Improving Air Mobility for Pre-Disaster Planning with Neural Network Accelerated Genetic Algorithm

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Abstract

We propose an optimized framework to adjust airport schedules during impending weather disasters by aggregating data from multiple airports and determining the optimal number of evacuation flights. Our Neural Network-accelerated Genetic Algorithm enhances efficiency, enabling faster convergence with reduced computational overhead, and remains effective even when trained on data from different airports.

Introduction

- Emergency situations, particularly natural disasters, pose significant challenges to air mobility, requiring robust strategies to maintain airport and airspace operations. Effective pre-disaster planning is essential to optimize airport schedules and manage the surge in evacuation flights without disrupting regular air traffic.
- Natural disasters often trigger a mass movement of populations toward safer areas, leading to increased traffic across all modes of transportation, including airways. This creates a critical challenge: balancing the normal operations of evacuation airports while expanding their capacity to handle the additional demand.
- Our research proposes a novel pre-disaster scheduling framework designed to optimize the outbound capacity of airports during emergencies. This approach leverages non-critical airport resources, such as those allocated for military and general aviation operations, ensuring that evacuation flights can be accommodated without affecting regular air traffic.
- To enhance the efficiency of evacuation planning, we introduce a Neural Network (NN) accelerated Genetic Algorithm (GA). This innovative combination reduces computational overhead and improves the GA's performance, even when applied to airports on which the NN was not originally trained.

Methodology

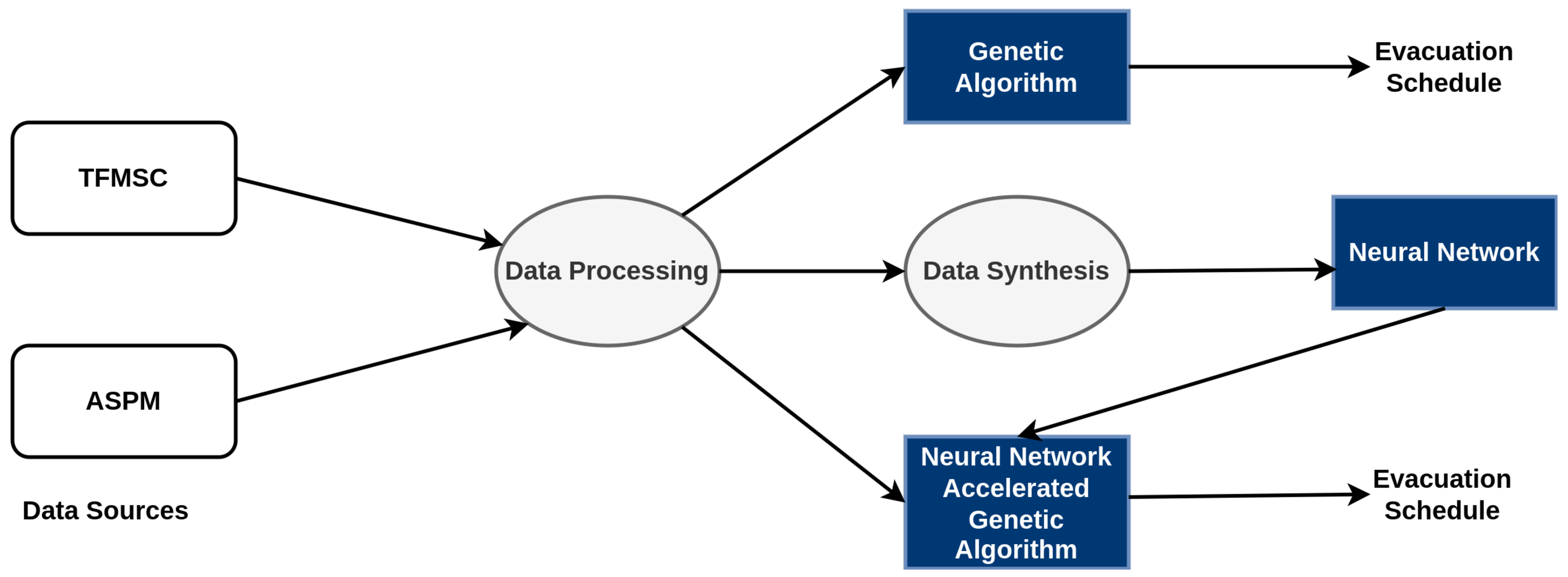

Figure 1. Research Flow

1. **Problem Formulation:** We analyzed the operational capabilities of nine major airports in Florida, focusing on aircraft categories such as Air Carrier (AC), Air Taxi (AT), General Aviation (GAV), and Military (MIL). The goal was to maximize the outbound evacuation capacity without disrupting regular air traffic by leveraging the non-commercial capabilities of GAV and MIL operations.
2. **Data Collection and Processing:** Data was sourced from the FAA's Traffic Flow Management System Counts (TFMSC) and Aviation System Performance Metrics (ASPM) databases. TFMSC dataset provided capabilities of the airports and ASPM dataset was used for city pair analysis, determining flight duration, and retrieving the top ten destination airports.

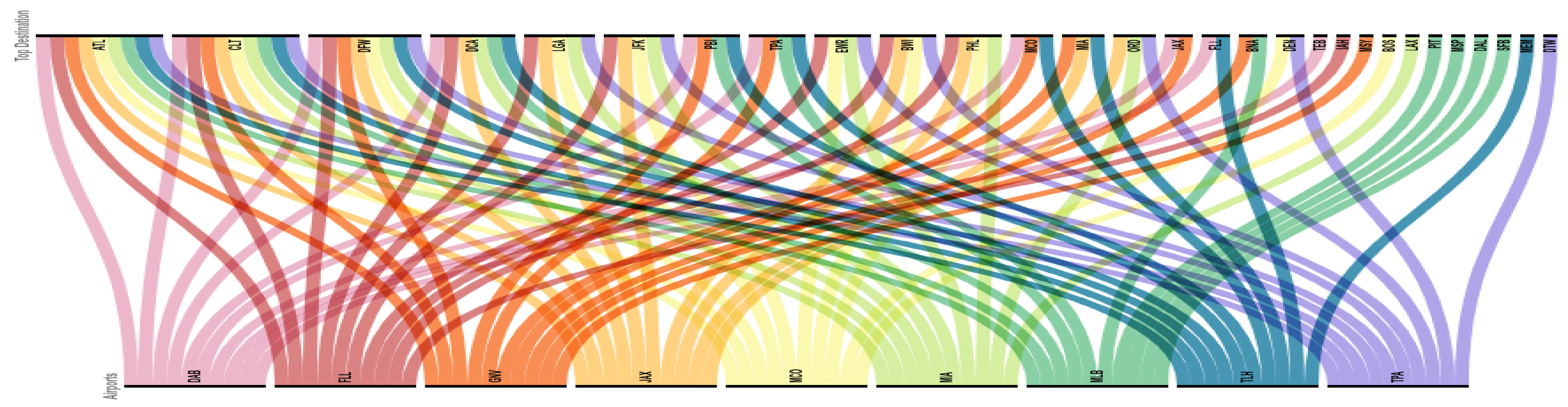

Figure 2. Top ten destination airports from the nine major airports in Florida

3. **Genetic Algorithm:** A Genetic Algorithm operated by selecting flights to top destination airports based on a fitness function using the equation:

$$FitnessScore = 0.5 * p + 0.2 * c - 0.3 * s - penalty \qquad (1)$$

where
- p is the popularity value of the destination airport based on the number of flights from evacuating airport
- c is the mean of the combined capability
- s is the standard deviation of the combined capability
- $penalty$ equals to 1 when choosing more number of flights in destination airports beyond the capability of evacuating airport

4. **Data Synthesis and NN training:** To train NN, we synthesized a dataset by excluding the airport under test to prevent the model from being trained on data from the same airport. The synthesized data included the popularity (p), mean capability (c), and standard deviation (s) of the top ten destination airports, as well as the mean capability of the evacuating airport. A simple Neural Network was trained using synthesized data to predict optimal flight selections.

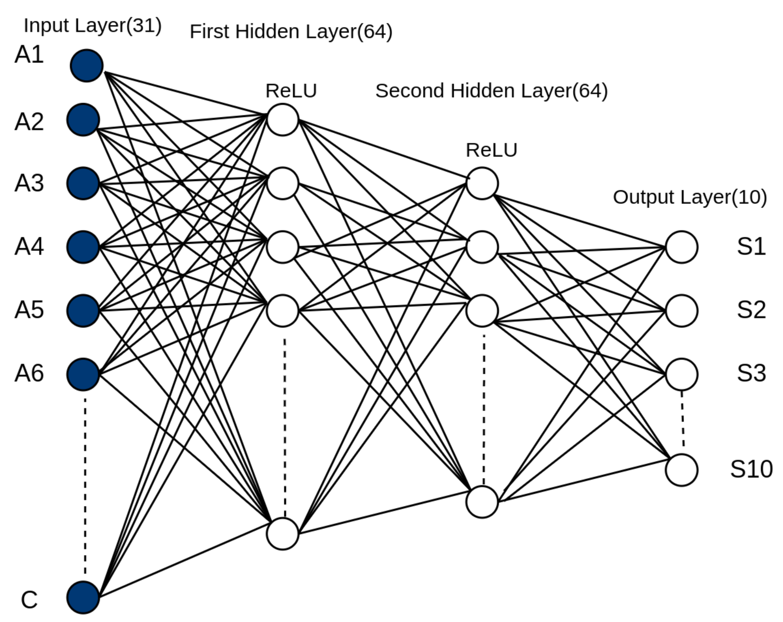

Figure 3. Neural Network Architecture

5. **GA-NN Integration:** The NN's predictions were used to initialize the GA population, accelerating convergence and reducing computational overhead in two different ways:
   - **Approach 1:** Population generated by the NN are directly added to the pool by replacing the random population generated by the GA.
   - **Approach 2:** In this approach before inserting the population generated by NN, the population is sorted in descending order on the basis of fitness score. The lower order of population are replaced by the population generated by NN.

Evaluation and Results

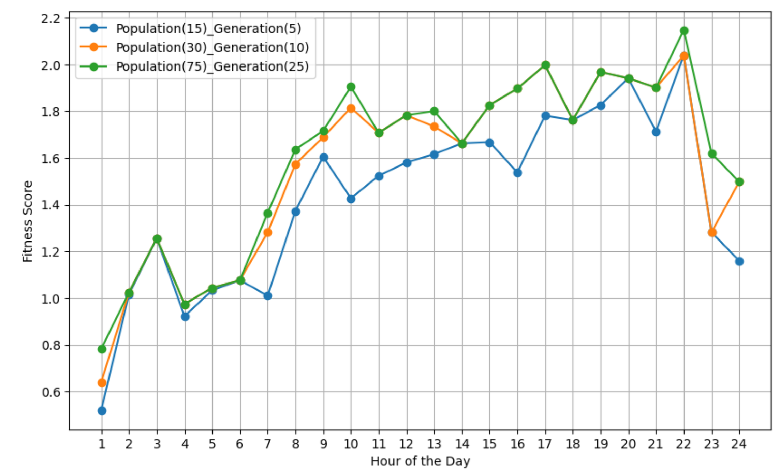

Figure 4. Fitness Score for various combinations of population size and number of generations for Genetic Algorithm during different hours of the day.

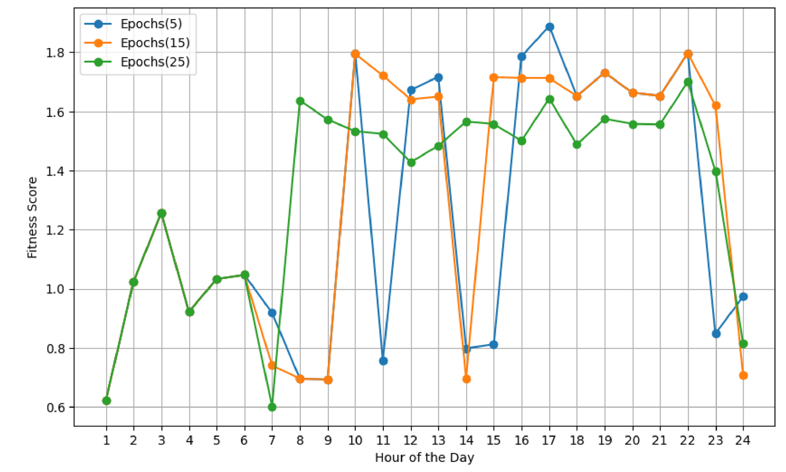

Figure 5. Fitness Score for various neural networks trained under different numbers of epochs.

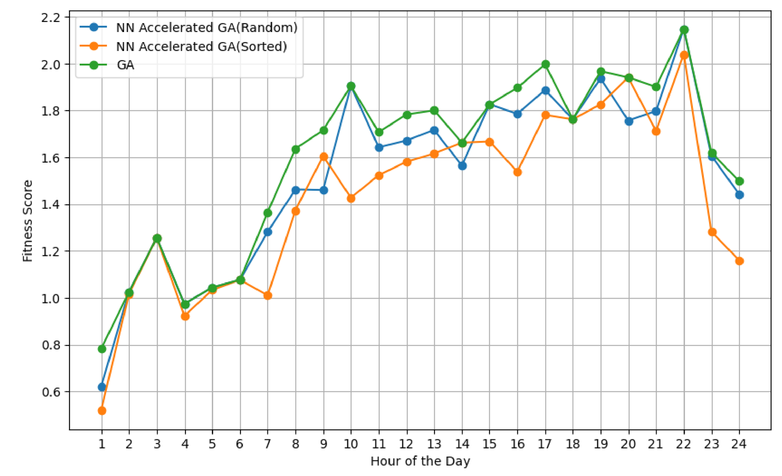

Figure 6. Fitness Score of GA and two different NN accelerated GA.

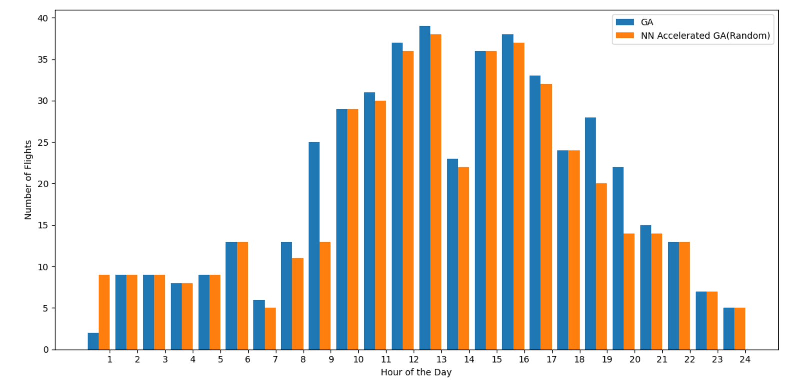

Figure 7. Number of evacuation flights scheduled by the GA and NN accelerated GA

Conclusion

This research presents a novel approach to pre-disaster evacuation planning for air mobility, leveraging a Neural Network (NN) accelerated Genetic Algorithm (GA). The integration of NN with GA significantly improved the efficiency of evacuation planning by reducing the computational overhead and accelerating convergence. The proposed framework was validated using real flight operation data, demonstrating its ability to optimize airport operations during emergency situations without disrupting regular air traffic. These findings suggest that the NN-accelerated GA is a powerful tool for enhancing air mobility planning in critical scenarios, with potential applications extending to various airport environments and emergency response strategies.

Acknowledgement

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