UC targeting an hybrid terrestrial/satellite backhaul orchestrated as part of end to end network slicing strategies. In particular, we focus on the establishment of enhanced Mobile Broadband (eMBB) services exploiting Geostationary Earth Orbit (GEO) satellite constellations. Current modern satellite facilities rely on multiple ground stations dislocated in different geographical areas in order to guarantee high-bandwidth communications and enough redundancy to mitigate signal attenuation effects due to adverse weather conditions. Dynamic allocation of satellite resources and their runtime configuration are crucial to optimize and maximize the usage of satellite segments. Orchestration and AI/ML-based decision mechanisms are used in combination with in-place satellite optimization techniques e.g, Satellite smart gateway diversity, that allows the runtime selection of target gateway in a multi-gateway environment and the Adaptive Coding and Modulation (ACM), for dynamic change of the transmitted signal characteristics, enabling high-availability of satellite infrastructure while guaranteeing the required level of Quality of Service (QoS).

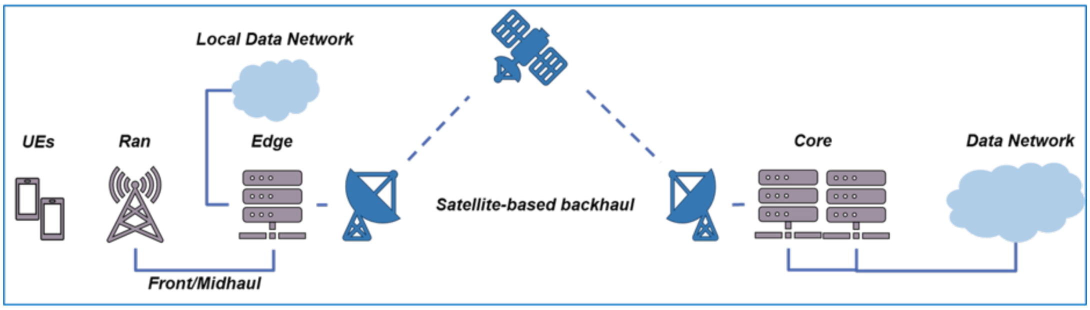


**Figure 1:** Satellite-base 5G backhaul

## 2.2. Architecture

The ANChOR architecture [11] adopts some of the concepts related to Network Function Virtualization (NFV), network programmability, and slicing management in 5G networks, identifying three major functional components:

- **Management and Orchestration**, implementing the management of end-to-end network slices and coordinating the resource orchestration for domain-specific slice subnets, including a core network with user plane functions moved towards the edge of the network and a satellite-enabled transport network for the backhaul. Open interfaces are offered towards the AI/ML platform to enable the automated re-configuration of network slices at runtime.
- **Multi-technology Network Controllers**, implementing the control plane of the transport network and enabling the dynamic reconfiguration of the satellite segment.
- **Monitoring and AI/ML**, which embeds the AI/ML algorithms implementing the data-driven intelligence to assist the system in the multi-layer automation of the ANChOR infrastructure. A specific Monitoring Platform collects the monitoring data generated from

several data sources later ingested by AI/ML algorithms to make automation decisions, applied and enforced by the Management and Orchestration facility.

## 2.3. Closed-loop for automated hybrid backhaul reconfiguration

Data-driven automatic reactivity/proactivity of control and management platforms is a very well-known and popular concept adopted in 5G networks to guarantee service continuity while minimizing human interventions. ANChOR implements such a concept by following a Data-Driven AI-based closed loop for the runtime reconfiguration of the hybrid 5G backhaul and, in particular, its satellite segment.

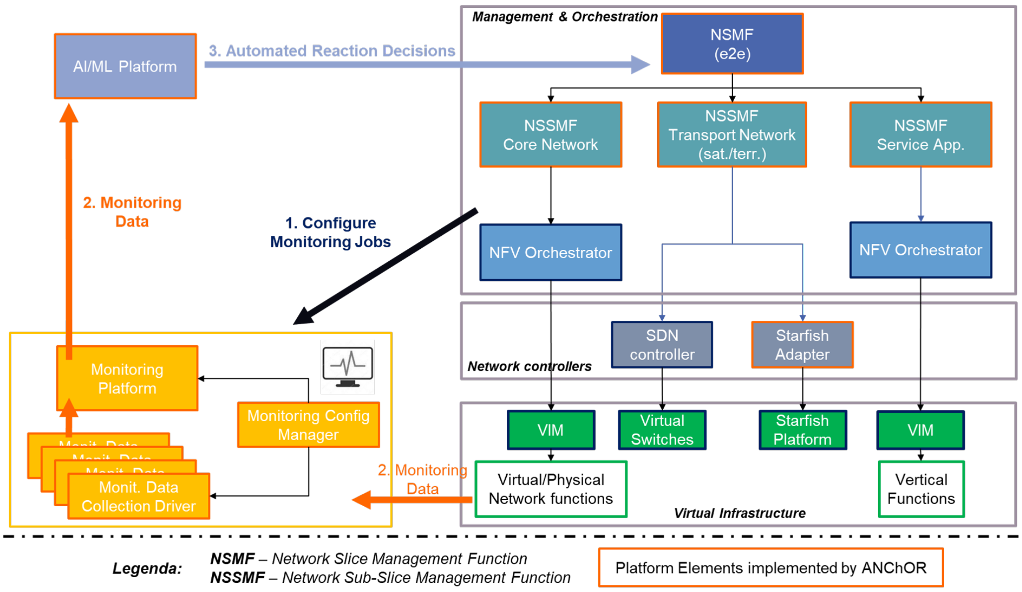


**Figure 2:** ANChOR closed-loop automation

The ANChOR Management and Orchestration platform, as part of the slice provisioning process, configures the Monitoring Platform in order to continuously collect data relevant to determine the current status of each slice and related resources. The collected data are heterogeneous, related to different slice subnets (e.g., core, satellite-based transport network, etc), and may involve third party sources, e.g., weather forecast services, relevant for satellite communications. The Monitoring Platform collects and stores the data, making them available for the AI/ML platform that continuously takes decisions based on the monitored status. In case of detection of a sub-optimal condition, the AI/ML platform automatically requests a network re-configuration to be enforced by the ANChOR Orchestrator. The Orchestrator translates such requests to real actions that affect one or more network slice subnets composing the target (monitored) end-to-end slice. Three specific decisions can be made by the AI/ML algorithms in the case of 5G backhaul. In the case of congestion or failure of the terrestrial link, the AI/ML platform may decide to relocate the traffic (or part of it) into a satellite link minimizing the risk of service outages. In case of adverse weather conditions, which may affect the satellite transmission, the reconfiguration may consist in a redirection of the traffic towards a new target satellite gateway placed into a geographical area characterized by better weather conditions. Finally, the characteristics of satellite channels can be tuned at runtime by reconfiguring ACM parameters.

### 2.4. System prototype implementation

The first prototype of the ANChOR Platform consists of several software components building the different parts of the functional architecture. At the top of the system, a centralized Slice Manager[3] implements the Management and Orchestration platform. With reference to figure 2, the Slice Manager implements the Network Slice and Network Slice Subnet Management Functions (NSMF and NSSMF) of a 5G management system, as defined by the 3GPP architecture. In particular the Transport Network (TN) NSSMF orchestrates the 5G backhaul. Here a specific adapter allows the configuration of the Starfish platform [12], which creates and manages the satellite slice subnets, and an instance of OpenDaylight controller [13], which is used to configure the virtual switches in the terrestrial network to switch towards the satellite backhaul and vice-versa. The Monitoring platform is a micro-service Docker-based application, encompassing several open-source tools and frameworks. The data are collected through a set of Telegraf agents [14], deployable on demand and configurable at runtime, that collects data from the 5G Core, Satellite platform and from OpenWeather [15], the external service selected to get weather forecast information. The data collected are pushed into a Kafka bus [16], where the AI/ML is listening to new events. Historical data are stored with InfluxDB[17] and used for AI/ML model training. Prometheus [18] has been selected as the data aggregation platform. The runtime configuration of the elements building the Monitoring platform is implemented through a specific Config Manager built from scratch. The AI/ML platform along with preliminary validation activities in the context of the use case described in subsection 2.1, is widely discussed in the following section.

## 3. AI-based Methodology

### 3.1. Task definition

AI models aim to drive the dynamic selection of the optimal satellite gateway station, which will be performed by combining different kinds of information (i.e. traffic profile, network and weather conditions). In particular, this task identifies the appropriate gateway on the basis of the analysis of the obtained status associated with a given station in a specific time interval (that is defined according to a sliding window).

### 3.2. Workflow

The proposed methodology consists of three steps (see Figure 3): labeling, pre-processing and model training. First step is mandatory to perform a supervised training where each instance has the related label while the pre-processing has the goal of extracting the sequences from

[3] https://github.com/nextworks-it/slicer

historical data. Furthermore, the extracted sequences are properly normalized before they are fed into the model. Finally, a deep learning Long Short-Term Memory (LSTM)-based model is used to predict the state of each gateway in a specific time interval.

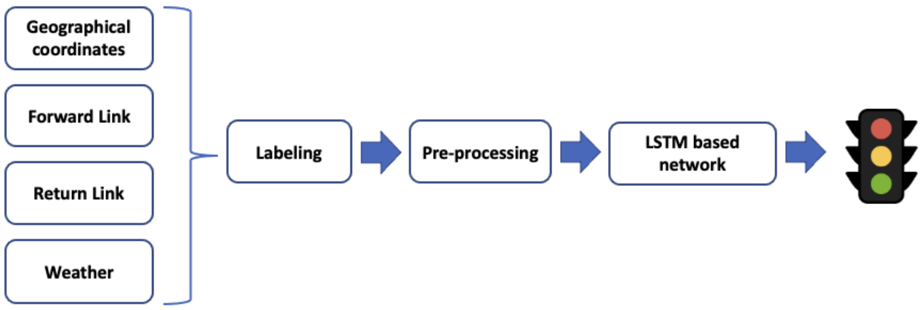


**Figure 3:** An high-level overview of the framework.

Specifically, the choice of LSTM-based model is motivated by the nature of analyzed data which are time series without any kind of regularity. This type of model has been designed to capture both short and long term information within the historical data.

The model's decisions will be taken based on a mix of network topology information, historical data (for the training phase), real-time monitoring data and service requirements, that can be classified in: i) Geographical coordinates of available satellite gateways and satellite terminals; ii) Service profile characterizing the data traffic on the eMBB network slices, in terms of: required bandwidth, tolerable delay and maximum acceptable Bit Error Rate (BER); iii) Real-time monitoring data; iv) Weather information.

## 4. Experimental Protocol

In this section we discuss about the experimental analysis made for evaluating the efficacy of the proposed AI model in terms of accuracy, precision and recall.

As mentioned in the previous section, the dataset is composed by different features provided by several sources. The platform analyzed for the network features is *Eurobis* considering data referred to a time span 2021-01-25 00:00 to 2021-02-08 00:00 with 5 minutes step, producing a dataset having 4032 samples.

The features used to train models concerning to Forward Link (FL), Return Link (RL), weather, and number of logged-on terminals. In particular, we considered the following features for:

- FL: throughput in terms of packets and bits per seconds, Signal Noise Ratio in dB;
- RL: throughput in terms of packets and bits per seconds, Signal Noise Ratio (SNR) in dB, BER, frequency error in Hz, Normalized Signal Noise Ratio in dB.

The weather data are gathered by OpenWeather API for historical data (i.e. temperature, wind, humidity and pressure).

The dataset has been labeled on the basis of specific rules defined by domain experts to consider two different events. The former concerns the presence of interference leading to the increase in total received power and BER and the decrease of the RL-SNR and the aggregate platform throughput. The former is related to a rain event on the teleport which involves a decrease of the total received power, RL-SNR and the aggregate throughput while increasing BER.

The obtained dataset has been split in training, validation and test sets in order to find the best hyper-parameters and to estimate the performance of the designed model. We have tuned the hyper-parameter, using Adam optimizer [19] with binary cross-entropy as loss function, of the LSTM-based model on training and validation set; in particular, the final designed model is composed by LSTM cell with 128 units, Dropout, LSTM cell with 128 units and finally a Dense layer with 2 units with softmax as activation function and batch size equals to 16. The proposed model has been implemented in Tensorflow 2.0 using the corresponding Keras layers.

## 5. Results

In this section we discuss about the achieved results. In particular, in Table 1 some performance metrics (Accuracy, Precision and Recall) are reported by varying the time window size, that has been defined for correlating temporal information. The best results in terms of Accuracy have been reached considering a time window of 10 samples. This result could be due to the fact that this size is the best in order to capture both short and long information, while with 5 and 15 samples we are able to consider only short or long ones; in fact, the size of window can strongly affect the result of our analysis because it could consider too many or few samples along time.

Figure 4 reports the training curves related to the best solutions, where it is possible to see how the loss function decreases as the epochs increase, and at the same time the accuracy of the model increases. This trend of decreasing loss and increasing accuracy indicates how much the model is learning in a correct way.

Finally, the proposed model takes into account features provided by *Monitoring Platform*, processes and predicts status of gateways, chosen the one with higher probability score, whose information is then sent to *Anchor Orchestrator*.

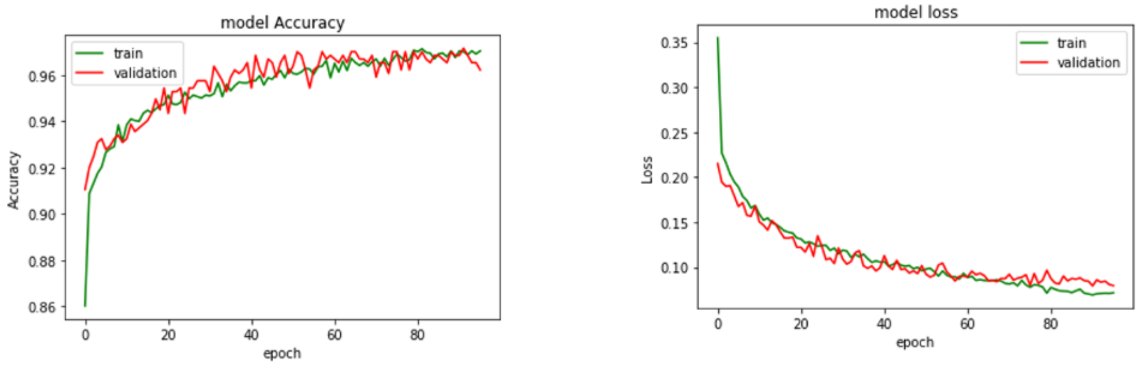


**Figure 4:** Training curves of Accuracy and loss function.

| Time Window (sample) | Accuracy | Precision | Recall |
|---|---|---|---|
| 5 | 90.68% | 72.72% | 80.00% |
| 10 | 91.25% | 72.00% | 72.00% |
| 15 | 89.37% | 71.87% | 74.19% |

**Table 1**
Results of the proposed LSTM-based model in terms of Accuracy Precision and Recall by varying the Time Window size.

## 6. Conclusions

The interest in applying AI/ML-based methods in different research fields is increasing and leading to multiple solutions aim to solve multiple problems or at least improving the currently available solutions. This is true also in the telecommunication network field and, in particular, in the development of new solutions for a better satellite/terrestrial network integration and an enhanced resource allocation and management.

This paper shows the current development status of a research project, called ANChOR. The project description is focused on the considered network architecture, the system prototype under development, and the AI/ML-based technique that we are developing and testing to properly address the satellite gateway selection problem. The included preliminary performance show encouraging trends and good results in terms of the three considered metrics.

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