Chapter 7
Intelligent Space Communication Networks

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7.1 Introduction

Different fields are currently benefiting from the introduction of more intelligent solutions in space systems and devices. In most cases, this means the use of Artificial Intelligence (AI) based techniques to solve problems already addressed by previous solutions, but in a more efficient and effective way, and tackle issues not addressable yet due to the limitations of the available solutions. AI techniques are currently under study, development, and deployment in a huge plethora of scenarios and applications for improving a high number of services in terms of different performance indicators.

In communication networks, including satellite communication networks, AI-based solutions may differ in different aspects:

- *Scope*: AI techniques can be applied for different purposes related to the offered applications, i.e. to improve the quality of the user's exploited applications, or to the offered connectivity service, i.e., to improve the quality of the user's experienced connectivity and/or the number of users that can join the network.
- *Algorithm*: AI solutions can be based on different Machine Learning algorithms that can be categorised in different subsets depending on how they perform the training phase, such as supervised, unsupervised, and semi-supervised learning,

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or their basic principles, such as Deep Learning (DL) and Reinforcement Learning (RL).

- *Input information*: AI techniques may use typically big datasets as input in the training phase before being able to perform well in the operational phase. These sets of information may refer to single or multiple variables analysed over time. If the analysed data are reported in terms of multiple and heterogeneous variables, correlating them is another task that AI solutions may perform differently.
- *Implementation location*: AI algorithms can run on different nodes of the network depending on their scope, the needed input information, and the nodes' available data processing and storing capabilities. For example, moving AI capabilities to the edge of the network, i.e., closer to the users, may bring some advantages, especially in terms of users' perceived service, but it needs a higher control overhead and nodes with enough available resources.
- *Improved performance*: different AI solutions can be the best solutions depending on the problem to solve and the performance we aim to improve. For example, some algorithms may offer better performance in terms of accuracy and reliability but suffer from high computational delays. This is suitable for applications with high-reliability requirements but may be intolerable for delay-sensitive ones, which instead prefer much faster decision times and tolerate higher error rates.

7.2 AI Improvements in Satellite Networks

Space communication networks are benefiting from the employment of AI techniques in multiple ways [1]. Multiple issues can be addressed by AI-based solutions, leading to several improvements compared to the previously available techniques.

7.2.1 Communication Resource Allocation

Communication resources are typically limited and have to be properly managed in order to, on one hand, satisfy each user's QoS requirements and, on the other hand, avoid waste. This is even more prominent in satellite communication networks due to the stronger resource limitations compared to terrestrial networks. AI techniques can help address several sub-aspects:

- *Network traffic prediction*: being able to predict network traffic evolution over time is an advantage that can improve multiple processes, such as congestion control, routing, and handover. Concerning routing, for example, currently designed and deployed satellite communication networks show an increasing trend in terms of the number of satellites to offer connectivity to a high number of possible interested users spread in wider, potentially worldwide, areas. Most of them are composed of LEO satellites which are deployed on multiple orbital planes at different altitudes. Hierarchical solutions are also envisioned where LEO, MEO, and GEO satellites have different roles and cooperate to offer Internet connectivity and exchange data among them through RF or optical Inter-Satellite Links (ISL). The routing process and the consequent resource allocation are of primary importance due to the high availability and variability of end-to-end paths and the numerous parameters that can be taken into account related to both the user performance requirements and network (satellites, ISLs, satellite-ground links, ...).

Traffic forecasting techniques not based on AI solutions suffer from two major difficulties: the limited onboard computational resources and the Long-Range-Dependence (LRD) of satellite network traffic that makes lower complexity Short-Range-Dependence (SRD) models to fail achieving accurate forecasting.

For these reasons, AI solutions have been proposed to further optimize this task. Some examples are a high-accuracy traffic forecasting method with lower training time which applies Principal Component Analysis (PCA) and then a generalized regression NN [2], an Extreme Learning Machine (ELM)-based technique employed for traffic load forecasting of satellite nodes before routing [3], and a method based on Fly Optimization Algorithm—Extreme Learning Machine (FOA-ELM) which uses the Empirical Mode Decomposition (EMD) to decompose the traffic of the satellite with LRD into a series with SRD to decrease the predicting complexity and improve the prediction speed [4].

- *Channel model*: the features of satellite channels may differ depending on multiple parameters, such as the satellite altitude, and may change over time. Considering a channel model as close as possible to the real scenario, it is useful to have a very clear idea about the transmission and interference conditions and so usefully allocate the available communication resources. However, the creation of precise satellite channel models and the consequent estimation of the channel parameters is a challenge due to the multiple factors to take into account.

  Even if several techniques are already consolidated with satisfactory performance, such as ray tracing, they all suffer from many limitations, such as the need for a huge amount of information that may not be available and the high required computational effort that are in contrast with the real-time optimization needs.

  AI-based solutions have proven to be effective in overcoming these limitations. Some examples are solutions based on more traditional ML techniques, such as NN [5], and more sophisticated DL-based solutions [6] aim to forecast packet losses, an aspect related to the channel modelling for optimal resource allocation.
- *Signal Detection*: As each signal must be separated before classification, modulation, demodulation, decoding, and other signal processing, localization and detection of carrier signals in the frequency domain are crucial.

  Most of the traditional techniques are based on single or multiple threshold values, rely on tractable mathematical models under known noise process and/or deterministic interference, and required human intervention, making the process

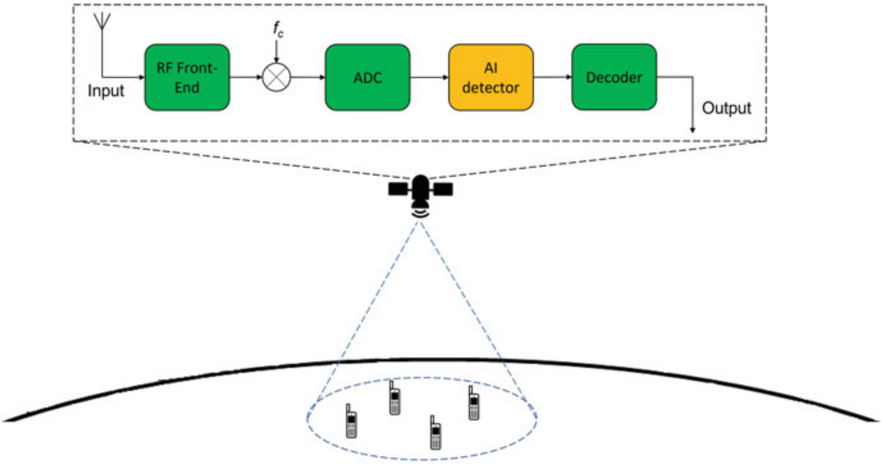

Fig. 7.1 DL-based signal detection and demodulation strategy [7]

more complex and the needed effort more significant in an environment full of signals to identify and differentiate.

AI approaches can be efficiently used under dynamic interference to effectively detect the target signals. AI detectors can be trained for detecting various modulation and coding techniques and be based on different algorithms [7] (see Fig. 7.1). A DL-based solution is proposed in [8] to morse signals blind detection in wideband spectrum data, while a FCN model is proposed in [9] to detect carrier signal in the broadband power spectrum.

- *Interference management*: interference is a phenomenon that strongly affects communications, in particular through satellite links. It is a common event whose effects are worsening with the increasing congestion of the satellite frequency bands due to a higher number of deployed communication satellites, active satellite network users, and expected applications. As a consequence, interference management is essential to allow high-quality and reliable communications through detection, classification, and suppression of interference, as well as minimization of its occurrence.

  Interference detection is a well-studied subject that has been extensively addressed also for satellite communications. Most common solutions are based on theoretical models for signal characteristics and satellite channels used to estimate interference and techniques to properly counterbalance the transmitted signals optimizing interference cancellation [10].

  To further minimize interference effects, examples of the proposed AI-based solutions include a framework combining Support Vector Machine (SVM) , unsupervised learning, and DRL-based approaches for satellite selection, antenna pointing, and tracking [11], an approach to forecast the signal spectrum to be received in absence of anomaly by using LSTM trained on historical anomalyfree spectra [12] and a DNN and LSTM-based method to detect and classify interference [13].

- *Beam hopping*: conventional satellite systems uniformly allocated resources across beams, which may lead to lower resources than needed in some beams and the resource under-utilization in other beams due to the typical not uniform geographical distribution of the users underneath. Beam hopping has emerged as a promising technique to achieve great flexibility in managing non-uniform, time and spatial variant traffic requests. It is based on a dynamic allocation of the available resources to only a subset of the overall beams depending on the current users' traffic demands. The problem is to optimally decide when to allocate resources to a new beam and for how long.

  Even if this problem has been already addressed by proposing solutions not based on AI techniques, the technological evolution is leading to complications that are difficult to properly take into account with traditional methods. For example, as the number of beams increases (reaching hundreds or thousands of beams per satellite), it is becoming more difficult and time consuming to find the optimal choice rather than one of many local optima.

  Some of the proposed AI solutions involve the use of DRL to reduce the transmission delay and increase the system throughput [14] (see Fig. 7.2), fully-connected NNs to predict non-optimal beam hopping patterns [15], and low-complexity Multi Objective-DRL to ensure the fairness of each cell and, at the same time, improve the achievable throughput [16].
- *Energy management*: communication satellites typically require a high amount of energy to transmit data due to the physical nature of the space environment

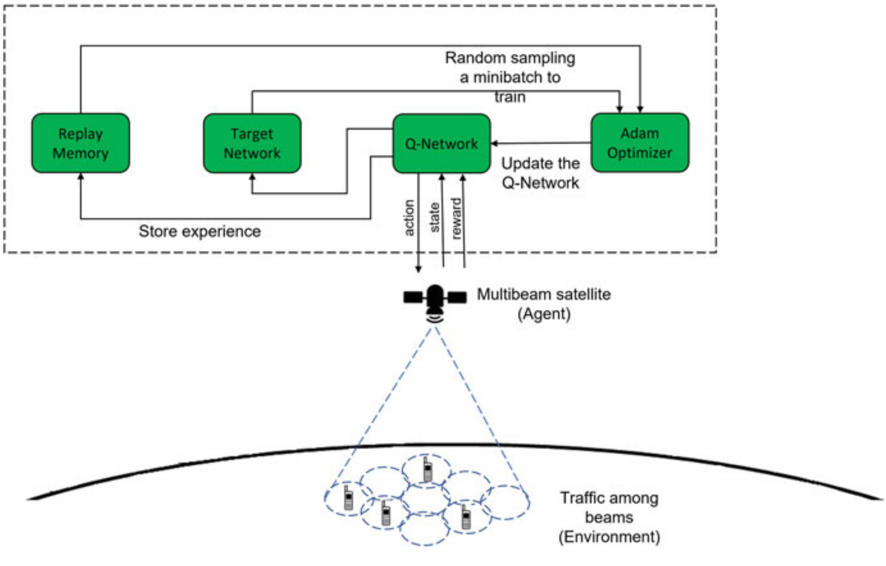

Fig. 7.2 DRL-based beam hopping algorithm [14]

and the high attenuation and interference factors than a typical terrestrial environment. Satellites suffer, at the same time, from severe energy limitations, considering the Sun as the only energy source, the generated power depending on the extension and orientation of the satellite's solar panels, and the available energy depending on the satellite's battery capacity. Besides, the increasing number of users and the decreasing satellite size is further stressing these limitations, imposing a careful management of the satellite energy consumption to avoid service disruptions.

Resource scheduling schemes, even involving temporary complete or partial shutdown of the single identified satellite communications, have been designed to dynamically adjust the data overload of each satellite distributing the energy consumption throughout the satellite segment.

Examples of AI solutions include using DNN compression before data transmission to improve latency and optimize the power allocation in satellite-to-ground communications [17], RL to share the workload of overworked satellites with near satellites with lower load [18], and DRL to allocate communication slots with high energy efficiency [19].

7.2.2 Security

More satellite communication networks will be widespread with a higher number of users, the more they will be appealing for malicious attacks, especially cyber-attacks, aiming to disrupt the offered service or even damage the network apparatus. Recent solutions focus more attention on security, following the principle of security-by-design, but there is still room for improvements, especially considering the problem of improving security of the already deployed satellite systems. Also in this case, AI techniques can help address several sub-aspects:

- *Anti-jamming*: jamming is one of the simplest but most effective attacks that can be carried on against communication networks to interfere and, in the worst case, completely disrupt the offered service, isolating the users located in the attacked area from the network or making a base station incapable of offering connectivity. Traditional solutions have been proposed to alleviate the jammer effects, such as the FHSS and DSSS strategies. However, these solutions are not able to dynamically adjust their action depending on the jammer characteristics.

  AI principles have already been considered to develop more sophisticated attack methods. For example, a smart jammer able to automatically adjust the jamming channel and power in order to maximize the jamming effect is proposed in [20]. This makes of primary importance the use of AI-based anti-jamming solutions able to automatically protect the network nodes against jamming attacks, AI-based or not. Some examples include: a hierarchical learning approach proposed in [21] to improve the frequency selection process where both jamming and co-channel interference are present; a frequency-spatial

2-D anti-jamming scheme to resist jamming and interference and a fast DQN based 2-D mobile communication algorithm that applies DQN, macro-actions and hotbooting techniques to achieve the optimal frequency selection described in [22]; a spatial anti-jamming scheme based on DRL to take proper data routing choices to make the network more robust against jamming attacks that can disrupt a subset of the network links presented in [23].

- *Monitoring telemetry data*: telemetry is the group of information describing the status of the system, especially, in our case, the satellites. They are control packets that are sent in downlink to help ground operators to monitor the satellite status, such as satellite position, satellite attitude, and solar panel orientation, and operations to be sure that they are operating within the defined limits. All these data are recorded and can be analysed to detect abnormal events and predict possible upcoming abnormal situations in order to minimize failure risks. However, how to correlate heterogeneous data coming from multiple sources of information to find correlations, recognize patterns, and so detect anomalies, may be a challenge. Simple solutions involve setting operational ranges for the monitored parameters and periodically checking their values to detect single or systematic out-of-range events. Even if simplicity is their best advantage, they suffer from severe limitations as the systems are becoming more complex with a higher number of parameters to monitor. This in turn leads to a higher volume of data to send through the satellite links with a consequent higher delay needed to process all the data and close the loop with proper reactive actions. AI-based solutions help build more sophisticated and reactive health monitoring systems by using different techniques, such as probabilistic clustering [24]. Other examples involve using linear regression to forecast short-lifetime satellite behaviours (3–5 years) and NNs for long-lifetime satellite behaviours (15–20 years) [25] and a self-learning classification algorithm able to achieve onboard telemetry data classification with low computational complexity and low time latency [26].

7.2.3 Orbital Edge Computing (OEC)

Orbital Edge Computing (OEC) is a recent vision in next-generation satellites, seen as powerful nodes equipped with additional data computational and storage capabilities that can be exploited by the offered services. Process data directly onboard satellites can help several applications reduce latency compared to centralized cloud processing platforms where raw data have to be forwarded through satellites from users to the platform and processed data on the backward path. Store a significant amount of data onboard satellites can help further reduce latency avoiding that data requests and responses traverse the satellite path to reach the data repositories and vice versa.

Allocation of tasks to process and data batches to store among satellites is the main problem to address related to the OEC concept [27]. The dynamic and

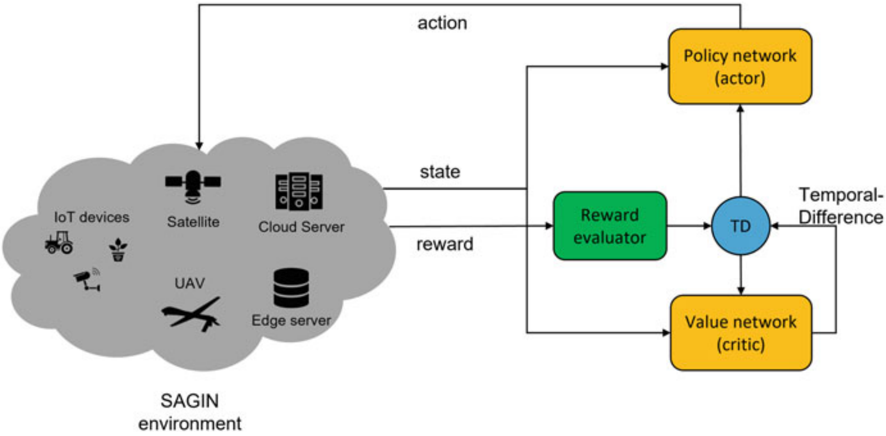

Fig. 7.3 RL-based computing offloading approach [28]

time-varying nature of satellite networks, such as in terms of satellite-satellite and satellite-ground user links, require a careful task and data distribution strategy that should take into account different factors, such as the network topology changes over time and estimations of the user traffic flows and data processing requests.

Some examples of AI-based solutions are a joint resource allocation and task scheduling approach that aims to allocate the computing resources to virtual machines and schedule the offloaded tasks for Unmanned Aerial Vechile (UAV) edge servers, whereas an RL-based computing offloading approach handles the multidimensional network resources and learns the dynamic network conditions [28] (see Fig. 7.3), and a joint user-satellite association and task offloading decision with optimal resource allocation methodology based on DRL to improve the long-term latency and reduce the energy consumption [29]. A novel AI-based architecture for Earth Observation satellites which embeds AI DNN algorithms for consuming data at source rather than on the ground aim to minimize the downlink bandwidth usage is presented in [30].

7.2.4 Remote Sensing

Multiple applications and functionalities benefit from the use of AI-based solutions. Remote Sensing is the operation of collecting and processing information about the observed areas, objects, or phenomena from their reflected and emitted radiation. Its applicability regards numerous scenarios and applications with multiple advantages, such as the possibility to remotely monitor dangerous or unreachable areas.

Traditional approaches are in use since the beginning of this discipline with considerable results. However, the need to monitor more complex phenomena and the development of more precise sensors able to collect a much wider set of different information from the monitored subject to analyse and correlate to take useful conclusions recently emerged, with the consequent need to have more flexible and versatile solutions.

The evolution of computer vision capabilities due to DL has led to the increased development of remote sensing solutions adopting state-of-the-art DL algorithms on satellite images. An example is a combined kNN and CNN-based solution to map coral reef environments by using remote sensing images [31]. Object detection and recognition are another set of applications whose capabilities have improved thanks to AI. CNN-based object detection algorithms have been developed to recognise different kinds of objects, such as clouds [32] and ships [33].

7.2.5 Space-Air-Ground Integrated Network

Space-Air-Ground Integrated Network (SAGIN) is a recent evolution of satellite communication networks is not only leading to the deployment of Mega LEO satellite constellations made of thousands of satellites, but also to hierarchical networks composed of multiple layers of space (satellites), aerial (UAVs and/or HAPs), and ground communication nodes. This is also leading to a higher number of users interested in exploiting the connectivity services of this kind of networks which were previously limited to giving telephone, tv, or Internet coverage to unserved areas. Integration with terrestrial mobile communications, such as 5G, is another aspect deeply under investigation and standardization within the 3GPP.

SAGINs aim to provide users with improved and flexible end-to-end services thanks to a hierarchical network where different kinds of nodes typically have different roles but they all collaborate and exchange users' data to offer them the required QoS.

AI-based solutions can help optimize the achievable performance improving multiple aspects. For example: a CNN-based solution is proposed in [34] to optimize the network overall performance by using traffic patterns and the remaining buffer size of GEO and MEO satellites as input information (see Fig. 7.4); a DRL-based solution that jointly optimises the satellite selection and the UAV location to maximise the end-to-end data rate of the source-satellite-UAV-destination communications is presented in [35]; a low-complexity technique for computing the capacity among satellites by using a time structure based augmenting path searching method and a long-term optimal capacity assignment RL-based model to maximize the long-term utility of the system is suggested in [36].

7.2.6 Satellite Operations

Potential applications of AI are also being thoroughly investigated in satellite operations [37], in particular to support the operation of large satellite constellations,

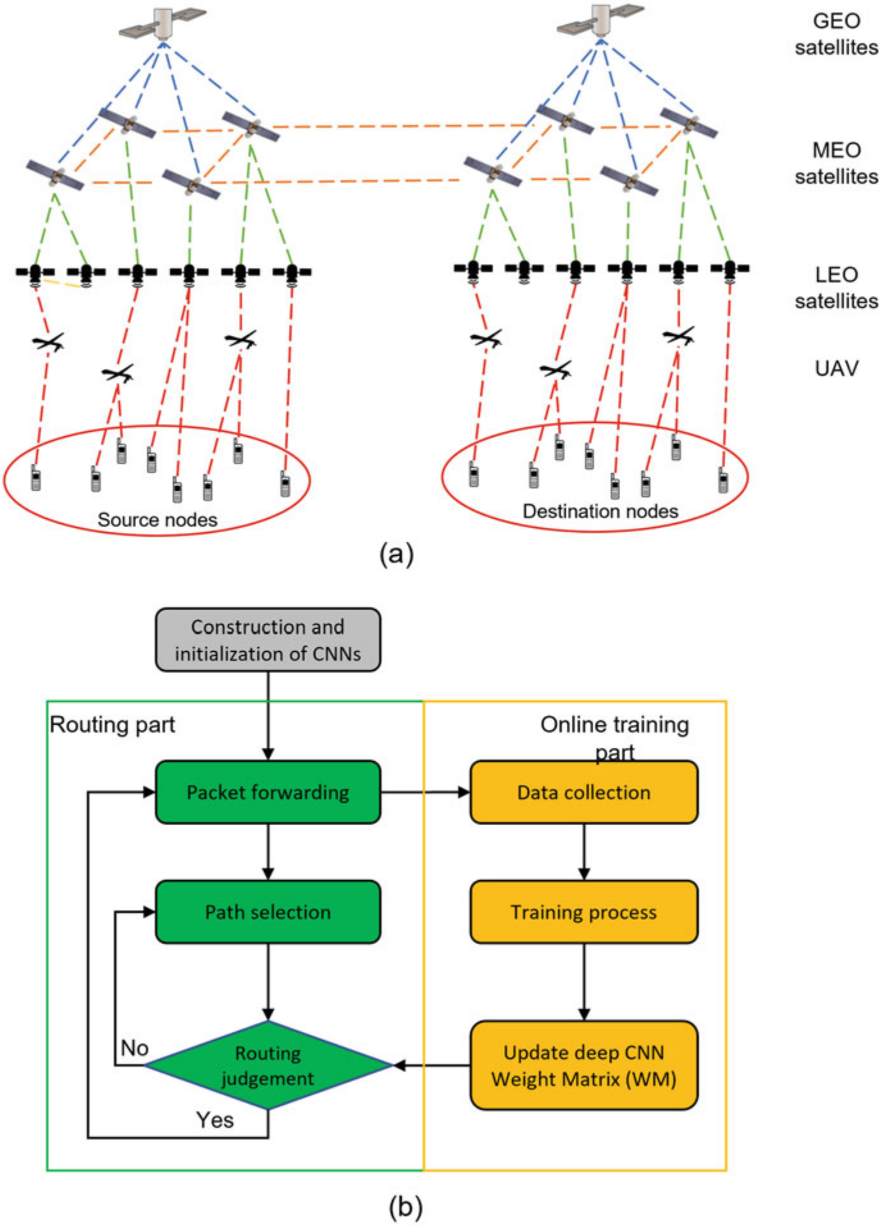

Fig. 7.4 Typical SAGIN network topology (**a**); flow chart of the proposed AI-based routing solutions (**b**) [34]

including relative positioning, communication and end-of-life management. To this aim some of the experiments that have been planned on the OPS-SAT mission [38] included artificial intelligence: as a matter of facts, to develop autonomous spacecraft that use artificial intelligence to take care of themselves would be very useful for exploring new parts of the Solar System and reducing mission costs.

In addition, it is becoming more common to find ML systems analysing the huge amount of data that comes from each space mission, including spacecraft telemetry and product data; another application of AI would be the analysis of all this data. It is worth stressing that data coming from some Mars rovers is being transmitted using AI: particularly, intelligent data transmission software on board rovers removes human scheduling errors which can otherwise cause valuable data to be lost. The same technology could also be used in long-term missions that will explore the Solar System, meaning that they will require minimal oversight from human controllers on Earth.

Nonetheless AI also currently lacks the reliability and adaptability required in new software; these qualities will need to be improved before it takes over the space industry.

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