Optimizing Route Planning for C-17 Operations Utilizing Artificial Neural Networks for Weather Prediction

THESIS

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I. Introduction

1.1 Background

The Department of Defense (DoD) has an obligation to the American people to be stewards of their tax dollars in all defense related spending. As such, the DoD is always searching for ways to minimize spending while also increasing combat capabilities, military readiness, and operational effectiveness. Aircraft are an integral part of the United States Air Force (USAF) and by its very nature, fulfilling these goals incurs a substantial cost for procuring and consuming fuel. From the 2019 fiscal year budget for the DoD, $24 billion was requested for fuel consumption with $6.6 billion going to operations and $4.5 billion going to transportation [1]. The USAF consumes around half of this budget for aviation fuel with majority of it being used by Air Mobility Command (AMC), a major command (MAJCOM) within the USAF structure [2]. Of the many aircraft within the AMC inventory, the C-17 fleet represents the primary aircraft responsible for global transportation and cargo, and as such consumes the largest amount of the aviation fuel [3]. Increasing efficiency in fuel consumption within this fleet can have an immense impact on cost savings for the USAF, and the DoD as a whole.

1.2 Overview

There are a multitude of ways to address increasing efficiency in fuel consumption among C-17s. This study focuses particularly on headwind and temperature predictions in the upper atmosphere relating to mission planning for C-17 operations. Having accurate predictions for the varying spatial regions of the atmosphere will enable mission planners to develop the most fuel efficient route from origin to destination. Thereby being able to optimize altitude and flight path which are natural parameters of constructing a fuel-efficient route [4].

There are two distinct classes of weather models to look at, which are deterministic and ensemble. While a deterministic model will be comprised of a single model, an ensemble model will be comprised of multiple deterministic models [5]. In an ensemble model, each of its members is initialized with slightly different values for their parameters. This will generate a forecast giving a variety of results, which provides keener insights into accurate forecast predictions. The weather data for this study comes from the Global Data Assimilation System (GDAS), which is run by NOAA. The GDAS takes in all available global satellite, conventional (rawinsonde, aircraft, surface), and radar observations to report weather conditions across the globe every six hours. This report details conditions for every latitude and longitude coordinate across 31 different pressure layers. The system is responsible for providing the initial conditions for the deterministic and ensemble weather forecast produced by the global forecast system (GFS) [6]. Currently operations within AMC still rely on the deterministic forecast while NOAA has switched to utilizing results from the ensemble forecast.

Temperatures and wind speeds are known to follow a nonlinear behavior when modeled over time. Their discontinuous and stochastic nature makes it difficult to provide accurate predictions utilizing linear approximation techniques [7]. Artificial neural networks (ANN) can learn the underlying structure of datasets and provide accurate predictions for seemingly complex weather problems [8]. This ability has generated a huge research surge in investigating the application of ANNs to solve varying weather related problems [9].

The following section will discuss background literature relating to the methodologies being deployed within this work, including the difference in weather model types, ANNs, and shortest path problems (SPP).

II. Literature Review

2.1 Overview

There are many different methodologies being employed to construct a model to address this study. As such, this section will examine some of the previous research done in these areas, along with providing background information on the techniques themselves.

2.2 Weather Models

Two main techniques for weather forecasting are used in the industry today, these being deterministic and ensemble forecasting [7]. A deterministic forecast focuses on making a single forecast of the most likely weather outcomes given the best approximation and modeling of the initial conditions. This is done by having the initial state of the atmosphere established using observational data. Then an atmospheric model simulates evolution from the initial state. From this the output is processed and made available. According to a reference document put out by NOAA this method has some drawbacks due a few reasons relating to error. These being that the equations used by the model do not fully capture processes in the atmosphere, model resolution is not sufficient to capture all features in the atmosphere, the initial observations are not available at every point in the atmosphere, and the observational data cannot be measured to an infinite degree of precision. In an ensemble forecast, multiple deterministic forecast are developed representing a set of possible future states. These can be developed in many different ways, but one technique used is to slightly perturb the initial conditions then develop deterministic models from each instance of perturbation. This addresses certain sources of uncertainty that are not captured in a deterministic forecast. These being uncertainty introduced as part of imperfect model formulation, and uncertainty introduced as part of imperfect initial conditions [5].

Ensemble modeling for weather is the current method employed by large organizations, such as NOAA. It has been shown to be better at forecasting than deterministic models in a myriad of applications [10]. For example, Keith and Leyton displayed how weather models were better predictors of adverse weather conditions, which would require aircrafts to consume more fuel than originally expected [11]. In a different study by Taylor and Buizza, ensemble forecasting showed higher accuracy levels than deterministic for a one to ten day weather forecast looking at electricity demand [12]. Ensemble forecasting is not always superior in every instance though. An incident in Venice showcased this, where the accuracy for predicting flooding due to storms more than four days out with a deterministic model was comparable to the ensemble model [13]. In another instance, Leonardo and Colle found that a deterministic model gave the lowest total track error when predicting North Atlantic tropical cyclones, even when compared against several different ensemble models [14]. In general though, it is noted by the World Meteorological Organization that ensemble forecast produce more reliable results than deterministic forecast, especially when the forecast is for more than 1-3 days out [15]. This is due to their ability to capture the uncertainty

2.3 Weather Factors

While some of the factors in this study may be self-explanatory, others require further detailing. Within the GDAS, wind speeds are expressed in terms of their orthogonal velocity components, which is the zonal velocity (u) and meridional velocity (v). If relating to an x-y Cartesian coordinate system, u runs parallel to the x-axis and v runs parallel to the y-axis. Therefore positive u values represent winds blowing east while positive v values represent winds blowing north. These components are then combined using the Pythagorean Theorem to acquire the magnitude of the wind. With the magnitude calculated, it is a simple trigonometric expression to discover the direction, or angle, of the resulting wind vector [16].

Weather measurements are recorded in the GDAS by latitude, longitude, and atmospheric pressure. Earth's atmosphere can be divided up into multiple layers which are measured for similarity around the globe by their pressure levels as opposed to actual altitude. For example, the upper edge of the troposphere may be 13 km in altitude above England, but may be 12 km high above China. Both though will have similar pressure levels, typically around 5 kPa. Geopotential height is then used to approximate the actual height of a pressure layer above the mean sea level, at the specified coordinate. Geopotential height is measured in geopotential meters (gpm), and can be thought of as an adjustment to geometric height that accounts for the variation of gravity with latitude and altitude. The definition for geopotential height is expressed below [17].

$$\Phi(H) = \int_0^h g(\phi, z)dz \tag{1}$$

2.4 Neural Networks

ANNs are brain inspired systems which are intended to loosely replicate the way humans learn. They consist of input and output layers, as well as one or more hidden layers containing neurons (nodes, units, or processing elements) that transform the input into something that the output layer can use. The strength of an ANN is obtained as the result of the connectivity and collective behavior of the neurons within the layers. The mathematical goal of the network being to approximate some function f^*, where f^* can be a continuous function or a classifier [18]. This technique has been shown to have a high degree of accuracy when predicting weather forecasts, especially when modeling temperature, and wind speed [19].

The architecture of a basic ANN is shown in Figure 1. The neuron is the basic building block of the network and exist in all the layers. The number of neurons in a layer is commonly referred to as the width of the layer. The width of the input layer reflects the number of features or variables used to characterize an observation or function f. The output layer width represents how many outputs the model is attempting to approximate for function f^*. This could be multiple in the case of classification problems or multi-output regression, or one if approximating a single output function.

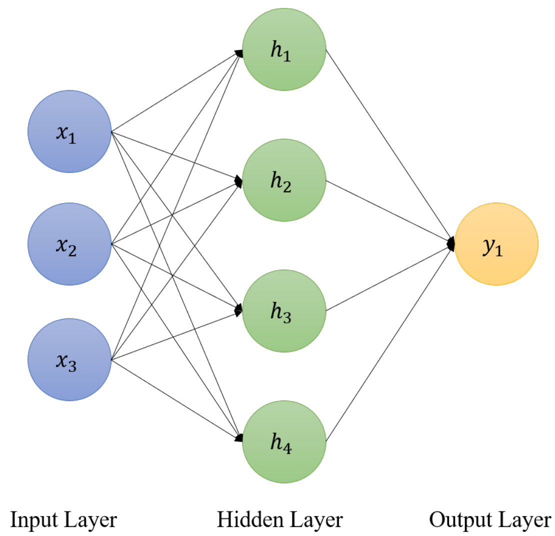

Figure 1. Basic architecture of an ANN with one hidden layer, three inputs, and one output

2.5 Recurrent Neural Networks

2.6 Long-Short Term Memory

2.7 Ensemble Neural Networks

2.8 Shortest Path Problem

In examining the mission planning problem, a network for potential flight routes can be created and treated as a SPP. This technique solves the problem of finding the path between two nodes such that the sum of its weights is minimized [13]. Recent studies looked at using stochastic SPP with correlated arcs for finding the optimal path through a future instance of the network [14]. Others have explored time-optimal paths for the solution of aircraft routing [15].

III. Methodology

3.1 Overview

This section will explore in detail the methodology used within this study. The first section will detail the preprocessing done with the data, as this is an essential step in the process of a machine learning pipeline. Following that will be the exploratory data analysis, and architecture for the LSTM model. Finally, the training and testing process will be examined along with the measures of performance for comparing against previous methodologies.

3.2 Data Preprocessing

Weather data for this study was obtained from NOAA's data archives developed from the deterministic GFS model. The set used ranges from 20 August 2017 to 18 December 2017, with readings taken every six hours. Each reading contains weather data for each integer latitude and longitude intersection with latitudes ranging from $-90°$ to $90°$, and longitudes ranging from $-180°$ to $180°$. Additionally each coordinate has data for 31 different pressure levels within the atmosphere, with a range from 2000 kPa to 20000 kPa. This yields 2,008,800 unique coordinates across the entire globe, with each coordinate having 603 observations within the time range.

The original data was contained in a Grib2 file format which does not readily readable on a Windows operating system. To mitigate this, MATLAB has a free tool called the "nctoolbox" which converts Grib2 files to NetCDF. This new file format is readable by Windows, and can be manipulated in MATLAB to extract the variables of interest for any specific coordinate. Appendix A details the code used in MATLAB to pull the data and structure it into a time series sequence for any specific coordinate.

3.3 Exploratory Data Analysis

3.4 LSTM Architecture

Designing the architecture for the LSTM network requires defining parameters along with choosing the coordinates to use for training and validation. The base model was trained off a single coordinate in the upper atmosphere, to determine the ability of the network to learn the underlying relations within the weather dynamics in order to generalize across different hemispheres and lower altitudes. From this, three different model alternatives were looked at to the augment the base model design. This included adding additional variables, and creating an ensemble network.

Parameters that were tuned for the LSTM architecture were the number of layers, layer width, optimizer, learning rate, activation function, and early stopping criteria.

Table 2 shows the

Parameter Options					
Layers	Layer Width	Activation Function	Optimizer	Learning Rate	Patience
1	8	Relu	SGD	0.001	25
2	16	Tanh	Adam	0.01	50
	32	Elu	RMSprop	0.05	75
	64	Sigmoid		0.1	100
	128				
	256				
	512				

Table 1. All options for parameter tuning looked at for designing the LSTM network. This gives 2,688 different designs and parameter values to test.

3.4.1 Base Model

3.5 Training and Validation

3.6 Previous Work Comparison

IV. Analysis

4.1 Analysis Datasets

V. Conclusions and Future Research

5.1 Conclusion

5.2 Appendix

Appendix A. Relevant Theses

After speaking with my advisor, we could not find any previous theses that were relevant to my thesis.

Advisor: Raymond R. Hill

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