A New Spectrum Management Concept for Future NAS Communications

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***Abstract*— With the growth of aviation operations and the emergence of new entrants into the National Airspace System, there has been an increasing demand for aeronautical communications. However, the existing VHF/UHF frequency allocations for NAS operations have become increasingly scarce and unable to support the projected growth in demand. While traditional approaches to address the spectrum scarcity issue (such as reduction of channel bandwidth) have provided some relief, there is a need for a more scalable and sustainable solution. Consequently, NASA is investigating a new approach to spectrum management within the NAS using Artificial Intelligence and other advanced technologies. The concept considers both air-ground and air-air communication networks with the anticipated outcome that the proposed concept will meet the spectrum needs of future NAS communications.**

Keywords—communications, aeronautics, machine learning, artificial intelligence, spectrum, resource management, national airspace system, UAM

I. Introduction

The continued growth of aviation operations has resulted in a corresponding demand for aeronautical communications. To manage the increasing demands for radio spectrum, the Federal Aviation Administration (FAA) has developed initiatives designed to alleviate the congestion resulting from increased air traffic and new technology deployment. The Very High Frequency (VHF) radio spectrum has been in use for over 50 years, and the increased voice communication demand has primarily been addressed by reducing channel bandwidth. However, there are limitations to this approach, and the continued reduction of channel bandwidth is not a sustainable solution. Meanwhile, autonomous data communication will become a necessity in future National Airspace System (NAS) operations. As a result, a new concept/paradigm is required to address limitations with the current voice communication-based approach.

The increased demand for wireless communications, the reduction of spectrum availability due to auctioning, and the emergence of new vehicles in the airspace (such as Urban Air Mobility (UAM), Unmanned Aircraft Systems Traffic Management (UTM), and supersonic aircraft) will result in an increased mission diversity and airspace density that will saturate the availability of existing aviation spectrum channels. Consequently, there is a pressing need to develop a new approach for spectrum management that employs modern technologies in communication and networking, artificial intelligence (AI), cloud/edge computing and others to maximize the utilization efficiency of spectrum available for aviation use.

The National Aeronautics and Space Administration (NASA) is investigating concepts and technologies to modernize aviation spectrum management and use. This paper describes a new concept and approach to spectrum management based on the use of AI and new communication and networking technologies. The research will primarily consider two communication scenarios in the NAS, including an air-ground communication network, and an air-air communication network. This paper will discuss the concepts of both networks and the associated high-level requirements, functions and challenges.

This study is carried out in two phases. The first phase is the concept development that identifies the needs and challenges of future NAS communications and provides a spectrum management framework to optimize the spectrum utilization efficiency by leveraging existing technological advancements. The second phase is the technical investigation of an AI-assisted spectrum management approach, which includes preliminary studies on air traffic and communication demands predictions, channel allocations for the air-ground network, and spectrum access for the air-air network. It is anticipated that the outcomes of this autonomous spectrum study will meet the spectrum needs of future NAS communications including existing air traffic control system as well as future UAM, high-altitude Class E airspace communications, and others.

In the literature, there is a large number of spectrum studies for a variety of wireless communication networks, ranging from theoretical capacity study and interference management to protocol/algorithm design and system-level validation. In recent years, the revival of AI is reshaping almost every aspect of science and technology, including the field of wireless communication and networking. The combination of AI with wireless technologies has led to the emergence of a new learning-based wireless communication paradigm, which refers

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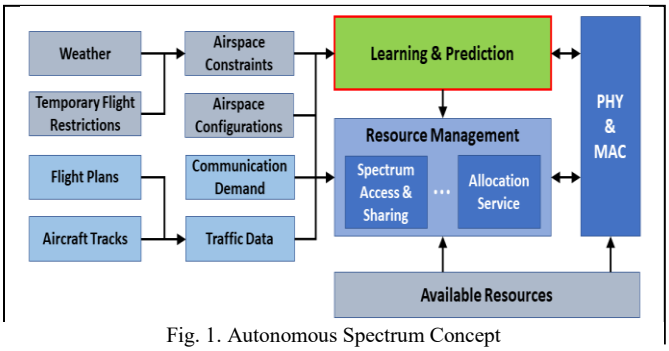


Fig. 1. Autonomous Spectrum Concept

to the deployment of machine learning algorithms including supervised, unsupervised, and reinforcement learning at every node of the communication networks [1] [2] [3]. In particular, supervised learning has been studied in wireless networks for link quality prediction [4] [5] [6], modulation classification [7], SNR ordering [8] and signal detection [9]. On the other hand, unsupervised learning has been studied in wireless networks for clustering [10] [11], multiple-input and multiple-out (MIMO) beamforming [12], tracking and localization [13]. Finally, it is well known that reinforcement learning (RL) can be used to solve large-scale problems with complex Markov decision process (MDP). For example, a recent paper [14] studied reinforcement learning in a competitive and cooperative spectrum sharing system for the DARPA Spectrum Collaboration Challenge.

Section I of this paper describes the problem statement and how the presented concept addresses that challenge. Section II provides a description of the overall system concept, functional decomposition, process flows, and the simulation/visualization environment. Section III presents concluding remarks.

II. Concept and System Overview

A. Concept Description

The proposed concept for autonomous spectrum management aims to provide an intelligent, efficient, flexible, and scalable solution to improve spectrum utilization (allocation, access and sharing) using recent advancements in artificial intelligence, communication, networking and computing technologies. The system under consideration is the band of frequencies used for NAS air traffic control including the air-ground communication network and the air-air communication network.

Fig. 1 depicts the generic flow chart of the proposed autonomous spectrum management concept. Based on the input of available data items (i.e., air traffic, communication demands, airspace configurations and constraints), the learning and prediction module (the core functions distinct from previous systems) uses various AI algorithms to predict traffic and communications demands, to perform resource management (spectrum allocation, access and sharing) and to guide the selection of RF transceiver parameters (physical (PHY) and medium access control (MAC) layers) to meet the overall communication requirements throughout the NAS.

1) Data Items:

Learning and prediction algorithms require various datasets in order to train, test, and validate model performance. Of particular note, the diversity and size of the datasets will continue to grow as the NAS evolves with new applications. For now, as shown in Fig. 1, the concept focuses on three types of data: flight traffic data, communication data, and airspace regulatory data including constraints and configurations. More specifically, airspace traffic data can be obtained using data items such as flight plans and aircraft tracks; additionally, airspace constraints data can be determined by information contained in weather data and Temporary Flight Restrictions (TFRs). The learning and prediction algorithms use both the historical traffic & communication data and the airspace constraints and configurations to predict future airspace traffic and communication demands. All the data items combined with the predicted data will serve as the input for dynamic resource management. The following is a brief description of candidate data items; others (not mentioned) are candidates as well.

- *Flight Plans*: documents filed by pilots or other flight dispatchers prior to departure, and typically include intended flight path, departure and arrival points/times, estimated flight duration, and alternate airports in cases of severe weather or other adverse conditions.
- *Real-time Flight Tracks*: observations of aircraft trajectory (e.g., latitude, longitude, altitude, ground speed, course/heading, rate of climb) as a function of time.
- *Weather Information*: 1) adverse conditions, e.g., thunderstorms, aircraft icing, turbulence, wind shear, mountain obscuration, 2) major weather systems along or near the route of flight, 3) current surface weather observations, 4) pilot reports (PIREPs), satellite, and radar data along the route of flight, 5) destination forecasts, and 6) winds and temperatures aloft.
- *Communications Data*: transmission data from various communication links that are demodulated, decoded, and stored in a database. AI algorithms will process the captured data and their associated communication parameters (duration, data rate, power, etc.) to obtain a prediction of communications demands throughout the NAS. The data gathered can also be used for real-time visualization of radio traffic, for planning for future communication infrastructure deployments, and for validation of network-level simulations.
- *Temporary Flight Restrictions*: regulatory actions that temporarily restrict aircraft from operating within a defined area in order to protect persons or property in the air or on the ground. TFRs include various fields, including the location of the TFR area, the effective period, and altitudes affected.

2) Resource Management

The term "resource" could have different meanings. From a systems point of view, a resource can be divided into hardware and software. From a functional point of view, a resource can be classified as communication resources and computing resources. This paper considers key communication resources

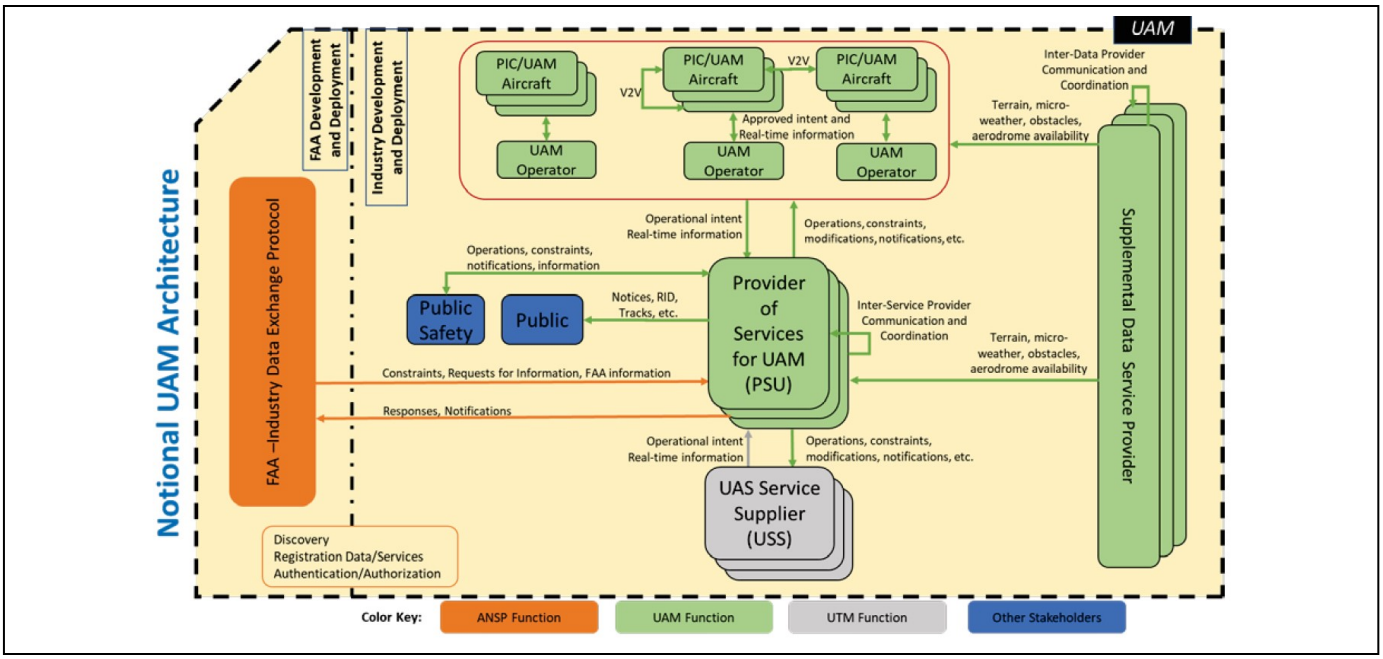


Fig. 2. Elements of UAM [15]

including spectrum and power. In particular, the spectrum resource spans over three parallel dimensions: time, frequency and space. For decades, available spectrum is largely shared in time and frequency. In space, spectrum can be reused at different geographical locations as long as they do not interfere with each other. Over the past two decades, with the prodigious advancements in MIMO communication systems, the same spectrum can be simultaneously shared by multiple antennas on the same device to create additional parallel channels in space. Another important communication resource is the power to transmit and receive signals. Resource management is the core function striving to maximize the utilization efficiency of available resources while meeting the desired Quality of Service (QoS) of individual communication links. The resource management function takes the flight traffic, communication demands and airspace regulatory data as inputs, performs frequency engineering, and determines the amount of resource required for each intelligent agent (defined later), which will be implemented at the PHY and MAC layers of the RF transceiver.

3) PHY and MAC

The proposed concept needs to be implemented at all intelligent agents. In particular, the PHY and MAC layers are the key in the protocol stacks for air-ground and air-air communication networks. For example, joint power and channel allocation/access is a PHY/MAC cross-layer optimization problem, which can be solved by the resource management function shown in Fig. 1. Additionally, there are a number of PHY/MAC configurations that can be determined by our learning-based approach. For example, the channel state information of communication links can be estimated using AI-based prediction. The modulation and coding scheme can also be adaptively selected using our learning-based approach. For air-air mobile ad-hoc networks, PHY/MAC design mostly involves spectrum access and sharing (interweave, underlay, and overlay) among distributed agents.

4) Learning and Prediction

Compared to traditional approaches, the learning and predication module in Fig. 1 is the unique and essential component in our approach. Enabled by AI technologies, intelligent agents in dynamic environments are capable of making quick decisions (channel allocation/selection, spectrum sharing, etc.) to maximize the spectrum utilization efficiency. To this end, intelligent agents have to predict the flight traffic and communication demands that serve as the input for decision making. A key challenge will be predicting when a communications exchange will occur. It is worth noting that the learning and prediction algorithms throughout the entire process continue to refine their decisions and predictions based on feedback from the performance measured at the PHY and MAC layers.

5) System Integrity and Resilience

With the envisioned transition of current NAS operations into a future concept with autonomous spectrum management capabilities, it is essential that the system continues to operate with minimal interruption, and continues to meet or exceed the current commitments. Ideally, the infusion of the autonomous spectrum concept would lead to enhanced system capacity and enhanced resource efficiency, which would lead to an overall system benefit. The system must also exhibit resiliency and continue to carry out its mission in the face of outage and adversity. Accordingly, the system must incorporate controls that detect outage and adverse events and conditions, respond appropriately to these disturbances, and rapidly recover afterwards.

6) Elements of UAM

Advanced Air Mobility is an air transportation initiative that enables movement of people and cargo in urban, rural and regional locations using newly-design aircraft. A new breed of vehicles capable of vertical takeoff and landing, with electric

propulsion and low noise profile, are anticipated to enable a new transportation option.

The UAM project is developing a modern air traffic management approach that employs modern technologies to enable a highly collaborative, automated, networked and information rich environment. It is anticipated that air operations in the urban environment will need robust air-ground and air-air communications technologies to satisfy safety critical information distribution among airspace users. Communications systems will be required to seamlessly connect the aircraft with a variety of information sources to enable safe travel in different conditions and environments.

The UAM system utilizes principles developed for the UTM concept of operations, and it is likely that some UAM elements will have similar functions. The following is a brief description of key UAM components, which are illustrated in Fig. 2.

- The Provider of Services for UAM (PSU) is an automated system that performs multiple functions. The PSU is a repository that provides information and data services to stakeholders, provides weather and airspace advisories, disseminates FAA critical operational information and more. The PSU is able to provide strategic deconfliction, resolve tactical conflicts, deliver separation management services and exchange information with other PSU systems.
- The Supplemental Data Service Providers (SDSP) are third party suppliers servicing stakeholders with different types of specialized information. Access to SDSP services can be directly from the provider or through the PSU services.
- Aerodrome is a facility where vehicle arrival and departure operations take place, and passengers or cargo are able to enplane or deplane.
- UAM Operator manages vehicle operations and can be responsible for one or more vehicles in a fleet.
- Pilot in Command (PIC) is a person responsible for piloting the aircraft and ensuring flight safety.

The UAM architecture will have interfaces to the Air Navigation Service Provider for the exchange of airspace status, information requests and others. Additionally, interfaces to the UTM UAS Service Supplier will be available to share relevant information between UAM and UTM airspace operations [15]. It is anticipated that UAM flight operations will require frequent information exchanges between the ground and vehicle. At the time of this writing, the communications system that will be employed to serve the needs of UAM has not been determined. However, frequency assignments in a specific spectrum band will be required to meet anticipated communication needs.

B. System Functionality

As described previously, the primary functional elements of the architecture include artificial intelligence, prediction, resource allocation, optimization, and frequency engineering. The following sections provide an overview of the functionality of the various aspects of the autonomous spectrum concept.

1) Artificial Intelligence

Artificial intelligence is the study of intelligent agents: any machine or device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. In aeronautical communication networks, many centralized and distributed intelligent agents (a.k.a. decision engines or "brains") embedded in numerous communication nodes adopt different mathematical models (e.g., neural networks) to make decisions that maximize the spectrum utilization efficiency while satisfying the quality of service. In our spectrum study, AI is the key function to enable smart, autonomous, and efficient decision making in various aeronautical communication scenarios.

The proposed AI approach will leverage the latest advancements in machine learning (ML), which is a method of data analysis that automates analytical model building. As a branch of AI, ML is based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention. In aeronautical communications, the learning-based system is able to alter dynamically its operational modes, communication patterns and parameters in a rapidly changing environment.

It must also be emphasized that, while many ML algorithms have been around for a long time, the ability to automatically apply complex mathematical calculations to big data in aeronautical applications is still an open challenge as of yet. In particular, most ML algorithms cannot be applied directly to big data due to the curse of dimensionality. For big data, pre-processing including dimensionality reduction is usually required for ML applications.

2) Prediction

Prediction focuses on forecasting future data values and/or patterns through the analysis of previous data. In this research, prediction is an important function closely related to other functions. For example, in AI-enabled resource allocation, making an optimal allocation often needs prior knowledge on the locations and the communication demands of all aircraft at future time instances, which requires air traffic and communication demand predictions throughout the NAS.

In aeronautic communications, since many of the relevant datasets are a function of time, prediction in this research focuses on time series data. Relevant datasets would include aircraft position throughout its flight path (in terms of latitude, longitude, and altitude), air-ground and air-air communications occurrences during specified time windows, channel state information of communication links, and weather conditions over time. Notable characteristics of time series patterns include trends, which are specific directions of the time series data (such as upward or downward trends), seasonality where patterns repeat at predictable intervals, and noise which are essentially random values that are not predictable at all.

Prediction can be accomplished using various approaches, ranging from simple methods such as those based on analysis of historical trends, to more sophisticated algorithms such as those that utilize machine learning techniques. This research studies a number of prediction techniques including both model-based methods and learning-based methods. For example, time series forecasting is the use of a model to predict future location/demands based on previously observed values. In

learning-based predictions, neural networks (e.g., recurrent neural network (RNN), deep neural network (DNN), long short-term memory (LSTM)) are trained by partitioning the dataset into training, validation, and test periods. Once the neural network model is trained, various metrics (e.g., mean square error, root mean square error, and mean absolute error) can be employed to evaluate model performance in terms of the difference between forecasted versus actual values.

3) Resource Allocation

In wireless communications, there are three independent and parallel signaling dimensions for data transmission: time, frequency and space (i.e., multiple antennas). Accordingly, the spectrum resource spans over these three dimensions. In addition, according to information theory, signal power is also a key factor in determining the data transmission rate. Apparently, resource allocation is mostly required in a multiuser scenario (i.e., multiple communication links) where different users/links must share available resources. In this spectrum research, resource allocation is the core function that will be thoroughly studied under various network configurations.

In general, spectrum and power must be jointly allocated to maximize the system performance. In a system where each communication node is equipped with one antenna, a channel may refer to a fixed carrier frequency with given bandwidth, or a set of time-frequency resource blocks. In a system where each transmitter/receiver has multiple antennas, the added spatial degree of freedom creates additional parallel channels by proper channel decomposition through spatial encoding and decoding. In all cases, our new concept explores and leverages AI/ML to enable autonomous and dynamic resource allocation.

4) Optimization

In AI-assisted NAS operations, all decision making is essentially an optimization process. For example, most resource allocation problems in wireless communication can be boiled down to mathematical optimizations under resource constraints.

Combing machine learning and conventional model-based optimization techniques, we propose a learning based optimal decision making framework. Fig. 3 depicts the schematic diagram of our learning-based approach, which comprises two steps: *offline training* and *online running*. In offline training, the training datasets will be generated by solving the mathematically formulated problem using conventional modeled based techniques (e.g., integer programming, convex or nonconvex optimizations). In some cases, we may not be able

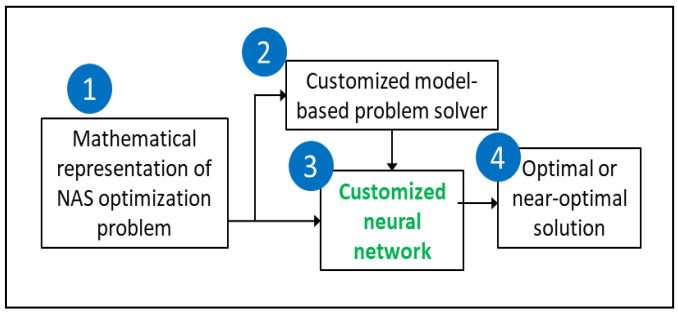


Fig. 3. Learning-based Optimization Approach

to obtain the optimal solution due to the NP-hardness of the problem. Then, near-optimal solutions will be used to produce the training datasets. Since neural networks typically require massive datasets for training, this step may take a long time to complete, so it will be conducted offline. In online running, we feed the network settings and parameters into the well-trained neural network to seek optimal or near-optimal solutions in real time. By combining the conventional model-based approach and the latest neural-network-based machine learning techniques (i.e., data-driven approach), each intelligent agent is able to make decisions in real-time in dynamic NAS environments.

5) Frequency Engineering

Due to the limited number of available VHF/UHF frequencies for air-ground communications, the frequency engineering function implements a frequency reuse capability while simultaneously striving to minimize RF interference between communication facilities throughout the NAS. Frequency engineering consists of three analysis areas: inter-site (or co-channel), adjacent channel, and co-site. It is anticipated that frequency engineering will be accomplished at various levels in the network structure. Allocation services will draw inference from prediction services input and frequency engineering computations, which will be conducted in near real-time to mitigate the potential of interference by enabling

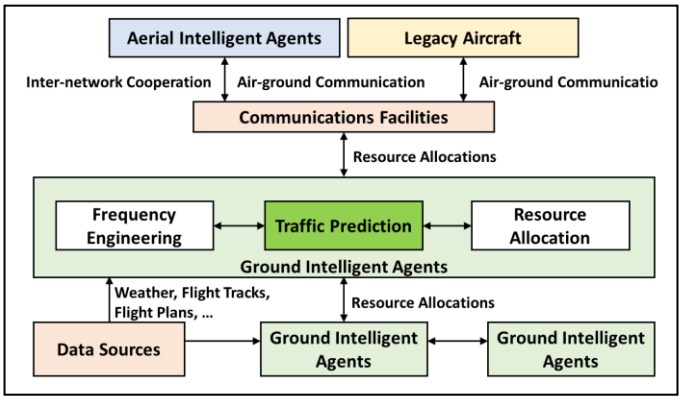


Fig. 4. Air-Ground Process Flow

expeditious channel assignments and power control.

C. Process Flows

The following sections provide an overview of the functionality of the various aspects of the autonomous spectrum concept.

1) Air-Ground Process Flow

Fig. 4 illustrates the air-ground process flow. Intelligent agents located at regional centers process data items such as flight plans and weather information to obtain a prediction of air traffic for the region. Based on the predicted demand, the regional allocation service generates and disseminates a pool of candidate channel assignments to sector-level intelligent agents, which further refine the predictions based on local information, including real-time aircraft tracks and local weather. From these

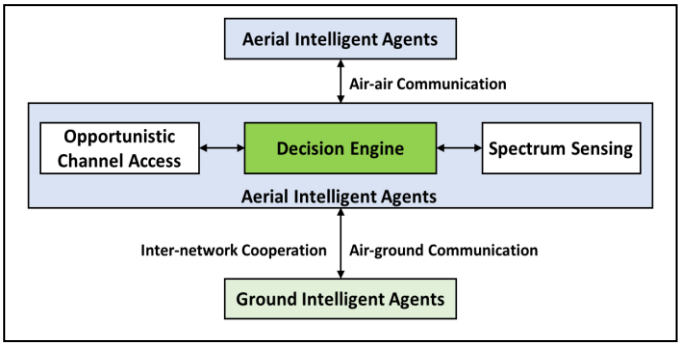


Fig. 5. Air-air Process Flow

refined predictions, the intelligent agents calculate air-ground communication parameters (e.g., channel assignments, power constraints, and modulation/coding assignments) for each sector, and distributes the information to the various sector stations.

2) Air-Air Process Flow

In an air-air communication network, aerial intelligent agents (i.e., aircraft) operating in proximate airspace form a distributed mobile ad-hoc network. Fig. 5 shows the functional diagram of an intelligent agent. The decision engine is the central component responsible for learning and making critical decisions. For example, whenever an aircraft needs to communicate with its neighbor(s), the decision engine first selects a set of channels that may be available based on channel quality and occupancy predictions, then the spectrum sensing unit will sense these channels and feedback the results to the decision engine, which will select a vacant channel based on the channel state information and nearby interference level to maximize the signal-to-interference-plus-noise ratio (SINR) of the communication link.

While the air-air and air-ground communication networks can operate independently, the concept also considers inter-network cooperation between the two networks. More specifically, the two networks may share the same spectrum (licensed or unlicensed) to further maximize the spectrum efficiency. For licensed spectrum sharing, the cognitive radio concept is adopted where the air-ground links are the incumbent (primary) and the air-air links are secondary. For unlicensed spectrum, both networks will follow the same opportunistic channel access principle.

D. Testing/Validation/Simulation Environment

In order to evaluate spectrum management concepts and evaluate performance of AI algorithms, a testing and simulation environment is necessary. The incorporation of a simulation environment allows for real-time testing and analysis of the autonomous spectrum concept. An important feature will be the ability to conduct investigations utilizing live or virtually-generated traffic. The simulation environment will include a variety of modules including a visualization module, a scenario developer module, a simulation manager module, flight plan creation with corresponding trajectory generation and an accompanying database module. The architecture for the testing/validation/simulation capability is illustrated in Fig. 6.

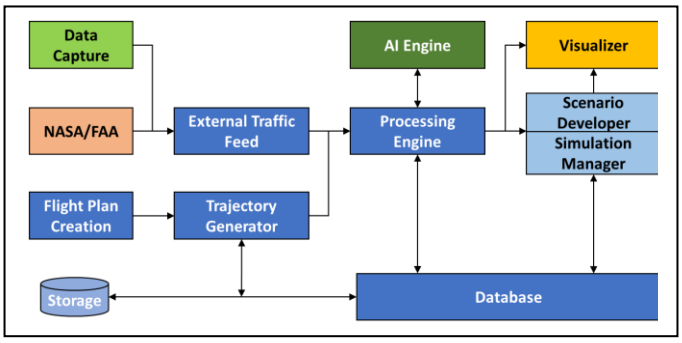


Fig. 6. Testing/Validation/Simulation Architecture

The visualization module, implemented as a Graphic User Interface (GUI), will allow for a dynamic, real-time performance evaluation of Air Traffic Control (ATC) spectrum utilization and management. The GUI will display airspace configurations including airspace sectors, communications transceivers, and aircraft tracks as well as the RF signal properties of the communication systems under evaluation. Each sector graphically shown will be interactable allowing the user to observe the chosen sector's individual properties as well as its frequency allocations and link signal strength information. The visualizer will be supported by the NASA WorldWind application programming interface [16], shown in Fig. 7, which will enable the rapid production of graphical results for evaluation purposes.

The scenario development module allows for the initiation and configuration of test cases that can be evaluated using the simulation capability. The versatile range of scenarios presented will permit the analysis of several ATC communication scenarios as well as expose unforeseen risks which can then be mitigated through further experimentation. The scenario development module will be supported by several randomization algorithms to produce the most inclusive range of scenarios possible.

The simulation manager module controls the execution of the simulation by determining and assigning the order of modules being executed. The module also includes a fail-safe functionality where it will be able to cancel or reject module execution if presented with an unexpected error.

The database module will be used to store the overall simulation configurations, inputs, and results. The storage of simulation results is supported by Structured Query Language (SQL) and allows for comparative analysis between several

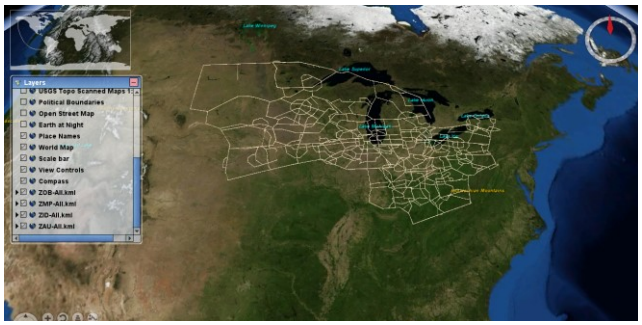


Fig. 7. NASA WorldWind Visualizer

simulation scenarios. The database module will also serve as a large-scale, testing tool that determines if different variations of the system architecture improve over time.

III. Conclusions

Spectrum depletion is a concern for aviation worldwide. This problem is limiting growth and modernization of the overall air transportation system with likely economic implications. This study investigates the collaborative use of artificial intelligence and spectrum management concepts for dynamic allocation of frequencies based on communications demand. More specifically, we proposed a learning based spectrum management framework by combining the conventional model-based approach and the emerging data-driven approach. Key functionality and process flow are discussed for air-ground and air-air communications. This new concept is expected to meet the spectrum needs of future NAS applications including UAM and UTM. Our future work includes technical implementation and evaluation of the proposed concept.

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