Dynamic Channel Assignments for Efficient Use of Aviation Spectrum Allocations

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***Abstract*—The demand for voice and data communications continues to rise with the emergence of new aerial vehicles into the airspace and the continued growth of aviation operations throughout the National Airspace System (NAS). Recent studies have shown that the anticipated growing demand for spectrum resources will exceed the capacity of existing aviation spectrum allocations. Further, airspace configurations, via assignment of fixed channel allocations within standard service volumes, do not allow for the dynamic and efficient distribution of spectrum resources based on airspace demand; as a result, a new approach to aviation spectrum management is needed to support the forecasted needs of new airspace users. The National Aeronautics and Space Administration (NASA) is investigating applications of artificial intelligence (AI), machine learning (ML), and other advanced concepts to solve a dynamic constraint satisfaction problem which is analogous to the frequency assignment problem faced by aviation. Procedures and strategies for dynamic channel allocation can be borrowed from other large-scale mobile services (i.e., 4G/5G applications) and can provide a novel spectrum management approach that allows for the intelligent utilization of aviation spectrum throughout the airspace while maintaining the strict quality of service prescribed by aeronautical standards.**

***Index Terms*—Communications, aeronautics, machine learning, artificial intelligence, spectrum sharing, resource management, prediction, national airspace system, AAM. graph coloring**

I. Introduction

NASA's aeronautics research programs are focused on the transformation of aviation for enhanced sustainability and accessibility, including new initiatives such as electric-powered aircraft, commercial supersonic flight, and enhanced air traffic management with increased automation for safer and more efficient air travel. The Advanced Air Mobility (AAM) concept is another initiative that focuses on the development of air transportation capabilities for the movement of passengers and cargo throughout regions of airspace not previously served by traditional aviation operations. As part of this effort, the AAM project is investigating novel air traffic management approaches that enable a more collaborative and information-rich environment. Recent studies have indicated that the complexity of air operations in the AAM environment will require diverse air-ground and air-air communications capabilities to ensure safety and crucial information distribution for users within the airspace. The communications systems of the new aerial users must seamlessly interconnect to other aircraft and ground assets for the timely exchange of data for ensured safe travel throughout varying conditions and environments. As of this time, the specific requirements for AAM applications are still in formulation; however, recent studies performed by the AAM community indicate that the existing spectrum management approach will not scale to meet the anticipated needs [1].

Accordingly, researchers at the NASA Glenn Research Center and the University of Louisville are investigating approaches to enhance the management of aviation spectrum through the implementation of artificial intelligence (AI) and machine learning (ML). The identified techniques for assigning channels for communication links are applicable to both existing applications, such as today's air traffic control (ATC) system, as well as to future applications, such as the AAM initiative.

Recent efforts within this investigation have evaluated the use of a Deep Reinforcement Learning approach for spectrum management in air-ground and air-air AAM use cases, as described in [2], [3]. This paper focuses on the examination of a graph coloring approach to address the channel assignment problem for a hypothetical AAM use case under interference constraints. The investigation compares the performance of a relatively simple (e.g., "greedy") algorithm to the performance gained by using a learning-based algorithm, specifically a graph convolutional neural network, to solve the resource allocation problem. Additionally, various predictive methods are described, which are used to simplify the problem space in situations where obtaining a valid solution may be difficult or impossible for scenarios with large numbers of nodes and many edges.

To support this analysis, the team is also developing an aeronautical communications modeling and simulation capability for the evaluation of proposed spectrum management methods through the implementation and use of graphical, mathematical

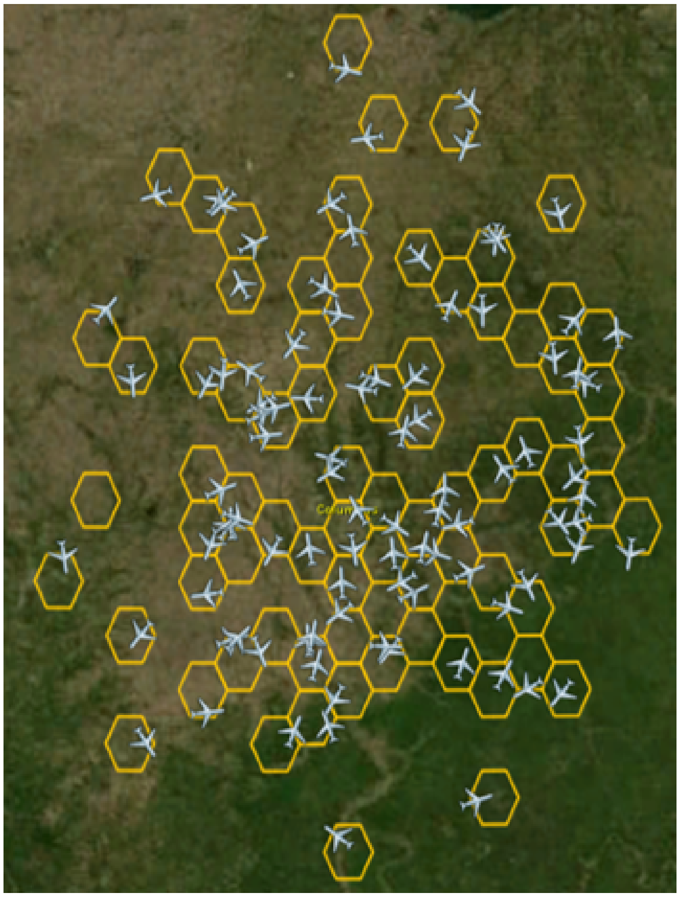

Fig. 1. Visualization of the airspace at one timestep using simulation tool. Aircraft move from their randomly selected origin to a randomly selected destination over 100 steps.

and data analysis tools. This simulation environment allows researchers to evaluate the performance of neural networks and other learning-based models using realistic airspace operational scenarios to assess concept feasibility, accuracy, scalability, and efficiency. It is anticipated that the outcomes of this study will enable the spectrum needs of future airspace communications to be met, including the existing air traffic control system as well as future AAM, high-altitude Class E airspace communications, and others.

II. Problem Statement and System Model

A. Problem Statement

Spectrum is an already finite and limited resource, and considering new aviation initiatives such as AAM are envisioning new complex airspace scenarios with new aerial vehicles and diverse communications requirements, the current infrastructure will likely not scale to meet the anticipated demand. Accordingly, this study examines if the proposed spectrum management strategies can support the demand given a traffic scenario with defined airspaces, aircraft trajectories and supporting ground stations. Areas of investigation include determining: 1) how spectrum "real estate" is required depending on the traffic scenario, 2) if there any limits or "stress points" in a particular region or regions, and 3) how much time the allocation is required for a given flight path. In general the resource allocation function will attempt to minimize interference while utilizing a constrained number of available channels.

For this initial study, the team is evaluating the performance of a graph coloring approach for dynamic resource allocation in a simulation scenario that attempts to align with the current assumption for Urban Air Mobility (UAM) Maturity Level 4 (UML-4), which is defined as a late-intermediate level of maturity in the anticipated evolutionary stages of the UAM transportation system. The UAM maturity levels are described in detail in [1].

B. System Model

In accordance with the assumptions of UML-4, this use case considers approximately 100 aircraft traveling at an altitude of 3000 feet above ground level (AGL). For simplicity, this study assumes that all aircraft traverse a linear lateral trajectory at a constant altitude and velocity between randomly-defined departure and arrival points over 100 simulation steps, as depicted in Fig 1. Future work will focus on more realistic aircraft flight trajectories (vertically and laterally) between defined vertiports through structured air routes referred to as UAM corridors.

Communications links are assumed to be only established between aircraft and ground stations (i.e., no vehicle-to-vehicle communications). Transceiver parameters assume constant transmit power, antenna gain, and channel bandwidth. Free-space path loss is assumed for the link equations, with more complex channel models being planned for future efforts.

This scenario assumes a finite number of available frequency channels to share among all aircraft within the airspace. Wherever possible, the resource allocation function will strive to provide a unique channel to each aircraft to eliminate the possibility of interference. Further, predictive methods are employed such that channels are only allocated when needed (i.e., event-based), which simplifies the allocation process.

For interference calculations, this study focuses on the inter-site frequency engineering procedures for very high frequency (VHF) air-ground links as described by the Federal Aviation Administration (FAA) in [4]. Specifically, the procedures require that at worst-case, an aircraft will receive the desired signal at a level that is 14 dB stronger than from a co-channel interferer, i.e., the desired-to-undesired signal level (D/U) is at least 14 dB. Given the constant transceiver parameters described above, the ratio (D/U) becomes dependent only upon the free-space path loss.

Distance becomes the dominating variable and the desired-to-undesired ratio of 14 dB translates to a distance ratio d_U/d_D of at least 5. Consequently, any co-channel interfering node must remain at least five times the distance from the desired transmitter in order to meet the 14 dB specification. For additional interference protection, this study assumes that any

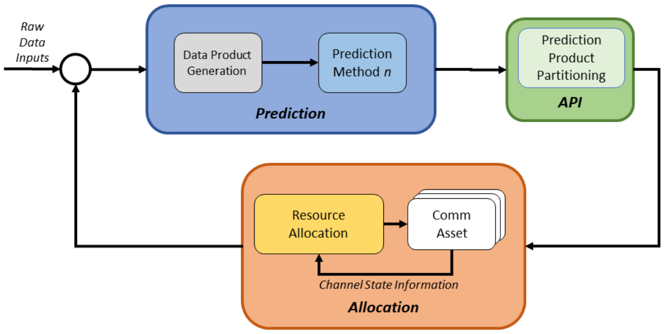

Fig. 2. Prediction and allocation functional flow

transmitting node that is within a distance ratio of 6 will be considered a co-channel interferer.

III. Spectrum Management Approach

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 and machine learning. Fig. 2 depicts the functional flow chart of an intelligent spectrum management concept. The prediction module is a prerequisite for the ensuing allocation module. Specifically, the prediction module outputs air traffic and communications demands (i.e., prediction products) throughout the airspace, whereby the resource allocation module dynamically reserves resources based on the predicted results and other inputs. Then these reserved resources are dynamically allocated to communication assets throughout the air and ground portions of the airspace system. To achieve the goal of safe and efficient air operations, the resource allocation function strives to maximize the utilization efficiency of available resources (spectrum, power, time, etc.), while meeting the desired Quality of Service (QoS) requirements for users throughout the airspace.

A. Resource Allocation

The use of graph coloring in the context of resource allocation has been a widely-studied problem for spectrum management applications [5]–[9], and this investigation focuses on the use of a graph coloring approach to address the channel assignment problem in the AAM scenarios identified previously. Graph coloring is a method that assigns colors to vertices of a graph such that no two vertices linked by an edge share the same color, and Fig. 3 provides an example of how aircraft proximity can be translated to an intersection graph whose vertices and edges are defined by regions of airspace where an aircraft may experience detrimental interference. Aircraft that are sufficiently separated in space would not present a risk of interference and would thus not be joined by an edge in the graph representation.

Utilizing multiple methods to dynamically assign resources allows for selection depending on the complexity of the problem. In cases where the number of available resources exceeds demand, a simple greedy (or first-come first-serve) algorithm is more than sufficient. However, in cases where demand exceeds the available resources, there is potential for interference between many of the aircraft in the scenario. In such cases, the use of a more sophisticated approach based on machine learning may serve to provide a better solution. Accordingly, the following sections compare the performance a relatively simple greedy algorithm to the performance gained by using a learning-based algorithm, specifically a graph convolutional neural network.

B. Prediction

Depending on the complexity of the airspace modeling scenario, determining a valid solution via graph coloring may be difficult or impossible considering the large number of nodes with many edges. One approach to simplify the problem complexity is to only assign spectrum when needed, whereby predictive methods may be used to eliminate interference scenarios that may not be relevant at the time of consideration. For example, airspace nodes will likely not interfere with each other if there is no need for concurrent transmission. Additionally, airspace nodes that are substantially separated in distance are not able to pose unwanted interference, and may also be eliminated from the problem space. As a result, the implementation of methods to predict when communication events may occur can substantially reduce problem complexity and allow for the determination of a solution. Elimination of irrelevant airspace users will remove potential instances of interference, resulting in a simpler graph representation with fewer edges.

Aircraft trajectory prediction can be considered a first step in determining when communication events may occur. Based on environmental factors such as aircraft positions, airspace restrictions, and weather information, the prediction algorithms may determine when an aircraft will have a need for communication, as not all airspace users require an uninterrupted communications link (such as the case for unmanned aerial vehicles). Accordingly, implementation of these prediction methods can simplify the problem complexity, and thereby increasing the possibility of the resource allocation function obtaining a valid solution. Reducing the amount of time required for communications contact allows for more

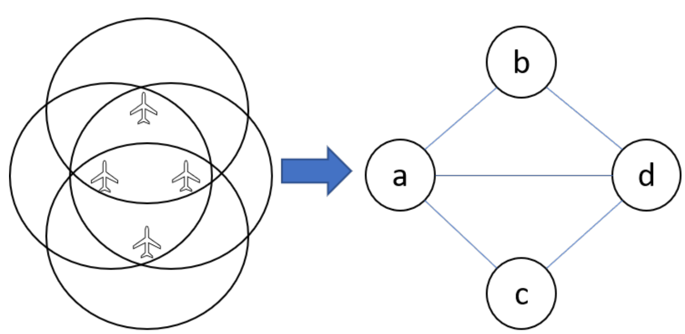

Fig. 3. An example areas of potential interference around aircraft and translating it to a graph.

channels to be used by more aircraft, and therefore increasing airspace communication capacity.

The team is investigating methods of prediction using various approaches, such as 1) flight trajectory prediction using recurrent neural network approaches [10], and 2) communications demand prediction using a federated learning approach [11]. These research areas are still evolving towards maturity and will eventually be incorporated into the modeling and simulation capability. However, for this effort, a more simple approach is used to 1) generate flight tracks between vertiports and 2) estimating communication demand by evaluating airspace sector crossing events. Future work will include consideration for additional events, such as altitude changes, aircraft vectoring around weather systems, and others.

IV. Graph Coloring Method

A. Greedy Algorithm

The most fundamental method to solve the graph coloring problem is via a greedy algorithm, which is analogous to a "first-come, first-served" scheduling process or the functionality of cognitive radios that "listen" for open channels and make use of any unoccupied spectrum at the time. The greedy algorithm has at its disposal a list of available channels (or colors) for each node within the airspace. For each node that requires a channel, the algorithm will assign the first available color, which is then removed as a color option for all other connected nodes. This process is repeated until all nodes are assigned a color. In this implementation, the algorithm will randomly assign a color in cases where there is no available color that would satisfy the problem. Clearly, this method may not provide an optimal solution and may even fail when a valid solution exists. More complex methods may implement sorting or backtracking functionality to determine solutions or to reduce conflicts. Computational complexity is an additional consideration and may become an issue when examining larger systems. Future efforts may explore other heuristic approaches for graph coloring, such as Recursive Largest First, DSatur and others.

B. Graph Convolutional Network

As airspace scenarios become more complex, artificial intelligence and machine learning can be used as tools to aid in the resource allocation problem [12]. However, given the large number of possible scenarios that may or may not have solutions nor labeled training data, investigation of unsupervised learned techniques allows for a viable approach. Accordingly, the team has chosen to implement a graph convolutional neural network inspired by [13], [14]. As an input to the network, an adjacency matrix is formed based on the relative positioning of aircraft within a region of airspace. Given the adjacency matrix as an input, the neural network model returns a coloring solution that attempts to satisfy the graph coloring problem, or in the absence of a solution, minimizes the number of conflicts through an energy-based loss function.

For this study, a graph G is represented by $N \times N$ adjacency matrix $\mathbf{A}$ describing the relation of nodes in edges in the graph. The adjacency matrix serves as the input to the neural network, as illustrated in Fig. 4. The output of the network is an $N \times C$ matrix $\mathbf{C}$ that contains the set of probabilities that a node N would be assigned any color C such that $\sum_c \mathbf{C}_{N,c} = 1$. Ideally, the probability of a single color should approach 1 in a well-trained network. In this context, reducing the loss to zero indicates a coloring solution with no conflicts. However, in cases where there may be no valid solution, the network will minimize conflicts in accordance with the loss function.

The graph network implemented in this work utilizes two topology adaptive graph convolutional layers from [15], with dimensional embedding and hidden layer sizes both set to 60. The input layer uses a ReLU activation function, and the output uses a Softmax activation to generate the output probabilities for each color. Network training is performed using a slightly modified version of the physics-inspired loss function from [13]. The loss is calculated as

$$Loss = \sum_{i}^{C} p_i^{\intercal} \mathbf{A} p_i \tag{1}$$

where p_i is a length N column of $\mathbf{C}$, the probability of assigning the i^{th} color to each node in the graph represented by the adjacency matrix $\mathbf{A}$.

V. Simulations

To implement the intelligent spectrum management concept and evaluate its performance, a modeling and simulation platform consisting of computational tools and environment visualization is being developed. An important aspect of the tool is the development, integration, and evaluation of learning-based models in a simulated airspace operational environment. Additional design objectives include the development of a live, virtual and constructive operational mode in which concepts can be incrementally evaluated as maturity and confidence is achieved.

A modularized architecture design is employed to enable a flexible and scalable approach to evaluate and test various communications systems, airspace environments, and neural network models. The tool is designed to enable rapid development of new airspace configurations and to apply new channel assignment strategies for evaluation. Simulations generate a dataset that is representative of the airspace environment (i.e., adjacency matrix) and provides this information to either internal or external functions for additional processing. External functions may include various artificial intelligence or machine learning applications. The simulation software then utilizes the outputs of these prediction and allocation functions to examine the quality of services for each active communication link in the airspace. Using this simulation tool, the previously-described graph coloring methods are implemented as allocation functions for channel resource assignment.

A. Graph Coloring Allocation Functions

The allocation function utilizes the information on the state of the airspace in the form of an adjacency matrix.

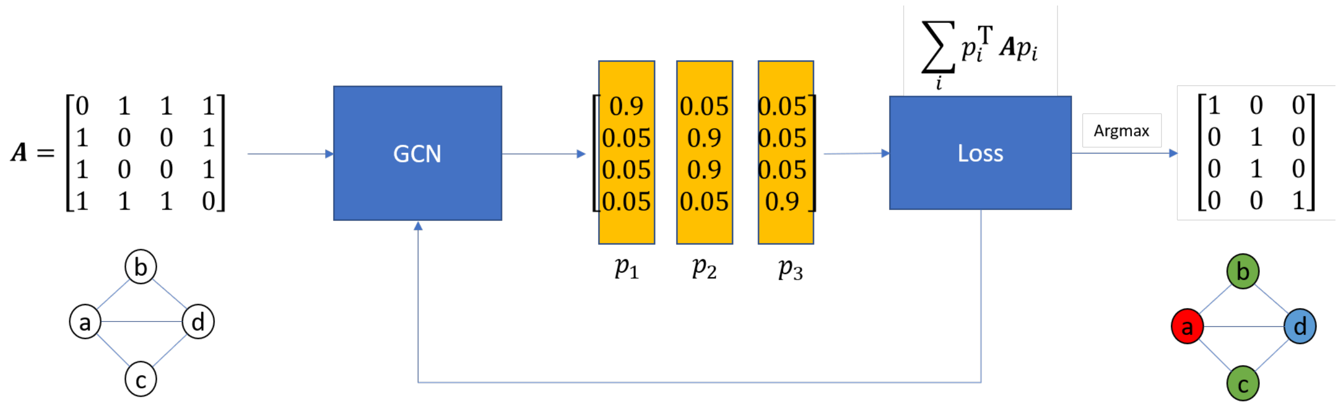

Fig. 4. GCN ex chart with input adjacency matrix A and output coloring assignments.

Initial simulations compare the number of interference events observed within a scenario described by the system model in Section II-B.

Given these assumptions, a graph is created to represent the state of the airspace at each simulation step, and three allocation methods are examined: 1) greedy allocation, 2) a graph network trained using the entire simulation dataset (i.e., iterate over 100 input graphs), and 3) a graph network trained for each simulation step (i.e., a new network is trained for each input graph). In each case the number of available channels was constrained to 20.

The results of the simulations are displayed in Figs. 5 and 6. The number of observed interference events is greatest when the aircraft density is highest, represented by graphs with the greatest number of edges. The greedy algorithm performs the worst when the aircraft density is high, while the graph network methods show improved performance. The graph network that was trained with the entire data set shows a number of instances of worse performance compared to the greedy algorithm.

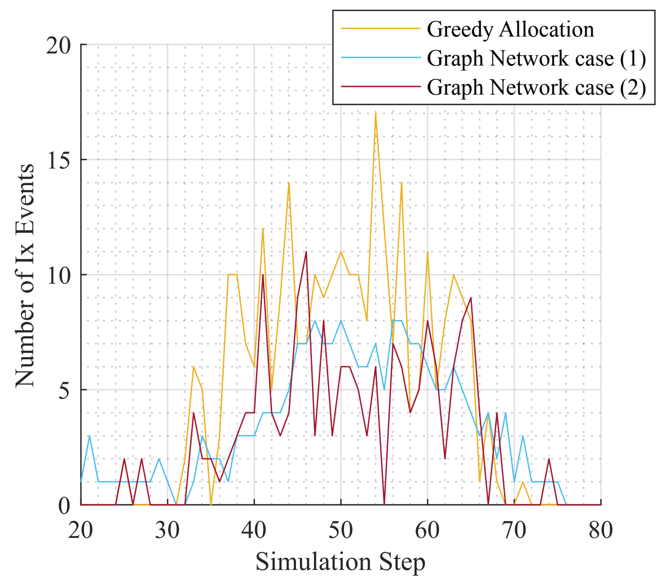

Fig. 5. The number of interference events per simulation time step determined for the greedy allocation algorithm and graph convolutional network cases. Graph Network case (1) was trained using 100 graphs. Graph Network case (2) involved a single trained network per graph.

B. Communication Prediction

In order to simplify the graph provided to the allocation network, this work also considers the case where an aircraft is only assigned a channel when it needs to communicate. Rather than allocate channels to each aircraft in the simulation, the allocation function will only allocate resources to aircraft that are predicted to require communications. The use of machine learning can provide insight into when an aircraft would need to communicate. However, in this paper, a simple method for communication prediction is explored by examining the flight path of the aircraft with respect to airspace boundaries. So this simple method assumes that an aircraft only requires an allocated channel when transitioning between regions of airspace. In the examined scenario, the airspace boundary crossing lies approximately 7.5 km from a ground station, and aircraft that are greater than 6 km from a ground station are considered to require communications for a boundary-crossing event. Fig. 7 displays how the number of edges in the graph, i.e., the number of potential interference events, is reduced from the full airspace scenario.

The three allocation methods are re-examined for the resulting simplified adjacency matrix. In both the greedy allocation and the graph network that was trained for each simulation step, there are no instances of interference. However, the graph network that was trained using all simulation data continues to show instances of interference, albeit significantly fewer with only two instances of interference occurring at four simulation steps.

VI. Conclusions

This study compared different allocation techniques to evaluate communications capacity in a hypothetical airspace scenario. Based on the simulations and their results, key items of observation are as follows:

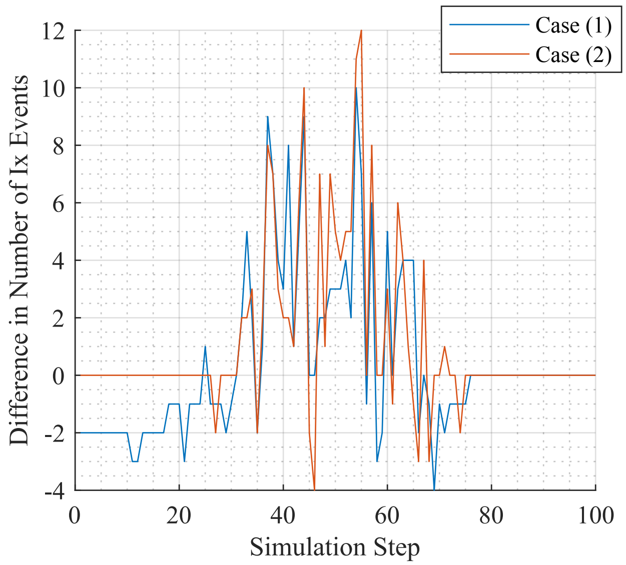

Fig. 6. The difference in the number of interference events between the greedy allocation algorithm and the graph convolutional network cases. Case 1: Greedy Allocation - Graph Network Case 1. Case 2: Greedy Allocation - Graph Network Case 2. Values greater than zero indicate improved performance over the base greedy allocation case.

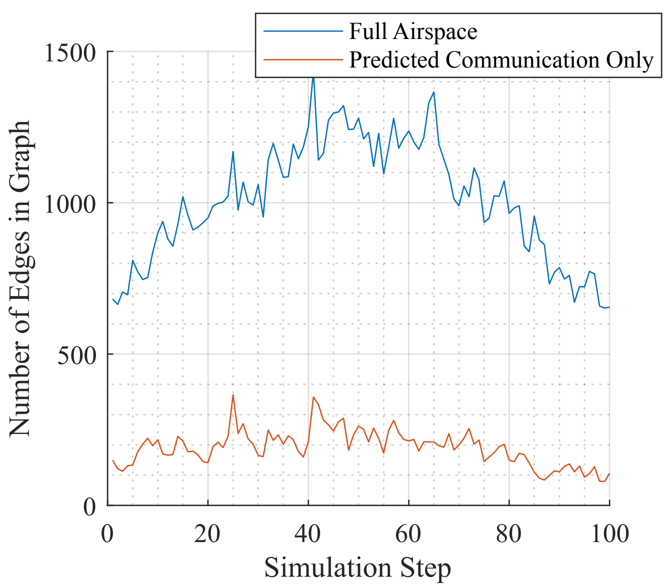

Fig. 7. The number of edges in the generated graph adjacency matrices for the full airspace communication scenario and the simplified predicted communication scenario.

1) Graph coloring using AI shows improved performance over greedy coloring in high density/demand use cases.
2) Graph convolutional networks by themselves are not well-suited to accommodate time-dynamic situations.
3) This weakness in the time dynamic scenarios may be remedied by using structured airspace configurations and separation standards that are under development for AAM. Introducing these configurations would create a finite number of possible graph representations of the airspace. However, such configurations are not yet clearly defined.
4) Combining the graph convolutional network with a recurrent neural network is another potential solution to address the challenge of a time-dynamic structure [16]–[18].
5) There are instances where it may be best to choose which allocation method to use based on available resources and complexity of the scenario.
6) The level of structure in airspace configurations will greatly impact the ability for communication systems to appropriately allocate resources [19], [20].

Future work will include additional constraints in the defined graphs such as power, velocity, etc. Methods of introducing time dynamics into the graph neural network will be explored along with more sophisticated communication prediction algorithms to reduce the complexity of the graph structure. Further analysis in a variety of different configurations of structured airspaces and corridors will aid in the development of AAM communications by enabling more efficient use of aeronautical spectrum resources.

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