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Theoretical scenarios and Use Case definitions for AI processing

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List of Acronyms

AI: Artificial Intelligence

AI/ML: Artificial Intelligence and Machine Learning

ANNs: Artificial Neural Networks

CNN: Convolutional Neural Networks

DNN: Deep Neural Networks

EML: Edge Machine Learning

GA: Genetic Algorithm

HAPS: High Altitude Platforms

MEC: Mobile Multi-Access Edge Computing

ML: Machine Learning

NFV: Network Function Virtualization

PCA: Principal Component Analysis

PSO Particle Swarm Algorithm

SDN: Software-Defined Networking

SVM: Support Vector Machines

UCs: Use Cases

1. Introduction

Artificial Intelligence (AI) processing has transcended conceptual boundaries to become a fundamental tool in a wide range of applications.

In this document we study applications in different scenarios, such as, for example, in the use of remote sensing data to identify environmental patterns, in active protection through connected vehicle security systems, in the implementation of advanced algorithms for the precise search of people and finally in the prevention and prediction of forest fires.

AI has revolutionized the way we address crucial challenges in various fields. This detailed exploration looks at theoretical use cases and practical scenarios where AI processing plays a critical role.

2. Overview and Research Directions

According to [1] numerous research areas are being explored in the context of AI within cloud-enabled High-Altitude Platforms (HAPS), with some examples being:

- HAPS Security via Blockchain and Machine Learning (ML)

The proposed research direction involves implementing a blockchain model enhanced with ML for securing data and access to HAPS cloud services. This model leverages blockchain's capabilities to encrypt and decrypt data exchanged between cloud users and providers. Combines blockchain technology with ML to enhance the security and transparency of HAPS cloud services, safeguarding financial transactions and data while actively detecting and preventing attacks on the blockchain network.

The blockchain model consists of two components: Financial Transactions Blockchain and Data Blockchain.

A machine learning model is employed to monitor and manage blockchain operations, detecting any attempts at attacks on blockchain data and messages. For example, if an attacker tries to insert malicious transactions into the blockchain, the ML algorithm analyses node behaviour and messages to identify the attack. The ML model continually monitors exchanged messages, encrypted content, and compares them to known attack signatures and behaviours from its training data. Detected attacks are incorporated into the training data to improve the model's ability to identify similar future attacks.

- Intelligent Cloud-Enabled HAPS

Edge computing involves bringing some cloud computations closer to the data source, reducing data bandwidth, improving latency, and easing cloud computing demands. Network Function Virtualization (NFV) and software-defined networking (SDN) complement edge computing, allowing for modular and reconfigurable network adaptability, particularly through network slicing.

Artificial Intelligence and Machine Learning (AI/ML) are expected to play a significant role in cloud-enabled HAPS systems. ML excels in dealing with complex, large design spaces and can replace cumbersome rule lists with automated feature extraction. In HAPS systems, which have vast and time-varying parameter spaces, ML can help set and adapt network parameters based on actual usage patterns.

Edge Machine Learning (EML) is used for training, inference, and Mobile Multi-Access Edge computing (MEC) to enhance latency, reliability, and distributed network resources. However, EML faces challenges like long training times and computational demands.

ML techniques vary in suitability depending on the service and application domain. For instance, Artificial Neural Networks (ANNs) are apt for prediction services, while reinforcement learning is useful for optimization with specific goals like service latency. Each ML technique has advantages and drawbacks, making them suitable for specific applications.

Selecting an ML platform is challenging as there's no one-size-fits-all solution. Factors like scalability, speed, coverage, usability, extensibility, and programming language support must be considered. The choice should align with application requirements and cloud-enabled HAPS architecture constraints.

In summary, the integration of AI/ML into cloud-enabled HAPS systems offers improved adaptability and optimization, but careful consideration of ML techniques and platforms is essential to match specific application needs.

- **AI-Based Resource Allocation**

The performance of proposed cloud-enabled HAPS systems relies heavily on interference management techniques, especially those designed to handle radio resource management across HAPS, air, and ground networks. These techniques aim to strike a balance between various network functionalities, including data rate, energy efficiency, power usage, latency, coverage, and security. The optimization of system parameters, such as spectrum allocation, HAPS transmit power, traffic routing, inter-HAPS links, and edge/core processing capabilities, presents a complex resource allocation challenge in cloud-enabled HAPS networks.

Considering the dynamic nature of ground communication infrastructure and the stochastic behaviour of HAPS-to-ground and HAPS-to-air channels, AI-based techniques are expected to play a pivotal role in designing and optimizing future cloud-enabled HAPS networks. ML in particular holds promise for solving complex optimization problems in this context. This opens numerous research opportunities in the field of dynamic resource optimization within cloud-enabled HAPS networks, making it a vibrant area for future research.

3. Scenarios for the use of on-board AI processing

In this part of the document, we define some applicability scenarios showing how onboard AI processing improves efficiency, responsiveness, and capabilities in a wide range of applications, allowing devices and systems to perform complex tasks with less dependence on external computing resources.

3.1. Remote sensing

AI has become an invaluable tool in the analysis of satellite images for the identification and classification of land use and land cover. Here is some ways AI is applied in this context:

- **Image Segmentation and Classification:** AI algorithms can analyze large sets of satellite images to automatically segment and classify different types of terrain, such as urban areas, forests, crops, bodies of water, etc. AI can identify visual patterns to assign labels to different regions in images [2].
- **Change Detection:** AI can compare satellite images taken at different times to identify changes in land cover over time. This is useful for monitoring deforestation, urban growth, crop expansion, among other changes [3]
- **Prediction and Modeling:** AI models can predict future land cover changes using historical data and environmental variables. For example, they can predict areas prone to deforestation or identify optimal locations for certain types of crops. [4]

3.2. Search and location of people

The search and location of people plays a critical role in emergency situations, rescue operations and in solving important cases. AI processing has emerged as a fundamental ally in this work, using different techniques and tools.

- **Image and Video Analysis:** AI algorithms can analyse images and videos from surveillance cameras, drones, or body cameras to recognize faces or distinctive characteristics that help identify a missing person. This technique is useful in search and rescue systems. [5]
- **Mobile Data Analysis:** Mobile phone data, such as GPS location, call logs or app data, can be analysed by AI algorithms to track a person's last known location, and predict possible movements.
- **Biometric Recognition:** AI can use biometric data such as fingerprints, irises, or even voice patterns to identify people of interest in public environments or security systems.

- **Use of Drones with AI Technology:** Drones equipped with cameras and AI algorithms can conduct aerial searches over large areas, identify unusual patterns or detect visual signals that indicate the presence of a person. [6]
- **Automatic Alert and Notification Systems:** AI can be part of early warning systems that identify emergency situations, such as disappearances, and automatically notify the appropriate authorities.

3.3. Early support in firefighting with forest fire alarm

Amid growing concerns about environmental preservation and community safety, wildfires represent an urgent challenge. Early detection and rapid response are critical to containing and extinguishing these fires before they become uncontrollable catastrophes.

In this context, AI processing has emerged as an important resource, playing a crucial role in the early detection of forest fires through advanced alarm and warning systems. By combining data analytics such as satellite imagery, weather data, and ground sensors, AI not only identifies fires in their early stages but also enables a rapid and coordinated response.

- **Satellite and Drone Image Analysis:** AI algorithms analyse satellite and drone images in real time to identify changes in the pattern and type of land use, which may indicate the presence of a light or moderate fire.
- **Machine Learning for Fire Patterns:** Machine learning algorithms can analyse historical fire patterns, combining data on weather conditions, topography, and fire-prone areas to predict higher risk areas.
- **Alert and Notification Systems:** AI processes the information collected to generate automatic alerts and precise notifications to response teams, streamlining the mobilization of resources and extinction equipment.

3.4. Connected Vehicle Security

Safety in connected vehicles is a central concern as the technology becomes more deeply integrated into modern automobiles. Artificial Intelligence processing plays a crucial role in ensuring safety in these connected vehicles, addressing a series of key aspects:

- **Cyber Security:** AI helps detect and prevent cyber-attacks on connected vehicle systems. Algorithms can constantly monitor car networks, identify anomalous behaviour, and activate protective measures to prevent unauthorized intrusions.
- **Personalization and Driving Profiles:** AI systems can adapt to individual driving patterns, providing personalized safety recommendations and adjusting vehicle parameters according to the driver's preferences.

- **Verification and Authorization:** If the detected facial features match the stored data, the system authorizes the ignition of the vehicle, allowing the driver to start the engine.

4. UCs for each scenario

This section presents a set of use cases that will be developed to verify the proposed metrics and architectures. We have selected these use cases for their breadth of functional coverage rather than embarking on the impossible journey of defining an exhaustive set of use cases that benefit from AI processing.

We have defined the use cases, considering the following system functionalities:

- Land cover classification using AI.
- Artificial vision for search/location of people.
- Detection of forest fires and alert calls to firefighters in high-risk forest areas using AI.
- Security of the connected car in terms of ignition, using facial recognition.
- Management of secure component certificates (supply changes) without AI to use as a control tool.

4.1. UC1- Fire detection and risk areas

4.1.1. UC1- description

Fire detection involves early identification of active or potential fires, while risk zone identification focuses on predicting and mapping areas prone to fire spread. The combination of these strategies allows for a faster and more efficient response for the prevention and control of forest fires.

4.1.2. UC1- situations

- **Situation UC1-A:** A forest fire prevention group wants to carry out controlled burning in a certain area, they need to control the perimeter in case there is a risk of fire dispersion.
- **Situation UC1-B:** A forest fire prevention group needs to control the perimeter using aerial vision of the terrain in case there is a risk of fire dispersion.
- **Situation UC1-C:** A fire prevention team wants to scan a high fire risk area to detect the fire as soon as possible.

4.1.3. UC1- Deployment requirements

- IR camera.
- Onboard AI processing (execution, not training, i.e. low computing needs).
- Geographic position of the cluster, or the air element, to know which one we deploy to.

4.2. UC2- Land use and cover

4.2.1. UC2- description

The determination of land use and cover is a process that involves identifying and classifying the different categories of land and their occupation by different forms of life (vegetation, crops, urban areas, bodies of water, among others). This analysis is carried out to understand how land is used and distributed in each geographical area.

4.2.2. UC2- situations

- **Situation UC2-A:** A fire prevention group wants to analyze a specific area to determine the risk of fire based on the types of forests present in the area.
- **Situation UC2-B:** An environmental group wants to analyze land cover to determine the presence of wetlands, types of crops, urban constructions and be able to do a multi-temporal analysis of land use.
- **Situation UC2-C:** A group of experts wants to train a neural network to make a model that detects the elements present in a satellite image.

4.2.3. UC2- Deployment requirements

For situations A and B:

- Hyperspectral camera.
- Medium computing capacity for AI.
- Expand all up.
- Geographic position of the cluster with the camera.

For situation C:

- Hyperspectral Camera.
- High computing capacity for AI.
- Mixed deployment (image sending, image processing).
- Geographic position of the cluster with the camera.

4.3. UC3- Connected Vehicle Certificate Validation

4.3.1. UC3- description

Validating the certificate of a connected vehicle for ignition involves ensuring the authenticity and legitimacy of the identity of the vehicle and the user authorized to use it. This process is essential to ensure security and protection against unauthorized access to key vehicle functions.

4.3.2. UC3- situations

- **Situation UC3-A:** The vehicle manufacturer wants to deploy a service that controls the certificate for the security of the connected vehicle (supply chain) to verify that third-party components are correctly certified by the corresponding manufacturer.
- **Situation UC3-B:** Due to the large influx of connected vehicles, the connected vehicle manufacturer needs to scale a certain service to the new demand of requests.

4.3.3. UC3- Deployment requirements

- Geographic position of cluster near the vehicle.

4.4. UC4- Verification and authorization for ignition of the connected vehicle

4.4.1. UC4- description

Verification and authorization for starting a connected vehicle involves an authentication and validation process that ensures that the user trying to start the vehicle is authorized to do so.

4.4.2. UC4- situations

- **Situation UC4-A:** The vehicle manufacturer wants to deploy a facial recognition service using AI to activate the vehicle with the authorized driver.

4.4.3. UC4- Deployment requirements

- Low AI processing capacity.

4.5. UC5- People search and location.

4.5.1. UC5- description

Locating and searching missing people is a crucial operation in a UC using AI. It covers multiple situations where lives can be saved.

4.5.2. UC5- situations

- **Situation UC5-A:** After an emergency alarm for a missing person, rescue teams want to activate a service to search and locate people in danger.
- **Situation UC5-B:** During a disaster or firefighting operation, the person in charge can deploy a service to locate all team members (agents, volunteers...)
- **Situation UC5-C:** During a chase, the security forces want to use a service that allows the location of fugitives.
- **Situation UC5-E:** At mass events, such as concerts or festivals, organizers can use AI-equipped drones to monitor the crowd and locate people who have become separated from their groups or who need immediate medical assistance.

4.5.3. UC5- Deployment requirements

- EO camera.
- High computing capacity High/Medium.
- Mixed deployment (image sending, image processing).
- Geographic position of the cluster with the camera.

4.6. UCs Diagram

The next diagram offers a visual representation of the system's structure and interactions tailored to specific scenarios. This diagram outlines how different components and modules work together to address various use cases, ensuring seamless integration and efficient operation. By illustrating the relationships and data flows between system elements, it provides a clear and comprehensive understanding of how the architecture supports specific functionalities and objectives. This foundational overview aids in the design, implementation, and management of the system, ensuring it meets the targeted needs and performance goals.

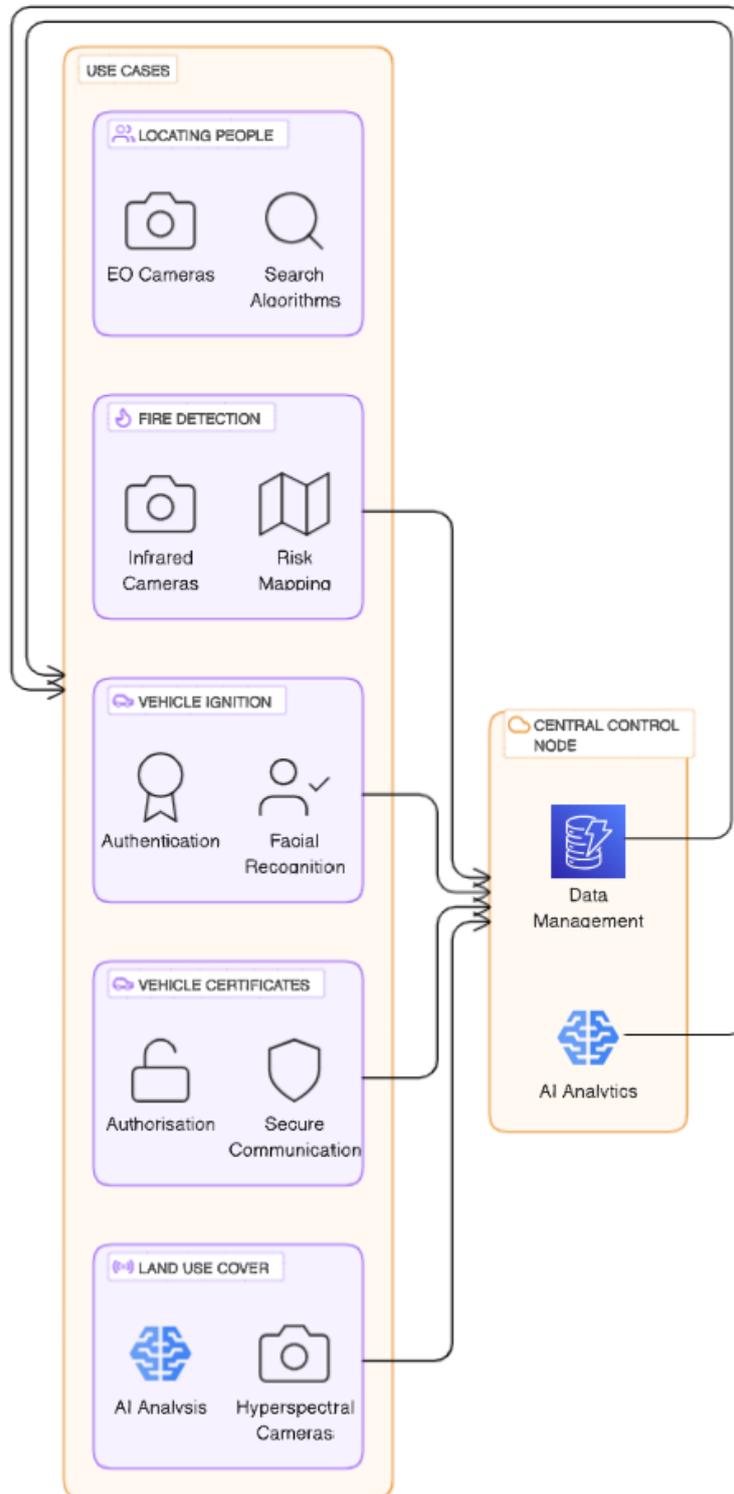


FIGURE 1 UCS ARCHITECTURE DIAGRAM

4.7. Flow diagram

The next Diagram illustrates the comprehensive process involved in managing and analysing data within a federated nodes environment. It provides a clear overview of the sequential steps and interactions between these components, highlighting the flow of data from collection to analysis and reporting.

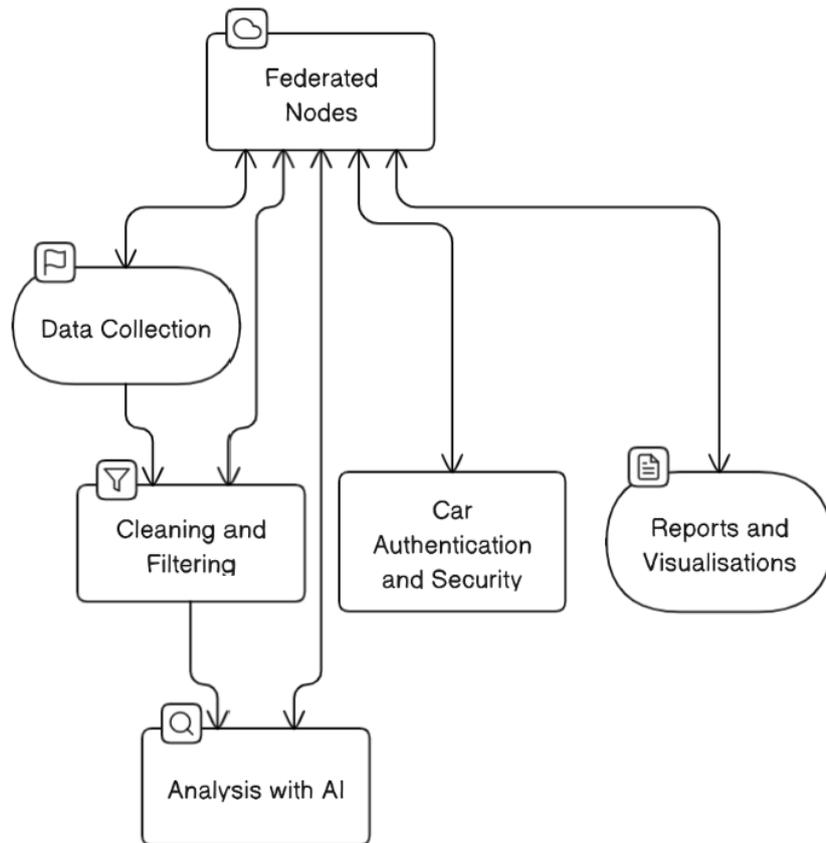


FIGURE 2 FLOW DIAGRAM

4.8. AI process type identification

This section outlines the processes driven by AI in each UC. AI is integrated to optimize and automate tasks, enhance the accuracy of analyses, and provide valuable insights. Through specific examples, we will explore how AI is applied in various scenarios to manage data, perform predictive analyses, optimize resources, and improve decision-making in complex environments.

4.8.1. UC2 – Land use and cover

In this part of the document, we will address the description of the AI processes applicable to the UC2. Following the objective established for the use case and the scenarios proposed in section 4.2, we have structured the use case into specific tasks. In each of these tasks, we will explore the various AI processes that can be implemented to optimize and enhance the execution of activities.

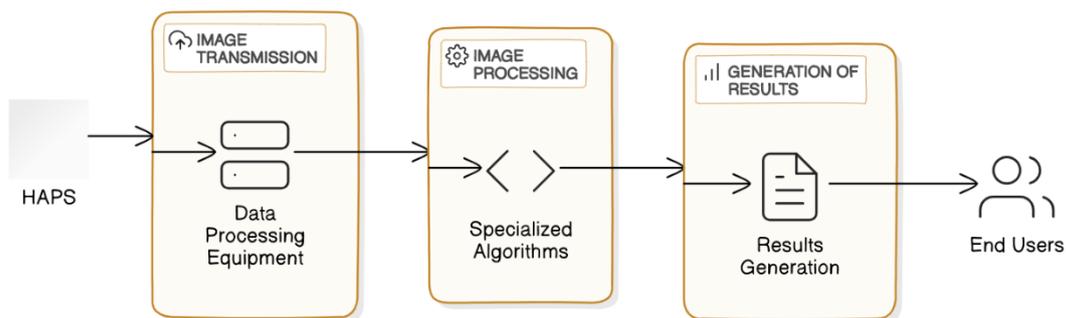


FIGURE 3 PROCESSING WORKFLOW

1. Capture of Hyperspectral Images from the HAPS

The HAPS performs flights over the area of interest, capturing high-resolution hyperspectral images. Images are acquired from a high altitude to obtain a panoramic and detailed view of the terrain.

Applicable AI processes:

- Intelligent Route Planning

Description: In this stage, trajectory planning algorithms are used to optimize the HAPS path, ensuring exhaustive coverage and high resolution of the areas of interest.

Detail: Trajectory planning algorithms, such as the Particle Swarm Algorithm (PSO) and the Genetic Algorithm (GA), are essential to determine the most efficient HAPS flight path. These algorithms have been successfully applied in the optimization of flight paths for the capture of hyperspectral images, maximizing coverage and minimizing the energy consumption of the aerial vehicle. [7]

- Autonomous Image Quality Monitoring

Description: This phase involves the use of AI systems to evaluate image quality in real time and adjust HAPS flight parameters to ensure high-quality data capture.

Detail: AI systems such as Convolutional Neural Networks (CNN) and Canny Edge Detection Algorithm play a crucial role in continuously monitoring the quality of images captured by the HAPS.

These methods have been shown to be effective in detecting image quality problems, such as blurring and distortion, allowing real-time adjustments to improve capture quality [8].

2. Image Transmission

The captured images are transmitted to data processing equipment on the ground. A reliable data connection is used to ensure fast and secure transfer of images.

Applicable AI processes:

- Optimization of Data Transmission

Description: Use of image compression algorithms and intelligent data selection methods to optimize the transmission of images from the HAPS to data processing equipment on the ground.

Detail: Image compression algorithms, such as JPEG and PNG, can reduce the size of images without significantly compromising their visual quality, resulting in more efficient transmission of data [9]. Additionally, intelligent data selection methods, such as the machine learning-based approach, can prioritize the transmission of identified areas of interest in real time, minimizing the bandwidth required for transmission and ensuring fast and secure delivery of images. [10].

3. Image Processing

The data processing team uses specialized algorithms to analyze the hyperspectral images. Tasks such as image segmentation, land use classification, and geographic feature identification are carried out.

Applicable AI processes:

- Image Segmentation

Description: Use of image segmentation algorithms to divide hyperspectral images into homogeneous regions, facilitating detailed analysis.

Detail: Segmentation methods such as CNN and Semantic Segmentation have proven to be effective in segmenting hyperspectral images. Deep learning models such as U-Net and Mask R-CNN are particularly useful in this context [11] [12].

- A self-developed method to create land use maps semi-automatically from hyperspectral images.

The process is based on a hyperspectral image, which contains multiple bands reflecting how the ground responds to different ranges of electromagnetic radiation. The first step is to apply a band reduction using Principal Component Analysis (PCA), which consolidates the bands into more manageable groups, representing most of the relevant information. For example, the visible

spectrum can be divided into groups corresponding to the colors red, green, and blue, while the non-visible spectrum can be divided into groups such as near and far infrared.

Images visible to humans are made up of RGB (red, green and blue) bands. However, for specific applications, bands of different electromagnetic ranges can be used in these components to highlight non-visible features, such as high radiation in hot areas of a fire. These combinations are called masks and are stored in a mask dictionary.

The semi-automatic part of the system involves generating a binary mask of each representation to identify relevant pixels. Clustering algorithms, such as controlled k-means, are then used to isolate and define the highlighted areas. Finally, the soil types in the image are identified using classification algorithms or clustering models developed for this purpose. The results obtained can be seen in the following image.

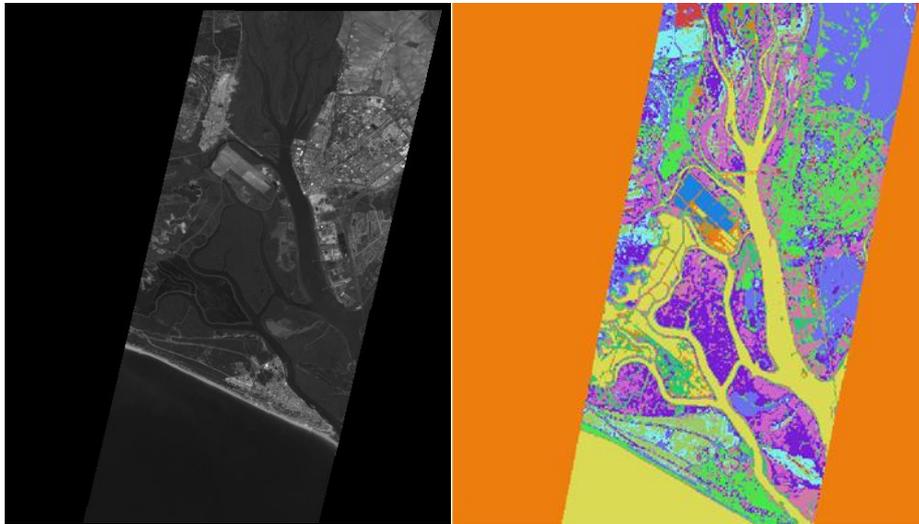


FIGURE 4 RESULT OF THE APPLICATION OF THE SEMI-AUTOMATIC CLASSIFICATION ALGORITHM

- Land Use Classification

Description: Application of classification algorithms to identify and categorize different types of land use in hyperspectral images.

Detail: Algorithms such as Support Vector Machines (SVM), Random Forest, and Deep Neural Networks (DNN) are commonly used for land use classification. CNN are also widely used to improve classification accuracy by extracting relevant features from hyperspectral images [13] [14].

The general objective of image classification is to interpret, from an image, the different classes that said image contains. In this case, the hyperspectral image aims to classify the different types of soil that the image contains.

We have developed an algorithm that takes multi-spectral data to perform the correct classification of each pixel. To do this, the patterns created from combinations of the data obtained from the hyperspectral image are used.

The interpretation algorithm was developed by training a neural network, which is responsible for using the processed hyperspectral image, transforming the values of each layer into different combinations, so that the algorithm can process said data, eliminating any type of anomaly or bias of these and transforming them into a range of defined characteristics, understandable for decision making.

- Identification of Geographic Features

Description: Use of feature detection and recognition algorithms to identify specific geographic features in hyperspectral images.

Detail: Deep learning techniques, such as CNN and Transfer Learning models, are essential for the accurate identification of geographic features. These algorithms can detect features such as water bodies, urban areas, and specific types of vegetation with high precision [15] [16].

Applicable AI processes:

- Self-developed classification algorithm

This section will explain the self-development process that uses artificial intelligence techniques to classify images. The following illustration shows a flowchart that describes the algorithm's journey to classify hyperspectral images. This process is divided into three large blocks, which are detailed below.

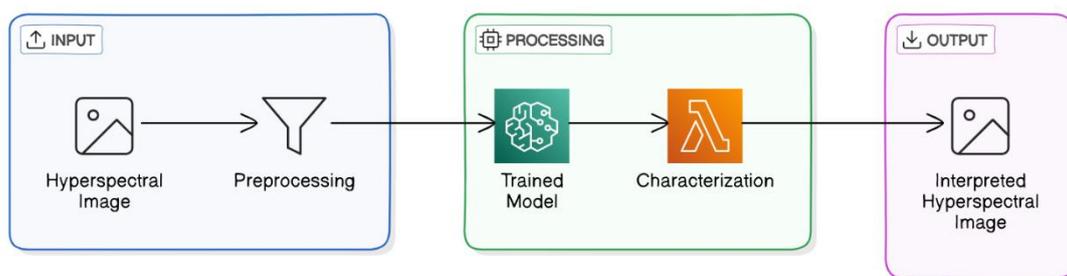


FIGURE 5 HYPERSPECTRAL IMAGE PROCESSING WITH AI

To start this algorithm, we start from a preprocessed hyperspectral image, in addition to a model trained using an interpretation algorithm. The image represents a portion of the map that contains information specific to the use of the geographic area.

In the processing stage, we have approached the problem using Artificial Intelligence, specifically supervised learning, where we previously know the input data of the network. For this, we have developed a CNN, widely used in image characterization. CNNs mimic the visual cortex of the human

eye to identify various features. They are made up of a convolution layer, which detects the different details of the image by taking groups of nearby pixels, and an ANN, which is responsible for learning by assigning different levels of importance to the neurons.

Once the network has been designed and the training data (images containing the classes we want to detect) has been obtained, we proceed to train the model. The training process involves passing data through the model multiple times, known as iterations or epochs. To ensure correct training, several tests are carried out modifying some basic parameters. When an acceptable success rate is reached, the training is considered completed and the configuration that provided the best results is saved.

As an output result in our scheme, we will obtain each pixel characterized with the class that the trained neural network model has decided best fits what has been trained. There is a possibility that a pixel has more than one class inside it. In that case, the pixel will take the characterization of the class that has the highest percentage.

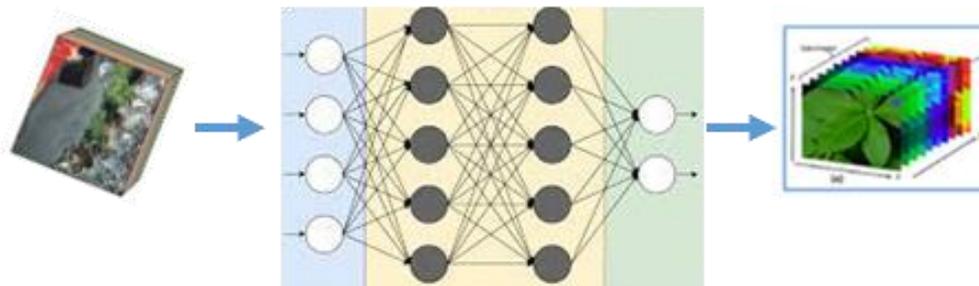


FIGURE 6 TRAINING NEURAL NETWORK MODEL

4. Generation of Results

Once processed, results are generated that show the distribution of land use and land cover in the area of interest. These results are presented in the form of maps, graphs, or other visual formats understandable to end users.

Applicable AI processes

- Generation of Thematic Maps:

Description: Thematic maps show the distribution of land use and land cover in a visually intuitive way.

Detail: Clustering and classification algorithms (e.g., K-means, Random Forest) to group and label different land cover types [17].

5. Use of Results by End Users

End users use the analysis results to make informed decisions in their respective fields such as urban planning, agriculture, environmental conservation, etc. These results can contribute to more effective

management of the territory and natural resources. These results provide valuable information that can contribute to more effective management of the territory and natural resources.

Applicable AI processes

- Predictive Analysis for Urban Planning:

Description: These models can predict urban growth and infrastructure expansion based on historical patterns and current data [18].

Detail: Machine learning models such as Random Forest and SVM.

- Optimization of Resources in Agriculture:

Description: These tools optimize crop management, predicting yields and recommending efficient agricultural practices [19].

Detail: ANN and GA.

- Environmental Monitoring and Conservation:

Description: CNNs are used to identify changes in vegetation cover and detect areas at risk of degradation [20]

Detail: CNN and Anomaly Detection Algorithms.

4.8.2. UC3 – Connected vehicle certificate validation

The third use case base is the comparison between manufacturer validated certification for the IoT devices deployed on the vehicle and the currently deployed version of the software used in these devices. So, is not necessary to implement any AI for that purpose, is a direct comparison between versions.

4.8.3. UC4 – Verification and authorization for ignition of the connected vehicle

On the fourth use case, for the verification and authorization of the driver, there are many processes. For example, the camera acquisition flow, the analysis of these images, the requests for allowed drivers or the vehicle ignition allowance. Nevertheless, only in the image analysis and the comparison between the driver and the allowed users, AI is used.

Face recognition and biometric authentication has been a much-studied topic during the last years. Specially with the Machine Learning and Artificial Intelligence development. The las studies have reached such a level of accuracy that the latest studies are going in the direction of optimizing real time recognition. For example, one of the latest articles [21] develops a method that now is being

used by Google. From the analysis of the utilization of TensorRT accelerated reasoning technology to improve the speed and performance of face recognition and the role of GPU in face recognition an algorithm with a speed of 0.6 milliseconds for mobile application has been developed.

Nevertheless, for a use case as the one being studied here. It is not necessary such good performance. The driver wants to power on the vehicle in a small period of time not in 0.6 milliseconds. For that, a simpler algorithm has been used.

The used algorithm uses a technique similar to the one presented in another paper in which the component-based approach is analysed in front of the classic holistic approach. [22]

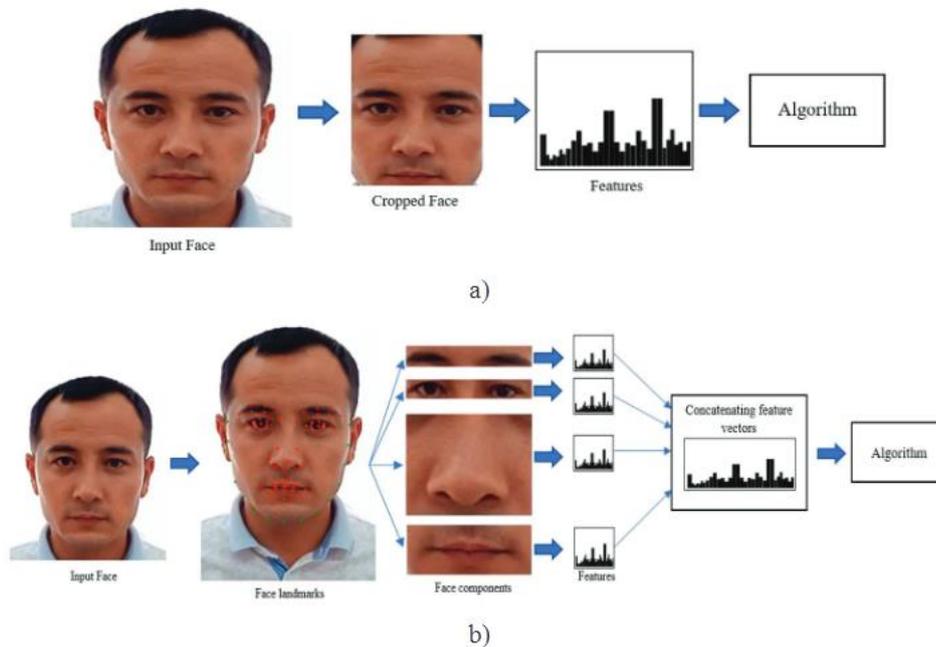


FIGURE 7 HOLISTIC VS COMPONENT-BASED APPROACHES IN FACE RECOGNITION [22]

In the classic way, the feature vectors are extracted from the whole face image. For the component-based approach, the first step is to locate the main features of the face. That could be, the mouth zone, the nose zone, the eyes, and the eyebrows. And from each one, a feature vector is obtained. The, all the vectors are integrated to generate a features vector more characteristic of each face.

In the use case, the library used [23] for that purpose implements a ResNet convolutional network with 29 convolutional layers in addition of a model for the face landmark's location. A 5-point landmark location model which identifies the corners of the eyes and the bottom of the nose.

There are not so strict latency requirements because it is not needed a frame rate flow of 25 fps for example, with a frequency of 1 or 2 frames per second is more than enough to detect the driver. So,

the processing power of the machine running the face recognition model is not needed to be so high.

4.8.4. UC5 – Search and location of people

The search and location of people involves the use of various techniques and tools to find individuals who may be missing, lost or are objects of interest in different contexts. These methods may vary depending on the specific situation, location, and circumstances.

For this purpose, a novel model, YOLO-NAS, has been used. YOLO-NAS is an advanced variant of YOLO (You Only Look Once) models that uses Neural Architecture Search (NAS) techniques to automatically optimize its structure. Developed by Deci AI, this combination allows YOLO-NAS to find more efficient and accurate network architectures than those designed manually. NAS optimization ensures efficient use of hardware resources, reducing power consumption and improving real-time object detection while maintaining high accuracy and processing speed [24].

YOLO is already an old acquaintance in the field of object detection, the new part is introduced by NAS [25] [26]. This is an automated method for designing task-optimized neural network architectures. It explores a space of possible layer and parameter configurations using search algorithms such as reinforcement learning or genetic algorithms. It evaluates the performance of each configuration by training models and adjusting according to the results. In YOLO-NAS, takes part in the following processes:

- Backbone optimization: Improves feature extraction.
- Neck Design: Optimizes the combination of features.
- Head Optimization: Improves prediction accuracy.

Specifically, the pre-trained “*yolo-nas s*” variant has been used, which has a lower latency than the others allowing the deployment in limited resources environments. It counts with 19M parameters and is pre-trained on leading datasets such as COCO, Objects365 and Roboflow 100 [24].

The use of this variant is due to it enables Real Time Object Detection. The way in which this model is used in the UC is as follows: the detection model is deployed on a machine with relatively high capacity. On the other side we have one or multiple drones that capture the video and publish it to an IP, which is read by the model, makes the detections and acts accordingly the situation. This configuration allows multiple drones to operate at the same time, with a low computational capacity since the predictions will be made by the machine on the ground. This will allow the drones to consume less energy and be deployed for longer periods of time or in more distant and difficult to access places. The requirement will be that the drones have internet connectivity to publish the video.

5. Computational elements (NTN and Terrestrial Federated) with different computational payloads

The following image shows a federation control system with several interconnected components. At the top, the "Federation Control Node" is a central device with multiple virtualization modules, acting as a robust server for data management and processing. The components are:

- Ground Station (Ground Station): has high processing power, equipped with NVIDIA technology for artificial intelligence, suitable for real-time data analysis and processing of large volumes of information.
- UAV + NVIDIA (Unmanned Aerial Vehicle + NVIDIA): Equipped with a camera for remote sensing and NVIDIA's "light" technology for artificial intelligence, it allows in-flight image and data analysis.
- UAV + NVIDIA (Unmanned Aerial Vehicle + NVIDIA): Similar to the previous one, this UAV has an EO/IR (Electro-Optical/Infrared) camera and uses NVIDIA's "light" technology for artificial intelligence, ideal for surveillance and reconnaissance in various conditions.
- UAV (Unmanned Aerial Vehicle): With limited processing power and ARM technology, it is designed for simpler tasks that do not require high processing power.

The central control node coordinates and optimizes the operations of these clusters, each with specialized capabilities according to its technology and purpose.

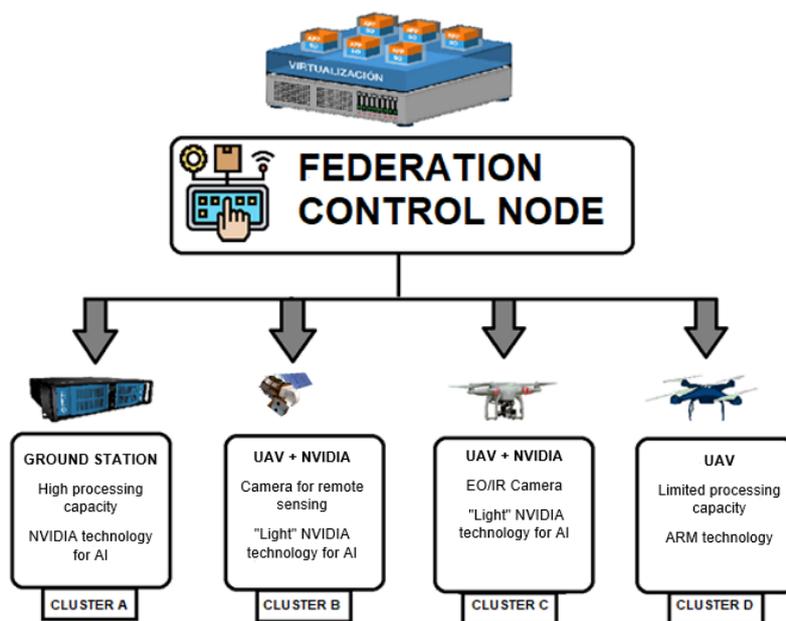


FIGURE 8 FEDERATION SCHEMA

5.1. Technical specification

1. **FEDERATED CONTROL NODE:** Compose by 3 Nodes.

Arch: x86_64.

System: Docker + Kubernetes + Karmada master + Kubesphere

- a. NODE MASTER: KVM Virtual machine

- i. **OS:** Ubuntu 20.04
- ii. **CPUs:** 8
- iii. **RAM:** 16GB
- iv. **HDD:** 100GiB
- v. **GPU:** No
- vi. **Number veth:** 3

- b. NODE MINION 1: KVM Virtual machine

- i. **OS:** Ubuntu 20.04
- ii. **CPUs:** 4
- iii. **RAM:** 8GB
- iv. **HDD:** 100GiB
- v. **GPU:** No
- vi. **Number veth:** 3

- c. NODE MINION 2: KVM Virtual machine

- i. **OS:** Ubuntu 20.04
- ii. **CPUs:** 4
- iii. **RAM:** 8GB
- iv. **HDD:** 100GiB
- v. **GPU:** No
- vi. **Number veth:** 3

2. **FEDERATED EARTH EDGE-NODE GPU:** KVM Virtual machine. Composed by 1 node

Arch: x86_64.

System: K8s-All-in-one Kubesphere + Karmada Agent

- a. **OS:** Ubuntu 20.04
- b. **CPUs:** 4
- c. **RAM:** 8GB
- d. **HDD:** 80GiB
- e. **GPU:** Yes (Tesla T4)

f. **Number veth:** 2

3. FEDERATED AERIAL EDGE-NODE NVIDIA-Xavier AGX: Bare Metal Machine Nvidia Jetson-Xavier AGX.

Arch: aarch64 (armv8)

System: K3s for Edge + Karmada Agent

- a. **OS:** Ubuntu 18.04.6
- b. **CPUs:** 8
- c. **RAM:** 32GB
- d. **HDD:** 30GiB + 1,8TB
- e. **GPU:** Yes (Nvida Jetson Xavier)
- f. **Number eth:** 2

4. FEDERATED AERIAL EDGE-NODE Lite: Bare Metal Machine Rapsberry Pi 4

Arch: armv7l

System: K3s-armhf + Karmada Agent

- a. **OS:** Linux mypi 5.10.103-v7l+
- b. **CPUs:** 4
- c. **RAM:** 4GB
- d. **HDD:** 57GiB
- e. **GPU:** No
- f. **Number eth:** 1

5.2. GPUs

The following table presents the specifications of our GPUs: [25]

SPEC	NVIDIA JETSON XAVIER AGX 32	NVIDIA TESLA T4	NVIDIA P100
NVIDIA CUDA Cores	512	2560	3584
TEXTURE MAPPING UNITS	32	160	224
ROPs	16	64	96

TENSOR CORES	64	320	-
MEMORY	32 GB LPDDR4X	16 GB GDDR6	16 GB CoWoS HBM2
MEMORY INTERFACE	256 bits	256 bits	4096 bits
GPU FREQUENCY	1377 MHz	585 MHz	1190 MHz
MEMORY BANDWIDTH	137 GB/s	320 GB/s	732.2 GB/s
POWER CONSUMPTION	30 W	250 W	600 W

TABLE 1 GPU SPECS COMPARATIVE

6. Estimation of the theoretical behavior of each UCs in each scenario

Theoretical behaviour for each UCs across various scenarios is estimated, aiming to predict performance under different conditions. This analysis highlights potential challenges and advantages, offering a deeper understanding of the dynamics and feasibility of each use case. The results guide practical implementation and optimization strategies.

The next table outlines the essential requirements and characteristics specific to each use case, detailing the necessary processes involved. It provides a structured overview of the operational needs and unique aspects associated with each scenario, facilitating a clear understanding of the distinct demands and functionalities required.

UC2: LAND USE AND COVER										
PROCESS	AI	SECURITY	DEPENDENCY	CPU	RAM	HDD	CAMERA	GRAPHICS CARD	BANDWIDTH	CONSUMPTION
camera_manager	No	http	N/A	1	<1GB	425MB	Yes (Hyperspectral)	No	High	Medium
normalize	No	http	camera_manager	1	<1GB	526MB	No	No	High	Low
extract_bands	No	http	camera_manager	1	<1GB	526MB	No	No	Low	Low
merge_bands	No	http	camera_manager	1	<1GB	525MB	No	No	Low	Low
radiance	No	http	normalize	1	<1GB	527MB	No	No	High	Low
reflectance	No	http	radiance	1	<1GB	527MB	No	No	High	Low
PCA	Yes	http	normalize extract_bands	2	1- 2GB	528MB	No	No	Low	Medium

clustering_cosine	No	http	PCA normalize reflectance	1	<1GB	526MB	No	No	Low	Low
AI training land analysys	Yes	http	PCA clustering_cosine	2	>1GB	10GB	No	Yes	Low	High
AI classification (generate map)	Yes	http	AI training land analysys	2	>1GB	10GB	No	Yes	Low	High

UC3: CONNECTED VEHICLE CERTIFICATE VALIDATION

PROCESS	AI	SECURITY (http/https)	PRIORITY	CPU	RAM	HDD	CAMERA	GRAPHICS CARD	BANDWIDTH	CONSUMPTION
Certificate Comparison	No	http	Medium	1	<1GB	614MB	No	No	Low	Low
Send the alarm	No	http	Medium	1	<1GB	614MB	No	No	Low	Low

UC4: VERIFICATION AND AUTHORIZATION FOR IGNITION OF THE CONNECTED VEHICLE

PROCESS	AI	SECURITY (http/https)	PRIORITY	CPU	RAM	HDD	CAMERA	GRAPHICS CARD	BANDWIDTH	CONSUMPTION
Face recognition	Yes	http	Medium	1	<1GB	2,46GB	No	No	Low	Medium
Image acquisition	No	http	Medium	1	<1GB	2GB	Yes	No	High	Medium
UC5: SEARCH AND LOCATION OF PEOPLE										
PROCESS	AI	SECURITY (http/https)	PRIORITY	CPU	RAM	HDD	CAMERA	GRAPHICS CARD	BANDWIDTH	CONSUMPTION
People detection	Yes	http	High	2	>1GB	10GB	Yes	Yes	Low	High
Video streaming	No	http	High	1	<1GB	1GB	Yes	No	High	Medium

TABLE 2 REQUIREMENTS AND CHARACTERISTICS OF PROCESSES FOR EACH UCS

6.1. Theoretical behaviour of UC2 under different scenarios

6.1.1. Scenario1: Service deployment with a critical energy system for aerial elements

In this scenario we take into account the following conditions:

- **Critical energy conditions:** It is crucial to optimize energy usage to minimize consumption.
- **No bandwidth constraints:** There are no limitations on data transmission, so there is no need to save on bandwidth usage.
- **No aerial elements reserved for emergencies:** All aerial elements are available for use, with none reserved for emergencies.
- **Sufficient hardware resources:** All hardware resources are sufficient and fully available for use.

This scenario prioritizes energy efficiency while allowing for extensive data transmission capacity and full access to all available hardware resources, without the need to reserve aerial elements for emergency situations.

Assignment of Tasks to Computing Elements SCENARIO 1

Objective: Minimize energy consumption by performing most tasks on the ground, using aerial nodes for data capture tasks.

Federated Control Node:

General Description: The Federated Control Node is the centralized processing core, responsible for the orchestration and management of tasks in the cluster. It is made up of three virtual nodes (master and two minions).

Node Master:

This node is exclusively responsible for the orchestration and management of tasks in the cluster, as well as communication between computing elements.

Assigned Tasks:

- Task Orchestration and Control: Manage and distribute tasks among the different nodes of the federation.
- Federation of Nodes: Control and maintain the federation of nodes.
- Communication Management: Facilitate communication between the different computing elements.

Justification: Centralizing these tasks ensures efficient control of data flow and optimizes the use of available computational resources, leaving the intensive data processing capacity to other nodes.

Federated Earth Edge-Node GPU:

Virtual node equipped with a GPU, designed to handle data-intensive tasks and AI applications.

Assigned Tasks:

- PCA: Principal Component Analysis.
- AI training land analysis: Training of AI models for land and land cover analysis.
- AI classification (generate map): Generation of maps classified by AI.
- normalize: Normalization of captured images.
- extract_bands: Extraction of spectral bands.
- radiance: Radiance calculation.
- reflectance: Calculation of reflectance.

Justification: The GPU allows you to quickly execute data-intensive tasks and AI models, optimizing processing and ensuring accurate and efficient results. This node does not have power consumption problems, so it is used for intensive tasks.

Federated Aerial Edge-Nodes Node NVIDIA-Xavier AGX:

Aerial nodes designed for initial data capture and processing in the field, with variable CPU, RAM and storage capacities. Robust and powerful node for edge computing applications in light environments, with a dedicated GPU for intensive processing.

Assigned Tasks:

- camera_manager: Capture of hyperspectral images.
- merge_bands: Merging of spectral bands.

Justification: Equipped with a powerful GPU and real-time processing capability, this node is ideal for hyperspectral imaging and band fusion, optimizing energy efficiency and data quality.

Federated Aerial Edge-Nodes Node Lite (Raspberry Pi 4):

Lightweight and economical node for basic edge computing tasks and as backup in critical operations.

Assigned Tasks:

- camera_manager: Capture of hyperspectral images.
- merge_bands: Merging of spectral bands.

Justification: Although its processing capacity is limited, its energy efficiency and integrated camera make it suitable for initial data capture, complementing the NVIDIA-Xavier AGX node.

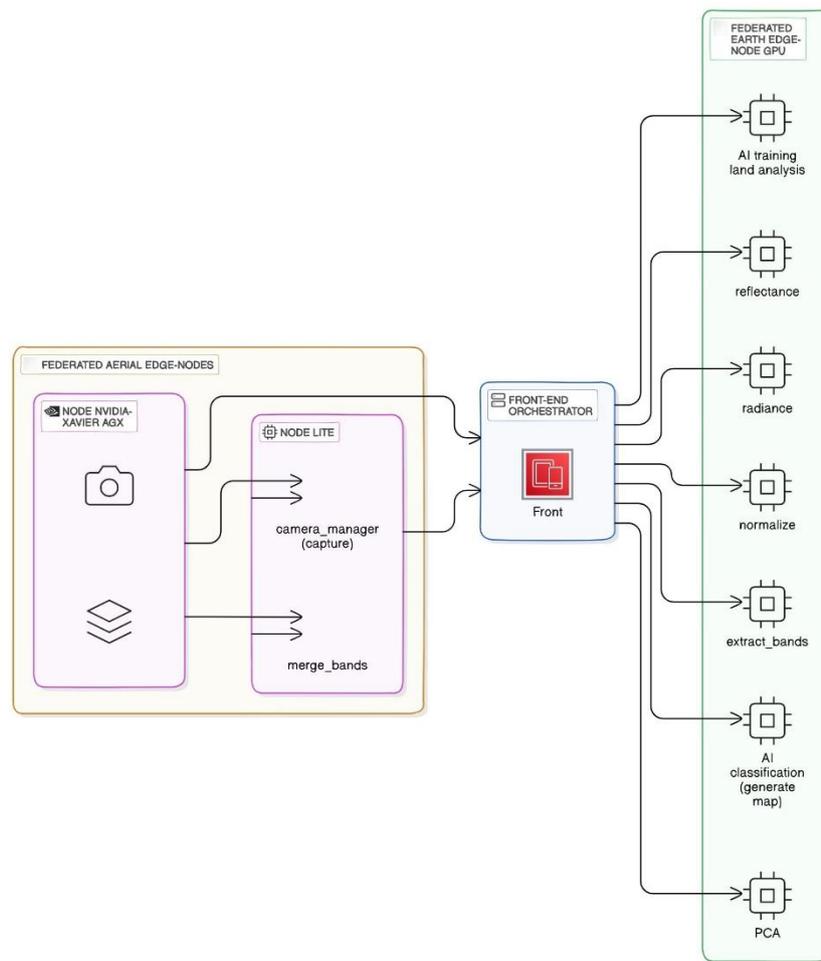


FIGURE 9 THEORETICAL BEHAVIOUR OF CU2 UNDER SCENARIO1

6.1.2. Scenario2: Service deployment with sufficient energy and bandwidth constraints

In this scenario we take into account the following conditions:

- **Sufficient energy in all computing elements:** All computing elements have adequate energy resources.
- **Bandwidth constraints:** There are limitations on data transmission, making it necessary to transmit only the essential amount of information to avoid latency issues.
- **No aerial elements reserved for emergencies:** All aerial elements are available for use, with none reserved for emergencies.

- **Hardware restrictions on HDD memory in one aerial node:** There are some hardware memory restrictions (HDD) in one of the aerial nodes.

This scenario focuses on managing bandwidth efficiently to prevent latency issues while ensuring sufficient energy resources across all computing elements. It also highlights the need to consider hardware memory limitations in specific aerial nodes.

Assignment of Tasks to Computing Elements SCENARIO 2

Federated Control Node:

Assigned Tasks:

- Orchestration of computing elements.
- Communications management.
- Federation of new knots.

Federated Earth Edge Node GPU:

Assigned Tasks:

- AI classification (generate map)

Federated Aerial Edge-Nodes Node NVIDIA-Xavier AGX:

Assigned Tasks:

- PCA
- clustering_cosine
- AI Training Ground Analysis

Justification: Despite HDD memory limitations, this node is still crucial for edge processing with tasks like PCA and clustering_cosine. The assignment of these tasks here ensures efficient processing of data close to the capture point, optimizing the utilization of available resources.

Federated Air Edge Node Lite (Raspberry Pi 4):

Assigned Tasks:

- normalize
- extract_bands
- merge_bands
- radiance
- reflectance

Justification: With limited resources, this node handles preprocessing tasks such as normalization and band extraction, optimizing the overall workflow without significantly relying on bandwidth. This

allocation minimizes the load on other, more powerful nodes and maximizes the efficient use of local resources.

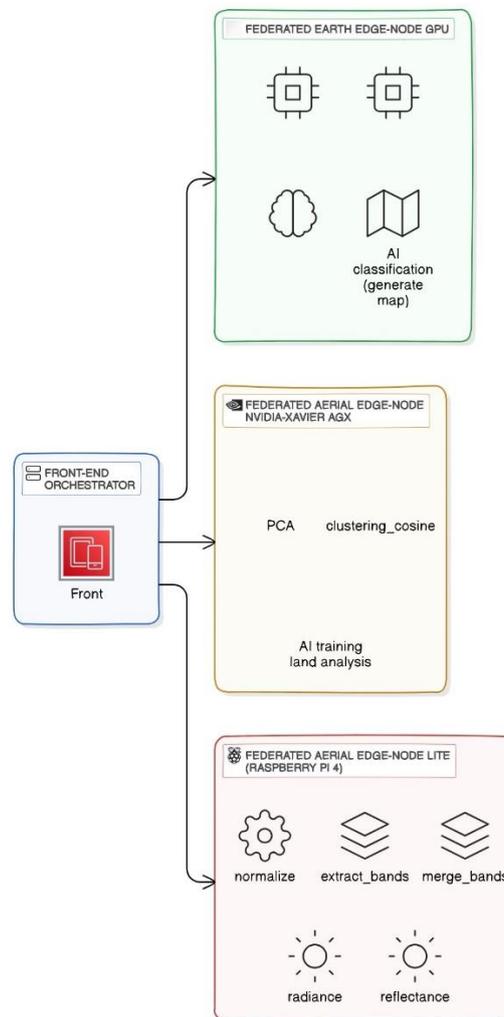


FIGURE 10 THEORETICAL BEHAVIOUR OF CU2 UNDER SCENARIO2

6.2. Theoretical behaviour of UC3 under different scenarios

6.2.1. Scenario1: Service deployment with critical energy conditions for aerial elements

This scenario prioritizes energy efficiency while allowing for extensive data transmission capacity. It also accounts for the reservation of some aerial elements for emergencies, ensuring that critical operations can continue without interruption.

- **Critical energy conditions:** It is crucial to optimize energy usage to minimize consumption.
- **No bandwidth constraints:** There are no limitations on data transmission, so there is no need to save on bandwidth usage.
- **Aerial elements reserved for emergencies:** Some aerial elements are reserved for emergency situations and are not available for regular use.
- **Sufficient hardware resources:** All necessary hardware resources are sufficient and fully available for use.

Assignment of Tasks to Computing Elements SCENARIO 1

Federated Control Node

Assigned Tasks:

- Task Orchestration and Control: Manage and distribute tasks among the different nodes of the federation.
- Federation of Nodes: Control and maintain the federation of nodes.
- Communication Management: Facilitate communication between the different computing elements.

Federated Earth Edge-Node GPU:

Assigned Tasks:

- No homework assigned.

Justification: It is not necessary to use this node since the tasks do not require AI processing and energy savings are prioritized.

Federated Aerial Edge-Node NVIDIA-Xavier AGX:

Assigned Tasks:

- No homework assigned.

Justification: Reserved for emergencies and more intensive tasks that may arise, not necessary for current validation and alarm tasks.

Federated Aerial Edge-Node Lite (Raspberry Pi 4):

Assigned Tasks:

- Certificate Comparison
- Send the Alarm

Justification:

- Task Requirements: Both tasks require minimal resources (CPU: 1, RAM: <1GB, HDD: 614MB each) that are well within the capabilities of the Raspberry Pi 4.
- Energy Efficiency: The Raspberry Pi 4 is a low energy consumption device, which is crucial given the scenario of critical energy conditions.
- Availability: Fully available for these tasks, without the need to use more powerful nodes with greater energy consumption.
- AI Relevance: These tasks do not require AI processing, making the use of the Raspberry Pi 4 convenient and efficient, without wasting resources from more powerful nodes.

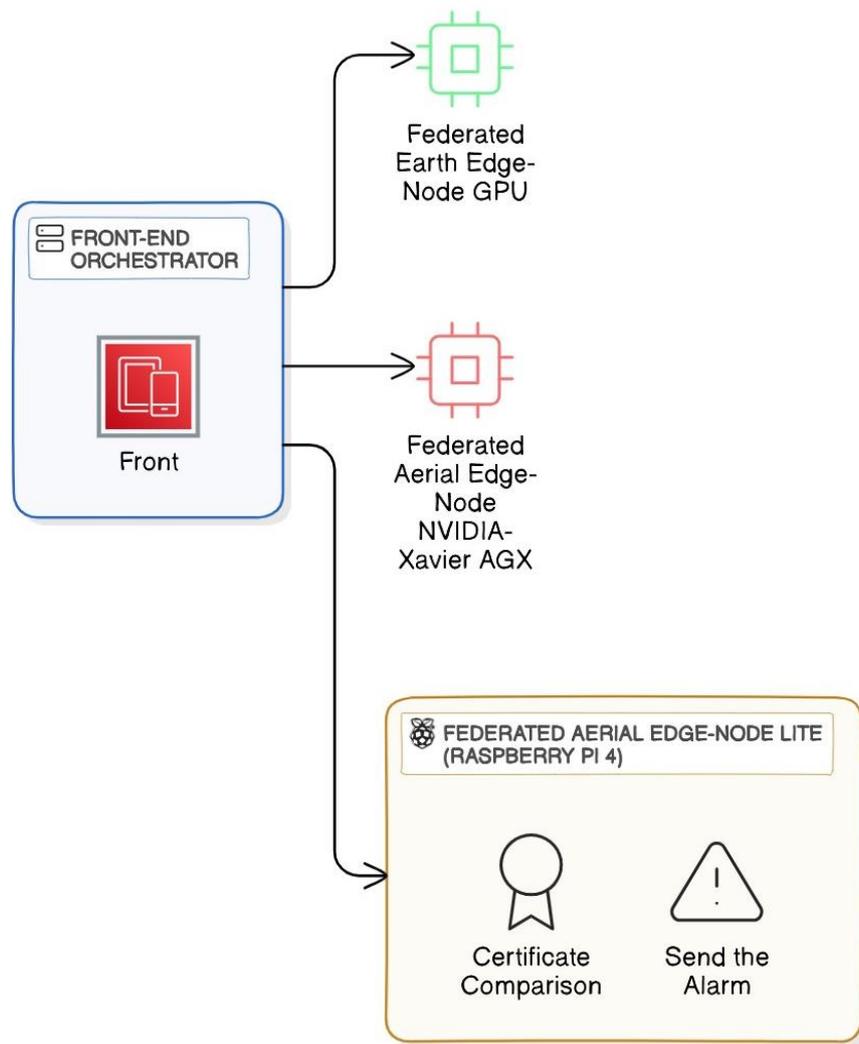


FIGURE 11 THEORETICAL BEHAVIOUR OF CU3 UNDER SCENARIO1

6.2.2. Scenario2: Service deployment with optimal energy conditions

This scenario allows for unrestricted use of energy and bandwidth, ensuring maximum performance and capacity. With no aerial elements reserved for emergencies and full availability of hardware resources, all operations can proceed without limitations.

- **Optimal energy conditions:** There is no need to prioritize energy savings as sufficient energy resources are available.
- **No bandwidth constraints:** There are no limitations on data transmission, allowing for unrestricted use of bandwidth.
- **No aerial elements reserved for emergencies:** All aerial elements are available for use, with none reserved for emergencies.
- **Sufficient hardware resources:** All necessary hardware resources are fully available for use.

Assignment of Tasks to Computing Elements SCENARIO 2

Federated Control Node

Assigned Tasks:

- Task Orchestration and Control: Manage and distribute tasks among the different nodes of the federation.
- Federation of Nodes: Control and maintain the federation of nodes.
- Communication Management: Facilitate communication between the different computing elements.

Federated Earth Edge-Node GPU

Assigned Tasks:

- Certificate Comparison

Justification:

- Capacity: It has advanced resources (CPU: 4, RAM: 8GB, GPU: Tesla T4) that can handle the certificate matching task with high efficiency.
- Power Conditions: It is not necessary to prioritize power savings, so the use of a GPU node is appropriate.
- Availability: Fully available and not reserved for emergencies, suitable for tasks that benefit from fast processing.

Federated Aerial Edge-Node NVIDIA-Xavier AGX

Assigned Tasks:

- Send the Alarm

Justification:

- Capacity: With 8 CPUs, 32GB RAM and NVIDIA Jetson Xavier GPU, it can handle the task of sending alarms quickly and with high efficiency.
- Energy Conditions: There is no need for energy savings, allowing full use of its resources.
- Availability: Not reserved for emergencies, ideal for tasks that can benefit from its advanced processing capabilities.

Federated Aerial Edge-Node Lite (Raspberry Pi 4)

Assigned Tasks:

No Tasks assigned.

Justification: With the most powerful resources available and without energy restrictions, tasks are assigned to nodes with greater capacity to ensure greater efficiency and processing speed.

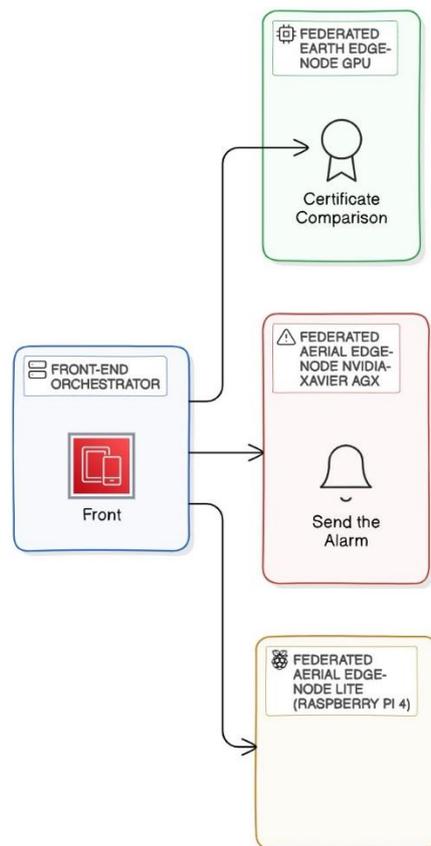


FIGURE 12 THEORETICAL BEHAVIOUR OF CU3 UNDER SCENARIO2

6.3. Theoretical behaviour of UC4 under different scenarios

6.3.1. Scenario1: Service deployment with optimal energy conditions and bandwidth constraints

This scenario allows for unrestricted use of energy while requiring efficient management of bandwidth due to transmission constraints. With all aerial elements and hardware resources available, operations can proceed effectively, focusing on optimizing data transmission to avoid latency issues.

- **Optimal energy conditions:** There is no need to prioritize energy savings as sufficient energy resources are available.
- **Bandwidth constraints:** There are limitations on data transmission, making it necessary to manage bandwidth usage efficiently to avoid latency and ensure smooth operations.
- **No aerial elements reserved for emergencies:** All aerial elements are available for use, with none reserved for emergencies.
- **Sufficient hardware resources:** All necessary hardware resources are fully available for use.

Assignment of Tasks to Computing Elements SCENARIO 1

Connected Vehicle with Camera for Facial Recognition:

Assigned Tasks:

- Image acquisition

Justification: Equipped with a camera for facial recognition, ideal for the task of Image acquisition. Does not require intensive AI processing, aligned with your processing capabilities and taking advantage of optimal power conditions.

Federated Aerial Edge-Nodes NVIDIA-Xavier AGX:

Assigned Task:

- Face recognition

Justification: Equipped with adequate processing capabilities to execute facial recognition tasks (Face recognition). There are no power saving restrictions, allowing full use of resources for this specific task.

Federated Earth Edge-Node GPU Lite:

Assigned Task: No assigned task

Justification: Not needed for current Image acquisition or Face recognition tasks. Reserved for AI-intensive tasks that are not within the current scope.

Federated Aerial Edge-Nodes (Raspberry Pi 4):

Assigned Task: No assigned task

Justification: Not needed for current Image acquisition or Face recognition tasks.

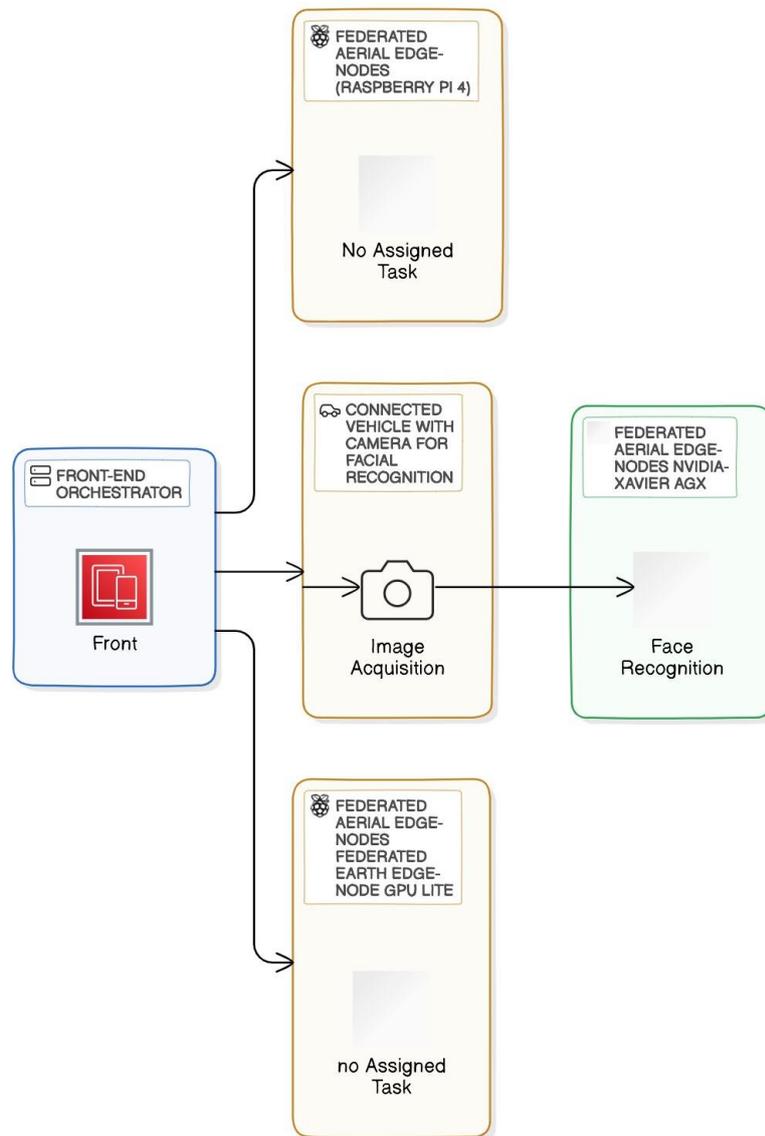


FIGURE 13 THEORETICAL BEHAVIOUR OF CU4 UNDER SCENARIO1

6.3.2. Scenario2: Service deployment with critical energy conditions

This scenario emphasizes the need to prioritize energy efficiency while allowing unrestricted data transmission. With some aerial elements reserved for emergencies, the focus is on optimizing the use of available energy and hardware resources to ensure effective operation under critical energy conditions.

- **Critical energy conditions:** It is crucial to optimize energy usage to minimize consumption and prioritize energy savings.
- **No bandwidth constraints:** There are no limitations on data transmission, allowing unrestricted use of bandwidth.
- **Aerial elements reserved for emergencies:** Some aerial elements are reserved for emergency situations and are not available for regular use.
- **Sufficient hardware resources:** All necessary hardware resources are fully available for use.

Assignment of Tasks to Computing Elements SCENARIO 2

Connected vehicle with camera for facial recognition:

Assigned Tasks:

- Image acquisition

Justification: Equipped with a camera for facial recognition, ideal for the task of image acquisition. Does not require intensive AI processing, aligned with your processing capabilities and taking advantage of optimal power conditions.

Federated Earth Edge Node GPU:

Assigned Tasks:

- Facial Recognition

Justification: Assignment of the Face Recognition task to this node due to its adequate processing capabilities to execute face recognition tasks, even under power consumption and memory capacity constraints.

Federated Air Edge Nodes:

Assigned Task: No assigned task.

Justification: No tasks currently assigned, reserved for specific air operations, and do not require running AI or image processing tasks at this time.

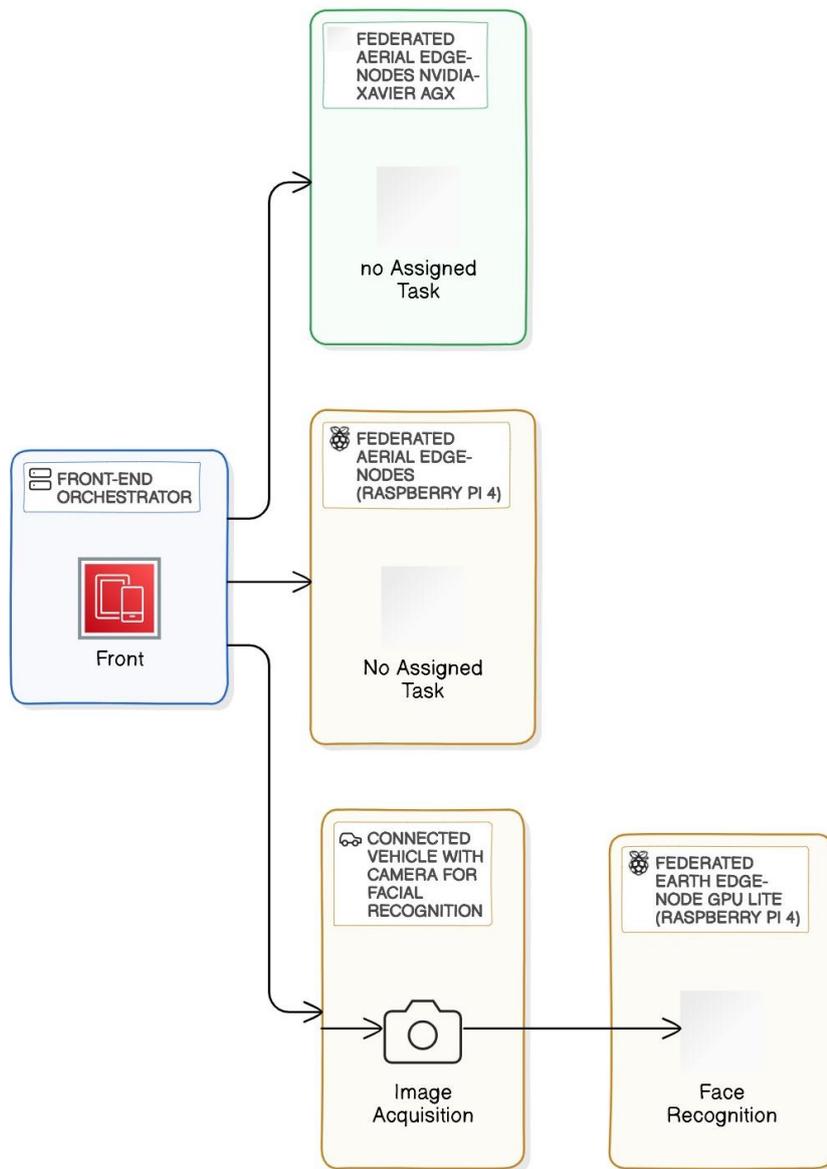


FIGURE 14 THEORETICAL BEHAVIOUR OF CU4 UNDER SCENARIO2

6.4. Theoretical behaviour of UC5 under different scenarios

6.4.1. Scenario1: Service deployment with critical energy consumption

This scenario focuses on optimizing energy usage while allowing unrestricted data transmission. With certain aerial nodes reserved for emergencies and hardware limitations, the emphasis is on efficiently

managing and allocating the available resources to ensure effective operation under critical energy consumption conditions.

- **Critical energy consumption:** It is crucial to prioritize energy savings and optimize energy usage.
- **No bandwidth constraints:** There are no limitations on data transmission, allowing for unrestricted use of bandwidth.
- **Aerial nodes reserved for emergencies:** Some aerial nodes are reserved for emergency situations and are not available for regular use.
- **Hardware limitations:** There are limitations in the available hardware resources, necessitating efficient management and allocation.

Assignment of Tasks to Computing Elements SCENARIO 1

Federated Earth Edge-Node GPU:

Assigned Tasks:

- People detection

Justification:

Equipped with a Tesla T4 GPU, this node is assigned the intensive processing task of person detection. The GPU optimizes image processing performance, crucial for identifying people in search and rescue situations. Additionally, the built-in camera is used to capture images necessary for detection.

Federated Aerial Edge-Node NVIDIA-Xavier AGX:

Assigned Tasks:

- Video streaming

Justification:

Despite the mentioned hardware limitations, this node can handle the task of video streaming with its optimized processing capacity and low power consumption. This assignment takes advantage of its ability to transmit real-time video from the drones to the Ground Node.

Federated Aerial Edge-Node Lite (Raspberry Pi 4):

Assigned Tasks:

- No tasks explicitly assigned in this scenario due to hardware limitations.

Justification:

Since there are hardware limitations and some air nodes are reserved for emergencies, in this scenario the Raspberry Pi 4 is not assigned specific tasks. May be on reserve for contingency needs or additional duties as needed.

Additional considerations:

- Optimization of Energy Consumption: Energy savings are prioritized in all operations, ensuring that computing resources are used efficiently to maximize the duration of search and rescue operations.
- Hardware Constraint Management: Task assignments are adjusted to meet specific hardware limitations, ensuring that each node operates within its capabilities without compromising the effectiveness of operations.
- Emergency Reserve: Air nodes are reserved for emergencies, ensuring the immediate availability of additional resources in case of critical situations during search and rescue operations.

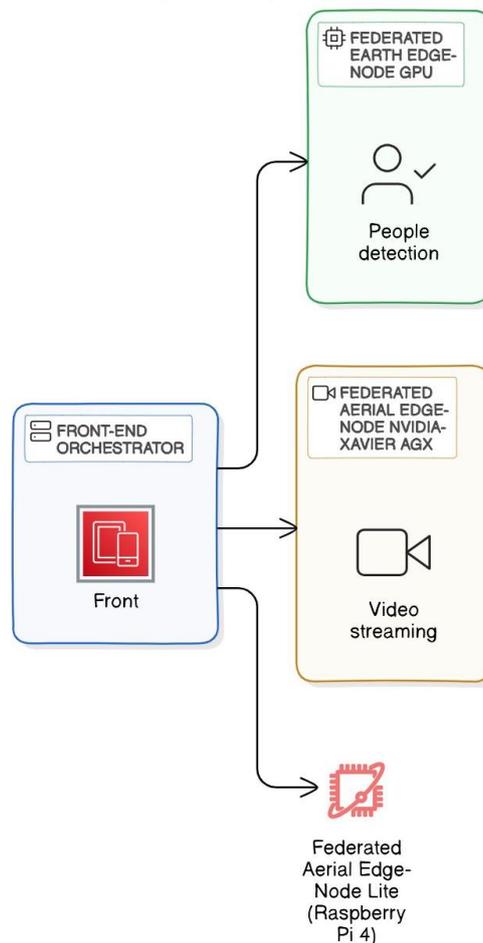


FIGURE 15 THEORETICAL BEHAVIOUR OF CU5 UNDER SCENARIO1

6.4.2. Scenario2: Service deployment with sufficient energy resources

This scenario allows for unrestricted use of energy and bandwidth, ensuring maximum operational capacity. With no aerial nodes reserved for emergencies, all resources can be fully utilized, though careful management of the available hardware is necessary to accommodate any restrictions.

- **Sufficient energy resources:** There are no restrictions on energy usage, allowing for optimal performance without the need to save energy.
- **Sufficient bandwidth:** There are no limitations on data transmission, providing ample bandwidths for all operations.
- **No emergency reservations for aerial nodes:** All aerial nodes are available for regular use, with none reserved for emergencies.
- **Hardware restrictions:** There are certain limitations in the available hardware resources, requiring careful management and allocation.

Assignment of Tasks to Computing Elements SCENARIO 1

Federated Earth Edge-Node GPU:

Assigned Tasks:

- No task

Justification: No task explicitly assigned in this scenario due to optimal conditions at air nodes

Federated Aerial Edge-Node NVIDIA-Xavier AGX:

Assigned Tasks:

- People detection
- Video streaming

Justification:

- This node is used for the task of detecting people, taking advantage of its graphical processing capacity to perform advanced and precise analysis.
- This node can handle the task of video streaming with its optimized processing capacity and low power consumption. This assignment takes advantage of its ability to transmit real-time video from the drones to the Ground Node.

Federated Aerial Edge-Node Lite (Raspberry Pi 4):

Assigned Tasks: No tasks.

Justification: No task explicitly assigned in this scenario due to optimal conditions at the air nodes.

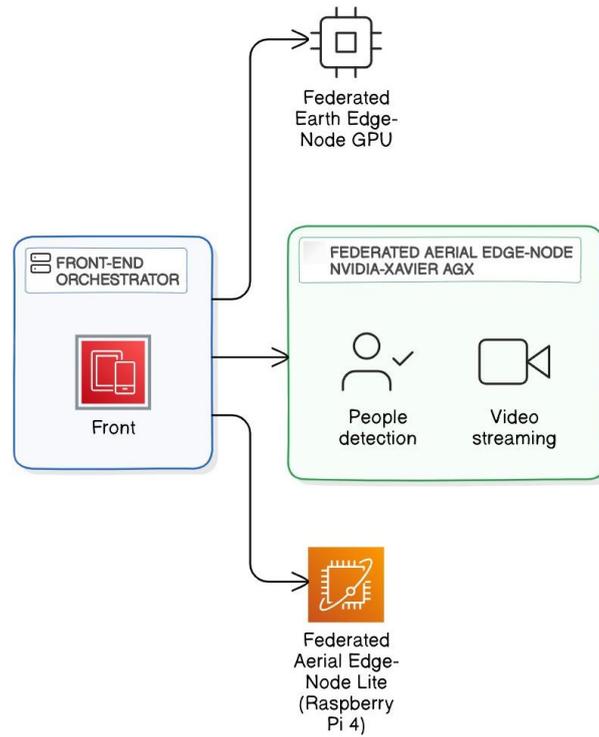


FIGURE 16 THEORETICAL BEHAVIOUR OF CU5 UNDER SCENARIO2

7. Conclusions

The exploration of scenarios involving on-board AI processing reveals its critical role across various applications. Each use case, including remote sensing, search and rescue operations, and connected vehicle security, presents distinct deployment requirements and operational contexts.

Remote sensing applications emphasize real-time data accuracy and analysis for informed decision-making. In search and rescue operations, AI facilitates swift and precise location of individuals, significantly improving operational efficiency and outcomes, leveraging NTN and Terrestrial Federated networks for managing extensive data and compute-intensive algorithms. In connected vehicle security, AI identifies and mitigates threats, ensuring robust protection against cyber-attacks and enhancing overall vehicular safety.

The identification of AI process types tailored to specific use cases underscores the adaptability and efficiency of on-board AI systems. Computational elements such as NTN and Terrestrial Federated networks play crucial roles by accommodating diverse computational payloads and integrating AI technologies seamlessly into operational frameworks.

These findings highlight the transformative impact of on-board AI processing on operational capabilities, enabling rapid response and safeguarding critical infrastructure and lives. Continued advancements in AI-driven applications are expected to further optimize efficiency and effectiveness across these domains.

The assignment of tasks in all the analyzed use cases demonstrated the need for careful and adaptive planning according to the capabilities of the available hardware and the constraints of the operating scenarios. The optimal distribution of tasks, which considers the specific capabilities of each computing element and the limitations imposed by context constraints (Scenarios), is crucial to achieve efficient and effective operation.

In the case of land use and land cover determination, the processing load was distributed so that each node took advantage of its strengths, while in the case of search and rescue, speed and effectiveness in locating missing persons were prioritized using drones and edge processing. This strategy not only maximizes systems performance, but also ensures resilience and adaptability to changes in the operating environment.

8. References

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