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Identification, Characterization, and Prediction of Traffic Flow Patterns in Multi-Airport Systems

Mayara Condé Rocha Murça and Robert John Hansman

***Abstract*— Efficient planning of airport capacity is key for the successful accomplishment of traffic flow management. Yet, the dynamic and uncertain behavior of capacity-determining factors makes it difficult to estimate flow rates precisely, especially for strategic planning horizons. Metroplex systems impose additional challenges in this decision-making process because of relevant operational interdependencies between the closely located airports. This paper presents a data-driven framework to identify, characterize, and predict traffic flow patterns in the terminal area of multi-airport systems toward improved capacity planning decision support in complex airspace. Through the identification and characterization of patterns in the terminal area traffic flows, we learn recurrent utilization patterns of runways and airspace as well as relevant decision factors, and use that knowledge to develop descriptive models for metroplex configuration prediction and capacity estimation. The framework is based on the application of machine learning methods on historical flight tracks, weather forecasts, and airport operational data. A multi-layer clustering analysis is first performed to mine spatial and temporal trends in flight trajectory data for identification of traffic flow patterns. Based on this knowledge, a multi-way classification model is developed to generate probabilistic forecasts of the metroplex traffic flow structure for look-ahead times of up to eight hours. Finally, an empirical approach for arrival capacity estimation is proposed based on historical flow pattern behavior. The observed variability in throughput and terminal area delay performance emphasizes the importance of metroplex configuration predictability toward improved flow rate planning and ultimately better traffic regulation.**

***Index Terms*— Air traffic management, machine learning, multi-airport systems, traffic flow pattern.**

I. Introduction

THE U.S. domestic air transportation market served 719 million passengers, with approximately 26,500 scheduled flights per day, in 2016 [1]. In order to enable such level of air travel activity, an intricate network of airport and airspace resources (National Airspace System – NAS) must be operated daily to ensure the airlines accomplish their flights in a safe and orderly manner. Traffic Flow Management (TFM) is a key component of the NAS operation. Its goal is to adjust the flows at a regional/national level in order to match demand with available capacity at airport and airspace resources and mitigate delay impacts when imbalances are expected to occur because of traffic volume, special events or weather conditions.

Airport capacity planning is a challenging aspect of TFM. Flow rate predictions are required to determine the need of Traffic Management Initiatives (TMI) (e.g., Ground Delay Programs) and plan the regulation of the traffic, but they depend on a number of factors/decisions that are uncertain, especially for long time horizons. For example, at any given time, airport capacity depends on the runway configuration selected by air traffic control personnel and on the conditions of the weather. For multi-airport systems (or metroplexes), the capacity planning process is even more challenging. Because the airports are closely located and the terminal airspace is shared, runway and terminal airspace configuration decisions have to be coordinated in order to de-conflict the arrival and departure flows and minimize interferences [2]. As a consequence of the existence of constraining inter-airport flow interactions, the capacity of individual airports becomes highly dependent on the global metroplex system configuration.

Currently, the planning of runway/airspace configurations and capacity in the NAS is typically done on the basis of experience and through the use of rules-of-thumb. Despite the availability of many weather forecast sources, few tools are available to directly assist traffic managers in the translation of weather forecasts into operational impact. As a result, they often come across unpredictable and undesirable situations resulting from these complex decisions. An overestimation of capacity can amplify airborne delays and require reactive undesirable actions (e.g., diversions, holding), whereas an underestimation of capacity can lead to resource subutilization and unnecessary ground delays. Recent studies have investigated whether artificial intelligence and data analytics techniques can be used to automatically provide capacity-related information for improved TFM decision support. Statistical approaches have been developed to predict runway configurations [3], [4] and throughput [5]–[8] based on historical data. Yet, they do not completely account for key system aspects that characterize the most complex operational environment of metroplex systems.

This paper contributes to fill this gap by presenting a data-driven framework to identify, characterize and predict traffic flow patterns in the terminal area of multi-airport systems. As the observed patterns in the terminal area traffic flow reveal recurrent utilization patterns of runways and airspace, a "reverse-engineering" approach is taken to identify the major

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configurations in which the metroplex collectively operates as well as key intervening factors. The knowledge generated by the characterization of metroplex flow patterns is then used to develop descriptive models for metroplex configuration prediction and flow rate estimation.

The data-driven framework is based on a sequential application of machine learning methods on historical flight tracks, weather forecasts and airport operational data. A multi-layer clustering analysis is first performed to mine spatial and temporal trends in flight trajectory data for identification of traffic flow patterns. Based on this knowledge, a multi-way classification model is developed in a supervised learning approach to generate probabilistic forecasts of the metroplex traffic flow pattern for strategic planning horizons. To the best of our knowledge, this is the first work that attempted to predict air traffic flow patterns based on knowledge extracted through flight trajectory data mining. Finally, a new empirical approach for metroplex arrival capacity estimation is developed based on performance curves derived from historical traffic flow pattern behavior. The framework is demonstrated for the New York metroplex, given its complexity and importance in the NAS. However, it should be mentioned the methodology is generalizable and can be applied to any multi-airport system in the world.

The paper is organized as follows. Section II reviews related works on airport runway configuration and capacity planning and on trajectory data mining for flow identification and prediction. It also provides additional background related to the New York metroplex (the test case for this study). Section III provides an overview about the methodology and datasets used. The identification and characterization of traffic flow patterns are discussed in Sections IV and V. Section VI describes the descriptive approach for prediction of traffic flow patterns, and Section VII discusses the empirical approach for metroplex capacity estimation. Finally, Section VIII summarizes the work and major achievements and identifies potential next steps.

II. Background

A. Airport Runway Configuration and Capacity Planning

Airport capacity is determined by a number of structural, operational and environmental factors. The runway configuration is typically the key structural/operational factor affecting the throughput performance of an airport [9], and it refers to the set of runways and active runway thresholds selected by air traffic control personnel at any given time to serve the arrival and departure demand. The selection of the runway configuration in which an airport will operate is a subjective human-based decision-making process, which is per se affected by various factors such as meteorological conditions (wind speed and direction, ceiling and visibility), demand, noise and workload related restrictions and terminal airspace constraints.

Another key driver of airport capacity is weather. Not only it influences the selection of runway configurations, but also directly impacts their throughput performance. Adverse weather conditions such as low ceiling and visibility or high surface winds can drastically reduce capacity and even cause the closure of the airport at extreme cases.

Analytical [10], empirical [9] and simulation [11] models have been extensively used for offline estimation of the expected number of movements that an airport can handle during a given period of time under a particular runway configuration and weather condition. However, during real-time TFM planning, the direct application of these models for capacity prediction is not straightforward because runway configurations, weather conditions and demand are not deterministically known a priori, especially for long forecast horizons.

Given the large amounts of operational data generated and recorded every day by the Air Traffic Management system and the advancements in computing power, a body of literature has emerged to investigate whether artificial intelligence and data analytics techniques can be leveraged to provide capacity-related information for improved TFM decision support [3]–[8]. Different methods for machine learning have been used to translate weather forecasts and/or historical observed throughput into probabilistic airport capacity profiles for strategic planning horizons [5]–[8]. In a similar fashion, historical airport operational data have been used to model the airport runway configuration selection process using discrete-choice methods and develop predictive tools for runway configuration planning [3], [4]. In a prescriptive mode, optimization models have been created to prescribe the optimal sequence of runway configurations so as to minimize delays while satisfying operational constraints [12], [13].

The statistical approaches developed for airport capacity management typically do not incorporate system-level aspects that arise in metroplex operations and affect throughput, such as the existence of runway configuration interdependencies and inter-airport flow interactions. As a consequence, they tend to show reduced performance and become less suitable for these more complex operational environments. For instance, Avery [14] found that predicting the runway configurations individually for the New York airports and then combining the results to obtain the aggregate metroplex configuration rather than directly predicting the combined multi-airport runway configuration led to much lower accuracy in the configuration forecasts. Donaldson [15] also ratified the existence of metroplex effects after identifying capacity gaps for specific combinations of runway configurations in the New York metroplex through the comparison between capacity envelopes for the individual airports and for the multi-airport system.

Given the existence of significant operational interdependency between airports in a metroplex, they require a system-level approach for capacity management. This paper contributes to fill this need by developing a data-driven framework to automatically learn the major configurations in which a metroplex system operates, assess their performance and predict their use. Through the identification of terminal area traffic flow patterns, we learn recurrent utilization patterns of runway configurations and arrival/departure route structure as well as relevant decision factors, and use that knowledge to develop descriptive models for metroplex configuration prediction and capacity estimation.

B. Flow Identification and Prediction

The problem of identification and prediction of air traffic flow patterns addressed in this paper can be framed as a problem of identification/prediction of spatial and temporal trends in the collective movement of aircraft through the airspace. Such problem appears in a variety of other domains in which the movement of objects tends to exhibit correlations in both spatial and temporal dimensions (e.g., vehicles in a road network).

Early approaches to spatial pattern mining involved indexing trajectory databases and performing basic analysis such as nearest neighbor queries [16]. More recently, trajectory clustering [17]–[21] has been extensively used for the identification of common trajectory patterns and outlier detection in tracking datasets of vehicles [18], people [19], animals [20], weather phenomena (e.g., hurricane, cyclone) [21], etc. In the aviation domain, clustering techniques have also been used to identify spatial traffic patterns from flight track data for monitoring, anomaly detection and airspace redesign purposes [22]–[27]. Eckstein [24] developed a flight track taxonomy based on filtering, segment identification, track decomposition and clustering for monitoring aircraft behavior and evaluating how well individual flight trajectories are performing their procedures in the terminal airspace. Gariel *et al.* [25] also developed a framework for airspace monitoring based on the use of density-based clustering to learn typical patterns of operation and assess the conformance of flight trajectories. Similarly, Rehm [26] and Enriquez [27] relied on hierarchical and spectral clustering respectively to identify nominal and abnormal spatial traffic patterns to/from a specific airport.

A smaller number of studies have incorporated the temporal dimension in the analysis to investigate trends in the occurrence of spatial clusters over time [28], [29]. However, such analysis is key for understanding the dynamics of the flow behavior and generating the knowledge necessary for prediction. Song *et al.* [30] manually extracted flow features from actual flight trajectories, which were aggregated into a vector-based representation and clustered to identify traffic flow patterns in airspace sectors. Flights entering and exiting an airspace sector through the same neighboring sector were considered to be part of the same flow regardless the shape of their trajectories. With the methodology, they idealized a framework for sector capacity prediction for longer look-ahead times, although little discussion was provided on the predictability of the flow features. Sidiropoulos *et al.* [31] proposed a framework to identify spatiotemporal patterns in traffic flows crossing the terminal area boundary in metroplex systems using flight plan data. However, as the spatial analysis was restricted to the location of crossings at the terminal area boundary, their framework did not provide complete flow information.

Finally, there has been substantial research dealing with the problem of trajectory prediction. Some works developed purely statistical approaches to predict motion patterns of moving objects from trajectory data [32], [33]. Others also relied on knowledge about the dynamics of the moving target. For instance, aircraft trajectory prediction methods usually use models of aircraft dynamics and intent information to predict future aircraft positions [34], [35]. While these methods focus on individual trajectory prediction especially for conflict detection and avoidance, they have been used to predict traffic flows for short time horizons (5 to 30 minutes) [36]. Yet, for long-term forecasts, these approaches tend to become inappropriate as the predictability of individual aircraft behavior significantly reduces. For strategic planning time frame, aircraft state information may not even be available at the time of the prediction. This paper takes a different approach by directly predicting traffic flows for longer time horizons using external variables (not related to individual aircraft state) found to be correlated with common flow structures.

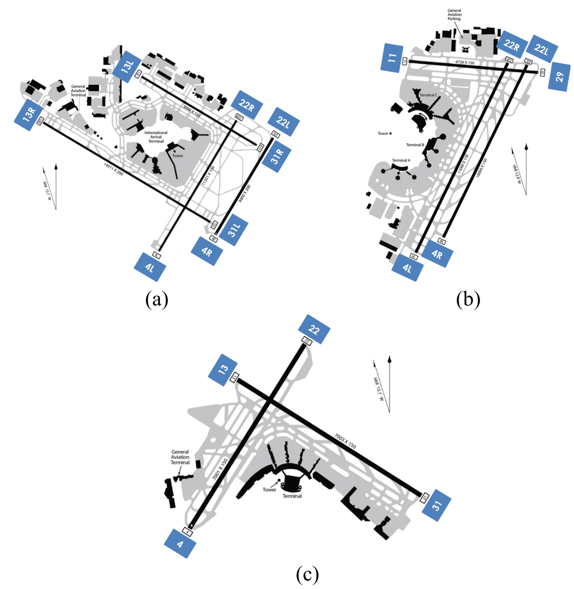


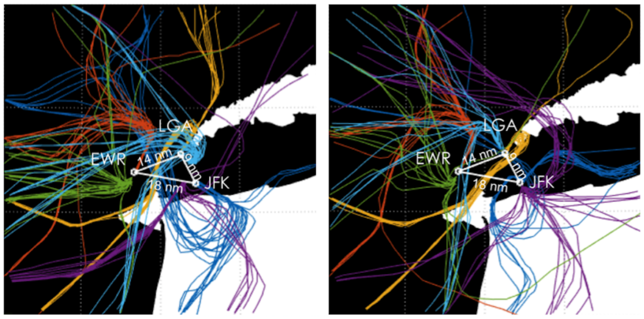
Fig. 1. Runway infrastructure. (a) JFK. (b) EWR. (c) LGA.

C. The New York Metroplex

The multi-airport system that serves the New York metropolitan region is composed of three primary commercial airports: John F. Kennedy International (JFK), Newark International (EWR) and LaGuardia (LGA). Together, they served 128.9 million passengers in 2016, being the world's second busiest multi-airport system [37].

The runway layouts of the New York airports are illustrated in Fig. 1. Air traffic control services are provided by the individual Air Traffic Control Towers (ATCT) and one consolidated Terminal Radar Approach Control (New York TRACON – N90). ATCT and TRACON rely on "Letters of Agreement" to use specific operating procedures and delegate airspace regions that need to be shared [38].

Given the high traffic volume and airport interdependency, the New York metroplex is often recognized as one of the most operationally complex multi-airport systems in the world. The terminal airspace is characterized by dense routes with small separation and very dynamic traffic flows during the course of a day. To exemplify, Fig. 2 shows the traffic flow structures at two different hours of one specific day.



(a) (b)

Fig. 2. New York metroplex traffic flows during a 1-hour period. (a) June 23, 2015 at 7-8AM. (b) June 23, 2015 at 4-5PM.

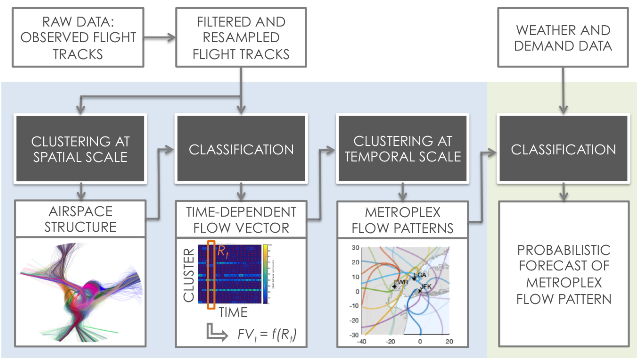


Fig. 3. Schematic overview of machine learning framework.

III. Methodology

A. A Machine Learning Framework for Identification and Prediction of Traffic Flow Patterns

The data-driven approach for identification, characterization and prediction of traffic flow patterns is based on a modular framework for sequential application of machine learning techniques. Fig. 3 provides a high-level description of the framework. In a first step, a multi-layer clustering analysis is performed to identify and characterize traffic flow patterns from historical flight tracks. For this, flight tracks are first clustered at the spatial dimension in order to identify spatial trajectory patterns, which define the as-flown route structure. Based on this knowledge, a trajectory classification scheme is developed to match new flight trajectories with the learned airspace structure. Once trajectories are classified, flows are identified as temporally associated flight trajectories conforming to the same standard route. Finally, clustering is performed at the temporal dimension to identify patterns in air traffic flows. Based on the knowledge generated by the multi-layer clustering process, classification techniques are used to predict traffic flow patterns over time. Each module of the framework as well as the datasets used are described in more detail in the following sections.

B. Datasets

1) ETMS/ASDI Radar Tracks: Historical radar tracks from the Aircraft Situation Display to Industry (ASDI) data feed provided by the Federal Aviation Administration (FAA) were used to mine spatial and temporal trends in flight trajectory data for traffic flow pattern identification. The data reports one-minute updates of aircraft state in the U.S. airspace, including flight id, latitude, longitude, altitude, speed, origin airport, destination airport and aircraft type. A set of 69 days from 2013-2015 with high operational variability was used.

2) ASPM Airport Reports: In order to enable the analysis and characterization of traffic flow patterns, airport reports ("Airport Information" and "Airport Efficiency Information") from the Federal Aviation Administration (FAA) Aviation System Performance Metrics (ASPM) database for the same period were used to obtain data about active runway configuration, arrival and departure demand/throughput and actual observed weather conditions (wind speed and direction, ceiling and visibility) on an hourly basis.

3) TAF Reports: Terminal Aerodrome Forecast (TAF) reports were used to obtain weather forecast data for traffic flow pattern prediction. The TAF is a concise weather report that states the expected meteorological conditions at an airport during a specified period of time (usually 24 hours). The TAF is routinely issued every 6 hours (at 0, 6, 18 and 24 UTC), but an amended TAF can also be issued at any time if the expected meteorological conditions significantly change. The following weather variables were extracted from TAF: wind direction, wind speed, visibility and ceiling (lowest height of broken or overcast cloud layer). For any given hour, the most recent TAF was considered and the weather features corresponding to the desired forecast horizon were extracted for prediction.

C. Clustering at Spatial Scale: Trajectory Clustering

A flow can be identified when a group of aircraft exhibits the same spatial pattern within the same time interval. In this module, a trajectory clustering scheme is developed to identify spatial patterns of aircraft movement as the first step towards flow identification. Clustering is an unsupervised learning method that aims to identify groups of similar observations in a dataset without prior knowledge about the existence of these groups or about how the observations are distributed among them. In the trajectory clustering problem, the goal is to find groups of similar trajectories in the spatial dimension, which are referred to as a *trajectory patterns*.

D. Trajectory Classification

In this module, a trajectory classification scheme is developed to match new flight trajectories with the airspace structure identified in the previous module. The purpose of the trajectory classification module is two-fold: 1) given the computational effort associated with the trajectory clustering process, the classification procedure provides a more efficient way for processing large sets of trajectory data for spatial pattern identification; 2) it is key for the online implementation of the framework, as it enables to consistently process new batches of trajectory data continuously generated by the surveillance system.

Classification is a supervised learning method that aims to predict the class of an observation given a set of predictors based on prior knowledge extracted from a training dataset. In the trajectory classification problem, the classes are defined by the trajectory patterns learned with the spatial clustering analysis. Given a new flight trajectory defined by its vector of spatial position, the goal is to predict the trajectory pattern that it most likely conforms to.

The output of the trajectory classification is organized and stored in daily flow matrices $W \in \mathbb{R}^{n \times p}$, with n rows representing the trajectory patterns and p columns representing the time periods. Each matrix element w_{ij} indicates the number of trajectories conforming to trajectory pattern i during time period j. A flow is identified whenever $w_{ij} > 1$. The matrix columns are vectors $\{R_t \in \mathbb{R}^n, t = 1, \ldots, p\}$ that indicate the time-dependent traffic flows.

E. Clustering at Temporal Scale: Time-Dependent Flow Vector Clustering

A second-layer clustering analysis at temporal scale is performed in the third module of the framework to identify temporal patterns in air traffic flows. The vector of time-dependent traffic flows R_t is transformed to a time-dependent characteristic flow vector $FV_t = f(R_t)$ to represent the traffic flow structure during each particular time period. The flow vectors FV_t are clustered to find patterns in the traffic flow structure, which are referred to as *traffic flow patterns*.

F. Traffic Flow Pattern Classification

Finally, in the last module, the knowledge generated by the second-layer clustering analysis is used to develop a classification scheme for prediction of traffic flow patterns.

IV. Identification of Trajectory Patterns

Trajectory clustering was first performed to identify spatial trajectory patterns and learn the metroplex terminal area route structure. To reduce the computational effort, the trajectory clustering analysis was performed on a subset of the data composed of flight tracks for sixteen days.

As any typical clustering process, the trajectory clustering analysis required a trajectory representation, a distance function to assess the similarity between trajectories and a method for clustering similar trajectories.

The raw flight tracking dataset is composed of time-series of aircraft position sampled every minute from the origin to the destination airport. First, the terminal area phase of each trajectory was extracted by filtering the aircraft positions inside a circle of 60-mile radius with center at the airport. The filtered flight trajectories are characterized by time-series of different lengths, depending on the time spent in the terminal area. A data resampling was performed to transform each time-series into a high-dimensional feature vector of fixed dimension. The resampling approach normalizes the time stamps for each trajectory into the interval $\tau = [0, 1]$, divides τ into a fixed number of equally sized time intervals and linearly interpolates the spatial position for the fixed number of normalized time stamps in τ. Each trajectory is then represented with a high-dimensional feature vector of 2D spatial position evenly spaced in time: $F_i = (x_{i1}, y_{i1}, x_{i2}, y_{i2}, \ldots, x_{in}, y_{in})$.

To allow each feature of the trajectory vector to equally contribute to the distance measure, the trajectory vectors were standardized so that each individual dimension was centered to have mean 0 and scaled to have standard deviation 1. With trajectory vectors of equal dimension and standardized, Euclidean distance was used to assess the similarity between flight trajectories.

Finally, a density-based clustering algorithm – DBSCAN [39] (Density-Based Spatial Clustering of Applications with Noise) – was used for flight trajectory clustering. As the name of the algorithm suggests, this method is suitable for datasets with background noise. In general, datasets are composed of a structured part (from which the underlying patterns are expected to be extracted) and an unstructured part (usually labeled noise or outlier). In these cases, in order to be able to produce reasonable clusters, the clustering process should take into account the existence of this unstructured portion either by applying noise detection algorithms prior the clustering or using algorithms that automatically handles noise. Flight trajectory datasets are such a case. The existence of standard routes/procedures produces a natural concentration of trajectories around them. However, abnormal trajectory profiles can also occur for a variety of reasons and can be considered noise. DBSCAN enables the identification of the core trajectory patterns in the presence of abnormal trajectory profiles. Other advantages of DBSCAN include the ability to discover non-convex clusters and no need to set the number of clusters a priori.

DBSCAN relies on two input parameters in order to cluster the data space:

- *MinPts*: a minimum number of points (observations);
- ε: a distance threshold.

Using these parameters, the algorithm is built on the three following fundamental concepts:

1) ε-Neighborhood: The ε-neighborhood of an observation F_i in a dataset D contains all the neighboring observations that are within a distance ε and is defined in (1).

$$N_\varepsilon(F_i) = \left\{F_j \in D / d\left(F_i, F_j\right) \le \varepsilon, d\left(F_i, F_j\right) = \left\|F_i - F_j\right\|_2\right\} \quad (1)$$

2) Density-Reachability: An observation F_j is directly density-reachable from an observation F_i if $F_j \in N_\varepsilon(F_i)$ and $N_\varepsilon(F_i) \ge MinPts$ (core point condition). An observation F_j is density-reachable from an observation F_i if there exists a chain $F_i, \ldots, F_j$ such that each observation is directly density-reachable from the predecessor.

3) Density-Connectivity: An observation F_j is density-connected to an observation F_i if there exists another observation F_k such that both F_j and F_i are density-reachable from F_k. A cluster is then defined as a set of density-connected observations.

The clustering process using DBSCAN was performed separately for each airport and for each type of operation

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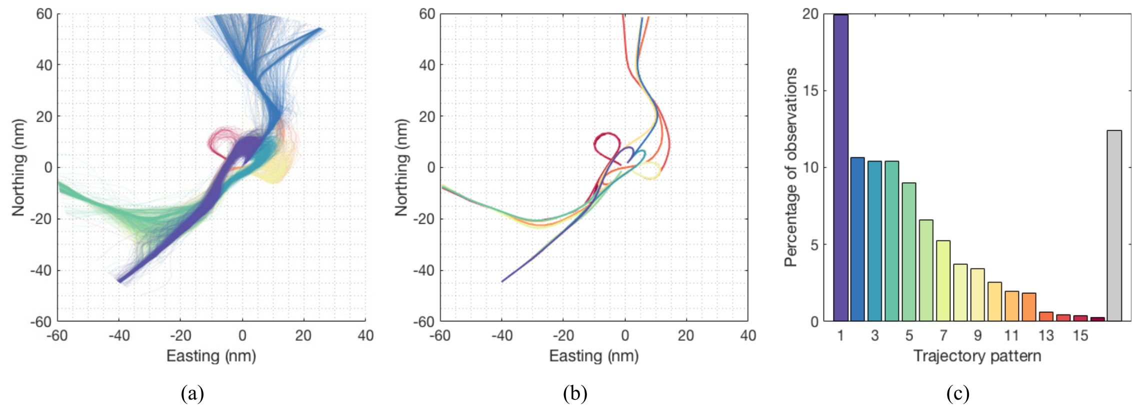

Fig. 4. Spatial clustering results for LGA arrival trajectories. (a) Clusters of arrival trajectories (trajectory patterns); each color represents one cluster. (b) Cluster centroids. (c) Percentage of observations by trajectory pattern (grey color represents non-conforming noise trajectories).

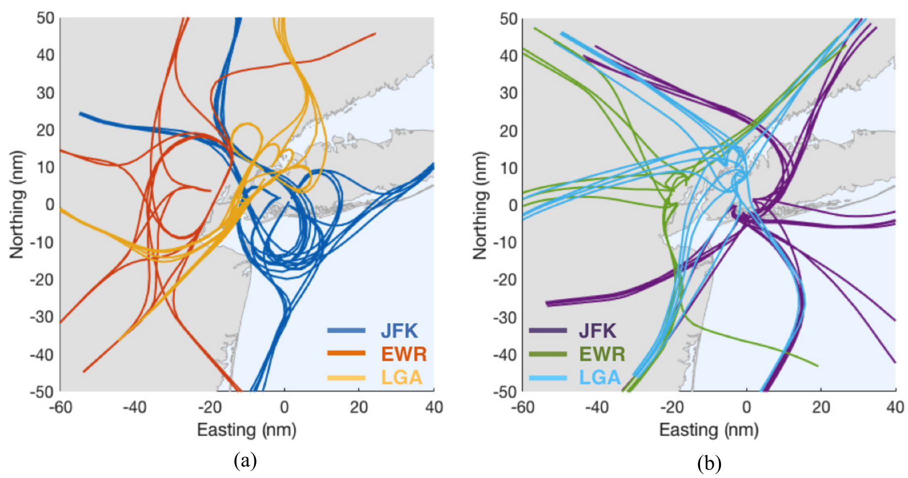

Fig. 5. (a) Centroids of arrival trajectory patterns for JFK, EWR and LGA. (b) Centroids of departure trajectory patterns for JFK, EWR and LGA.

(arrival or departure). In order to tune the parameters of the algorithm, quantitative evaluation of clustering quality using validity indices (Silhouette plots [40]) and visual inspection were used on a case-by-case basis.

As an example, the results of the trajectory clustering analysis for LGA arrival trajectories are shown in detail in Fig. 4. Sixteen trajectory patterns were identified; they are displayed with different colors in Fig. 4(a). The cluster centroids are displayed in Fig. 4(b). Finally, Fig. 4(c) shows the percentage of trajectories within each trajectory pattern. The identified as-flown route structure reveals that flights towards LGA are delivered to the terminal area by three major arrival gates and travel through three major channels that are split very close to the airport as a consequence of the maneuvers towards the different runway thresholds.

The trajectory clustering results for the multi-airport system are synthesized in Fig. 5. Fig. 5(a) shows the centroids of the arrival trajectory patterns learned for the three New York airports, and Fig. 5(b) shows the centroids of the departure trajectory patterns. It is possible to identify four major arrival areas by which arrival flights are delivered to the terminal area and five major departure areas. It is also observed a high number of route crossings potentially leading to flow interactions between the airports.

V. Identification and Characterization of Metroplex Flow Patterns

Once the metroplex airspace structure was identified, Random Forests [41] classifiers were created to discriminate the trajectory patterns for each type of operation (arrival/departure) at each airport. All trajectory classifiers showed multi-way classification accuracy higher than 98%. The classifiers were used to assign trajectories in the remaining dataset (not used for spatial clustering) to the learned routes. Flow matrices were then created for each day of operations, as explained in Section III.D.

In order to investigate the presence of patterns in the metroplex terminal area flow behavior, we performed a second-layer clustering analysis on the set of time-dependent traffic flows R_t. For this, a data representation was established for the time-dependent metroplex flow structure. The columns $\left\{\left(R^{m,Arr}\right)_t \in \mathbb{R}^{|\mathrm{K}^{m,Arr}|}, t = 1, \ldots, p\right\}$ and $\left\{\left(R^{m,Dep}\right)_t \in \mathbb{R}^{|\mathrm{K}^{m,Dep}|}, t = 1, \ldots, p\right\}$ of the daily arrival and

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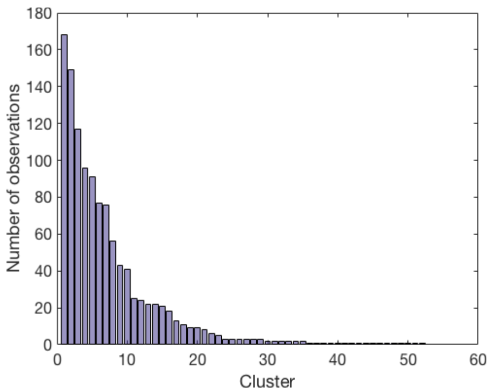

Fig. 6. Number of observations in each cluster of hourly flow vectors identified.

departure flow matrices of each metroplex airport m were aggregated into flow vectors to represent the hourly terminal area flow structure in the metroplex:

$$\left\{FV_t = \left(\left(C_i^{m,Arr}\right)_t, \left(C_j^{m,Dep}\right)_t\right), m \in \mathcal{M}, i \in A, j \in D, \quad t = 1, \ldots, p\right\}$$

with:

$$\left(C_i^{m,Arr}\right)_t = \begin{cases} \underset{k \in \mathrm{K}_i^{m,Arr}}{\operatorname{argmax}} \left\{\left(R_k^{m,Arr}\right)_t\right\}, & \text{if } \underset{k \in \mathrm{K}_i^{m,Arr}}{\max} \left\{\left(R_k^{m,Arr}\right)_t\right\} > 1 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$\left(C_j^{m,Dep}\right)_t = \begin{cases} \underset{k \in \mathrm{K}_j^{m,Dep}}{\operatorname{argmax}} \left\{\left(R_k^{m,Dep}\right)_t\right\}, & \text{if } \underset{k \in \mathrm{K}_j^{m,Dep}}{\max} \left\{\left(R_k^{m,Dep}\right)_t\right\} > 1 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where $\mathcal{M}$ is the set of metroplex airports, A is the set of arrival gates in the terminal area boundary, D is the set of departure gates, $\mathrm{K}_i^{m,Arr} \subset \mathrm{K}^{m,Arr}$ is the set of arrival trajectory patterns between arrival gate $i \in A$ and airport $m \in \mathcal{M}$, and $\mathrm{K}_j^{m,Dep} \subset \mathrm{K}^{m,Dep}$ is the set of departure trajectory patterns between airport $m \in \mathcal{M}$ and departure gate $j \in D$. Arrival/departure gates are defined as zones in the terminal area boundary intersected by a group of trajectory patterns.

It follows that the hourly flow vector FV_t is a categorical vector of dimension $|\mathcal{M}|\,|\mathrm{A}| + |\mathcal{M}|\,|\mathrm{D}|$ and indicates the dominant arrival flows from each arrival gate to each airport and the dominant departure flows from each airport to each departure gate.

Hierarchical clustering was applied under a complete linkage agglomerative approach for clustering the set of hourly flow vectors. The Hamming distance was used to assess the similarity between the categorical flow vectors and it corresponds to the number of elements in which they differ.

TABLE I

DESCRIPTION OF MAJOR NEW YORK METROPLEX FLOW PATTERNS

MFP		Description
South Flow Arrival Priority (*South-AP*)	1	- South landing flow configuration at all airports; - Favors arrival operations; - Right-hand arrival traffic pattern at LGA determined by departure configuration (runway 13); - Primarily observed during VMC.
	9	- South landing flow configuration at all airports; - Favors arrival operations; - Left-hand arrival traffic pattern at LGA determined by departure configuration (runway 31); - Primarily observed during VMC.
	4	- South landing flow configuration at all airports; - Favors arrival operations; - Right-hand arrival traffic pattern at LGA determined by departure configuration (runway 13); - Primarily observed during IMC; - Multiple climbs from runway 13 at LGA with Coney Airspace release.
South Flow Departure Priority (*South-DP*)	2	- South landing flow configuration at all airports; - Favors departure operations; - Right-hand arrival traffic pattern at LGA determined by departure configuration (runway 13); - Primarily observed during VMC ; - Restricted climbs from runway 13 at LGA.
	3	- South landing flow configuration at all airports; - Favors departure operations; - Left-hand arrival traffic pattern at LGA determined by departure configuration (runway 31); - Primarily observed during VMC.
North Flow Arrival Priority (*North-AP*)	6	- North landing flow configuration at all airports; - Favors arrival operations; - Primarily observed during IMC; - Multiple climbs from runway 13 at LGA with Coney Airspace release.
	7	- North landing flow configuration at all airports; - Favors arrival operations; - Visual approach at LGA runway 31; - Primarily observed during VMC.
	10	- North landing flow configuration at all airports; - Favors arrival operations; - Instrument approach at LGA runway 31; - Primarily observed during IMC.
North Flow Departure Priority (*North-DP*)	11	- North landing flow configuration at all airports; - Favors departure operations; - Visual approach at LGA runway 31; - Primarily observed during VMC.
	12	- North landing flow configuration at all airports; - Favors departure operations; - Primarily observed during VMC; - Restricted climbs from runway 13 at LGA.
Mixed Flow Arrival Priority (*Mixed-AP*)	5	- Mixed flow configuration with south landing flow dominance (EWR and LGA); - Favors arrival operations; - Primarily observed during VMC.
	8	- Mixed flow configuration with north landing flow dominance (JFK and LGA); - Favors arrival operations; - Primarily observed during VMC.

In this case, zero entries indicate absence of flow between the arrival/departure gate and the airport and were disregarded during the computation of the Hamming distance.

The resulting partitioning of the dataset is shown in Fig. 6. It is noticeable that few clusters dominate and capture the majority of the observations, revealing the primary operational modes of the metroplex. A cluster of similar flow structures is referred to as a *Metroplex Flow Pattern* (MFP). A detailed characterization of the dominant MFPs was performed in order to obtain insights about some of the factors that drive the behavior of the metroplex flows. For this, we considered the

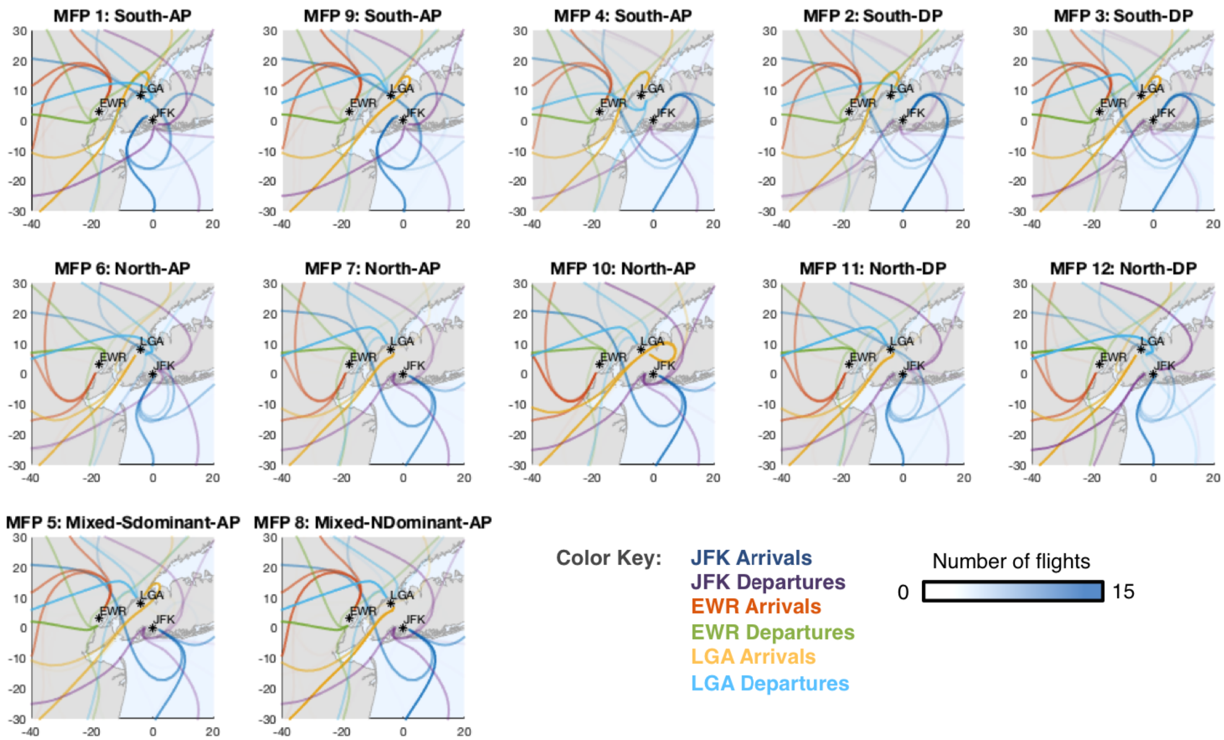

Fig. 7. Major New York metroplex flow patterns.

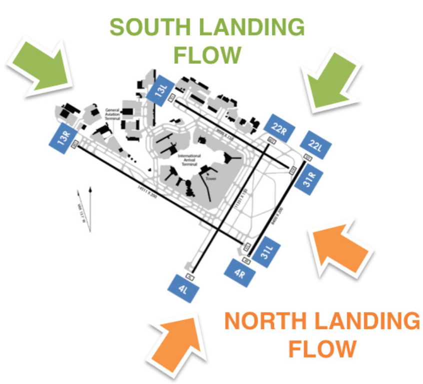

Fig. 8. Convention on flow direction.

TABLE II

MOST FREQUENTLY OBSERVED RUNWAY CONFIGURATIONS AT JFK, EWR AND LGA BY MFP

<table>
<tr><th rowspan="2">MFP</th><th colspan="3">RUNWAY CONFIGURATION</th></tr>
<tr><th>JFK</th><th>EWR</th><th>LGA</th></tr>
<tr><td>1</td><td>13L, 22L | 13R</td><td>22L | 22R</td><td>22 | 13</td></tr>
<tr><td>2</td><td>22L, 22R | 22R, 31L</td><td>22L | 22R</td><td>22 | 13</td></tr>
<tr><td>3</td><td>22L, 22R | 22R, 31L</td><td>22L | 22R</td><td>22 | 31</td></tr>
<tr><td>4</td><td>22L, 22R | 22R</td><td>22L | 22R</td><td>22 | 13</td></tr>
<tr><td>5</td><td>31L, 31R | 31L</td><td>22L | 22R</td><td>22 | 31</td></tr>
<tr><td>6</td><td>4L, 4R | 4L</td><td>4R | 4L</td><td>4 | 13</td></tr>
<tr><td>7</td><td>31L, 31R | 31L</td><td>4R | 4L</td><td>31 | 4</td></tr>
<tr><td>8</td><td>31L, 31R | 31L</td><td>22L | 22R</td><td>31 | 4</td></tr>
<tr><td>9</td><td>13L, 22L | 13R</td><td>22L | 22R</td><td>22 | 31</td></tr>
<tr><td>10</td><td>31L, 31R | 31L</td><td>4R | 4L</td><td>31 | 4</td></tr>
<tr><td>11</td><td>4L, 4R | 4L, 31L</td><td>4R | 4L</td><td>31 | 4</td></tr>
<tr><td>12</td><td>4L, 4R | 4L, 31L</td><td>4R | 4L</td><td>4 | 13</td></tr>
</table>

top twelve MFPs that account for 85% of the observations. Fig. 7 shows the different uses of the airspace structure associated with each dominant MFP; specifically, it shows the average number of aircraft within each spatial trajectory pattern. The detailed characterization of the New York MFPs is presented in Table I.

The most patent factor driving the behavior of the metroplex flows is the runway configuration in use at each airport. Five MFPs were characterized as south flow (which means that all airports operate in a south landing flow configuration), five MFPs were characterized as north flow and two MFPs were characterized as mixed of north and south flows (Fig. 8 illustrates the convention about landing flow direction using JFK as an example). It is noticeable the tendency of alignment between runway configurations across the airports. Table II lists the most frequently observed runway configuration for each MFP. They are designated in the form "A | B", where A indicates the arrival runways and B indicates the departure runways.

Besides the runway configuration, some differences are also driven by the airspace configuration in terms of the delegation of airspace regions that are shared. For instance, MFPs 2 and 4 are characterized by the same runway configuration at LGA. However, restricted climb procedures from runway 13 are observed for MFP 2. Analysis of current operating procedures reveals that whenever JFK uses runway 31L for departures, it remains with control of a shared airspace volume called Coney airspace, restricting the use of multiple climbs by LGA. This fact also explains the differences between MFP 6 and 12.

Fig. 9 shows that the time of day is an important variable determining the occurrence of MFPs. An an example, MFPs 1 and 4 are more likely to be observed in the afternoon

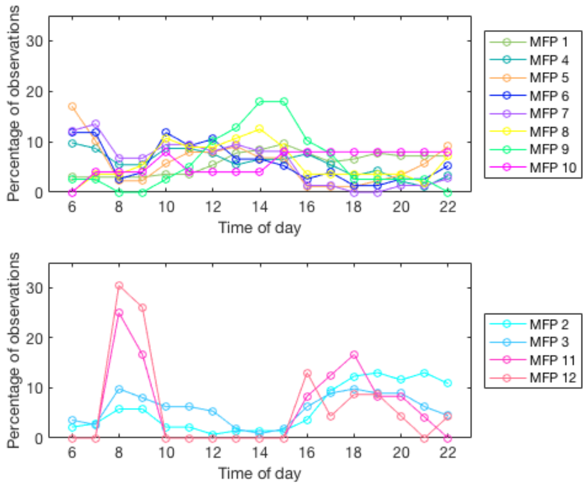

Fig. 9. MFP frequency of occurrence by time of day.

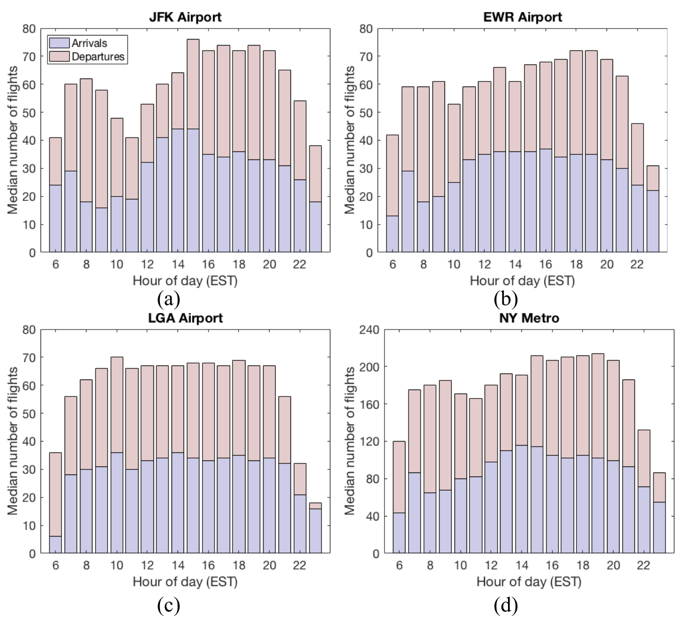

Fig. 10. Daily demand patterns, based on ASPM data from years 2013-2015. (a) JFK. (b) EWR. (c) LGA. (d) New York metroplex.

period, whereas MFPs 2 and 3 have a higher percentage of observations in the morning and evening periods. This was observed to be correlated with the daily demand profile in the New York metroplex. Analysis of the daily demand patterns reveals the existence of banks of arrivals in the afternoon, primarily driven by JFK and EWR demand profiles, and departures in the morning, as shown in Figure 10. Indeed, this demand profile, with unbalanced mix, is one important factor that drives the selection of runway configuration at these airports in order to favor arrival or departure operations. Figure 11 shows the distribution of arrival and departure throughput with a boxplot for each MFP. A clear imbalance is observed. MFPs 1, 4, 5, 6, 7, 8, 9 and 10 tend to favor arrival operations (third quartile was used for comparison). Indeed, they are more frequently observed in the afternoon period. By contrast, MFPs 2, 3, 11 and 12 tend to favor

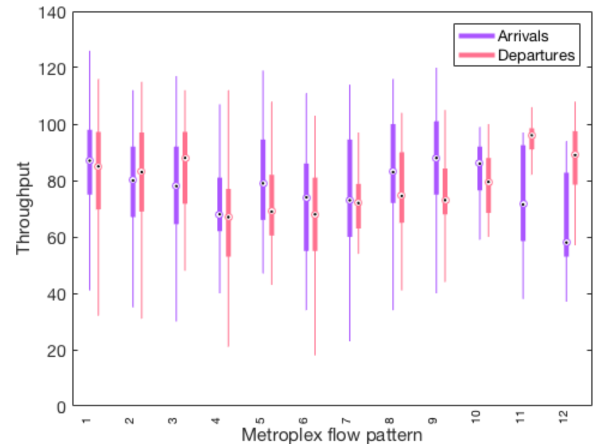

Fig. 11. Distribution of metroplex arrival and departure throughput by MFP.

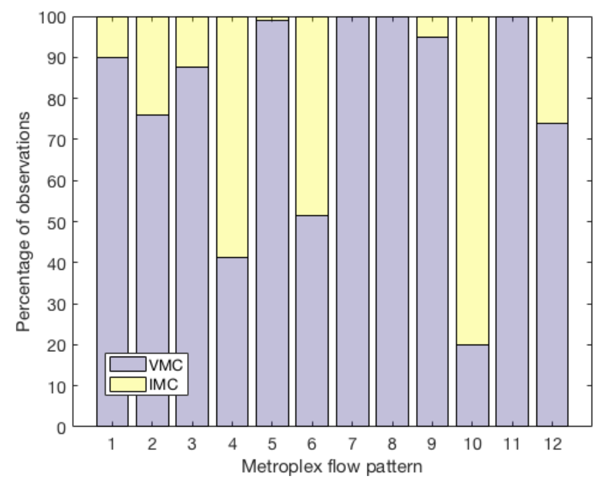

Fig. 12. MFP frequency of occurrence under VMC and IMC.

departure operations, and they are more frequently observed in the morning and evening periods.

Finally, it is also observed a particular influence of meteorological conditions in the operational mode in the New York metroplex. Figure 12 shows, for each MFP, the percentage of observations associated with periods of visual (VMC) and instrument meteorological conditions (IMC). For instance, MFPs 4, 6 and 10 are more likely to be observed during IMC. MFP 10 has 80% of its observations associated with periods of IMC. If we contrast MFP 10 and MFP 7, which was only observed during VMC, it is noted that the major difference between these two MFPs is determined by the LGA arrival flows: in MFP 7, they are tailored to a visual approach to runway 31, whereas a long and straight Instrument Landing System (ILS) approach to the same runway is noticeable in MFP 10. In other words, part of the New York metroplex behavior is driven by the existence of multiple routes tailored to the approach procedure, with use governed by meteorological conditions.

VI. Prediction of Metroplex Flow Patterns

The multi-layer clustering analysis enabled the identification of the dominant modes of operation in the metroplex, revealing recurrent utilization patterns of airport runway configurations and arrival/departure route structure as well as some of their key intervening factors. From this knowledge, a multi-way classification scheme was developed to predict the most likely pattern in which the metroplex flows might be for strategic time horizons. From an operational perspective, such information could be used to inform various air traffic management decisions. First, traffic managers could directly use the predictions for runway/airspace configuration planning. Additionally, given an anticipated complex metroplex configuration change and a temporary loss of throughput, tactical TMIs could be better planned to control the influx of flights into the terminal area and obtain more smooth transitions. Higher predictability of metroplex configuration changes and of required staff and coordination efforts between the airports could also lead to better resource allocation planning. As runway/airspace configuration changes generate significant increase in workload, if predictable, they could be considered in the assignment of air traffic controller shifts to achieve a more even workload distribution. Finally and mostly emphasized in this paper, as the metroplex configuration is a major driver of individual airport capacity, predicting their use is key for better predicting future flow rates and determining strategic TFM plans. This aspect is further discussed in Section VII. Given the potential operational benefits at both tactical and strategic time frames, an eight-hour planning horizon was considered for predictive performance evaluation.

Based on the characterization described in Section V, the following set of predictive features was used:

- Time of day;
- Meteorological conditions at each airport (VMC = 0 and IMC = 1);
- Wind speed and direction at each airport;
- Scheduled arrival and departure demand for the metroplex;
- Current flow pattern at the beginning of the planning horizon.

The data was randomly partitioned into a training dataset composed of approximately 70% (48 days) of the observations and a test dataset composed of 30% (21 days). Three candidate multi-way classification models were trained for traffic flow pattern prediction using different machine learning algorithms: Random Forests (RF), Support Vector Machines (SVM) and Multinomial Logistic Regression (MLR). For SVM, the multi-way classification was performed with an ensemble of binary learners using a one-versus-one encoding. Fig. 13 shows the prediction accuracy achieved by each model during 5-fold cross validation. The Random Forests model showed a slightly better predictive performance, and was therefore chosen for traffic flow pattern prediction.

In order to have useful predictions for decision-making under uncertainty, probabilistic forecasts are generated for each time period throughout the planning horizon. For this, Bayes' rule is sequentially applied: for the first hour, the prediction model is run and a probability for each MFP is obtained; for the subsequent hours in the forecast horizon, the prediction model is run assuming a given outcome for

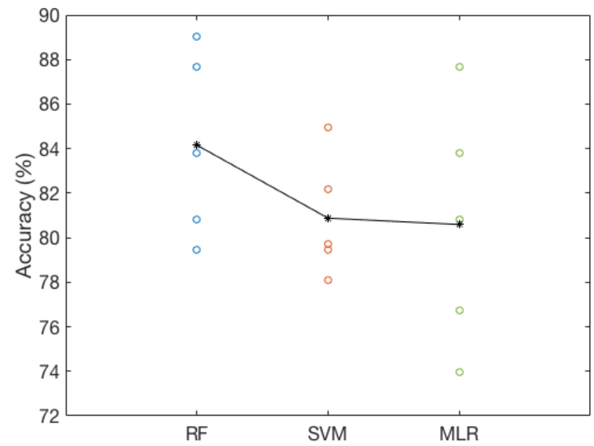

Fig. 13. Prediction accuracy by classification model for 1-h look-ahead time.

the previous hour and the final probability is computed conditioned on the probability of the assumed outcome for the previous hour. For each hour t, the predicted flow pattern y_t^* then corresponds to the feasible one with maximum probability p_t among all N flow patterns, as shown in (4) and (5):

$$y_t^* = \arg\max_x \left\{p_{t,x}\right\} \tag{4}$$

where:

$$p_{t,x} = \sum\nolimits_{n=1}^{N} p\left(y_t = x / y_{t-1} = n\right) \cdot p_{t-1,n} \tag{5}$$

The feasibility of each MFP is determined based on crosswind and tailwind thresholds derived statistically from the data. Specifically, these thresholds represent the 99$^{\text{th}}$ percentile of the observed crosswind and tailwind values on the major arrival/departure runways at each airport. For any given time, a MFP is considered to be feasible if the crosswind and tailwind values on the corresponding runways do not exceed the statistically derived thresholds.

Fig. 14 shows the overall prediction accuracy of the model on the test dataset throughout a planning horizon of eight hours based on ten independent model runs. The mean accuracy was 83% for a short-term 1-hour forecast, 63% for a 3-hour forecast and stabilized at about 52% for longer look-ahead times. For comparison, Fig. 14 also shows the prediction accuracy obtained with a static model that assumes the flow pattern observed at the beginning of the planning horizon remains throughout the entire planning horizon. It is observed that, for short look-ahead times, the Random Forests model outperforms the static model only by a small amount, revealing that the current flow pattern carries most of the predictive power for short-term predictions. Indeed, there is a lot of inertia in the runway/airspace configuration selection process since changes can generate a significant increase in workload. Therefore, a given flow pattern is expected to be seen until conditions turn it operationally infeasible. As the prediction horizon increases, the likelihood that current conditions will remain decreases and inertia starts to have a smaller impact (changes become necessary). The Random Forests model better predicts these changes as the gap between the models increases with the prediction horizon.

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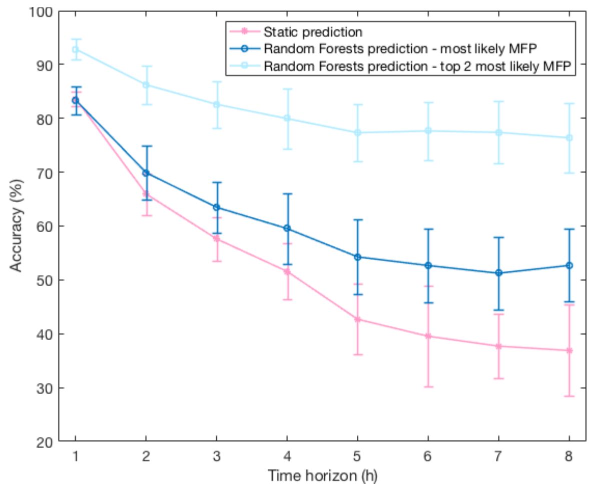

Fig. 14. Prediction accuracy as a function of look-ahead time.

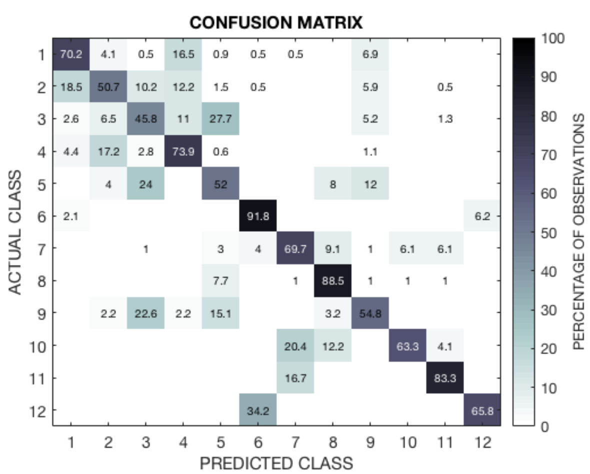

Fig. 15. Classification confusion matrix for 3-h look-ahead time.

Fig. 14 also shows the prediction accuracy obtained if the top two most likely flow patterns in the probabilistic forecast are considered instead of just the most likely one. For longer time horizons, the accuracy stabilizes at about 77%. The result indicates that, for many instances in which the model incorrectly predicted the MFP, it was right on the second best option, emphasizing the value of the probabilistic forecast. Indeed, the classification confusion matrix for a 3-h forecast horizon (Fig. 15) reveals the majority of the incorrect predictions occurred because of confusion between very similar flow patterns, especially for the south flow patterns and because of incorrect prediction of JFK flows.

VII. Empirical Approach for Metroplex Capacity Estimation

While predicting traffic flow patterns can be directly used to inform metroplex configuration planning, knowledge about their operational performance is required to inform capacity management.

Capacity generally refers to an upper bound on the allowable throughput of a facility. Two common definitions of capacity are the *maximum throughput capacity* (or *saturation capacity*) and the *practical throughput capacity* [43]. The *maximum throughput capacity* is defined as the expected number of movements under persistent demand. The *practical throughput capacity* extends this definition by including the notion of level of service and specifying a threshold on the expected level of delay experienced by the users of the facility. It recognizes that a certain level of delay should be acceptable in order to ensure a steady stream of demand at the facility, but it should also be reasonable to ensure a sustainable operation of the facility through time.

In this paper, we developed an empirical approach for extracting capacity information from historical flow pattern performance. Rather than treating each airport in isolation, metroplex airports are looked from a systems perspective. Besides, by analyzing both throughput and delay performance, we provide means for assessing both maximum and practical capacity. The proposed empirical approach is based on the estimation of airport performance curves that correlate flow rates and level of delay (excess transit time) in the terminal area for each metroplex configuration.

We formalize the airport throughput estimation problem as a regression problem. Based on the observed system behavior, the arrival throughput was modeled with a non-decreasing piecewise linear concave function of the arrival demand (number of arriving aircraft in the terminal area), and the excess transit time in the terminal area was modeled with a non-decreasing piecewise linear function of the arrival demand. The parameters of the curves were estimated using quantile regression [44]. The quantile regression problem was formulated as a linear programming model and solved with Gurobi 6.5.0. Different curves were estimated for each MFP. In order to marginalize out weather related throughput impacts and enable a cleaner assessment of MFP performance, the curves were also estimated separately for VMC and IMC observations (performance curves for IMC were only estimated for MFPs observed at least one third of the time under this meteorological condition).

Fig. 16 shows the performance curves obtained with a median regression fit for JFK under each MFP. Fig. 16(a,b) show the arrival throughput (aircraft/15 min) as a function of the number of aircraft in the terminal area under VMC and IMC, and Fig. 16(c,d) show the excess transit times as a function of the number of aircraft in the terminal area under VMC and IMC. It is observed that, as the arrival demand increases, the arrival throughput increases in a disproportionate fashion until reaching a saturation level, i.e., point at which delivering more aircraft to the terminal area does not significantly increase throughput because the system has reached its capacity. This behavior is reflected in the excess transit time curve. When the arrival demand increases, more aircraft are competing for the same resources and will encounter a higher probability of a delay assignment during the runway sequencing and scheduling process. When the saturation level is reached, the excess transit time increases much more rapidly.

While the throughput curves enable to quantify the maximum throughput capacity (inflexion point at which delivering more aircraft to the terminal area will not significantly

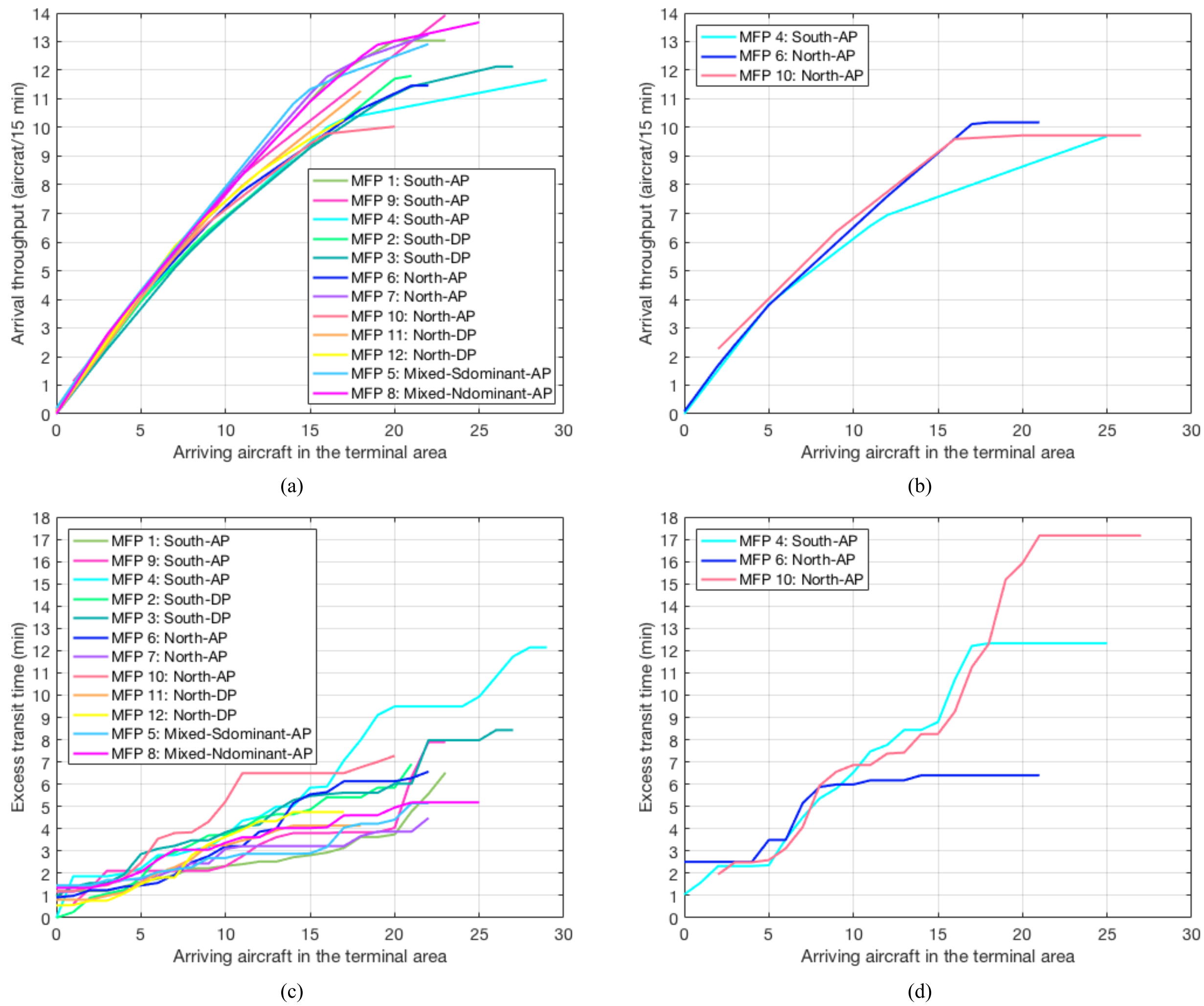

Fig. 16. JFK performance curves by MFP. (a) Throughput-demand curves for VMC. (b) Throughput-demand curves for IMC. (c) Delay-demand curves for VMC. (d) Delay-demand curves for IMC.

increase throughput), the delay curves enable to assess the practical capacity under the perspective of level of service.

In order to exemplify the use of the performance curves for assessing the practical capacity, we obtained, for each MFP, the airport arrival rates corresponding to a specific level of service of 4-minute of terminal area delay. The obtained metroplex arrival rates are shown in Fig. 17. They are compared with baseline metroplex arrival rates obtained by summing the individual airport arrival rates (AAR) reported by the FAA [45] for the runway configurations associated with each MFP.

The comparison reveals that, for some MFPs, the differences between the empirical and the baseline rates are large, indicating that higher levels of delay should be expected when the New York system is operating at the declared capacity under these operational modes. From a practical perspective, this knowledge could be leveraged to better regulate the traffic into the terminal area and avoid more costly reactive actions inside the terminal area when low throughput performing configurations are predicted to be used.

A second observation is that the empirical approach captured operational performance impacts caused by weather;

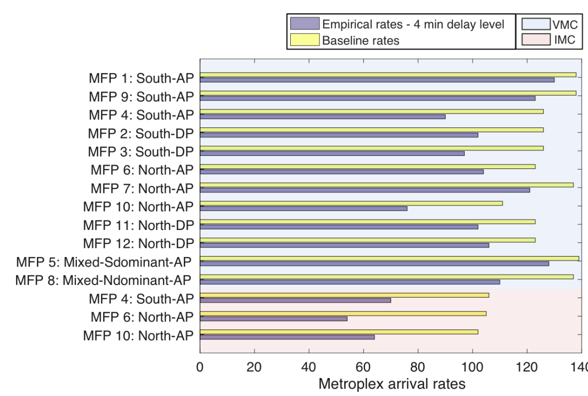

Fig. 17. Metroplex arrival rates by MFP.

IMC rates were systematically lower than VMC rates. Quantification of these throughput impacts is key for the setting of weather-related strategic TMIs.

Finally, it is also observed that MFPs with the same theoretical runway system capacity can show very different throughput performance. For instance, MFPs 2, 3 and 4 have the same declared runway system capacity, but the differences in metroplex practical capacity can be as great as 15 aircraft per hour. The results highlight the impacts of the terminal area flow structure on the multi-airport system capacity and emphasize the importance of taking a systems perspective for metroplex airport capacity and traffic flow management.

VIII. Conclusion

The planning of airport/airspace capacity is a challenging decision-making process accomplished by traffic managers during daily operations. Flow rate predictions are required to determine TMIs to regulate the traffic and mitigate delays, but they depend on a number of factors/decisions with very dynamic and uncertain profiles. Multi-airport systems impose additional complexity in the planning process because of significant inter-airport operational dependency.

This paper presents a data-driven framework to identify, characterize and predict traffic flow patterns in the terminal area of multi-airport systems towards improved capacity and flow management decision support. A "reverse-engineering" approach is taken in order to identify the major configurations in which a metroplex collectively operates from observed traffic flow patterns, and, from that knowledge, develop descriptive models for metroplex configuration prediction and flow rate estimation. The framework is demonstrated for the New York metroplex in this study. Although the discussion is focused on the U.S. National Airspace System, it should be mentioned the methodology is generalizable and can be applied to any multi-airport system in the world.

The data-driven framework is based on a sequential application of machine learning methods on historical flight tracks, weather forecasts and airport operational data. A multi-layer clustering analysis is performed to mine spatial and temporal trends in flight trajectory data for traffic flow pattern identification. Based on this knowledge, a multi-way classification model is developed using Random Forests to generate probabilistic forecasts of the metroplex flow pattern for an eight-hour planning horizon.

For the New York multi-airport system, the classification model showed an average prediction accuracy of 83% for a short-term 1-hour forecast, 63% for a 3-hour forecast, and 52% for longer look-ahead times. Despite the diminishing accuracy for long-term forecasts, it showed higher performance when compared with a static model that only considers the current flow pattern to predict the next hours. For an eight-hour forecast horizon, the performance gap was 16%. The classification confusion matrix revealed that most of the incorrect predictions occurred for very similar flow patterns, especially because of confusion about the JFK flows. Indeed, by using the probabilistic forecast to determine the top two most likely flow patterns, the prediction accuracy was 93% for a 1-hour horizon and stabilized at about 77% for longer look-ahead times, revealing an exciting potential in the use of the probabilistic forecast to inform runway and airspace configuration related decisions.

Finally, an empirical approach for arrival capacity estimation is proposed based on airport performance curves derived from historical traffic flow pattern behavior. Rather than treating each airport individually, metroplex airports are looked from a systems perspective and capacity is empirically assessed from realized operations and historical terminal area performance. The results revealed significant variability in throughput and delay performance for different metroplex configurations, emphasizing the importance of anticipating the behavior of the metroplex as a system when forecasting individual airport capacity. Future research goes along this direction by exploring the development of higher-fidelity models for airport capacity prediction that take as input detailed weather information and metroplex configuration forecasts in order to deliver probabilistic capacity forecasts for strategic TMI planning.

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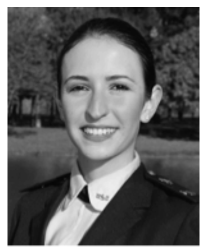

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