ESA-CLAIRE AI4SatCom workshop: Proposed use-cases

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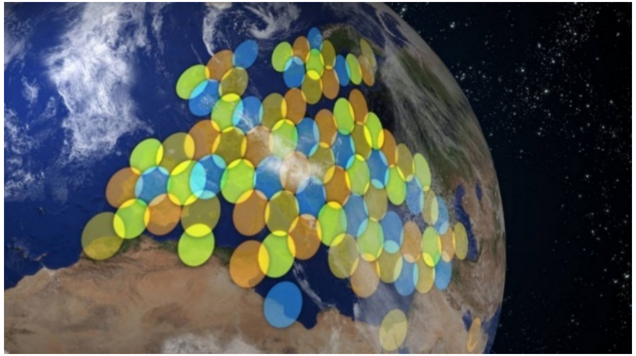
ESTEC, 10-11 January 2020

List of use-cases for use of Artificial Intelligence in SatCom

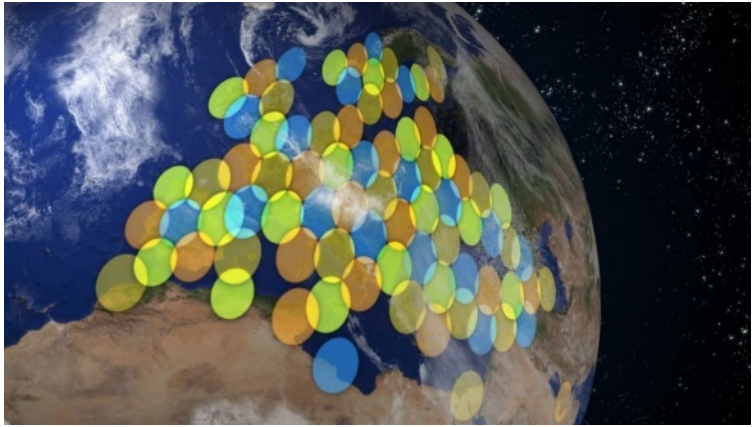
1. Flexible Payload Configuration
2. Spectrum management
3. Interference detection, classification and mitigation
4. Autonomous Operations for mega constellations
5. Anomaly detection, classification and prediction
6. Smart Manufacturing, Assembly, Integration and Testing



1- Flexible Payload Configuration

Management and optimization of the satellite payload resources, including control of carrier allocation, power transmission, beamforming and beam-hopping.

On-board payload systems self-configuration can be possible thanks to cognitive radios/payloads driven by AI algorithms.



1- Flexible Payload Configuration and Spectrum management: Use of AI trade-off

Strengths

- Use of neural networks (NN) proven in beamforming and beam-hopping allowing passive parallelism, adaptive learning capability, generalization capability and fast convergence rates.
- Already engaged with satellite operators who are willing to provide large datasets of telemetry and data to train and test AI algorithms.
- Pre-trained ML algorithms can be extremely fast in computing solutions on-board the spacecraft.
- Flexibility of algorithms to adapt to slightly different inputs.

Pre-conditions/ weaknesses

- Industry not ready to embrace technology requiring a considerable investment in computing resources and manpower for minor increases in performance.
- Not easy to benchmark performance with respect to state-of-the-art payload optimization tools based on deterministic algorithms.
- Many of the algorithms used so far are not outperforming results comparable to classical methods.
- ML algorithms limitation to convey the reasoning behind output selection.

Opportunities

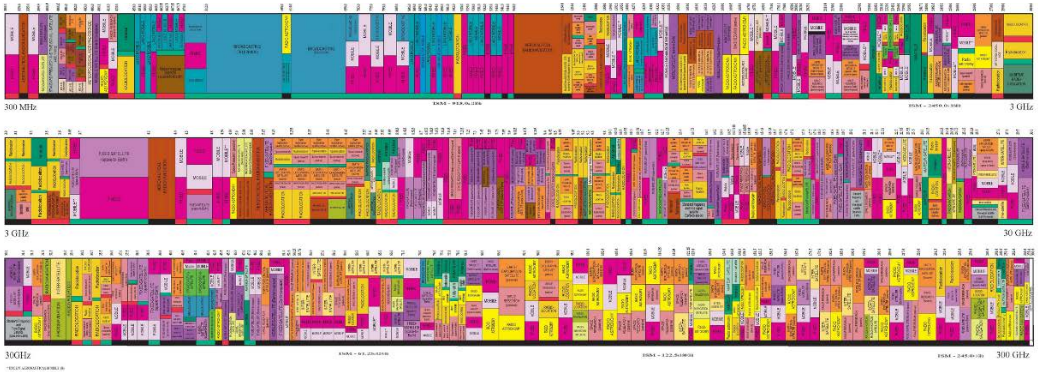
- Advancements in cognitive radio technology enable the integration of fast and efficient ML algorithms in SDRs (Software Defined Radios)
- Spin-in of state-of-the-art reinforcement learning algorithms for adaptive communication channels; modulation, carrier selection, power transmission selection.

Known performances

- Average accuracy higher than 80% demonstrated in channel adaptation using deep reinforcement learning [1].

2- Spectrum management

Emerging technologies like 5G and megaconstellations will add enormous pressure to the already existing spectrum congestion issue. Since most of the allocated frequency bands are unused or underutilized, automation of frequency allocations supported by AI could allow exploitation of the underused available spectrum resources.



2- Spectrum management: Use of AI trade-off

Strengths

- Optimization of frequency resources.
- Spectrum access enabler for 5G and Megaconstellations.
- Proven use of reinforcement learning as a way to improve spectrum utilization performance.
- State-of-the-art spectrum sharing research institutions (e.g. German and Spanish academia) and projects in Europe (e.g. CoRaSat [2], Sansa [3], Freestone [4], etc.).

Pre-conditions/ weaknesses

- Big latencies if the performance of the algorithm depends largely on RF sensing.
- Powerful computing resources required (RF sensing).
- Need to integrate cognitive radios within the satellite payload to enhance system capabilities.

Opportunities

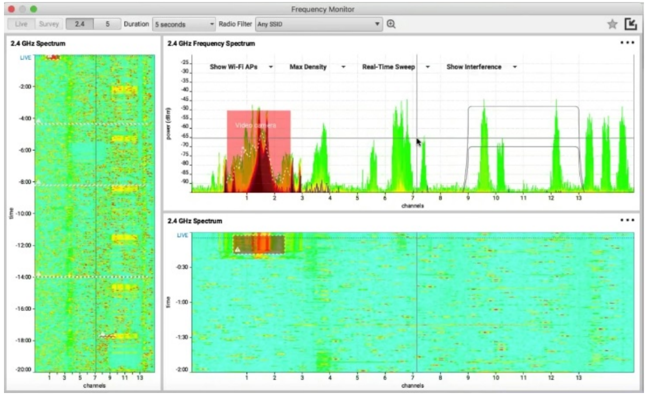
- Exploitation of ELAINE ESA internal project (*project about spectrum optimisation).
- Possibility to use advanced and tested CNN algorithms as a deep learning-based radio environment monitoring.
- Advancements in cognitive radio technology enable the integration of fast efficient ML algorithms in SDRs.
- Spin-in of state-of-the-art reinforcement learning algorithms for adaptive channel in communications; modulation, carrier selection, power transmission selection.
- In-depth research on the use of reinforcement learning for spectrum sensing in time-varying environments.

Known performances

- Proven use of reinforcement learning can improve performance of spectrum utilization by one order of magnitude.

3- Interference detection, classification and mitigation

At the present, although the communications payload may have features that support interference detection, classification and mitigation, human analysis and interaction is required to manage the interference environment and limit its negative impact on communication services. This is normally a time consuming process that can sometimes lead to serious service outages before the problem can be solved. AI offers the promise of autonomous or semi-autonomous on-board interference detection, classification and mitigation methods which would translate into almost immediate communications link recovery.



3- Interference detection, classification and mitigation: Use of AI trade-off

Strengths

- Precise and faster anomaly detection and classification methods.
- Interference compensation algorithms based on deep learning-based methods can simplify signal processing without accurate mathematical modelling.

Pre-conditions/weaknesses

- High latency of the performance of the algorithm depends largely on RF sensing.
- Powerful computing resources required (RF sensing).
- Need to integrate cognitive radios within satellite payload to enhance system capabilities.

Opportunities

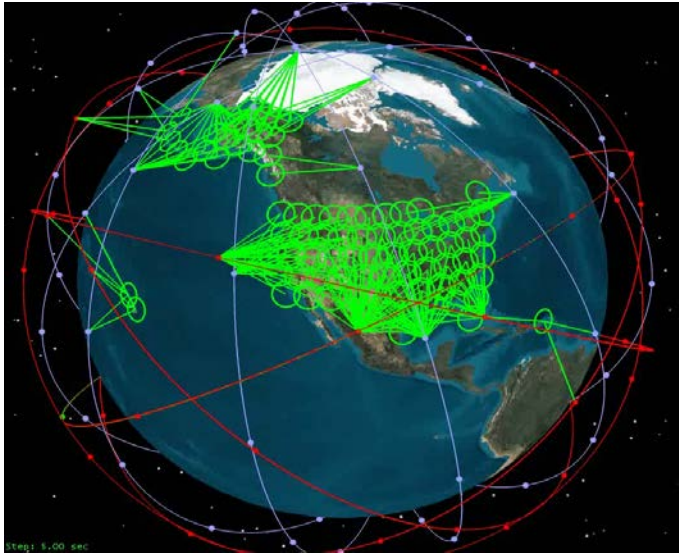
- Advancements in cognitive radio technology enable the integration of fast and efficient ML algorithms in SDRs.
- Spin-in of state-of-the-art reinforced learning algorithms for adaptive communication channels; modulation, carrier selection, power transmission selection.
- In-depth research on the use of reinforcement learning for spectrum sensing in time-varying environments.

Known performances

- Demonstrated increase in performance of co-channel interference optimization using neural networks with regard to state-of-the-art non-ML-based algorithms. [5]

4- Autonomous Operations for mega constellations

Constellations of 100s or even 1000s of spacecraft will require almost complete on-board autonomy in order to allow the operations to be run with minimum human control. ML is set to play a major role in enabling the autonomy necessary to operate enormous constellations and completely automate on-board collision avoidance systems.



4- Autonomous Operations for mega constellations: Use of AI trade-off

Strengths

- Possibility to test ML algorithms with simulated data (no prior need for real spacecraft data).
- Several projects already running in industry (Megaman[7] funded by Innovation Fund Denmark and run by 2Operate and AIKO[8] -> ACT involved).

Pre-conditions / weaknesses

- Industry not yet willing to accept non deterministic-based algorithms for critical tasks / missions (i.e. rendezvous and docking for on-orbit refueling) or fleet station-keeping.
- One of the major limitations is the need of a considerable amount of data from anomaly events in order to prevent false positives.

Opportunities

- Reduce the amount of operator hours required to manage satellite constellations and to identify the root-cause of operational events. That means that network incidents could be resolved much faster, thus improving the availability of the satellite services.
- Optimize ground station connectivity and thereby increase the overall data download efficiency / useful link capacity.
- There is no existing system today able to handle operations of hundreds or thousands of satellites. That is a big opportunity for ML to fill the gap and provide a workable solution to the problem.
- Strong OPS* heritage on autonomous operations. For example, the ML-based scheduling and planning system performed in the frame of FDL Mission Support challenge 2019 for Cluster II could be scaled up and applied for operations planning for commercial SatCom constellations.

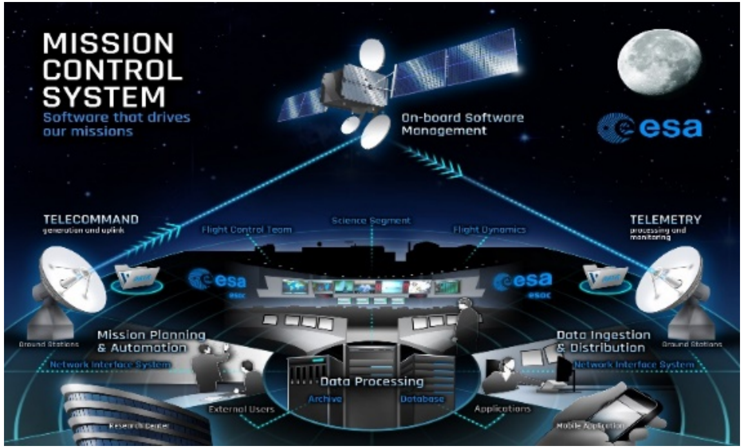
*OPS: ESA's Directorate of Operations based in Darmstadt, Germany

Known performances

- Performance and trade-off analysis against conventional manual management systems still not available (for megaconstellations).
- Performance for spacecraft pose-estimation / spacecraft attitude using CNN available as part of the Kelvins challenge (current prediction on real images still not mature).

5- Anomaly detection, classification and prediction

Advancements on AI-based classification and prediction methods have improved notably the capabilities of anomaly detection, classification and prediction. Some examples of the performance of such algorithms have been produced by OPS and their work can be used as heritage by AI experts for future developments applied to SatCom.



5- Anomaly detection, classification and prediction: Use of AI trade-off

Strengths

- Precise and faster anomaly detection and classification methods.
- Recent developments in deep anomaly detection [6] have notably empowered anomaly detection and classification as well as novelty detection.

Pre-conditions / weaknesses

- Classification-based methods for supervised or semi-supervised techniques have expensive training times.
- Unsupervised techniques require prior knowledge to be assumed on the anomaly distribution, hence the models are less robust in handling noisy data.
- Hybrid model approach is suboptimal because it is unable to influence representational learning in the hidden layers [6].
- Need of a considerable amount of anomaly data in order to prevent false positives.

Opportunities

- Anomaly detection is an important problem well-studied within diverse research areas including bank fraud, medical problems, structural defects, malfunctioning equipment, etc. We can spin-in developments from those industries into space.
- Internal ESA (OPS) know-how in this field could be merged with knowledge coming from academia and together build stronger solutions
- Industry supporting scientific anomaly detection and prediction activities for OPS could expand their portfolio into telecoms (e.g. OPS already developed TECO for Alphasat).

Known performances

- Very good performances in detection and classification of anomalies using multivariate statistical analysis (PCA + Mahalanobis distance) and artificial neural networks (e.g. autoencoders).

6- Smart Manufacturing, Assembly, Integration and Testing

Advancements in machine learning-based technologies have brought the opportunity to accelerate manufacturing processes and improving decision making. With the widespread deployment of sensors and Internet of Things, there is an increasing need of handling big manufacturing data characterized by high volume, high velocity, and high variety. Deep learning provides the necessary tools for processing and analysing big manufacturing data allowing companies to monitor manufacturing quality as well as optimizing operations

6- Smart Manufacturing, Assembly, Integration and Testing: Use of AI trade-off

Strengths

- Existing research on ML applied to smart manufacturing shows the benefits of computational methods based on deep learning to improve system performance [9].
- Allow monitoring and control of whole manufacturing network as well as check of major performance functions based on Internet of Things

Pre-conditions/ weaknesses

- Security and Privacy: Since many organizations store the data in virtual cloud platforms, a leakage or misuse of data can pose a threat and even the manufacturing process could be compromised.
- Increase of complexity in the manufacturing environment including also additional skills required by manufacturing operators to allow integration of smart manufacturing processes.

Opportunities

- Monitoring quality of assembly process while optimizing operations
- Bring down labor costs
- Reduce product defects and detect anomalies faster during testing
- Shorten unplanned downtimes
- Increase production speed (essential to enable fast manufacturing of megaconstellations)
- Major companies including GE, Siemens, Intel, Funac, Kuka, Bosch, NVIDIA and Microsoft have already been investing in machine learning-powered approaches to improve all aspects of manufacturing Know-how and technological developments from those companies can [10] be spin-in into space for smart manufacturing.

Known performances

- Machine learning can improve product quality up to 35% in discrete manufacturing industries, according to Deloitte [11].

References

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