Air Traffic Flow Analysis Based on Aviation Big Data using Machine Learning

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Abstract- *Air traffic flow management (ATFM) that is both timely and effective will be critical in future congested air travel. Increased demand for unmanned aerial vehicles and general aviation aircraft imposes more responsibilities on the ATFM. By enabling aerial vehicles to be tracked and monitored in real time and with more accuracy, the improved automated dependent surveillance-broadcast (ADS-B) technology enables the design of a more intelligent ATFM architecture. The dispersed ADS-B ground stations and collected ADS-B communications are used in this article to create an aviation Big Data platform. By analyzing the created dataset and mapping the extracted data to the routes, the air traffic flow between different cities may be calculated and projected, with the prediction task being handled by two machine learning algorithms. The experimental results using real-world data demonstrate that the suggested long short-term memory (LSTM) traffic flow prediction model outperforms the competition, even more so when irregular traffic management parameters are considered.*

Key Words: Air traffic flow management, automatic dependent surveillance-broadcast (ADS-B), aviation big data, machine learning, flight route.

1. INTRODUCTION

More and more people are choosing air travel as their primary means of transportation due to the advancements in civil aviation. With an increasing number of people opting to fly, airspace will become increasingly congested. This will place additional strain on air traffic management (ATM) and present new challenges for air traffic surveillance systems. The main objective of ATFM is to assist the flight control department in making timely and appropriate assessments regarding whether aviation traffic is approaching the upper limit, ensuring that air traffic stays acceptable and that available airspace capacity is appropriately utilised. It's crucial for the ATFM system's future processing, data analysis, and visualisation since trustworthy and accurate air route flow information is necessary. Until now, most air traffic controllers and other relevant organisations have depended on antiquated technologies like radar, which are both expensive and inaccurate at identifying aircraft. Based on vast amounts of real ADS-B messages, this article studies traffic flow facts and estimates for aviation routes. Long-term support vector regression (LSVR) and Long Short-term memory (LSTM) and long-term memory (LTM) are two machine learning techniques that can be used to predict flow. When applied to a large dataset, we found that both SVR and LSTM-based prediction models can accurately forecast air route flow, with the LSTM-based model outperforming the SVR-based model by a wide margin.

2. PROBLEM STATEMENT

To comprehend, In future congested air traffic, timely and efficient air traffic flow management (ATFM) will be critical. The ATFM's burden is exacerbated by the growing demand for unmanned aerial vehicles and general aviation aircraft.

3. LITERATURE SURVEY

Oliver Ohneiser, Vicki Ahlstrom, Kevin Tracy, Brett Williams .,"Comparison of Air Traffic Controller Display Techniques for Reaching Target Times at Significant Waypoints"[1], new display approaches are required to support controllers as a time-based air traffic control methodology is implemented. This is especially true when it comes to meeting aircraft target times at key waypoints. In this paper, a small scale, reduced complexity study looked at five potential visual aids: a Slot Marker, Time-To-Gain/Lose, Timeline, Target Window, and a Baseline display. Sixteen study participants were in charge of flying planes to ensure that they arrived at their destinations on time. Participants performed the worst when they had no visual guidance at all, according to simulation data. According to survey results, the Slot Marker display was the most straightforward and simple to use. High time accuracy is associated with a higher number of given orders, according to performance metrics. Multiple commands, on the other hand, result in inefficient flight trajectories due to speed modifications. As a result, for visual aids in air traffic control, a trade-off between high time accuracy and low economically feasible command rates is required.

Michael Finke, Ioannis Theodorou., "Towards Precise Performance Measurements in Live Air Traffic Validation Exercises"[2], each day, a plethora of factors influence air traffic, many of which are continually changing and resulting in tremendous volatility. Daily weather conditions, charter flights, flight cancellations, changes to the architecture of the airspace, and the temporary inaccessibility of supporting infrastructure such as navigation aids, runways, or taxiways are just a few examples. This scenario precludes meaningful performance measurements when validating with live air traffic, as SESAR's xStream project is doing. The beneficial effects of the system under evaluation may be unnoticeable, comparable to a low signal-to-noise ratio, particularly when the volatility of the air traffic under study is comparable to the system's expected benefit. To determine a minor influence statistically, one must either review a large data set or, if that is not possible, identify and eliminate potential sources of disturbance prior to the study. Within the xStream project, a technique has been developed to perform this removal in a rational and systematic manner, filtering out datasets that make meaningful baseline-solution comparisons difficult due to drastically different weather conditions, traffic mix, and so on. This is accomplished through the use of multiple systematic pair-wise comparability checks between designated reference and workout data sets. Among other things, these inspections look at local and regional meteorological conditions, the configuration of the airspace and air traffic control services, and the current traffic constellation. Algorithms based on the technique were developed at the German Aerospace Center's (DLR) Institute of Flight Guidance in Braunschweig and implemented in a variety of in-house software modules, enabling these tests to be conducted almost entirely autonomously.

Petr Bojda, Embry-Riddle Aeronautical University, Daytona Beach, Florida., "AIR TRAFFIC SURVEILLANCE METHOD USING AN EXISTING NETWORK OF DME NAVIGATION SYSTEM"[3], the goal of this study is to develop a novel technique to airspace surveillance. It identifies and subsequently determines the location of air vehicles that are currently using the RNAV DME DME technology to calculate their own positions. By analysing communications between an aeroplane and a ground-based DME beacon, the observer can determine the current distance between the two. This effectively changes the purpose of the DME from navigation to surveillance (an aircraft computing its own position) (an observer determining the position of a DME-equipped aircraft). There is no requirement for additional systems or signals, and the target can be recognised and located from a single point (the observer).

Rolf Klomp, Clark Borst, Rene van Paassen, and Max Mulder., "Expertise Level, Control Strategies, and Robustness in Future Air Traffic Control Decision Aiding"[4], future air traffic controllers adopting 4-D trajectory-based operations will necessitate the creation of new and more sophisticated "human-centered" decision support tools. One approach to creating human-centered decision aids is to use ecological interface design, which focuses on displaying the limits of safe system performance rather than prescribing established methods or discrete solutions. Humans occasionally choose control actions that are near to these restrictions, which raises concerns about the robustness of control actions. An ecological 4-D trajectory control interface developed in a previous work was tested to see if it helped maintain airspace robustness. A metric has been developed to measure sector and control-based resilience, with the minimum value being the lowest and the average value being the highest. Quantifying and assessing the impact of competence level on the long-term durability of human-generated control actions was given major attention. Expert participants performed better on control tasks than skilled or novice participants, according to the results of a human-in-the-loop experiment. End-user knowledge and control techniques had the greatest influence on boundary-seeking control behaviour at ecological interfaces, according to this finding.

Sarah K. Yenson, Shirley Phillips, Archer Davis, and James Won, MIT Lincoln Laboratory, Lexington, MA.,"EXPLORING HUMAN-SYSTEM RESILIENCY IN AIR TRAFFIC MANAGEMENT TECHNOLOGIES", [5]. The primary purpose for incorporating automated decision support tools (DSTs) into the National Airspace System in the mission-critical environment of air traffic control is to improve system efficiency in terms of cost, capacity, and safety (NAS). On the other hand, growing automation raises new concerns about the impact on operator situation awareness, over- or under-reliance on automation, and the system's ability to recover to an acceptable performance level following degradation or non-nominal events. As a result, a fragile system may be built, one that operates beautifully under normal conditions but catastrophically fails under adverse conditions. As automated technologies become more prevalent in air traffic control, it is critical to encourage human-computer systems while avoiding system brittleness.

4. PROPOSED SYSTEM

Input – Input as dataset of Air traffic.

Preprocessing – Pre-processing module to clean the dataset and extract the information.

Data Extraction – Extract the feature from the dataset in Data Extraction. The selection of data attributes can have a big impact on the model. The selected features, according to the associated studies, primarily contain time-series features.

Transformation – We define an air route as a path through airspace that connects two specified airports in order to collect extensive information about air routes and to increase the dataset for a more accurate task of air traffic prediction. The route's breadth is estimated to be ten kilometres, although its height is unknown.

Route Generation – We can determine the number of flights on a specific air route during a given period of time, i.e. the route's statistical traffic flow.

Flow Statistics – The statistic task is divided into the steps below. The exact range of longitude, latitude, and altitude determine the assessment region of a certain air route first. These parameters are defined by the positional information of the air route's ends. The defined ranges are also ready to be calculated and verified later.

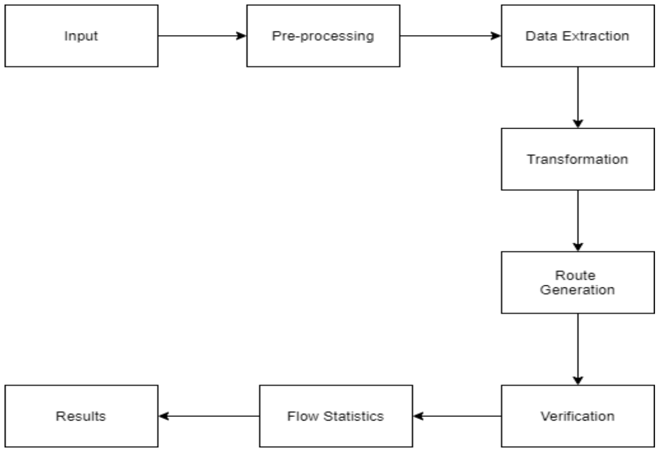

Figure 1. System Architecture

5. ALGORITHM

LSTM

The LSTM is a very effective recurrent neural network for processing and anticipating events in time series with extended inter- and delay periods (RNN). While recurrent neural networks are susceptible to the gradient vanishing problem, this one is not. The LSTM is particularly adept at understanding natural language, recognising targets, and detecting sounds. The gated neuron characteristic of LSTM cells is unique. Due to the LSTM's structure, it is capable of storing long short-term memories, making it ideal for dealing with temporal sequence prediction difficulties.

1: To define the LSTM Network, set the ip units, lstm units, op units, and optimizer (L)

2: Use 3 to normalise the dataset (Di) into values ranging from 0 to 1.

3: Choose the size of the training window (tw) and arrange Di accordingly.

4: do the following for n epochs and batch size

5: Educate Your Network (L)

6: Run Predictions Using L for

7: Using the loss function as a guide, calculate the loss function.

SVR

SVMs and Support Vector Regression are both based on the same concepts. SVR (Support Vector Regression) and SVM (Support Vector Machine) are both classification algorithms that utilise the same fundamental concepts. SVR is a variant of SVM that uses numerical rather than categorical dependent variables. One of SVR's key advantages is its non-parametric technique. The SVR approach constructs the model using kernel functions. Frequently, kernel functions such as linear, polynomial, sigmoid, and radial basis are used. Before the SVR approach can be utilised, the user must select the appropriate kernel function. Choosing which kernel functions to utilise is a time-consuming procedure that necessitates the use of optimization techniques. This article does not include a discussion of kernel selection. The SVR model was constructed using R's automatic kernel selection. The aforementioned model employs the Radius Basis Function (RBF) kernel. Due to this nonlinear relationship and the difficulties associated with selecting a kernel, we recommend RBF as the default kernel for beginners in machine learning. The kernel function is used to convert our data from non-linear to linear space. As a result, once the SVR has determined the best fit, data can be remapped to their original positions.

Now let us represent the constructed SVR model:

$$Y_i = W.K(x_i, x) + b$$

6. CONCLUSION

In this study, we suggested a model for predicting air traffic flow based on massive volumes of ADS-B data collected by our aviation big data platform. Using this model, we examined data from over 200 air routes and subsequently conducted certain visualization tasks for ATFM. In addition, two prediction models based on SVR and LSTM were proposed to aid in traffic flow monitoring and optimization.

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